WORKFORCE REDUCTION, SUBJECTIVE JOB INSECURITY, AND MENTAL HEALTH*†

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Abstract

We examine the link between workforce reduction, subjective job insecurity, and mental health using individual level panel data for private-sector employees in Germany. We first estimate the effect of firm-level workforce reductions on mental health, finding a strong, negative, and statistically significant relationship. We then extensively examine the role of subjective job insecurity as mediating variable and its importance relative to other possible channels for the effect of workforce reduction on mental health. Eventually, as an extension to our analysis, we use life satisfaction as alternative outcome variable.

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

Keywords: *mental health, life satisfaction, job insecurity, workforce reduction, fear of job loss, labor market dynamics*

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†The data used in this paper were extracted using the Add-On package PanelWhiz for Stata®. PanelWhiz (http://www.PanelWhiz.eu) was written by Prof. Dr. John P. Haisken-DeNew (john@PanelWhiz.eu). See Haisken-DeNew and Hahn (2006) for details. The PanelWhiz generated DO file to retrieve the data used here is available from the authors upon request.

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1 Introduction

The interdependence of labor market dynamics and health has been well established in the economic literature. Empirical research dates back to the nineteen-seventies, most notably to the research conducted by Brenner (see, e.g., 1971, 1979, 1987). Based on aggregated data, he reports a positive correlation of fluctuations in the unemployment rate with different health indicators, such as aggregate mortality, heart disease mortality, and the prevalence of schizophrenia. 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). Only the negative association between unemployment and psychological health has been warranted in the literature. For instance, by analyzing cause-specific mortality rates, Ruhm (2000) observes that suicide mortality is the only considered cause of death that significantly *increases* when unemployment rises. Breuer (2015) finds a similar result. In line with this, Tefft (2011) shows a positive association between weekly unemployment insurance claims and Google web searches for 'depression' and 'anxiety'.

Using individual level panel data[1], the present analysis finds a strong negative effect of company-level workforce reductions on psychological health of employees who remained employed with these firms. One plausible interpretation of this finding is that staff reductions make employees worried about their jobs and these worries negatively affect mental health. In line with this argument, we show a positive and statistically significant relationship between workforce reductions and subjective job insecurity[2]. Although we cannot firmly rule out other channels than fear of job loss that matter for the effect of workforce reductions on mental health, we find persuasive evidence for subjective job insecurity playing a major role as mediating variable. Our findings suggest that not only actual job loss but the mere fear of it adversely affects mental health.

The inverse relationship between job insecurity and mental health at the individual level was first documented in the psychological literature (for a comprehensive review, see Ferrie, 2001). Yet, there are several recent contributions in the economic literature. Relying on fixed effects estimation, Green (2011), for instance, observes an inverse association between (fear of) unemployment and mental health as well as life satisfaction. Knabe and Rätzel (2010) find negative effects of past unemployment on life satisfaction of reemployed individuals and Knabe and Rätzel

[1] Note that regression coefficients and their statistical significance may differ across degrees of data aggregation (e.g., Garrett, 2003).

[2] Throughout this article, the terms 'subjective job insecurity', 'self-perceived job insecurity', 'job worries', and 'fear of job loss' are used as synonyms. In the empirical analysis, all terms refer to a survey question asking about 'concerns about the own job being save'. Subjective job insecurity does not necessarily refer to a certain subjective probability and least of all to an objective probability of losing the job. In a robustness check we use a self-rated probability as an alternative, ratio scaled measure for 'subjective job insecurity'. Yet, for data reasons discussed in Section 2, we do not use this measure in the preferred specification.

(2011) observe a negative impact of perceived job insecurity on life satisfaction of the employed.[3] Luechinger et al. (2010) provide indicative evidence of a negative effect of fear of job loss on life satisfaction by showing that regional unemployment deteriorates well-being of German private-sector employees significantly more than that of public servants (the group with the highest dismissal protection).[4] Exploiting announced plant closures as source of variation in job insecurity, Ferrie et al. (1995, psychological literature) do not find an effect on mental health but one on general health.

In general, interpreting these findings in terms of a causal relationship is not straight forward because both, job insecurity and mental health, are likely correlated with unobserved factors. In addition, labor productivity may deteriorate with worsening mental health through a rise in sickness absence and on the job illness, rendering reverse causality an issue to be concerned about. Moreover, even if objective security of employment remains unaffected by a decline in mental health, subjective job security may still suffer.

The present paper adds to the existing literature by addressing the link between mental health and fear of job loss using an indirect approach, which rests on relatively weak identifying assumptions and is arguably robust to reverse causality. The key identifying assumptions are (i) that firm-level changes in the workforce are exogenous events form the perspective of an individual employee, and (ii) that endogenous sorting into firms rests – besides observables – on time-invariant unobserved heterogeneity, which can be accounted for by the use of individual fixed effects. The first step of the empirical analysis consists of simple OLS and fixed effects regressions that explain employees' mental health status by firm-level workforce reductions in the previous year. The inverse effect found in these regressions can hardly be attributed to reverse causality. Even if poor mental health negatively affects individual productivity, this will unlikely make co-workers lose their jobs at a scale that the workforce is declining at the company level. Moreover, relying only on individual-level within variation, fixed effects estimation prevents the estimated coefficient from capturing the effect of firms employing many workers with mental health problems performing poor and have to cut their personnel for this reason.

In the second part of the analysis, we show that also subjective job security is strongly and negatively affected by recent workforce reductions. This result argues in favor of fear of job loss acting as an intermediate variable in the established link between mental health and staff reductions. In the third part, we then preset results which reveal that the detrimental effects of workforce reductions on mental health are smaller (and even absent) for employees who, for institutional reasons,

[3]We discuss the difference between mental health and life satisfaction below.

[4]Using, *inter alia*, a similar approach with sector-level layoff rates serving as instrumental variable, Caroli and Godard (2016) find detrimental effects on mental health.

do not need to be concerned about their jobs. A similar pattern is found with respect to subjective reemployment prospects, where the effect vanishes for individuals who are very optimistic about finding a new adequate position if necessary. This suggest that fear of job loss acts indeed as an important mediating variable.[5] However, this approach has the drawback that the question to what extent job insecurity causally affects health remains open to interpretation, as it, unlike instrumental variable estimation, allows for the existence of alternative mediating variables.

It is not trivial to distinguish the concepts of mental health (unlike mental illness that refers to specific diagnoses), life satisfaction, and more generally well-being.[6] According to the definition of mental health that is used by the World Health Organization[7], impairments in everyday life seems to be a suitable criterion for distinction. Following this definition, sadness and frustration or just being in a bad mood represent deficits in life satisfaction, yet they are not sufficient conditions[8] for poor (mental) health as long as the ability to cope with everyday life is not affected. Following this logic, poor mental health tends to be a special – presumably especially restrictive or severe – form of deficits in well-being. By using the mental component summary scale (MCS) as measure of mental health, we adopt the notion of deficits in mental health being closely related to impairments in everyday life, as the MCS includes several components that directly refer to such limitations (see Table A1 in the Appendix for a detailed list of items that enter the MCS) and hence interpret the MCS as a measure of genuine mental health. In addition to the summary scale, we analyze effects separately for every component of the MCS. By focusing on mental health, this paper looks at the consequences of job insecurity from a health-policy perspective, where improving mental health is arguably a more obvious objective than improving well-being. A policymaker who is aware of possible genuine health effects of fear of job loss and, hence, does not consider job insecurity as a pure matter of individual life satisfaction is presumably more inclined to take action.

From the perspective of economic theory, welfare rather than (mental) health is the ultimate objective to be maximized. The former is regarded as just one – yet important – determinant of

[5]This approach follows a line of argument similar to estimating the effect of job worries on mental health using an instrumental variables (IV) framework, with workforce reductions serving as instrument for subjective job insecurity. Yet the crucial difference to IV is that we do not assume that fear of job loss is the sole channel through which mental health and workforce reductions are linked.

[6]Another frequently used term in relation to well-being is happiness. From a more theory-oriented perspective, evaluative well-being and hedonic (or affective) well-being are regarded as two distinct dimensions of well-being (Graham, 2013). While the latter is concerned with rather short-term environmental factors and is captured in survey questionnaires by questions about 'having felt happy' (or sad, angry etc.) in a reasonable short period of time, the former is concerned with how individuals value their lives in general (Graham, 2013). Yet, the empirical literature is generally imprecise in differentiating between these concepts (Winkelmann, 2014). In this article, we follow the common practice in the economic happiness literature and do not differentiate between happiness and life satisfaction.

[7]"Mental health is a state of well-being in which an individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and is able to make a contribution to his or her community." (WHO, 2014)

[8]Strictly speaking, these are not even necessary conditions. Mania, as a special form of poor mental health, for instance, is associated with peaks in happiness.

the latter (Graham, 2008; Helliwell et al., 2012). In an additional part of the analysis we examine the link between life satisfaction and workforce reduction and, ultimately, job insecurity. Life satisfaction has become a common proxy variable for welfare (Stutzer and Frey, 2010). This expands the scope of the paper in two important ways. First, following the previously presented indirect approach, we complement earlier findings on the effect of job insecurity on life satisfaction taking possible reverse causality into account. This connects the paper more closely to a broader literature on the well-being effects of labor market conditions (e.g. Clark and Oswald, 1994; Winkelmann and Winkelmann, 1998; Kassenboehmer and Haisken-DeNew, 2009; Ohtake, 2012; Helliwell and Huang, 2014; Binder and Coad, 2015a,b). Second, this enables us to analyze whether mental health and life satisfaction are equally affected or whether their sensitivities to workforce reduction differ, which contributes to a better understanding of both concepts.

Our analysis also contributes to the literature on the effects of unemployment on health that has not finally settled the questions of under which circumstances, to what extent, and within what time frame unemployment influences individual health. In fact, the relevant studies have yielded ambiguous empirical evidence.[9] In the present analysis, we do not focus on those individuals who actually lose their jobs but consider employed people potentially being affected by unemployment.[10] This is relevant as the latter group outnumbers the former by far. Hence, by focusing on realized job-loss events one may miss out on an important component of negative effects of labor market conditions.

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 present 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), which is the German counterpart to the British BHPS and the Australian HILDA, for instance. The SOEP in-

[9] 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 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. Marcus (2013) even finds a negative effect of unemployment on the mental health status of the spouse. On the other hand, 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 a related paper Schiele and Schmitz (2016) find adverse, yet heterogeneous, effects of plant-closer induced job loss on mental and physical health, but no effects on BMI.

[10] Green (2011) considers a pooled sample of employed and unemployed individuals and estimates both, effects of being unemployed and effects of the probability of job loss.

cludes 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 for estimation roughly covers 19,000 person-time observations for roughly 7,000 individuals and for four survey waves over the period from 2002 to 2010.

In our empirical analysis, we focus on employed[11] individuals who are potentially affected by unemployment. This, in particular, applies to private sector employees (i.e., we restrict the sample to individuals who are employed in the private sector), while other occupational groups cannot be laid off as, for instance, conscripts, self-employed, and civil servants.[12] In a similar – yet not as strict – way this also applies to private-law public-sector employees holding permanent work contracts.[13] In fact, individuals from the latter group are by far less concerned about their job security than private sector employees, as the data shows. Though the estimation sample is confined to individuals who have a paid job at the time of the survey, roughly one fifth of them have experienced unemployment in the past. For individuals whose labor market status changes, we consider those survey waves for which the individual is observed in employment. We focus on working-age individuals and do not consider individuals older than 65 years, though some rather old aged individuals do report to be still employed. In order to base the estimation of different model specifications on the same data, we do not consider 4,543 individuals who enter the estimation for a single year as these observations are immaterial for the fixed effects specifications. 47.8 percent of the remaining individuals are observed twice, 26.3 percent are observed three time, and 24.9 percent enter the estimation sample for all considered survey years. Estimating the model with OLS using the entire sample, including individuals who are observed only once, yields results that are very close to OLS results based on the restricted sample; see Subsection 4.6.

