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The Causal Impact of Fear of Unemployment on Psychological Health

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Arndt Reichert and Harald Tauchmann[1]

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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 Classification: I10, I18, J28

Keywords: Fear of unemployment; mental health; job insecurity; 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 is 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.

We also add 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.

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 the employed with 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 21,000 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 and anxiety disorders (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 somewhat or very concerned about their job security and 0 otherwise), which is used as a proxy for 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 dataset also contains a variable indicating employees who work at a companies which reduced the workforce during the last twelve months. It is used to construct a binary 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 dismissal protection. First, we use a set of dummy variables, capturing firm size, i.e., (i) up to five,

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

(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 lagged income variable takes on the value zero. This, however, is a very crude approximation, which is why we include a dummy variable indicating those employees to whom it applies, i.e., an unemployment indicator in terms of a one-year lag. Further covariates are employability[4], job satisfaction and a variable indicating whether employees work overtime, all also in terms of one period lags. In addition, year and state dummy variables are included.

We only consider employed individuals in the analysis. We further exclude conscripts, the self-employed, and public servants because these groups cannot be laid off and, thus, are likely to behave differently. 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). Public sector employees are also excluded from the analysis because they 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 show.

After excluding these groups of individuals[6] and individuals with missing information, the sample for 2002 consists of 4,928 individual-level observations. 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.

[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 define individuals to be employable if they would easily find an appropriate position.

[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).

[6]The elderly people in our sample (see Table 1) are a few pensioners who hold down a job in order to receive additional income.

Table 1: **Descriptive Statistics**

	Mean	**S.D.**	**Min.**	**Max.**
dependent variable				
MCS	50.192	9.193	5.324	77.774
endogenous regressor: *fear of unemployment*				
concerned about job-security (A_i): *not at all*	0.372	0.483	0	1
somewhat or very concerned	0.628	0.483	0	1
instrument				
staff reductiona	0.243	0.429	0	1
controls				
job satisfaction (lag): low[a]	0.125	0.331	0	1
medium	0.234	0.423	0	1
missing	0.013	0.111	0	1
overtime (lag)	0.509	0.500	0	1
employability (lag)	0.174	0.379	0	1
employability (lag) missing	0.003	0.051	0	1
age (*years*)	40.799	11.227	18	81
male	0.554	0.497	0	1
migration background: direct	0.133	0.339	0	1
indirect	0.048	0.215	0	1
years of education	12.143	2.487	7	18
married	0.633	0.482	0	1
living with partner	0.735	0.441	0	1
household size	2.939	1.257	1	13
number of kids under 18	0.667	0.940	0	9
personal gross income (*1,000 € per month, lag*)	2.571	2.229	0	35
occupation: blue-collar skilled	0.198	0.399	0	1
white-collar low skilled	0.380	0.485	0	1
white-collar high skilled	0.184	0.387	0	1
tenure (*years*)	9.359	9.093	0	49.8
mini job	0.078	0.269	0	1
midi job	0.036	0.186	0	1
temporary work contract	0.116	0.321	0	1
side job	0.055	0.229	0	1
unemployed (lag)	0.087	0.282	0	1
firm size: medium (*6-2,000 employees*)	0.502	0.5	0	1
large (*more than 2,000 employees*)	0.403	0.49	0	1
year 2002	0.233	0.423	0	1
year 2004	0.278	0.448	0	1
year 2006	0.235	0.424	0	1

Notes: Statistics for the sample used for estimating the basic OLS-model (21,158 obs.); cf. Section 4. *a* Statistics for the sample used for estimating the basic OLS-model (16,149 obs.). For the controls, no statistics for reference categories reported.
Source: Own calculations.

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 € 2,570. Most (64 percent) observations are satisfied with their job. The majority works overtime. Only 13 percent of the individuals report that it would be easy for them to find an adequate new job. For comprehensive descriptive statistics, see Table 1.