Our prime outcome measure is the *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 psy-

[11]That is, only individuals who were employed when the survey was conducted enter the estimation sample. This does not imply that we only consider individuals with continuous employment histories. Indeed, almost 19 percent of the individuals in the estimation sample report having been unemployed in the past for at least one period since 1999. As robustness check we report results for a specification that considers 'past unemployment' as additional control; see Section 4.6.

[12]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).

[13]Although they are – unlike civil servant – employed on the basis of a contract under private law, which also applies to all private sector 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).

chological 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 zero and 100, with higher values indicating a better mental health status. As a variable that lacks of an obvious scale to be measured on, *MCS* is standardized to a mean value of 50 and a standard deviation of ten. For the years 2003, 2005, 2007, and 2009 there is no information on the *MCS* available, because the SF12v2 questionnaire is not included in the SOEP survey in odd-numbered years.

We also consider general life satisfaction as alternative outcome variable. It is measured on a ten point scale, which ranges from 'completely dissatisfied' [0] to 'completely satisfied' [10]. For reasons of comparability of estimation results across both outcome variables, we rescaled life satisfaction to have the same mean and the same variance as *MCS*.

The data also contains an indicator whether the company, an individual is employed with, reduced its workforce during the last twelve months. It is used to construct a binary variable 'staff reduction' that serves as the key explanatory variable in all regression analyses discussed in this paper (see Section 3). This variable is available for the same years as the *MCS*, except for 2006. We hence have a panel structure that allows us to exploit variation over individuals and time. For reasons of comparability of results across different estimation methods, we focus on the waves 2002, 2004, 2008, and 2010 throughout the entire analysis.

To measure subjective fear of job loss, which represents the suspected mediating variable for the effect of staff reduction on mental health, we exploit the information from the survey question asking whether an individual is very, somewhat, or not at all concerned about his or her job security. Based on this variable, we construct the binary variable 'fear of job loss' (taking the value one if the individual is very concerned about their job security and zero otherwise), which is used as a proxy for self-perceived job insecurity. This variable is available in the SOEP for the same years as the *MCS*.[14] It has substantial predictive power for future unemployment[15] and, hence, conveys some real information about a job being secure.

As control variables, we use usual socioeconomic characteristics, such as sex, age, years of

[14]The SOEP also includes the self-assessed probability of job-loss as an alternative, cardinal measure of subjective job insecurity, which is more similar to the one used by Green (2011) and has been advocated by Dickerson and Green (2012). However, it is only available for the years 2001, 2003, 2005, 2007, and 2009. In a regression explaining subjective job insecurity by workforce reduction, this requires that the key regressor enters the right-hand-side as lagged variable. Hence we prefer the qualitative measure; see Table A3 in the Appendix for regressions results using the alternative left-hand-side variable.

[15]Using the estimation sample at hand, the *t*-statistic takes the values of 6.54 (OLS) and 4.91 (ind. fixed effects); more detailed results are available upon request. The predictive power of subjective job insecurity for actual future job loss has already been established elsewhere in the literature, e.g. by Dickerson and Green (2012), who also used SOEP data but employed a different measure for job insecurity; cf. footnote 14.

Table 1: **Descriptive Statistics for Estimation Sample**

	Mean	S.D.	Median	Min.	Max.
dependent variables:					
MCS	50.275	9.031	51.621	7.736	79.432
life satisfaction†	50.275	9.031	49.892	9.656	67.136
key explanatory variable: *staff reduction*	0.268	0.443	0	0	1
suspected mediating variable: *fear of job loss*	0.170	0.375	0	0	1
controls:					
employability (lag): moderate	0.647	0.478	1	0	1
good	0.192	0.394	0	0	1
age (*years*)	42.399	10.195	43	18	65
age^2 (*years*^{2}/100)	19.016	8.607	18.490	3.240	42.250
male	0.578	0.494	1	0	1
migrant	0.122	0.328	0	0	1
years of education (*years*)	12.194	2.467	11.5	7	18
years of education^2 (*years*^{2}/100)	1.548	0.670	1.322	0.490	3.240
married	0.676	0.468	1	0	1
living with partner	0.773	0.419	1	0	1
household size	2.919	1.237	3	1	14
# of kids under 18	0.665	0.936	0	0	9
# of employed persons in household	1.721	0.730	2	1	5
occupation: blue-collar skilled	0.221	0.415	0	0	1
white-collar low skilled	0.389	0.488	0	0	1
white-collar high skilled	0.200	0.400	0	0	1
tenure (*years*)	10.852	9.195	8.4	0	48.9
type of job: mini	0.058	0.234	0	0	1
midi job	0.032	0.175	0	0	1
temporary work contract	0.061	0.240	0	0	1
side job	0.053	0.225	0	0	1
firm size: medium (*5-200 employees*)	0.495	0.500	0	0	1
large (*200 or more employees*)	0.419	0.493	0	0	1
gross household labor income (*€1,000 per month, lag*)	4.731	3.274	4.040	0	50.418
year 2002	0.248	0.432	0	0	1
year 2004	0.276	0.447	0	0	1
year 2008	0.258	0.438	0	0	1

Notes: **key sample characteristics**: 18,616 observations for 6,695 individuals; private sector employees only; unemployed excluded; years 2002, 2004, 2008, and 2010 considered; individuals aged between 18 and 65 years; only individuals considered who enter the estimation sample in two or more survey waves. †Originally measured on a ten point scale; rescaled to have equal mean and equal variance as *MCS*; statistics for org. scaled variable: 7.067 (mean), 1.571 (s.d.), 7 (median), 0 (min.), 10 (max.).

education, a dummy indicating being born abroad, and household size. 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 individuals and those with dependent children. For this reason, both variables are potential determinants of individual fear of job loss. One may also think of direct effects on mental health, e.g. emotional benefits of marriage and detrimental effects of marital transitions (Simon, 2002). Yet, as this line of argument rather applies to living in a partnership than to the legal status of being married, we also include an indicator for living together with a partner. In order to allow for non-linear relationships between mental health and age as well as mental health and education, we let these two variables enter the model as levels and squared values.

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) less than five, (ii) five or more, and (iii) 200 or more employees. Here, small firms serve as the reference category. The choice of the threshold values is motivated by firms with up to five employees

Table 2: **Mean *MCS* by *staff reduction* over survey years**

mean *MCS*	survey year				pooled sample
	2002	2004	2008	2010	
no staff reduction	50.143	50.577	50.936	50.414	50.537
staff reduction	49.689	49.535	49.316	49.641	49.558
test for equal means (p-value)	0.037	0.000	0.000	0.017	0.000

Note: Results for estimation sample.

having been exempted from strict dismissal protection regulations over the entire study period. For large firms ($>$ 200 employees) – though subject to the same regulations as medium size firms – at least one full-time work-council member is mandatory, who is released from any regular workers' tasks. For this reason, workers' representation can be expected to be better organized in firms with 200 or more employees, which may result in more effective resistance against possible dismissals. 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.

Household gross labor income, measured in €1,000 per month, also enters the empirical model as a control variable. To make this variable more meaningful when being compared across different households compositions, we also include the number of working household members as a control. In order to avoid potential bias resulting from reverse causality, income enters the analysis lagged by one year.[16] Another covariate that enters the model in terms of a one year lag is subjective employability captured by two indicators,[17] which allows us to compare our results to those of Green (2011). In addition, year and state dummy variables are included.

After excluding 1,259 observations with missing values[18] in at least one relevant variable, the estimation sample consists of 18,616 person-time observations for 6,695 individuals. The number of observations by year is 4,612 for 2002, 5,147 observations for 2004, 4,812 observations for 2008, and 4,045 observations for the year 2010. The distribution of the *MCS* by sex, averaged over all

[16] As alternative income measures, we use total gross household income and total net household income. Moreover, we let income enter the regression models as contemporaneous variable rather than as lagged variable. All these model variants yield almost identical estimation results.

[17] 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 adequate position?' We use two dummy variables to indicate individuals who report to find an adequate position with some difficulties and easily, respectively. The reference category considers themselves as hardly reemployable. These dummies have significant power for predicting future reemployment among unemployed individuals in the SOEP.

[18] Applying the 'missing indicator method' (cf. Morris, 2006; Spenkuch, 2012) instead for dealing with item specific missing information – i.e. assigning covariates with a missing value the value of zero and including as set of binary indicators indicating missing information in the respective variables – has little impact on the estimated coefficients.

Table 3: **Share of employees in *fear of job loss* by *staff reduction* over survey years**

mean *fear of job loss*	survey year				pooled sample
	2002	2004	2008	2010	
no staff reduction	0.123	0.169	0.120	0.123	0.134
staff reduction	0.256	0.305	0.242	0.245	0.266
test for equal means (p-value)	0.000	0.000	0.000	0.000	0.000

Note: Results for estimation sample.

four years, is displayed in Figure A1 in the Appendix. Figure A2 displays equivalent information for life satisfaction.

For comprehensive descriptive statistics, see Table 1. Reporting some key features of the estimation sample, the average sample age is 42.4 years, almost 58 percent of the individuals are male, white-collar workers comprise almost 60 percent, and the average sample individual has 12 years of education. Median tenure is roughly eight years, while some individuals spent their entire working life with the same employer. Only 19 percent of the individuals report that it would be easy for them to find an adequate new job. Average monthly household gross labor income is €4,731. Reported income exhibits pronounced heterogeneity and ranges from zero to more than €50,000 per month. While the minimum value of zero represents an artifact of Table 1 displaying descriptive statistics for the explanatory variable 'lagged income' rather than for current income, reported labor income still seems to be questionably small for several households. As a robustness check, we confine the analysis to observations within the income range of €1,000 to €12,000. This roughly corresponds to trimming the income distribution in the estimation sample by three percent from below and from above; see Section 4.6 for results.

Regarding the key explanatory variable in 2002, 26.4 percent of the individuals experienced a workforce reduction in the firm they were employed with, in 2004 this share was 31.3 percent, in 2008 it was 19.4 percent and in 2010 it was 30.3 percent. Table 2 displays mean *MCS* separately for those who experienced staff reduction and those who did not over all survey waves considered. Table 3 displays equivalent figures for the fear of job loss indicator. The descriptive analysis shows that for any considered year the average *MCS* is significantly lower for those who experienced workforce reductions. The picture is even more clear with respect to fear of job loss. In any year, the share of employees who are concerned about their jobs is roughly twice as high among those whose employers have reduced its workforce in the previous year. These statistically significant deviations in mean *MCS* – though moderate in magnitude compared to the sample standard deviation of *MCS* — provide some descriptive evidence for a link between staff reduction and poor mental health, while the pattern of mean values displayed in Table 3 suggests that fear of job loss may play a role in this link.

3 Empirical Approach

Our estimation strategy includes multiple steps. First, we estimate the effect of workforce reduction in the firm an individual is employed with on individual mental health. We suspect that fear of job loss operates as a mediator in this relationship. To check for this, we secondly estimate the effect of workforce reduction on fear of job loss. Identifying a negative effect of workforce reduction on mental health and a (numeral) positive effect on subjective job insecurity is, however, not a sufficient condition for making causal statements about the relationship between fear of job loss and mental health. There may be different channels other than fear of job loss through which workforce reduction affects mental health. Among others, being frustrated about intimate coworkers losing their jobs, increased individual workload after job cuts, being transferred to a different workplace or to different work tasks due to company restructuring, and being depressed about the firm performance although the own job is save, can be mentioned as examples for such channels. While it is virtually impossible to rule out that these alternative channels play a role, in the third step of our analysis we analyze their importance relative to fear of job loss. We first compare the results for private sector employees from step one with corresponding results for civil servants and public sector employees. As the latter groups, civil servants in particular, are much better protected against job loss, fear of job loss should play only a minor or even negligible role in mediating the effect of staff reduction on mental health. Finding for these groups a smaller estimated effect compared to private sector employees can be interpreted as indicative evidence for fear of job loss representing the major channel through which mental health and workforce reductions are linked and in turn for fear of job loss exerting an adverse effect on mental health. Second, we differentiate the estimated effect with respect to different categories of subjective reemployment prospects. Similar to the above line of argument, if subjective job insecurity plays a major role for the link between mental health and workforce reductions, one should find a much stronger effect for those who are pessimistic about finding a new adequate position. We eventually analyze the relationship between workforce reductions and alternative mediating variables.

The econometric methods used in this approach are fairly simple. Given that *MCS* is a continuous interval scale variable, in implementing step one, we start with estimating the coefficients of the linear equation.

$$MCS_{it} = \alpha_1 + \gamma_1 \, \mathit{staff\ reduction}_{it} + \beta_1' x_{it} + \theta_1' w_i + \varepsilon_{1it} \qquad (1)$$

Unlike losing her or his own job, workforce reductions that make other jobs redundant elsewhere in the firm, can hardly be influenced by the individuals own behavior.[19] Hence reverse causality turns into a negligible issue in our empirical approach. The key coefficient is therefore unlikely to suffer from this possible source of endogeneity bias and is estimated using OLS. Besides the key regressor *staff reduction* the *MCS* is regressed on a set of control variables, described in the previous section. The set of covariates includes a vector of time-varying personal and job-related variables x_{it}, such as 'living with a partner', 'married' and 'firms size'. State and year indicators are also included in x_{it} to control for regional differences and time trends in *MCS*. Besides x_{it}, a vector of few time-invariant personal characteristics w_i, such as gender and migration status, enter the list of controls.

Step two requires estimating the exactly the same model using the same sample with the sloe exception that in stead of mental health an indicator for fear of job loss $fear_{it}$ enters the model at the left-hand-side.

$$fear_{it} = \alpha_2 + \gamma_2 \, staff\ reduction_{it} + \beta_2' x_{it} + \theta_2' w_i + \varepsilon_{2it} \tag{2}$$

Due to the binary nature of $fear_{it}$ equation (2) represents a linear probability model that allows for OLS estimation. Finding a significantly negative estimate for γ_1 coupled with a significantly positive one for γ_2 would give indication for fear of job loss mattering for mental health.

Though the key regressor $staff\ reduction_{it}$ is very unlikely to suffer from endogeneity due to direct reverse causality, unobserved heterogeneity may still render OLS biased. This concern roots in potentially endogenous job choice. For instance, the OLS estimates of γ_1 and γ_2 may capture that generally more optimistic individuals are more inclined to choose employers with volatile workforce and, at the same time, are less concerned about their jobs and eventually have a better health status. Given that this source of endogeneity originates from time-invariant individual characteristics, using fixed effects regressions instead of OLS provides a convenient approach for eliminating this source of bias. In order to difference out unobserved heterogeneity, we hence run also fixed effects (FE) regressions:

$$\begin{aligned} MCS_{it} &= \alpha_{i1} + \gamma_1 \, staff\ reduction_{it} + \beta_1' \tilde{x}_{it} + v_{it1} && (3) \\ fear_{it} &= \alpha_{i2} + \gamma_2 \, staff\ reduction_{it} + \beta_2' \tilde{x}_{it} + v_{it2} && (4) \end{aligned}$$

that correspond to (1) and (2). As the FE estimator only uses within-group variation for identification, the vector of coefficients θ is not identified that is the time-invariant covariates w_i do not enter the regression models (3) and (4). We also exclude several explanatory variables in x_{it} that

[19] Employees working in very small firms represent a potential exception. We address this issue by excluding individuals working in small firms in a robustness check; see Table 12.

exhibit very little variation over time, such as the federal state of residence and years of education[20]. For similar reasons, we also exclude variables that in the fixed effects model are perfectly or nearly collinear with the year dummies such as age[21] and tenure. For the latter, identification in the fixed effect model would exclusively rest on job changers and, hence, capture something different than a genuine tenure effect. The reduced set of covariates used in the FE model is denoted $\tilde{x}_{it}$.

At the third step, we reestimate the equations (1) and (3) using data for civil servants. Civil servants are strictly protected against dismissal and, in turn, will not be concerned about becoming unemployed if the workforce is reduced at their workplace.[22] However, the above mentioned channels that link staff reductions to mental health through other mediators than fear of job loss are arguably equally relevant to civil servants as they are to private sector employees. Hence, finding a much smaller, or even no, effect for civil servants provides strong evidence for fear of job loss being an important mediator the effect of staff reduction on mental health.

One may, however, argue that civil servants are a rather special group of individuals that deviate from private sector employees in various respects and, hence, represent a questionable comparison group. We address this concern in two ways. First, we use nearest neighbor matching to make both groups more homogeneous and, in turn, more comparable. Besides the time-invariant individual characteristics (age, gender, years of education, migration status) that are not identified in the FE specifications, we matched on the self-reported level of risk aversion. Since economic security can be considered the prime advantage of working in the civil service, matching on risk preferences is likely to account for the key channel for self-selection into the group of civil servants. Thus, we not only compare civil servants with the estimation sample of private sector employees but also with a matched sub-sample of the latter, consisting of individuals that, according to the matching procedure,[23] are particularly 'civil servant-like'. Second, we use private-law public sector employees as another comparison group, which is presumably less selective than civil servants and typically better (less) protected against dismissal than private sector employees (civil servants). If fear of job loss is the prime channel through which mental health

[20]Since we only consider working individuals, the vast majority of them has already completed eduction when entering the estimation sample.

[21]This does not apply to age squared, which enters the fixed effects specifications. However, in FE models, age squared serves as pure control. Since the linear age effect is not identified, the interpretability of its non-linear counterpart is limited.

[22]Though civil servants cannot be dismissed – except for severe disciplinary reasons – staff reductions are frequent at civil servants' workplaces. This can be explained by vacant positions left unfilled and private-law (temporary employed) employees, who often work side-by-side with civil servants, losing their jobs.

[23]We applied the mahalanobis distance approach for matching the estimation sample to the sample of civil servants. We confined to analysis to observations on common support and considered each survey wave separately in the matching procedure. We included only observations in the matched private sector employees sample that are the nearest or the second nearest neighbour to a civil servant in at least one of the considered waves. Due to the relatively small number of observations on civil servants, we abstain from reversing the roles of the two groups in the matching procedure and considering a matched sub-sample of civil servants.

is linked to workforce reduction, we expect to find an inverse association for this group that is stronger than for civil servants and weaker than for private sector employees. Consistent with the analysis based on civil servants, we additionally estimate the regression for a matched sample of private sector employees, which is more comparable to the sample of private-law public sector employees and generated via nearest neighbor matching.[24] Eventually, we run the same analysis with life satisfaction as the outcome variable; see Table A4 for results.

4 Estimation Results

4.1 Results for the Reference Models

In this section, we present the estimation results obtained from the different regression models discussed above. Starting with the results obtained from OLS regressions presented in Table 4, left columns, we find a highly significant and negative effect of *staff reduction* on mental health. In quantitative terms, employees working in firms that reduced the workforce in the previous year – yet kept their own jobs – experience a loss in *MCS* of roughly one unit. This seemingly small coefficient is not negligible as it corresponds to a shift from the median to the 45th percentile of the distribution of the *MCS* in the estimation sample. Since we are particularly interested in subjective job insecurity as a possible mediator of this effect, we turn to the results of the regression of *fear of job loss* on *staff reduction*; see Table 5 left columns. The key estimated coefficient is positive and highly significant. Those who experienced job cuts in the firm are roughly thirteen percentage points more likely to be concerned about their jobs being safe, compared to employees of firms with a stable or even increasing workforce.

However, as discussed above, these results may suffer from bias due to unobserved heterogeneity. This issue is addressed by including individual fixed effects in the regression; see Tables 4 and 5 (right columns). Relying only on within variation, FE estimation yields a substantially smaller effect of *staff reduction* on the *MCS*. This points to individuals in good mental health being more successful in finding jobs in well performing firms that do not cut jobs, biasing the OLS coefficient away from zero. However, despite its smaller magnitude in the FE regression, the estimated coefficient remains clearly significant and negative, providing strong evidence for workforce reductions exerting detrimental mental health effects on those who keep their jobs in

[24]One may also think of estimating reestimating (2) and (4) using the civil servant and the public sector employee sample in order to test the key assumption that they do not – or far less – suffer from job worries due to workforce reductions. Yet, this hardly possible for civil servants as the number of individuals from this well protected group who report to be concerned their jobs is very low, more precisely, just above 1 percent in the estimation sample. This does not equivalently apply to private-law public-sector employees. But still, the share of concerned individuals is substantially smaller than for private sector employees.

Table 4: **Estimated effects of *staff reduction* on *MCS***

	OLS		Fixed Effects	
	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *MCS*				
staff reduction	-1.009^*	0.153	-0.334^*	0.163
employability (lag): good	0.975^*	0.205	0.193	0.238
moderate	1.566^*	0.256	0.144	0.314
age	-0.300^*	0.053	–	–
age^2	0.426^*	0.062	0.249^*	0.116
male	1.780^*	0.162	–	–
migrant	1.185^*	0.210	–	–
years of education	-0.757^*	0.269	–	–
years of education^2	2.401^*	0.987	–	–
married	0.150	0.228	-0.227	0.370
living with partner	0.350	0.244	1.236^*	0.376
household size	0.067	0.100	-0.087	0.154
# of kids under 18	-0.125	0.127	0.027	0.179
# of employed persons in household	0.119	0.115	0.124	0.150
household income (lag)	0.123^*	0.023	-0.013	0.036
occupation: blue-collar high skilled	0.406^+	0.219	0.414	0.337
white-collar low skilled	0.721^*	0.212	0.671^*	0.339
white-collar high skilled	0.669^*	0.280	1.004^*	0.463
tenure	0.007	0.009	–	–
mini job	0.739^*	0.305	0.060	0.521
midi job	-0.211	0.401	-0.878^*	0.432
temporary work contract	0.099	0.301	1.207^*	0.336
side job	-1.274^*	0.308	-0.106	0.394
firmsize: medium	0.116	0.250	-0.199	0.365
large	0.092	0.264	-0.103	0.427
year 2002	0.019	0.204	1.600^+	0.817
year 2004	0.232	0.192	1.386^*	0.626
year 2008	0.415^*	0.192	0.848^*	0.249
constant	57.835^*	2.100	–	–
federal state indicators	included*		not included	
# of observations	18,616		18,616	
R^2 (within for FE)	0.035		0.006	
joint significance (p-value)	0.000		0.000	

Notes: *significant at 5%; $^+$significant at 10%; robust standard errors reported.

the respective firm. The effect of *staff reduction* on *fear* also keeps its sign and stays statistically significant.[25] Moreover, its size becomes just slightly smaller compared to OLS. This points at more pessimistic individuals working in firms with higher job instability. This may be explained by fewer choice options precisely due to this individual characteristic. Yet, most important for our analysis, the results from fixed effects regressions – just as their OLS counterparts – are in line with the hypothesis that fear of job-loss acts as an mediator in the link between workforce reductions and mental health and, hence, exerts detrimental effects on the latter.

If fear of job loss was the only channel through which *staff reduction* and *MCS* were linked, the above results would directly allow for backing out the estimated effect of fear of job loss on

[25]Using *self-assessed probability of job loss* as alternative, ratio scaled measure of subjective job insecurity, in qualitative terms, yields an equivalent result; see Table A3. In quantitative terms, the FE result indicates that experiencing workforce reductions increases the self-assessed probability of job loss by 2.4 percentage points. Note that these results are not fully comparable to the reference model. For data reasons the alternative regression (i) rests on different waves of the SOEP and (ii) uses the *lagged* value of *staff reduction* as explanatory variable.