Regarding the key explanatory variable in 2002, we observe that 45.1 percent of the individuals were at least somewhat and 18.6 percent were very concerned about their job security. In 2004, these shares amounted to 44.2 and 16.6 percent, in 2006 to 44.5 and 17.4, and in 2008 to 45.7 and 18.9 percent. The mean *MCS* among employees who were not concerned about their job security amounted to 52.1. In contrast, for employees who were concerned about their job security, the corresponding figure was 49.1. This difference indicates that job worries worsen mental health – 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. 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:

$$MCS_{it} = X1_{it}\beta_{A1} + X2_{i}\beta_{A2} + J1_{it}\delta_{A1} + J2_{it}\delta_{A2} + A_{it}\gamma_{A} + \mu_i + \nu_t + \epsilon_{it}. \tag{1}$$

$X1_{it}$ is the vector of time-varying personal characteristics including, e.g., the marital status. $X2_i$ is the vector of time-constant personal characteristics including, e.g., the employees' sex. $J1_{it}$ is the vector of time-varying job characteristics and $J2_{it}$ represents tenure. The state (μ_i) and year dummies (ν_t) are included to control for regional fixed effects and time trends. The random error term is represented by ϵ_{it} while γ_A, β_A, and δ_A 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, 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 coefficient γ_A captures the effect of being optimistic. In order to tackle this problem, we re-estimate Equation 1 by regressing the time-demeaned dependent variable on the time-demeaned regressors. For the FE estimation, we exclude the time-constant vector $X2_t$ and vector $J2_{it}$.

3.3 IV and IV-FE estimation

The FE estimate of γ_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) estimation, using staff reduction D_{it} to instrument A_{it}:

$$A_{it} = X1_{it}\kappa_1 + X2_{it}\kappa_2 + J1_{it}\lambda_1 + J2_{it}\lambda_2 + D_{it}\rho + \mu_i + \nu_t + \epsilon_{it}, \tag{2}$$

$$MCS_{it} = X1_{it}\beta_{B1} + X2_{it}\beta_{B2} + J1_{it}\delta_{B1} + J2_{it}\delta_{B2} + \widehat{A}_{it}\gamma_B + \mu_i + \nu_t + \epsilon_{it}. \tag{3}$$

Equation 2 is the instrumental equation, where job insecurity is regressed on the covariates and the instrument. Equation 3 is the structural equation which differs from Equation 1 in that it includes the fitted values of job insecurity $\widehat{A}_{it}$ instead of A_{it}.[7] The 2SLS estimation isolates γ_B from confounding factors if the instrument is valid. Instrument validity presumes that the instrumental variable is uncorrelated with ϵ_{it} conditional on the included covariates (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. To reduce this problem, we control for the employees' employability, job satisfaction and overtime in terms of one period lags.

The instrument validity assumption is not directly testable. Fortunately, we can indirectly assess whether staff reduction operates through other channels than job insecurity. Because 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 model of Equation 2 and Equation 3 for

[7] We correct the variance–covariance matrix by applying the correct mean squared errors. We use the *ivreg2* Stata ado-file (Baum et al., 2002).

public servants. The point estimate (-0.142) is close to zero, yielding 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, consisting of private sector employees, yields a significant and positive coefficient of staff reduction (left part of the table). The corresponding point estimate (-0.773) is five times the size of the point estimate for the sample of public servants. 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 and, for this reason, can serve as a valid instrument for the latter.

Lately, we estimate the 2SLS system with FE.[8] The advantage of IV/FE is that it assures that the instrument is uncorrelated with unobserved time-constant personal characteristics.

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. One results that is robust to the relevant variations of the regression model is 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*.

[8]We use the *xtivreg2* Stata ado-file (Schaffer, 2005).