Table 5: **Estimated effects of *staff reduction* on *fear of job loss***

	OLS		Fixed Effects	
	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *fear of job loss*				
staff reduction	0.130*	0.007	0.095*	0.008
employability (lag): good	−0.090*	0.009	−0.030*	0.011
moderate	−0.168*	0.010	−0.059*	0.014
age	0.013	0.002	–	–
age^2	−0.016*	0.003	−0.007	0.005
male	0.014	0.006	–	–
migrant	0.046	0.009	–	–
years of education	−0.016	0.011	–	–
years of education^2	0.047	0.039	–	–
married	−0.007	0.009	0.019	0.015
living with partner	0.009	0.009	−0.005	0.015
household size	0.003	0.004	0.006	0.007
# of kids under 18	−0.011*	0.005	−0.018*	0.008
# of employed persons in household	−0.001	0.005	−0.004	0.007
household income (lag)	−0.006*	0.001	0.001	0.002
occupation: blue-collar high skilled	−0.008	0.010	0.001	0.017
white-collar low skilled	−0.047*	0.009	−0.016	0.016
white-collar high skilled	−0.075*	0.011	−0.027	0.020
tenure	−0.002	0.000	–	–
mini job	−0.045*	0.011	0.008	0.022
midi job	−0.037*	0.014	0.016	0.017
temporary work contract	0.112*	0.014	0.079*	0.017
side job	−0.013	0.011	−0.022	0.015
firmsize: medium	0.012	0.009	−0.002	0.016
large	−0.003	0.010	−0.007	0.019
year 2002	−0.005	0.008	−0.040	0.036
year 2004	0.037*	0.008	0.023	0.028
year 2008	−0.008	0.007	−0.018	0.011
constant	0.113	0.087	–	–
federal state indicators	included*		not included	
# of observations	18,616		18,616	
R^2 (within for FE)	0.089		0.033	
joint significance (p-value)	0.000		0.000	

Notes: *significant at 5%; +significant at 10%; robust standard errors reported.

mental health as $\hat{\gamma}_1/\hat{\gamma}_2$. This is equivalent to running an instrumental variables regression of *MCS* on *fear* with *staff reduction* serving as instrument for *fear of job loss*.[26] For OLS this leads to an estimated effect as big as -7.768, which corresponds to a shift in the distribution from the median to the 22nd percentile that is a huge detrimental effect of developing job worries. Yet, even if the exercise is based on the fixed effects coefficients that are not contaminated by unobserved time-invariant individual heterogeneity, the estimate remains large. More precisely, the estimate is -3.523, which corresponds to a shift from the median to the 35th percentile. One explanation is that this result represents an upper bound estimate for the effect, whose true value is smaller to

[26] If the true model determining mental health was $MCS_{it} = \alpha_0 + \gamma_0 fear_{it} + 0 \cdot staff\ reduction_{it} + \beta_0' x_{it} + \theta_0' w_i + \varepsilon_{0it}$, i.e. if *staff reduction*$_{it}$ was a valid instrument for *fear*$_{it}$, Equation 1 represents the reduced form of the model with $\gamma_1 = \gamma_0 \cdot \gamma_2$. Hence one could back out γ_0 as γ_1/γ_2. If, however, the true coefficient attached to *staff reduction*$_{it}$ in the equation above deviates from 0 by the value τ, γ_1/γ_2 does not equal γ_0 but equals $\gamma_0 + \tau/\gamma_2$, i.e. the IV estimator is biased. Yet, making the plausible assumption $\tau \leq 0$, i.e. the direct effect of *staff reduction* on the *MCS* is non-beneficial, the IV estimate $\hat{\gamma}_1/\hat{\gamma}_2$ still represents an – in absolute terms – upper bound estimate for the true (negative) effect γ_0. For comparison, see full results for two-stage least squares estimation Table A2 in the Appendix.

the extent that other channels play a role for the link between *staff reduction* and *MCS*. In addition, even if fear of job loss was the only mediating variable, IV estimation yields a LATE (local average treatment effect), i.e an average treatment effect for those who become particularly worried if the employer reduces its workforce. It seems plausible that affected individuals are of particularly vulnerable mental health. In other words, IV estimation is likely to estimate an upper bound effect for a group of individuals for which the effect is particularly strong.

4.2 The Role of Subjective Job Insecurity as Mediating Variable

While it is virtually impossible to clean the estimate from this confounding channels, in this section, we compare above results with results for civil servants and private-law public-sector employees. If subjective job insecurity plays a substantial role as mediating variable, the effect of workforce reduction should be smaller once comparison groups are considered which enjoy a stricter dismissal protection. We find exactly this patter in the data (Table 6). Using OLS as estimation method (Table 6, upper panel), the estimated coefficient for private sector employees – irrespective of whether the original or a matched sample is used – is roughly twice as big as for public sector employees and civil servants. The deviation is weakly statistically significant (p-values ranging between 0.06 and 0.10).

The general pattern found for the FE specification (Table 6, lower panel) is fairly similar although the point estimates are generally smaller. In consequence, a significant negative effect of workforce reductions on mental health is only found for private sector employees. This holds for the full and the matched samples. For the latter, the estimated coefficients are even larger in absolute terms, which might reflect that the matched sample consists of particularly risk averse private sector employees (Table 6, lower panel). For the fixed effects specification, one cannot reject effects of equal size at conventional levels of statistical significance, though for civil servants the p-values are still fairly small (0.11 and 0.15). This lack of statistical significance is likely attributable to insufficient levels of power. According to power calculations, the type-II error probabilities of misleadingly accepting the null of equality of coefficients between private sector and public sector employees (one-sided test, confidence level 0.05) would be as high as 0.725 (full sample) and 0.654 (matched sample) if the true differential was the difference in the estimated coefficients. Considering private-law public sector employees (Table 6, lower panel, second from right column), the estimated reduced-form coefficient is in between its counterparts for civil servants and for private sector employees. If private-law public sector employees are compared with the matched sample of public sector employees, this pattern does not change.

Table 6: **Est. effects of *staff reduction* on *MCS* for different groups of employees**

	Private Sector Employees			Private-Law Pub. Sect. Empl.	Civil Servants
	full sample	sample matched to priv.-law pub.	sample matched to civil serv.		
dependent variable: *MCS*					
			OLS estimation		
est. coefficient of *staff reduction*	-1.009	-1.096	-1.107	-0.536	-0.418
test results (***p*-value**):					
individual significance (one-sided†)	0.000	0.000	0.000	0.037	0.164
deviation from priv.-law pub. sect. empl. (one-sided†)	0.080	0.064	–	–	–
deviation from civil servants (one-sided†)	0.097	–	0.096	–	–
# of observations	18,616	9,852	4,633	4,989	2,272
			Fixed Effects estimation		
est. coefficient of *staff reduction*	-0.334	-0.469	-0.519	-0.124	0.161
test results (***p*-value**):					
individual significance (one-sided†)	0.020	0.019	0.051	0.351	0.642
deviation from priv.-law pub. sect. empl. (one-sided†)	0.283	0.192	–	–	–
deviation from civil servants (one-sided†)	0.147	–	0.106	–	–
# of observations	18,616	9,886	4,633	5,062	2,300

Notes: †Alternative hypothesis: coefficient (deviation from coefficient of reference) is smaller than zero; for comprehensive regression results, including estimated coefficients for the controls; see Tables A5 to A8.

In order to strengthen the previous argument and following Green (2011),[27] we investigate whether employability matters for the effect that *staff reduction* exerts on mental health. If fear of job loss was the key mediating variable, one should expect an – in absolute terms – much smaller coefficient for individuals with good subjective reemployment perspective, because losing a job is arguably a less threatening event. In order to address this question, we reestimate the regression models explaining *MCS* including interaction terms of *staff reduction* with the two categories of 'employability' (moderate/good). Green (2011) finds strong evidence for good employability attenuating detrimental effects of unemployment and job insecurity on life satisfaction as well as mental health. Our results, both from OLS and FE estimating, are in line with his finding. We find that the detrimental effect of workforce reductions is almost twice as big for individuals with a small job-finding probability compared to those with moderate reemployment prospects. Good employability matters even more. Here, the negative effect of staff reductions disappears. That is, employees that easily find an adequate job are not negatively affected in their mental health. Moreover, testing for homogeneous effects clearly rejects the null. This is further indication for fear of job loss playing a major role in the link between workforce reductions and mental health.

We conducted further tests that argue against mediating variables other than than fear of job loss play a dominant role in the link between workforce reduction and mental health. For instance, further fixed-effects regressions do not yields effects of workforce reductions neither on official 'hours worked overtime' nor on subjective indicators for work related burdens such as 'increased amount of work' and 'high time pressure'.[28] If work related burdens were a major

[27]Besides not directly using a measure of job insecurity but analysing its effect in an indirect way and using a different measures for reemployment prospects, our analysis differs from Green (2011) by focussing on employed individuals.

[28]Though the SOEP data includes some information on these variables it is only available for (few) survey waves. We are nevertheless able to estimate FE regressions with work-related burdens as outcome variables by using recent workforce

Table 7: **Estimated effects of *staff reduction* on *MCS* by different *employability* categories**

	OLS		FE	
	Est. Coef.	S.E.	Est. Coef.	S.E.
staff reduction (by categories of 'employability'):				
almost non-employable (lag)	-1.882^*	0.367	-0.842^*	0.366
moderate employability (lag)	-1.066^*	0.186	-0.390^*	0.191
good employability (lag)	0.220	0.358	0.461	0.370
test for homogeneous effects (*p*-value)	0.000		0.035	

Notes: *significant at 5%; $^+$significant at 10%; 18,616 observations; robust standard errors reported.

channel through which workforce reductions did effect mental health, this should show up in these auxiliary regressions.

Summing up this discussion, the estimation results suggest that fear of job loss acts as relevant channel through which workforce reduction affects the *MCS* among private sector employees. In consequence, fear of job loss is likely to exert detrimental effects on mental health. Making quantitative statement about the size of this effect is, however, not straight forward, since we cannot clearly disentangle it from effects that operate through other mediating variables.

4.3 Results for Control Variables

Having discussed the coefficients of prime interest, we also briefly mention some results for the controls displayed in Table 4. Focussing on the OLS estimates, one result is that males are of significantly better psychological health than females. Estimating the regression model yields a non-linear relationship between age and mental health, whereby for OLS an age of 35 years is ceteris paribus associated with the lowest *MCS*. A nonlinear effect is also found for years of education, where over a wide range of possible lengths of education, the association with mental health is negative. According to the OLS coefficient, immigrants suffer less from mental health problems as compared to natives. 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*. Higher income seems to be associated with better mental health status. One result from the fixed effects specification seems to be puzzling at first sight. Working on a temporary contract, i.e. a relatively high level of job insecurity, is associated with better mental health. However, this result is found only in the FE specification and hence most likely captures rather specific short-term effects of switching from a temporary to a tenured position, or from switching in the opposite direction. The coefficient may, hence, capture what in the academic world is referred to as post-tenure depression syndrome (Perlmutter, 2015). Having struggled for

reductions with lagged values.

a long time to get tenured, individuals might eventually become disappointed, demotivated, and even depressed after finally reaching this goal. Another possible explanation rests on the idea of self-selection into a new non-tenured job. More specifically, the coefficient might capture that only individuals who are unhappy with a permanent position are willing to quit it in favor of a temporary one and hence feel released after the job change.

With respect to the controls in the equation explaining *fear of job loss*, as expected, we find a significant negative effect for a good and even moderate employability both in the OLS and the FE specification; see Table 5. In contrast, having a temporary contract is positively linked to subjective job insecurity. Being parent to underage kids, both for OLS and FE, is negatively associated with fear of job loss. This may capture that in Germany dismissal protection is particularly strict for this group of individuals. According to results from both, OLS and FE, moderate and good reemployment perspectives are inversely related to job worries.