Table 2: **Estimated Effects on MCS (all available observations)**

	OLS		FE		IV		IV/FE	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
fear of unemployment	-2.697^{***}	0.131	-1.420^{***}	0.175	-5.485^{***}	1.182	-1.819	2.754
job satisfaction (lag): low[a]	-4.809^{***}	0.281	-0.612^{*}	0.323	-4.188^{***}	0.368	-1.058^{**}	0.445
medium[a]	-3.090^{***}	0.153	-0.218	0.184	-2.766^{***}	0.231	-0.270	0.250
overtime (lag)	-1.301^{***}	0.137	-0.363^{**}	0.176	-1.399^{***}	0.159	-0.601^{***}	0.233
employability (lag)[a]	0.144	0.172	0.091	0.224	-0.497	0.322	0.179	0.359
age	0.057^{***}	0.008			0.052^{***}	0.009		
male	2.243^{***}	0.152			2.378^{***}	0.177		
migration background: direct	1.061^{***}	0.191			1.426^{***}	0.234		
indirect	0.150	0.309			0.080	0.357		
years of education	-0.100^{***}	0.033			-0.101^{***}	0.038		
married	0.235	0.208	0.058	0.410	0.118	0.240	-0.352	0.513
living with partner	0.154	0.215	1.307^{***}	0.397	0.377	0.248	1.494^{***}	0.501
household size	0.354^{***}	0.074	-0.015	0.145	0.418^{***}	0.086	0.049	0.184
# of kids under 18	-0.573^{***}	0.099	0.215	0.193	-0.610^{***}	0.113	0.094	0.238
personal income (lag)	-0.017	0.044	-0.195^{**}	0.077	-0.010	0.051	-0.153^{*}	0.092
occupation: blue-collar skilled	0.400^{**}	0.200	1.091^{***}	0.339	0.390^{*}	0.235	1.095^{**}	0.430
white-collar low skilled	0.568^{***}	0.187	0.763^{**}	0.347	0.512^{**}	0.216	0.892^{*}	0.462
white-collar high skilled	0.597^{**}	0.276	1.192^{**}	0.480	0.241	0.332	0.822	0.643
tenure	-0.007	0.008			-0.015	0.010		
mini job	0.006	0.269	-0.055	0.503	-0.425	0.356	0.374	0.679
midi job	0.194	0.361	-0.150	0.457	-0.114	0.399	-0.644	0.527
temporary work contract	0.404^{*}	0.229	0.194	0.304	0.457^{*}	0.265	0.688	0.472
side job	-1.262^{***}	0.283	-0.243	0.429	-1.249^{***}	0.323	-0.127	0.520
unemployed (lag)[a]	2.781^{***}	0.346	0.806^{*}	0.421	1.871^{***}	0.438	0.990^{*}	0.585
firm size: medium	0.239	0.225	0.250	0.415	0.585^{**}	0.274	-0.261	0.536
large	0.167	0.238	0.061	0.484	0.443	0.287	-0.523	0.625
constant	50.671^{***}	0.694			52.067^{***}	0.985		
# of observations	21,158		17,460		16,149		11,511	
joint significance (p-value)	0.000		0.000		0.000		0.000	

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%; robust standard errors computed; [a]missing values set to zero and regressor augmented by 'non-missing' indicator; state and year indicators included.
Source: Own calculations.

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 -2.697 indicates a pretty strong effect of becoming at least somewhat concerned about the individual job security as it corresponds to a shift from the median to the 39th 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 about 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 FE, a highly significant and adverse effect is found.

Since FE fails to address a possible bias that originates from from reverse causality and confounding factors that vary over time, we turn to the IV estimation results. Concerning the instrumental equation (left part of Table A3), staff reduction exhibits the expected positive sign. The test on instrument relevance yields an F-statistic as high as 294.44, dispelling any concern about the instrument being weak. With respect to the controls, we find that age, having a direct migration background, and tenure exhibit the expected negative effect on fear of being laid off. However, we do not observe a significant effect either of being married or of the number of under-age dependents. This result might be explained by people who bear family responsibilities being genuinely more concerned about unemployment but also being particularly well protected by the relevant regulations. Somewhat surprisingly, staff employed at small firms seem to be less concerned about job loss. Moreover, the marginally employed and those who hold a side-job are less worried about being laid off. As expected, white-collar and highly qualified workers feel more secure about their jobs than blue-collar and low-qualified workers.

Turning to the estimate for the effect of fear of unemployment in the structural equation, in accordance with OLS and FE results, it is negative an highly significant. The coefficient, amounting to -5.485, corresponds to a shift from the median to 29th percentile of the distribution of the *MCS* which corresponds to a quite substantial deterioration in the mental health status. The estimated effect size exceeds by far 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 estimation should yield more moderate estimated effects. One possible explanation for this pattern is that the IV 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 loosing 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 approach. In turn, the IV result may primarily rest on individuals of vulnerable mental health.

Finally, we turn to the regression model that combines FE with the 2SLS estimation. Though this model still yields a negative point estimate for the effect of job insecurity, it is not statistically significant. The corresponding standard error is rather large, which is most likely be explained by IV/FE using just a small fraction of the variation in the data to identify the effect of fear of unemployment on mental health. Though it stems from an IV approach, the coefficient is much smaller then the corresponding IV estimate without FE. Hence, the question comes up why IV/FE estimation – though also representing a LATE – apparently estimates a LATE for a different group of individuals than IV without FE does.

In order to shed some light on this, we re-estimate the regression models discussed above using an uniform sample for all four model variants. More precisely, we only use the sample of those observations that effectively drive the IV/FE results. There are only $4,066$ units that exhibit variation in staff reduction over time and, in addition, belong to the greatest subset of

Table 3: **Estimated Effects on MCS (sample of obs. that drive IV/FE results)**

	OLS		FE		IV		IV/FE	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
fear of unemployment	−2.579***	0.311	−1.330***	0.371	−1.645	3.518	−2.382	2.710
job satisfaction (lag): low[a]	−5.231***	0.629	0.053	0.665	−5.369***	0.821	0.062	0.675
medium[a]	−3.032***	0.326	0.251	0.373	−3.136***	0.509	0.276	0.384
overtime (lag)	−1.991***	0.306	−1.249***	0.376	0.593	0.838	−1.247***	0.382
employability (lag)[a]	0.395	0.393	0.666	0.471	−0.861	2.906	0.581	0.522
age	0.034*	0.019			0.035*	0.020		
male	2.165***	0.356			2.143***	0.366		
migration background: direct	0.960**	0.407			0.887*	0.482		
indirect	−0.036	0.682			−0.068	0.694		
other								
years of education	−0.067	0.073			−0.066	0.073		
married	−0.193	0.484	−0.671	0.826	−0.221	0.495	−0.728	0.842
living with partner	0.834	0.511	1.811**	0.858	0.847*	0.512	1.811**	0.838
household size	0.151	0.174	−0.224	0.323	0.140	0.178	−0.224	0.316
# of kids under 18	−0.315	0.220	0.756*	0.428	−0.310	0.219	0.765*	0.418
personal income (lag)	−0.126	0.112	−0.244	0.166	−0.119	0.114	−0.243	0.164
occupation: blue-collar skilled	0.053	0.437	0.735	0.660	0.021	0.453	0.741	0.679
white-collar low skilled	0.138	0.452	1.149	0.787	0.138	0.449	1.133	0.775
white-collar high skilled	0.547	0.613	1.271	1.026	0.564	0.615	1.247	1.029
tenure	0.011	0.018			0.013	0.020		
mini job	−0.405	0.778	2.053	1.396	−0.213	1.020	1.854	1.510
midi job	−0.933	0.979	−0.305	1.039	−0.872	0.995	−0.294	1.058
temporary work contract	0.601	0.599	0.644	0.728	0.579	0.600	0.684	0.733
side job	−1.027	0.700	−0.091	0.947	−0.966	0.726	−0.113	0.908
unemployed (lag)[a]	0.772	0.958	−1.422	0.949	0.932	1.130	−1.499	0.961
firm size: medium	0.027	0.595	0.619	0.799	−0.061	0.688	0.656	0.842
large	−0.350	0.612	0.547	0.891	−0.381	0.626	0.549	0.931
constant	54.216***	1.613			53.924***	1.958		
# of observations	4,066		4,066		4,066		4,066	
joint significance (p-value)	0.000		0.000		0.000		0.000	

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%; robust standard errors computed; [a]missing values set to zero and regressor augmented by 'non-missing' indicator; state and year indicators included.
Source: Own calculations.

observations common to all regression models.[9] Note that observations that exhibit no variation in the indicator for staff reduction in the respondent's firm across years, i.e., staff reductions either never occurred during the observation period or were a regular phenomenon, are technically not excluded from the IV/FE regression. However, they effectively do not contribute to the identification of the effect of fear of unemployment since the fitted values obtained from the first stage regression are perfectly explained by the controls used at the second stage of the estimation procedure.

Coefficient estimates for regressions based on individuals driving the IV/FE results are displayed in Table 3. While for OLS, FE, and IV/FE, the estimated effect of fear of job loss just marginally differs form the results for the entire sample (see Table 2) and the largest common sample (see footnote 9), this does not hold for the coefficient obtained from the IV estimation. It is reduced to almost one fourth of its value and is closer to the estimated coefficients from the other models.

This pattern can be explained by the original IV estimate – indicating an effect of exceptionally

[9]We also estimated the models using the greatest common subset of observations ($N = 11,244$), irrespective of whether or not the instrumental exhibits within-group variation. Here the estimated effects of fear are very close to those reported in Table 2, in detail (SEs in parentheses), OLS: -2.496 (0.177); FE: -1.535 (0.230); IV: -4.577 (1.290); IV/FE: -2.464 (2.870). That is it is not the difference in estimation samples that drive the pattern in estimated coefficients.

large magnitude – being driven by individuals that have either never or frequently encountered staff reductions in their firm. One can easily imagine that an estimating procedure that rests on comparing these two groups of individuals reveals a large differential in the self-reported fear of unemployment due to the variation in the instrumental variable. This means that comparing individuals who have permanently been working in a stable working environment with individuals who are frequently confronted with staff reductions will most likely reveal that the former are less concerned about their job security. In contrast, comparing individuals that all have experienced both times of staff reductions and times without staff reductions, but whose companies differ in the current status of staff reductions, is likely to reveal a smaller differential in the fear of unemployment. A comparison of the IV and IV/FE coefficients in the instrumental equation provides evidence of this (see Table A3 in the Appendix). The model variant that uses the entire sample yields an effect of staff reduction on the fear of unemployment that is almost twice as large than the one found for the variant that excludes individuals with no variation over time in the instrument.