4.4 Effects on Life Satisfaction

Health has been established to be closely related to well-being (Helliwell et al., 2012). In this section, we broaden the perspective of the analysis and consider life satisfaction as another outcome measure.[29] We report estimation results for exactly the same regression models as discussed above, utilizing the same data[30], except for using re-scaled (cf. Section 2) life satisfaction in stead of the *MCS* as left-hand-side variable. This approaches evidently ignores the ordered categorical nature of the measure of life satisfaction. However, estimating the model by ordered probit yields – up to a scaling factor of the significant coefficients – virtually identical results as the linear regression; see Table A11 in the Appendix for a comparison of results.

In both, the OLS and the fixed effects specification, the estimated effect of staff reduction on life satisfaction is roughly one-and-a-half times bigger than its counterparts in the model that explains mental health; see Table 8. Workforce reduction seems to deteriorate life satisfaction more strongly as compared to mental health. Please note that standardizing both variables allows us to compare the point estimates. Yet, the 95 percent intervals of confidence clearly overlap. Hence it is not obvious whether the effects qualitatively differ.

One argument in this direction would be that mediating channels other than fear of job loss play a more important role with respect to life satisfaction as compared to mental health. For instance, witnessing colleagues losing their jobs may well reduce general life satisfaction, while it

[29]Life satisfaction and *MCS* are positively correlated in the estimation sample. Taking the value of 0.45 the correlation is however far from perfect.

[30]Due to very few missing values for life satisfaction, the estimation sample is marginally smaller than in the reference model.

Table 8: **Effects of *staff reduction* on *general life satisfaction*†**

	OLS		Fixed Effects	
	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *general life satisfaction*†				
staff reduction	−1.421*	0.153	−0.599*	0.153
employability (lag): good	1.675*	0.210	0.109	0.227
moderate	2.668*	0.256	0.218	0.295
age	−0.648*	0.053	–	–
age^2	0.667*	0.062	0.080	0.111
male	0.172	0.160	–	–
migrant	0.552*	0.218	–	–
years of education	−0.109	0.273	–	–
years of education^2	0.518	0.991	–	–
married	0.091	0.214	−0.858*	0.357
living with partner	1.647*	0.228	2.036*	0.354
household size	0.064	0.101	0.165	0.149
# of kids under 18	0.175	0.127	−0.262	0.176
# of employed persons in household	0.008	0.113	0.032	0.150
household income (lag)	0.276*	0.024	0.038	0.040
occupation: blue-collar high skilled	0.525*	0.227	0.418	0.338
white-collar low skilled	1.247*	0.218	0.899*	0.329
white-collar high skilled	2.229*	0.274	1.809*	0.425
tenure	0.067*	0.009	–	–
mini job	0.302	0.318	−0.699	0.519
midi job	0.155	0.403	0.045	0.385
temporary work contract	−0.014	0.297	0.610+	0.324
side job	−0.637*	0.301	0.411	0.377
firmsize: medium	0.007	0.247	−0.186	0.372
large	0.357	0.260	0.131	0.437
year 2002	−0.241	0.195	1.120	0.776
year 2004	−1.049*	0.187	−0.116	0.592
year 2008	−0.202	0.186	0.177	0.234
constant	61.763*	2.105	–	–
federal state indicators	included*		not included	
# of observations	18,591		18,591	
R^2 (within for FE)	0.074		0.014	
joint significance (p-value)	0.000		0.000	

Notes: *significant at 5%; +significant at 10%; robust standard errors reported. †Originally measured on a ten point scale; rescaled to have equal mean and equal variance as *MCS*.

may not result in impairments in everyday life, which would be a criterion for an genuine mental health effect (cf. Section 1). If this was the case, one should find a substantial effects of workforce reductions on life satisfaction also in the comparison groups, i.e. for civils servants and private-law public-sector employees, for which fear of job loss plays no or just little role. At least, the estimated coefficients should deviate less pronounced from their counterparts for private sectors employees, compared to the pattern found for mental health as left-hand-side variable. Indeed, for civil servants the estimated coefficient are negative and substantially bigger in absolute terms, compared to the regression explaining *MCS*. In the OLS regression the coefficient is even highly statistically significant; see Table A4 in the Appendix. However, this does not apply to private-law public-sector employees for which the point estimates are very close to their counterparts from the regression explaining mental health. It hence remains unclear to some extent whether general live satisfaction and mental health are affected by workforce reductions in different ways and whether fear of losing the own job plays a different role in mediating this effect.

We further address the question of whether life satisfaction and mental health are essentially indistinguishable concepts – at least with regard to the detrimental effects workforce reduction, and possibly fear of job loss, exert on them. For this purpose we include the respective other variable as additional control.[31] If in these axillary regression the effect of workforce reductions disappeared, this would point to life satisfaction and mental health being interchangeable. Yet, the regressions yield a different picture. In the OLS model explaining the *MCS*, the coefficient of staff reductions gets substantially smaller (-0.378) if life satisfaction is included as control, however it clearly stays statistically significant. This does not fully apply to the fixed effects specification. There, the point estimate is still negative (-0.150) but turns statistically insignificant. When life satisfaction is the left-hand-side variable and the *MCS* is included as control, the estimated coefficient of workforce reduction changes remarkably little, taking the values -0.987 (OLS) and -0.504 (FE), and stays highly significant. In each auxiliary regression, the respective other outcome variable proves to by a highly significant predictor for the left-hand side, importantly, however, the coefficients are clearly smaller than one; see Tables A9 and A10 in the Appendix for detailed results. This suggests that the effects that workforce reduction exerts on life satisfaction and mental health are not identical such that one can regard both outcomes as synonyms. In particular, the results seem to point to life satisfaction being affected by workforce reductions through channels that are immaterial for mental health, which provides another argument for our above interpretation.

Concerning the controls, in the FE specification, being married is significantly negatively associated with life satisfaction. This seems to conflict with what is regularly found in the literature (Graham, 2008). However, since fixed effects models identify the coefficients from changes in martial status and relationship status is controlled for, one may interpret the negative sign such that actually terminating an unhappy marriage makes individuals more satisfied with their lives. Living in a partnership, in contrast, is positively associated with live satisfaction. This also holds for white-collar occupation and for working on a temporary contract, regarding the latter cf. the discussion in Section 4.3.

[31] As these additional controls are outcome variables themselves, they are obviously 'bad controls' (Angrist and Pischke, 2009, p. 66) that should not be included in a regression model that is meant to reproduce the true data generating process and allows for interpreting the estimated coefficients in terms of causal effects. Yet this is not the propose of this axillary regressions.

Table 9: **Estimated effects of *staff reduction* on *MCS* by gender**

	OLS		FE	
	Est. Coef.	S.E.	Est. Coef.	S.E.
men	-0.987^{*}	0.189	-0.226	0.198
women	-1.092^{*}	0.260	-0.495^{+}	0.282
test for homogeneous effects (p-value)	0.744		0.435	

Notes: *significant at 5%; $^{+}$significant at 10%; 10,761 male observations and 7,855 female observations; robust standard errors reported.

4.5 Heterogeneity in Effects

In this section, we dig deeper into the effect of staff reductions on mental health by looking possible dimensions of effect heterogeneity beyond employability, which has already been considered in Section 4.2. More specifically, following Green (2011), first we estimate separate models for males and females. Second, our analysis adds a further facet by addressing whether effects on *MCS* vary with the mental health status itself. To this end, we estimate separate models for employees with a mental health score below the 25th quantile in 2002 and employees with a respective score above the first quartile threshold.

Estimating the model separately for men and women does not yield a statistically significant gender differential in γ_1 in any specification, though the point estimate for women exceeds the one for men in both the OLS and the FE regression. This result is not in line witch the finding of Green (2011) that, conditional on good reemployment prospects, male employees suffer substantial more from job insecurity than female employees. However, Green (2011) also finds that this gender differential almost vanishes if reemployment prospects are poor.

Separate results for the effect of workforce reductions on psychological health by mental health scores in 2002, excluding the observations for the year 2002, are displayed in Table 10. We observe pronounced effect heterogeneity across mental health quartiles in both the OLS and FE model, which is at least marginally (OLS) significant.[32] This finding indicates that in particular individuals who are in poor mental health already are detrimentally affected by staff reductions. In fact, the results from FE regression suggest the *MCS* of employees in good or even moderate mental health is not affected at all if his or her employer reduces its workforce. Moreover, comparing the coefficients of staff reduction in the regression explaining 'fear of job loss' between both subsamples, we observe that a reduction of the workforce has a somewhat stronger impact on perceived job insecurity of the mentally more vulnerable employees. This can be regarded as indication for 'fear of job loss' playing an important role as mediating variable first of all for individuals with vulnerable mental health.

[32] If we use the all waves, i.e. including the year 2002 which serves as reference for splitting the sample, the general pattern remains the same, yet for OLS effect heterogeneity gets less pronounces and is statistically insignificant.

Table 10: **Est. effects of *staff reduction* on *MCS* by mental health status in 2002 (years 2004–2010)**

	OLS		FE	
	Est. Coef.	S.E.	Est. Coef.	S.E.
position in distribution of MCS (year 2002):				
lowest quartile	-1.366^{*}	0.373	-1.806^{*}	0.427
other quartiles	-0.625^{*}	0.178	0.010	0.219
test for homogeneous effects (p-value)	0.073		0.000	

Notes: *significant at 5%; $^{+}$significant at 10%; 3,332 and 10,672 observations with a MCS score below and above the quartile threshold, respectively; years 2004, 2008, and 2010 considered; robust standard errors reported.

Splitting the estimation sample by categories of the left-hand-side variable is always subject to concerns about generating sample selection bias. In the present application this source of bias should not play a significant role, since we split the sample according to the initial value of *MCS* (not according to the contemporaneous value of *MCS*) which is not used in the results displayed above and, in addition, use only within-group variation in the FE-specifications. We nevertheless take a further approach to identifying effect-heterogeneity with respect to mental health status, by running quantile regressions based on the OLS specification that dissolve the effect under scrutiny over the entire distribution of *MCS*. Results for quantile regressions also point at pronounced effect heterogeneity; see Figure 1 for the estimated quantile coefficient curve. Except for the very lowest quantiles, for which the quantile coefficients are measured rather imprecise as indicated by the particularly wide confidence intervals, the effect decreases in absolute terms with increasing quantiles of the *MCS*. This points to individuals with rather robust mental health being less affected by workforce reductions at their workplaces. This finding is in line with what is found in several related studies. Schiele and Schmitz (2016) and Binder and Coad (2015a,b) report an equivalent pattern of heterogeneity for the effect of *actual* job loss on mental health and well-being, respectively. At least for some of the considered explanatory variables, this also applies to Contoyannis and Li (2013) who analyse several early live-time characteristics as determinants of depression among adolescents and young adults. In contrast, Kolodziej (2011) finds that retirement exerts the strongest negative effects on mental health around the median, but not in the tails of the distribution of mental health.

All in all, our results suggest that severe adverse effects of workforce reduction on employees who keep their jobs – and possibly instable working environments in general – is an issue that concerns particularly vulnerable groups of individuals, while less vulnerable employees may well be able to cope with this kind of workplace related stress. Hence, strengthening dismissal protection across the board seems not be a reasonable policy response.

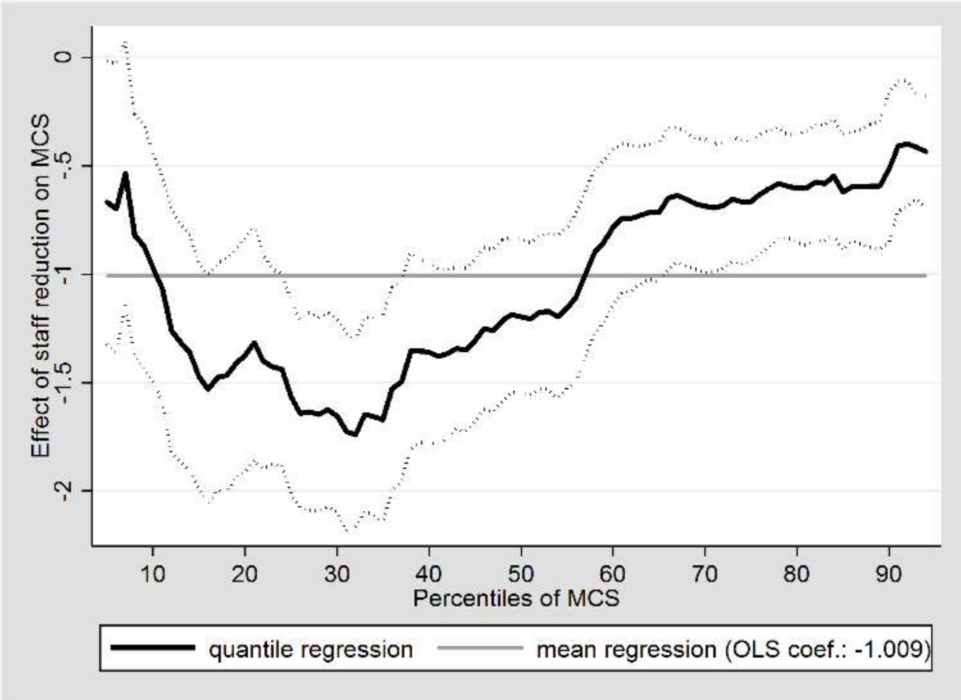

Figure 1: Estimated quantile coefficient curve for the effect of *staff reduction* on *MCS*; dotted lines indicate the 95-percent interval of confidence.

4.6 Robustness Checks

The *MCS* is a well established mental health measure in the literature that condenses information on various questions into a scalar index. Hence, the estimated effect on *MCS* represents some kind of summary of effects that job insecurity has on each variable that enters the *MCS*. In order to better understand the sources of the estimated effects, and to rule out that the overall effect is driven by the effect on one single *MCS* component, we run the regression model separately for each component, using the same specification and estimation sample as in previous regressions. All components are measured on an ordinal scale (see Table A1 in the Appendix). We harmonized the variables in a way that they uniformly point to worse (mental) health-related problems with higher values, leaving the number of categories unchanged.[33] For each component of the *MCS*, Table 11 displays the estimated effects of staff reduction, the corresponding standard error and the corresponding *p*-values for one-sided tests for statistical significance. One-sided tests seem to be more appropriate because of the alternative hypotheses, i.e. detrimental effects of workforce reduction, being clearly directional. The categories are ordered by the magnitude of the *p*-values in the FE regressions.

[33]The variables on the intensity of the reported health impact on 'ascending stairs' and 'coping with other tiring everyday tasks' contain three categories (not at all = 0, slightly = 1, greatly = 3). All other *MCS* components are measured on five scales that indicate the frequency of the health problem (0 = never, 1 = almost never, 2 = sometimes, 3 = often, 4 = always).

Table 11: **Est. effects of *staff reduction* on *MCS components*, *sleep satisfaction*, and *doctor visits***

	OLS			FE		
	Est. Coef.	S.E.	p-value†	Est. Coef.	S.E.	p-value†
used up a lot energy	0.065*	0.014	0.000	0.037*	0.016	0.010
problems with ascending stairs	0.015*	0.009	0.041	0.020*	0.009	0.014
run-down or melancholy	0.106*	0.016	0.000	0.037*	0.017	0.014
emotionally unbalanced	0.101*	0.014	0.000	0.032*	0.016	0.020
strong physical pain	0.066*	0.016	0.000	0.024+	0.017	0.083
limitations at daily tasks (physical problems)	0.026*	0.015	0.042	0.019	0.017	0.133
limited socially	0.039*	0.014	0.003	0.016	0.015	0.143
pressed for time	0.082*	0.016	0.000	0.013	0.018	0.232
achieved less due to mental problems	0.036*	0.016	0.011	0.011	0.018	0.270
achieved less due to physical problems	0.063*	0.015	0.000	0.007	0.016	0.337
problems with tiring tasks	0.016+	0.010	0.052	0.003	0.010	0.373
carry out daily tasks less thoroughly	0.039*	0.013	0.001	0.002	0.015	0.458
dissatisfaction with sleep	0.049	0.054	0.184	0.086+	0.060	0.075
number of doctor visits	0.186*	0.040	0.000	0.083*	0.048	0.043

Notes: †one-sided test; *significant at 5% (one-sided test); +significant at 10% (one-sided test); robust standard errors reported; results for covariates ommitted.

The OLS model yields that *staff reduction* exerts a detrimental and clearly statistically significant effect on every single variable that enters the *MCS*, with the exception of 'problems with tiring tasks' which is only weakly significant. Yet, the magnitude of the point estimates varies considerably. The FE model exhibits pronounced effect heterogeneity across *MCS* components, also in terms of statistical significance. Significant effects are only found on few components. Reassuringly, every single coefficient exhibits a positive sign, which is consistent with the result found for the aggregated measure. The components of the *MCS*, for which significant effects of staff reductions are found, are problems with 'ascending stairs due to bad health' and (weakly) 'strong physical pain' and the reported frequencies of time that respondents felt 'run-down and melancholy', 'emotionally unbalanced', and 'exhausted'. The latter three components exhibit a direct relationship with certain mental disorders. 'Ascending stairs due to bad health' and 'strong physical pain', are more physical oriented problems. We interpret effects on these variables as suggestive evidence that a deteriorated mental health state translates into tangible impairments in everyday life. It is well established in the psychological literature that various mental disorders are associated with physical problems. For instance, depression has been shown to provoke fatigue or specific gait patterns including reduced walking speed (Michalak et al., 2009). Thus, FE results yield effects of workforce reduction on key components of the *MCS* and hence can be interpreted as effects on genuine mental health as defined by the WHO.

In order to provide further evidence in favor of genuine (mental) health effects, we use the number of doctor visits[34] in the previous three months as dependent variable. In the FE regression, the coefficient is statistically significant at the 10 percent level and points to workforce reductions inducing health problems. According to the point estimate, those who experienced

[34] We excluded observations with an excessive number of 20 or more reported doctor visits, with accounted for less than 0.5% of the estimation sample size.

Table 12: **Estimates effects of *staff reduction* on *MCS* for various robustness checks**

	OLS		FE		# of obs.
	Est. Coef.	S.E.	Est. Coef.	S.E.	
singleton groups included	-1.007^*	0.140	–	–	23,159
$20 \leq$ **age** ≤ 60 only	-0.977^*	0.157	-0.347^*	0.165	17,804
employees holding **permanent contracts** only	-1.034^*	0.159	-0.348^*	0.168	17,062
no employees of **small firms**	-1.051^*	0.158	-0.348^*	0.170	16,699
€1,000 $\leq$ **hh. income** $\leq$ €12,000 only	-0.955^*	0.158	-0.281^+	0.169	17,153
employability indicators excluded	-1.073^*	0.153	-0.336^*	0.163	18,616
indicator for **East Germany** included	-1.030^*	0.154	-0.334^*	0.163	18,616
five categories for **firm size**	-1.016^*	0.154	-0.332^*	0.163	18,616
self-assessed health included	-0.871^*	0.150	-0.323^*	0.163	18,590
indicator for **past unemployment** included	-1.014^*	0.154	-0.336^*	0.164	18,348
change in employment (alt. occupation) included	-1.011^*	0.153	-0.336^*	0.163	18,616
reference specification	-1.009^*	0.153	-0.334^*	0.163	18,616

Notes: *significant at 5%; $^+$significant at 10%; robust standard errors reported; results for covariates ommitted.

workforce reduction at their workplace on average have roughly one tenth of an additional doctor visit per quarter, which seems to be of economic significance compared to the sample average of 1.76 visits. Yet, taking the 10 percent interval of confidence into account $[0.001, 0.163]$, it appears hardly possible to say anything definite about the magnitude of the effect. For dissatisfaction with sleep, we find a (weakly) significant and detrimental effect only for the fixed effects specification.

Besides the variations to the reference model discussed above, we ran a battery of robustness checks that address different aspects of the model specification. Our key results proved to be robust to these changes to the model specification. In detail, we (i) estimated the model with OLS, considering also individuals for which only one observation is available (singleton groups), which had virtually no impact on the results. (ii) We confined the analysis to individuals aged between 20 and 60 years. This yields results very close to those of the reference regression. (iii) We only considered employees holding permanent work contracts, which had just marginal effects on the results. (iv) We did not consider individuals employed with small firms in the estimation sample. This also hardly affects the results. (v) We further only considered individuals living in households with a gross monthly income between €1,000 and €12,000. The point estimates remained, by large, unchanged. (vi) We excluded the employability indicators and got almost identical results as for the specification of reference. This also held for (vii) including an indicator for living in East Germany as control that – in the case of OLS – replaced the state indicators. (viii) Instead of three, we used five categories for firm size ($<$ 5, 5-20, 21-200, 201-2,000, and $>$ 2,000 employees), which also had just marginal effect on the key coefficient. (ix) Including self-assessed health as further control slightly reduces the estimated effect for OLS, yet it does not change the results in qualitative terms. (x) We tried another specification with an indicator for past unemployment as additional control. Including this indicator has virtually no effect on the estimated coefficient of staff reduction. Finally, (xi) we included the recent change in employment for the respective alternative occupation (i.e., the change in white-collar employment for blue-collar workers and the change in blue-collar employment for white-collar workers) at the national level in order to control for labor market conditions that are not directly related to individual job security. This has virtually no effect on the estimated coefficient of prime importance. Table 12 displays the estimates for the coefficient attached to the key explanatory variable staff reduction; comprehensive regression output is available upon request.

5 Conclusion

Based on German panel data, the present analysis yields evidence for company-level workforce reduction exerting detrimental effects on the mental health of employees who remain working in the respective firm. We also find a qualitatively equivalent effect on general life satisfaction. Our result proves to be robust in qualitative terms with respect to different estimation methods and model specifications. In quantitative terms, OLS yields and estimated effect of roughly one MCS unit, while fixed effects, as the more conservative estimation method, suggests that workforce reductions reduce the MCS by one third of a unit. Though small in absolute magnitude, these effects are still equivalent to shifts from median mental health to the 45th and the 47th percentile of its sample distribution.

The analysis further addresses the question whether this effect is mediated through subjective job insecurity. Several findings point in this direction. First, according to our estimation results, staff reductions do not only affect the phycological health of employees but also their subjective job insecurity. This means that individuals who experienced staff reductions in their firms are more concerned about their jobs being save. In quantitative terms, our result suggests that individuals who experienced company-level job cuts are about ten percentage points more likely to be concerned about their jobs. Second, for comparison groups of individuals who are much better protected against job loss, more specifically private-law public-sector employees and civil servants, for which fear of job loss should hence have little or no relevance, we find substantially smaller and in terms of economic as well as statistical significance negligible effects on mental health. Finally, we find consistent heterogeneity of effects with respect to subjective reemployment prospects. Staff reductions have virtually no effect on mental health for individuals who regard finding a new job as fairly easy, while those who are pessimistic about finding a new job are most adversely affected. We cannot rule out other impact channels such as experiencing coworkers and even friends losing their jobs, increased workload, and stress due to a new workplace and new tasks as a result of a possible restructuring, and frustration because of the firm is doing bad. Nonetheless, our findings point to individual fear of job loss representing a relevant determinant of mental health. This in turn means that the mere fear of job loss, as opposed to actually being dismissed, is likely to adversely affect mental health and life satisfaction.

Regarding heterogeneity in the effect of staff reduction on mental health, we find that those who are in mediocre or poor mental health seem to be hit more compared those in good mental health. This suggests that workforce reduction and possibly subjective job insecurity is an relevant source of mental health problems for a particularly vulnerable group of the population.

To the extent that our results speak to the relationship between job insecurity and mental health, improved dismissal protection may have important benefits in terms of preventing psychological health problems among vulnerable employees. Yet, this does not necessarily call for strengthening dismissal protection. We advocate taking a differentiated view on dismissal protection as well as on measures aimed at making the labor market more flexible in order to achieve efficiency gains. Flexicurity policies, for instance, aimed at limiting the short-term consequences of potential unemployment and increasing the job-finding probability may represent a compromise between the objectives of increasing efficiency and protecting vulnerable individuals. Yet, as we only look at one side of the coin, determining the optimal policy is out of scope of the present analysis and a promising avenue for future research.