One may argue that comparing individuals that have never encountered staff reductions with individuals that have frequently encountered staff reductions will indicate the latter to have also a much lower mental health, as not only the instantaneous impact but also a possible cumulative effect of fear of unemployment on mental health is captured. However, there is no such cumulative effect for individuals with no variation over time in the instrument. This is in line with our previous argument of IV estimation yielding a LATE that basically rests on a selected group of individuals for whom the instrument has much explanatory power, while, at the same time, the effect of interest is particularly strong.

This implies that not only IV but also any FE estimation estimates a local treatment effect as the latter effectively excludes observations in a selective way, too. In the present application, IV/FE estimation – by effectively excluding individuals that in the past have never or frequently come in direct contact with staff reductions – ignores individuals for which one may well expect to find particularly strong effects of job worries on mental health. In essence, this means that IV as well as IV/FE yield estimates for selected sub-populations which substantially differ. The implication of this finding is twofold, (i) determining the population average effects is virtually impossible, and (ii) the effect of fear on *MCS* exhibits pronounced heterogeneity across individuals.

4.2 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 (all observations). For each component of the *MCS*, Figure 1 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.

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.[10] We are, thus, confident that the above results do allow for being interpreted as effects on individuals' mental health.

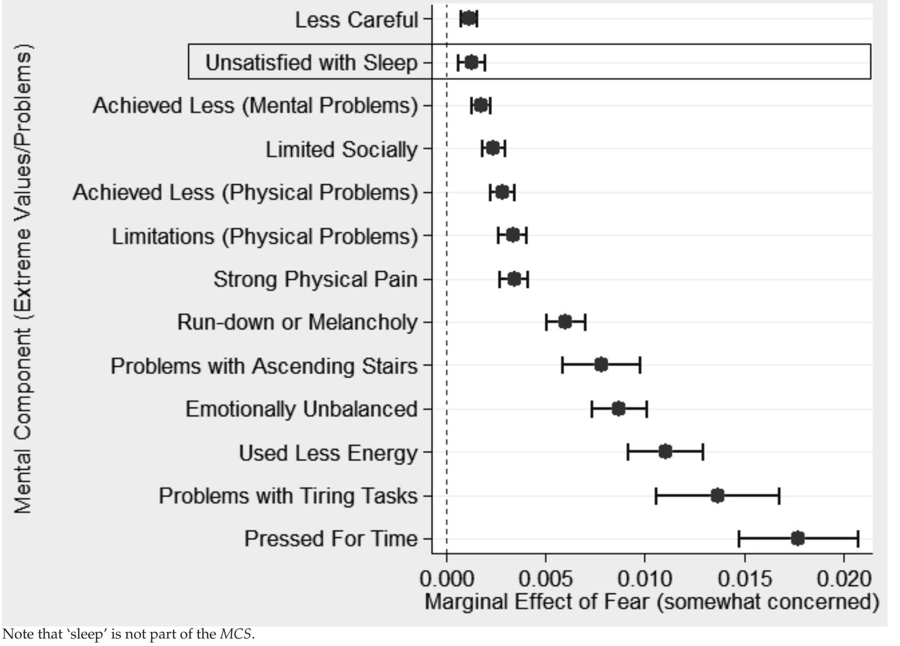
To further validate our results, we run an ordered probit regression with an ordinal variable indicating the respondents' satisfaction with their sleep as the dependent variable and job insecurity along with the other covariates as regressors. Note that this variable does not form part of the questions 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 Table 2). This gives further reason to interpret the observed effect as fear of unemployment causing genuine mental health problems.

4.3 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) estimate separate models for males and females and (ii) interact the variable 'fear of unemployment' with the regressor capturing employability. Second, we address effect heterogeneity across the mental health status by estimating quantile regressions. In either case, the simplest approach for estimating an overall

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

Figure 1: Estimated Effects of Fear on Each Component of the MCS



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

Source: Own calculations.

mean effect, i.e., OLS using all available observations, serves as reference.[11]

Estimating the model separately for males and females yields a moderate gender differential. In detail, the estimated coefficients are -2.46 for males compared to -2.91 for females; see Table 4. Surprisingly, females seem to suffer more from job worries than males, although the traditional males' gender role, i.e., the family's breadwinner, suggests that job-security is more important for mens' psychological stability. Yet, the estimated gender differential is just marginally significant at the 10 percent level and compared to the estimated overall mean effect of moderate size. Hence, gender does not seem to be the key driving source for the effect heterogeneity.

Alternatively, we investigate whether employability matters for the effect that fear of job loss exerts on mental health. In order to do so, we re-estimate the reference specification including an interaction term of 'fear of unemployment' and 'employability'. 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. Yet, based on our data, we cannot confirm this result because the estimated coefficient for the relevant interaction term is very small in

[11]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 Heterogeneous Effects on MCS**

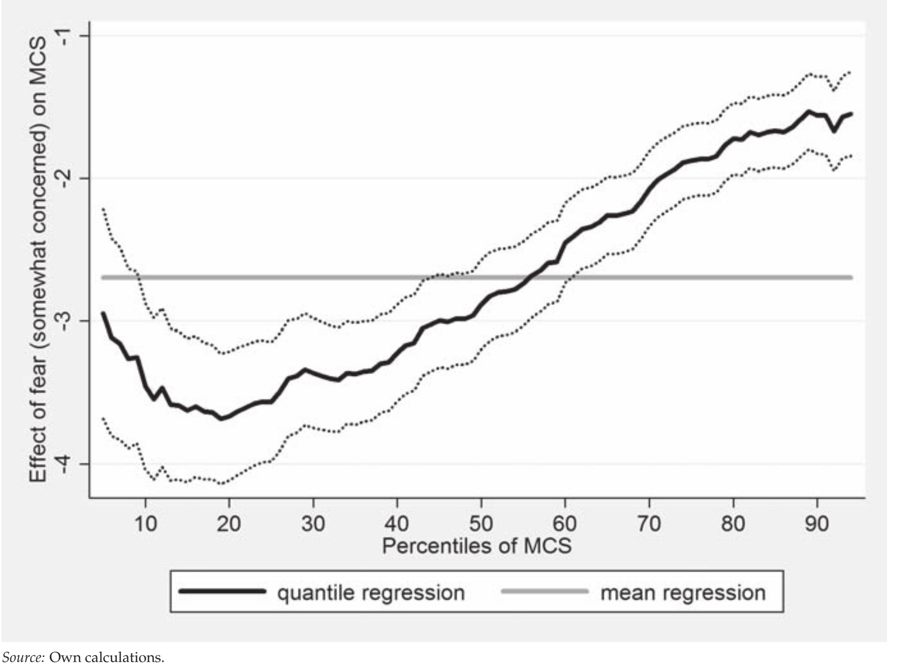
	Males		Females		Interaction	
	Coefficient	S.E.	Coefficient	S.E.	Coefficient	S.E.
fear of unemployment (A_i)	-2.458^{***}	0.170	-2.907^{***}	0.204	-2.723^{***}	0.144
fear of unemployment × employability (lag)					0.133	0.323
job satisfaction (lag): low[a]	-5.313^{***}	0.373	-4.095^{***}	0.425	-4.807^{***}	0.281
medium[a]	-3.204^{***}	0.198	-2.953^{***}	0.239	-3.089^{***}	0.153
overtime (lag)	-1.421^{***}	0.176	-1.135^{***}	0.218	-1.301^{***}	0.137
employability (lag)[a]	0.215	0.222	0.060	0.268	0.080	0.227
age	0.065^{***}	0.011	0.051^{***}	0.011	0.057^{***}	0.008
male					2.244^{***}	0.152
migration background: direct	1.063^{***}	0.245	1.065^{***}	0.305	1.061^{***}	0.191
indirect	0.840^{**}	0.376	-0.787	0.517	0.147	0.309
years of education	-0.094^{**}	0.043	-0.113^{**}	0.051	-0.100^{***}	0.033
married	0.145	0.281	0.317	0.308	0.236	0.208
living with partner	-0.258	0.291	0.509	0.316	0.154	0.215
household size	0.225^{**}	0.095	0.501^{***}	0.117	0.354^{***}	0.074
# of kids under 18	-0.254^{**}	0.127	-0.923^{***}	0.159	-0.573^{***}	0.099
personal income (lag)	0.033	0.051	-0.119	0.101	-0.018	0.044
occupation: blue-collar skilled	0.230	0.234	0.508	0.465	0.400^{**}	0.200
white-collar low skilled	0.167	0.265	0.992^{***}	0.268	0.567^{***}	0.187
white-collar high skilled	0.117	0.343	1.614^{***}	0.485	0.597^{**}	0.276
tenure	-0.013	0.010	0.005	0.014	-0.007	0.008
mini job	1.080^{*}	0.598	-0.110	0.326	0.006	0.269
midi job	0.838	1.038	0.141	0.403	0.194	0.361
temporary work contract	0.143	0.310	0.668^{**}	0.339	0.403^{*}	0.229
side job	-0.531	0.358	-2.099^{***}	0.446	-1.261^{***}	0.283
unemployed (lag)[a]	3.418^{***}	0.475	2.120^{***}	0.513	2.778^{***}	0.346
firm size: medium	0.565	0.364	0.038	0.289	0.240	0.225
large	0.393	0.373	0.143	0.321	0.168	0.238
constant	52.936^{***}	0.906	50.269^{***}	1.081	50.686^{***}	0.695
# of observations	11,717		9,442		21,158	
joint significance (p-value)	0.000		0.000		0.000	