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Appendix

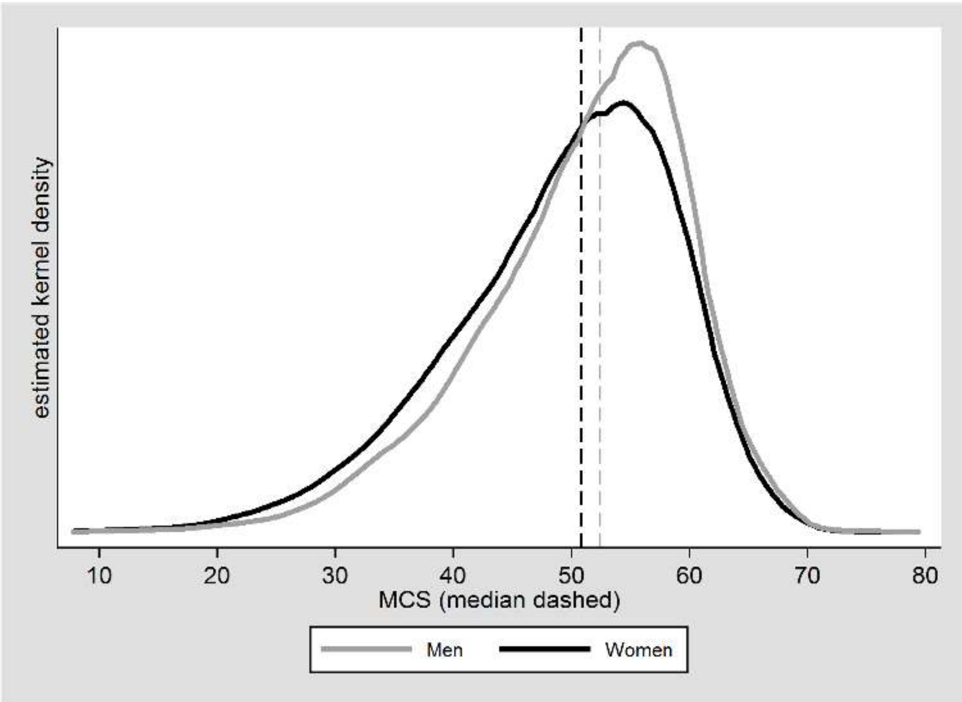

Figure A1: Distribution of the *MCS* by Sex.
Note: Density estimates based on estimation sample (10,761 male obs. and 7,855 females obs.).

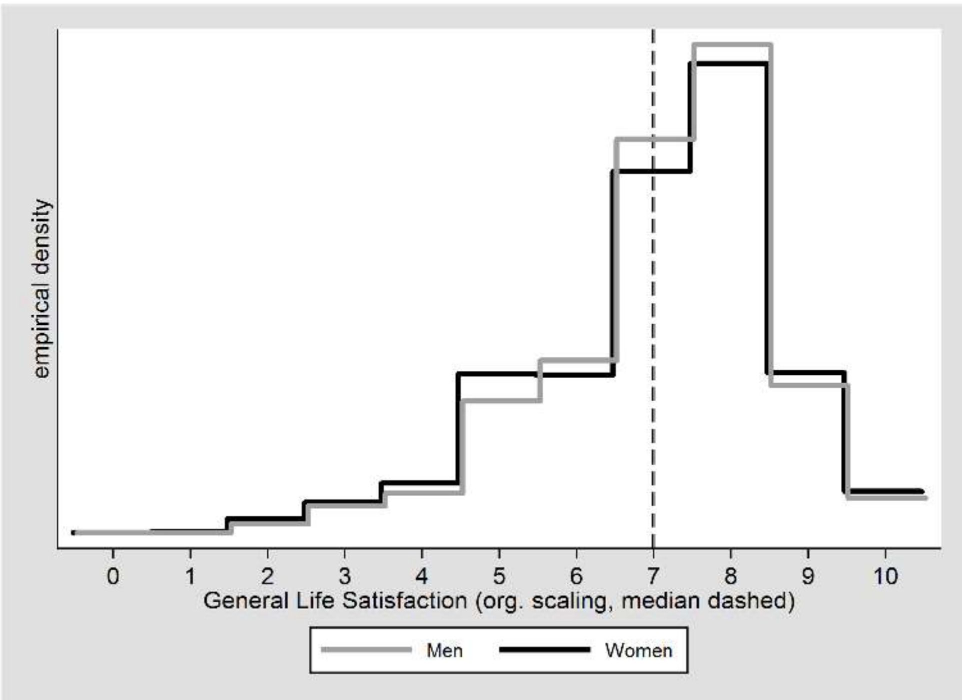

Figure A2: Distribution of the Life Satisfaction (org. scaled) by Sex.
Note: Density estimates based on estimation sample (10,746 male obs. and 7,848 females obs.).

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?					

Table A2: **IV Estimation: est. effects of *fear of job loss* on *MCS***

	IV		Fixed Effects IV	
	Est. Coef.	S.E.	Est. Coef.	S.E.
main equation (dependent variable: *MCS*)				
fear of job loss	-7.768^{*}	1.182	-3.523^{*}	1.726
employability (lag): good	0.273	0.237	0.086	0.245
moderate	0.263	0.332	-0.065	0.334
age	-0.197^{*}	0.056	–	–
age^2	0.302^{*}	0.066	0.225^{+}	0.117
male	1.891^{*}	0.164	–	–
migrant	1.546^{*}	0.220	–	–
years of education	-0.884^{*}	0.272	–	–
years of education^2	2.769^{*}	0.996	–	–
married	0.094	0.226	-0.161	0.369
living with partner	0.421^{+}	0.243	1.220^{*}	0.376
household size	0.087	0.101	-0.067	0.154
# of kids under 18	-0.211^{+}	0.128	-0.037	0.183
# of employed persons in household	0.107	0.116	0.111	0.151
household income (lag)	0.075^{*}	0.024	-0.009	0.037
occupation: blue-collar high skilled	0.341	0.223	0.418	0.338
white-collar low skilled	0.359	0.222	0.614^{+}	0.339
white-collar high skilled	0.084	0.297	0.909^{*}	0.463
tenure	-0.009	0.009	–	–
mini job	0.390	0.313	0.087	0.519
midi job	-0.496	0.400	-0.821^{+}	0.432
temporary work contract	0.971^{*}	0.334	1.486^{*}	0.357
side job	-1.376^{*}	0.305	-0.185	0.392
firmsize: medium	0.212	0.252	-0.206	0.364
large	0.069	0.265	-0.127	0.426
year 2002	-0.020	0.204	1.458^{+}	0.821
year 2004	0.523^{*}	0.198	1.468^{*}	0.629
year 2008	0.353^{+}	0.192	0.786^{*}	0.254
constant	58.714^{*}	2.116	–	–
federal state indicators	included*		not included	
# of observations	18,616		18,616	
joint significance (p-value, main equ.)	0.000		0.000	
instrument relevance (F-statistic, first stage†)	361.15		143.13	

Notes: *significant at 5%; $^{+}$significant at 10%; robust standard errors reported; †for first stage results, see Table 5.

Table A3: **Estimated effects of lagged *staff reduction* on *self-assessed probability of job loss***

	OLS		Fixed Effects	
	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *self-assessed probability of job loss*†				
staff reduction *(lag)*	0.068*	0.005	0.024*	0.006
employability (lag): good	−0.029*	0.006	−0.002	0.009
moderate	−0.086*	0.008	−0.013	0.011
age	0.013	0.002	–	–
age^2	−0.015*	0.002	−0.010*	0.005
male	−0.006	0.005	–	–
migrant	−0.018	0.007	–	–
years of education	0.039	0.009	–	–
years of education^2	−0.128	0.031	–	–
married	−0.020*	0.007	−0.003	0.013
living with partner	0.021*	0.007	0.010	0.013
household size	−0.001	0.003	−0.002	0.006
# of kids under 18	−0.007+	0.004	−0.002	0.006
# of employed persons in household	0.008*	0.004	0.000	0.006
household income (lag)	−0.003*	0.001	0.001	0.001
occupation: blue-collar high skilled	0.008	0.007	0.011	0.012
white-collar low skilled	−0.018*	0.007	−0.031*	0.013
white-collar high skilled	−0.034*	0.009	−0.045*	0.018
tenure	−0.003	0.000	–	–
mini job	−0.017+	0.010	−0.038*	0.018
midi job	−0.034*	0.011	−0.025*	0.012
temporary work contract	0.142*	0.012	0.122*	0.015
side job	0.022*	0.009	0.008	0.014
firmsize: medium	0.023*	0.008	0.004	0.015
large	0.011	0.009	−0.002	0.017
year 2003	−0.031*	0.005	−0.071*	0.025
year 2005	−0.026*	0.005	−0.044*	0.017
constant	−0.245	0.069	–	–
federal state indicators	included*		not included	
# of observations	13,440		13,440	
R^2 (within for FE)	0.096		0.022	
joint significance (p-value)	0.000		0.000	

Notes: *significant at 5%; +significant at 10%; robust standard errors reported. †measured on the $[0, 1]$ interval; statistics for for dep. variable (*self-assessed probability of job loss*) in est. sample: 0.256 (mean), 0.246 (s.d.), 0.2 (median), 0 (min.), 1 (max.); years 2003, 2005, and 2009 included; singleton groups excluded.

Table A4: **Est. effects of *staff reduction* on *life satisfaction* for diff. groups of employees**

	Private Sector Employees			Private-Law Pub. Sect. Empl.	Civil Servants
	full sample	sample matched to priv.-law pub.	sample matched to civil serv.		
dependent variable: *general life satisfaction*					
	OLS estimation				
est. coefficient of *staff reduction*	-1.423	-1.545	-0.929	-0.494	-0.797
test results (***p*-value**):					
individual significance (one-sided†)	0.000	0.000	0.001	0.022	0.008
deviation from priv.-law pub. sect. empl. (one-sided†)	0.001	0.001	–	–	–
deviation from civil servants (one-sided†)	0.044	–	0.382	–	–
# of observations	18,594	10,451	4,837	6,829	3,074
	Fixed Effects estimation				
est. coefficient of *staff reduction*	-0.599	-0.742	-0.392	0.082	-0.237
test results (***p*-value**):					
individual significance (one-sided†)	0.000	0.000	0.076	0.626	0.236
deviation from priv.-law pub. sect. empl. (one-sided†)	0.011	0.007	–	–	–
deviation from civil servants (one-sided†)	0.160	–	0.359	–	–
# of observations	18,591	9,809	4,837	6,952	3,118

Notes: †Alternative hypothesis: coefficient (deviation from coefficient of reference) is smaller than zero.

Table A5: OLS est. explaining *MCS* (est. samp. and **civil servants** samp.)