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%; robust standard errors computed; [a]missing values set to zero and regressor augmented by 'non-missing' indicator; state and year indicators included.
Source: Own calculations.

magnitude and statistically insignificant, though exhibiting the expected positive sign; see Table 4. Thus, employability does not seem to be the key determinant of heterogeneity in the effect of fear of unemployment, either.

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 θ 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 θ. Hence, quantile regression allows for identifying the effect of job insecurity at any quantile of the distribution of the *MCS*. Figure 2 displays estimated quantile-coefficient functions for the fear of unemployment. Dotted lines indicate the 95-percent confidence interval. As a reference, this figure also displays the result from ordinary OLS estimation, which represents a horizontal line. The estimated quantile-coefficients function exhibits a distinct positive slope except at the lower quantile. This indicates that the detrimental effect diminishes for individuals with higher values of the *MCS*. In other words, in particular those, already of poor mental, are badly affected by job worries, while the effect is much smaller for

Figure 2: Quantile Regression: estimated Effects of Fear on MCS



Source: Own calculations.

the more healthy ones. 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 1.8 times stronger for the tenth percentile of the *M*CS than for the median, while compared to the 90th percentile, the ratio in the estimated effects even amounts to 2.2. An U-shape pattern with the magnitude of estimated effects becoming smaller for percentiles below the 20th quantile may be recognized.

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 unemployment 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.

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, our results prove to be robust in qualitative terms. Yet, in quantitative terms, the estimated mean effects vary substantially. 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.

The notion of heterogeneity in the effect of the fear of unemployment on mental health is supported 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 – which to identify from the data at hand seems to be hardly possible – 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. This 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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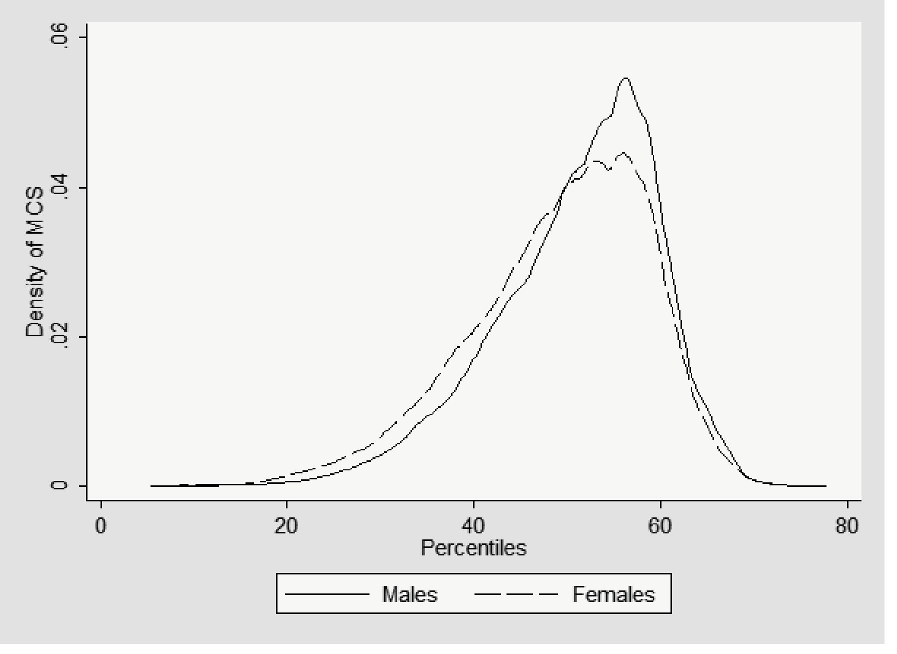
Appendix

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? • 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, ... • 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 problems you were limited socially, i.e. in contact with friends, acquaintances or relatives?					

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



Source: Own calculations.

Table A2: **Reduced From Results**

	Private Sector Employees		**Civil Servants**	
	Coefficient	S.E.	Coefficient	S.E.
staff reduction	−0.773***	0.166	−0.142	0.473
job satisfaction (lag): low[a]	−4.980***	0.287	−6.912***	1.028
medium[a]	−3.372***	0.170	−3.705***	0.548
overtime (lag)	−1.425***	0.158	−0.598	0.445
employability (lag)[a]	0.675***	0.188	0.852	0.554
age	0.060***	0.008	0.109***	0.038
male	2.189***	0.169	1.569***	0.507
migration background: direct	1.085***	0.222	−3.284**	1.441
indirect	0.067	0.329	0.234	1.560
years of education	−0.082**	0.037	−0.186**	0.095
married	0.060	0.225	−0.687	0.740
living with partner	0.214	0.228	0.558	0.795
household size	0.399***	0.084	−0.082	0.266
# of kids under 18	−0.601***	0.110	−0.015	0.354
personal income (lag)	0.013	0.050	0.156	0.203
occupation: blue-collar skilled	0.289	0.230		
white-collar low skilled	0.750***	0.207		
white-collar high skilled	0.771**	0.308		
tenure	0.007	0.010	−0.021	0.030
mini job	0.282	0.288	−12.098*	6.418
midi job	0.341	0.367	−0.067	1.475
temporary work contract	0.276	0.250	−0.094	1.033
side job	−1.131***	0.301	0.756	0.762
unemployed (lag)[a]	2.667***	0.351	7.021***	1.629
firm size: medium	0.333	0.245	7.322*	4.422
large	0.270	0.262	7.445*	4.422
constant	49.080***	0.763	45.607***	4.847
# of observations	16,619		1,815	
joint significance (p-value)	0.000		0.000	

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%; robust standard errors computed; [a]missing values set to zero and regressor augmented by 'non-missing' indicator; state and year indicators included.
Source: Own calculations.

Table A3: **First Stage Estimation Explaining Fear of Unemployment (all available observations)**

	IV		**IV/FE**	
	Coefficient	S.E.	Coefficient	S.E.
staff reduction	0.143***	0.008	0.080***	0.012
job satisfaction (lag): low[a]	0.139***	0.014	0.0422*	0.022
medium[a]	0.116***	0.009	0.075	0.051
overtime (lag)	0.005	0.008	0.004	0.013
employability (lag)[a]	−0.216***	0.010	−0.077***	0.016
age	−0.002***	0.001		
male	0.026***	0.009		
migration background: direct	0.073***	0.011		
indirect	0.004	0.018		
years of education	−0.005	0.002		
married	0.014	0.012	−0.027	0.027
living with partner	0.021*	0.012	0.002	0.025
household size	0.004	0.004	0.014	0.009
# of kids under 18	0.003	0.006	−0.019	0.012
personal income (lag)	−0.001	0.003	0.007	0.005
occupation: blue-collar skilled	0.039	0.011	0.018	0.022
white-collar low skilled	−0.028**	0.011	0.009	0.023
white-collar high skilled	−0.075***	0.016	−0.008	0.033
tenure	−0.004***	0.001		
mini job	−0.143***	0.016	−0.053	0.036
midi job	−0.061***	0.020	−0.013	0.030
temporary work contract	0.046***	0.013	0.092	0.021
side job	−0.028*	0.016	−0.008	0.030
unemployed (lag)[a]	0.070***	0.014	−0.033	0.028
firm size: medium	0.070***	0.014	−0.033	0.028
large	0.052***	0.014	−0.063*	0.032
# of observations	16,149		11,511	
joint significance (p-value)	0.000		0.000	

Notes: *** significant at 1%; ** significant at 5%; * significant at 10%; robust standard errors computed; [a]missing values set to zero and regressor augmented by 'non-missing' indicator; state and year indicators included.
Source: Own calculations.