	Priv. Sect. Employees (full sample)		**Priv. Sect. Employees** (matched sample)		**Civil Servants**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *MCS*						
staff reduction	-1.009^{*}	0.153	-1.107^{*}	0.308	-0.418	0.428
employability (lag): good	0.975^{*}	0.205	0.161	0.381	-0.046	0.440
moderate	1.566^{*}	0.256	0.646	0.506	0.688	0.553
age	-0.300^{*}	0.053	-0.190	0.120	0.125	0.174
age^2	0.426^{*}	0.062	0.300^{*}	0.136	-0.039	0.191
male	1.780^{*}	0.162	1.838	0.349	2.095	0.447
migrant	1.185^{*}	0.210	0.968	0.967	-3.000	1.983
years of education	-0.757^{*}	0.269	-0.940	0.732	-1.284	1.044
years of education^2	2.401^{*}	0.987	3.559	2.523	4.047	3.597
married	0.150	0.228	0.459	0.495	-0.945	0.638
living with partner	0.350	0.244	-0.314	0.536	1.405^{+}	0.762
household size	0.067	0.100	-0.303	0.201	-0.053	0.305
# of kids under 18	-0.125	0.127	0.487^{+}	0.253	0.172	0.367
# of employed persons in household	0.119	0.115	0.349	0.246	-0.375	0.387
household income (lag)	0.123^{*}	0.023	0.117^{*}	0.040	0.135	0.089
occupation: blue-collar high skilled	0.406^{+}	0.219	0.441	0.569	–	–
white-collar low skilled	0.721^{*}	0.212	0.497	0.556	–	–
white-collar high skilled	0.669^{*}	0.280	0.167	0.612	–	–
tenure	0.007	0.009	0.000	0.017	-0.027	0.026
mini job	0.739^{*}	0.305	1.611^{+}	0.840	–	–
midi job	-0.211	0.401	-0.236	1.016	0.313	1.250
temporary work contract	0.099	0.301	-0.975	0.733	0.940	0.987
side job	-1.274^{*}	0.308	-1.154^{+}	0.589	0.684	0.672
firmsize: medium	0.116	0.250	-1.045^{+}	0.573	7.229	6.365
large	0.092	0.264	-0.917	0.592	8.029	6.360
year 2002	0.019	0.204	0.299	0.418	-0.838	0.603
year 2004	0.232	0.192	0.333	0.390	-0.136	0.546
year 2008	0.415^{*}	0.192	0.136	0.388	0.162	0.537
constant	57.835^{*}	2.100	59.868^{*}	5.897	48.684^{*}	10.843
# of observations	18,616		4,633		2,272	
R^2	0.035		0.045		0.046	
joint significance (p-value)	0.000		0.000		0.000	

Notes: *significant at 5%; $^{+}$significant at 10%; robust standard errors reported.

Table A6: OLS est. explaining *MCS* (est. samp. and **priv.-law pub.-sect. employees** samp.)

	Priv. Sect. Employees (full sample)		**Priv. Sect. Employees** (matched sample)		**Priv.-Law Pub. Empl.**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *MCS*						
staff reduction	-1.009^{*}	0.153	-1.096^{*}	0.214	-0.536^{+}	0.300
employability (lag): good	0.975^{*}	0.205	1.150^{*}	0.279	0.840^{*}	0.364
moderate	1.566^{*}	0.256	1.840^{*}	0.352	1.440^{*}	0.501
age	-0.300^{*}	0.053	-0.178	0.078	-0.270	0.118
age^2	0.426^{*}	0.062	0.284^{*}	0.091	0.379^{*}	0.136
male	1.780^{*}	0.162	1.649	0.226	1.233	0.306
migrant	1.185^{*}	0.210	1.166	0.325	-1.009	0.510
years of education	-0.757^{*}	0.269	-1.037	0.384	0.939	0.599
years of education^2	2.401^{*}	0.987	3.175	1.385	-3.584	2.145
married	0.150	0.228	0.161	0.317	0.080	0.479
living with partner	0.350	0.244	0.632^{+}	0.347	0.785	0.512
household size	0.067	0.100	-0.042	0.142	0.223	0.202
# of kids under 18	-0.125	0.127	-0.107	0.178	-0.882^{*}	0.259
# of employed persons in household	0.119	0.115	0.096	0.162	-0.198	0.230
household income (lag)	0.123^{*}	0.023	0.163^{*}	0.030	0.102^{*}	0.043
occupation: blue-collar high skilled	0.406^{+}	0.219	0.741^{*}	0.338	1.736^{*}	0.649
white-collar low skilled	0.721^{*}	0.212	0.945^{*}	0.301	0.210	0.537
white-collar high skilled	0.669^{*}	0.280	0.734^{+}	0.396	0.667	0.656
tenure	0.007	0.009	0.008	0.012	-0.050	0.018
mini job	0.739^{*}	0.305	1.250^{*}	0.405	1.620^{+}	0.903
midi job	-0.211	0.401	-0.027	0.474	0.604	0.634
temporary work contract	0.099	0.301	0.004	0.435	-0.570	0.552
side job	-1.274^{*}	0.308	-1.592^{*}	0.431	-0.497	0.485
firmsize: medium	0.116	0.250	0.293	0.340	1.202	1.127
large	0.092	0.264	0.438	0.362	1.301	1.129
year 2002	0.019	0.204	-0.220	0.287	-0.484	0.429
year 2004	0.232	0.192	0.012	0.269	0.198	0.399
year 2008	0.415^{*}	0.192	0.218	0.268	0.530	0.398
constant	57.835^{*}	2.100	57.440^{*}	3.065	48.346^{*}	4.910
# of observations	18,616		9,852		4,989	
R^2	0.035		0.037		0.040	
joint significance (p-value)	0.000		0.000		0.000	

Notes: *significant at 5%; $^{+}$significant at 10%; robust standard errors reported.

Table A7: FE est. explaining *MCS* (est. samp. and **civil servants** samp.)

	Priv. Sect. Employees (full sample)		**Priv. Sect. Employees** (matched sample)		**Civil Servants**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *MCS*						
staff reduction	-0.334^{*}	0.163	-0.519^{+}	0.317	0.161	0.443
employability (lag): moderate	0.193	0.238	-0.422	0.459	-0.156	0.476
good	0.144	0.314	0.122	0.626	-0.498	0.642
age^2	0.249^{*}	0.116	0.190	0.233	0.324	0.350
married	-0.227	0.370	-1.407^{+}	0.728	-0.279	1.005
living with partner	1.236^{*}	0.376	2.276	0.779	0.859	0.985
household size	-0.087	0.154	-0.249	0.297	-0.084	0.413
# of kids under 18	0.027	0.180	-0.020	0.338	0.492	0.418
employed persons in household	0.124	0.150	-0.048	0.304	0.045	0.466
household income	-0.132^{*}	0.037	-0.112^{+}	0.064	-0.168	0.127
occupation: blue-collar skilled	0.414	0.337	1.027	0.783	–	–
white-collar low skilled	0.671^{*}	0.339	1.034	0.806	–	–
white-collar high skilled	1.004^{*}	0.463	0.731	0.919	–	–
mini job	0.060	0.521	1.003	1.128	–	–
midi job	-0.878^{*}	0.432	-0.105	1.128	0.272	1.477
temporary work contract	1.207^{*}	0.336	0.179	0.743	0.264	1.340
side job	-0.106	0.394	-0.777	0.797	0.798	0.965
firm size: medium	-0.199	0.365	0.759	0.803	9.296	6.918
large	-0.103	0.427	1.251	0.928	10.379	6.825
year 2002	1.600^{+}	0.817	1.312	1.707	1.642	2.609
year 2004	1.386^{*}	0.626	1.176	1.306	1.368	1.995
year 2008	0.848	0.249	0.479	0.520	0.377	0.747
# of observations	18,616		4,633		2,300	
R^2 (within)	0.006		0.011		0.011	

Notes: *significant at 5%; $^{+}$significant at 10%; robust standard errors reported.

Table A8: FE est. explaining *MCS* (est. samp. and **priv.-law pub.-sect. employees** samp.)

	Priv. Sect. Employees (full sample)		**Priv. Sect. Employees** (matched sample)		**Priv.-Law Pub. Empl.**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *MCS*						
staff reduction	-0.334^{*}	0.163	-0.345	0.235	-0.124	0.325
employability (lag): moderate	0.193	0.238	0.503	0.345	-0.588	0.417
good	0.144	0.314	0.312	0.464	-0.293	0.602
age^2	0.249^{*}	0.116	0.068	0.165	0.496	0.258
married	-0.227	0.370	-0.414	0.538	1.126	0.793
living with partner	1.236^{*}	0.376	1.036	0.545	0.313	0.776
household size	-0.087	0.154	-0.345	0.215	-0.393	0.297
# of kids under 18	0.027	0.180	0.005	0.262	-0.255	0.339
employed persons in household	0.124	0.150	0.287	0.217	0.018	0.316
household income	-0.132^{*}	0.037	-0.019	0.052	-0.024	0.063
occupation: blue-collar skilled	0.414	0.337	1.148^{*}	0.521	1.182	0.963
white-collar low skilled	0.671^{*}	0.339	1.052^{*}	0.504	0.830	0.768
white-collar high skilled	1.004^{*}	0.463	1.583^{*}	0.684	-0.303	0.951
mini job	0.060	0.521	-0.440	0.684	0.802	1.655
midi job	-0.878^{*}	0.432	-0.769	0.531	1.134^{+}	0.620
temporary work contract	1.207^{*}	0.336	0.674	0.516	-1.045	0.681
side job	-0.106	0.394	-0.571	0.559	0.813	0.690
firm size: medium	-0.199	0.365	-0.246	0.525	1.090	1.516
large	-0.103	0.427	0.128	0.603	0.931	1.561
year 2002	1.600^{+}	0.817	0.177	1.173	3.681^{+}	1.932
year 2004	1.386^{*}	0.626	0.162	0.897	3.391^{*}	1.469
year 2008	0.848	0.249	0.186	0.356	1.647^{*}	0.571
# of observations	18,616		9,195		5,062	
R^2 (within)	0.006		0.011		0.011	

Notes: *significant at 5%; $^{+}$significant at 10%; robust standard errors reported.

Table A9: **Reg. of *MCS* on *staff reduction* controlling for *life satisfaction***

	OLS		Fixed Effects	
	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *MCS*				
staff reduction	-0.378^{*}	0.137	-0.150	0.155
life satisfaction	0.447^{*}	0.007	0.309^{*}	0.011
employability (lag): good	0.208	0.183	0.166	0.228
moderate	0.354	0.229	0.084	0.300
age	-0.009	0.048	–	–
age^2	0.126^{*}	0.057	0.207^{+}	0.111
male	1.698^{*}	0.146	–	–
migrant	0.943^{*}	0.194	–	–
years of education	-0.709^{*}	0.243	–	–
years of education^2	2.175^{*}	0.888	–	–
married	0.113	0.201	0.035	0.343
living with partner	-0.383^{+}	0.215	0.598^{+}	0.354
household size	0.034	0.091	-0.147	0.147
# of kids under 18	-0.194^{+}	0.114	0.130	0.167
# of employed persons in household	0.119	0.103	0.126	0.143
household income (lag)	0.000	0.020	-0.023	0.035
occupation: blue-collar high skilled	0.162	0.201	0.264	0.325
white-collar low skilled	0.146	0.194	0.392	0.328
white-collar high skilled	-0.354	0.254	0.413	0.448
tenure	-0.023^{*}	0.008	–	–
mini job	0.587^{*}	0.282	0.268	0.495
midi job	-0.293	0.359	-0.902^{*}	0.414
temporary work contract	0.102	0.279	1.023^{*}	0.318
side job	-0.997^{*}	0.275	-0.252	0.375
firmsize: medium	0.111	0.226	-0.169	0.344
large	-0.079	0.238	-0.180	0.398
year 2002	0.133	0.183	1.137	0.778
year 2004	0.705^{*}	0.173	1.333^{*}	0.597
year 2008	0.507^{*}	0.172	0.758^{*}	0.239
constant	30.317^{*}	1.959	–	–
federal state indicators	included*		not included	
# of observations	18,591		18,591	
R^2 (within forFE)	0.220		0.093	
joint significance (p-value)	0.000		0.000	

Notes: *significant at 5%; $^{+}$significant at 10%; robust standard errors reported.

Table A10: **Reg. of *general life satisfaction*† on *staff reduction* controlling for *MCS***

	OLS		Fixed Effects	
	Est. Coef.	S.E.	Est. Coef.	S.E.
dependent variable: *general life satisfaction*†				
staff reduction	-0.987^*	0.136	-0.504^*	0.145
MCS	0.429^*	0.008	0.285^*	0.010
employability (lag): good	1.265^*	0.187	0.052	0.218
moderate	2.005^*	0.229	0.175	0.281
age	-0.520^*	0.048	–	–
age^2	0.485^*	0.057	0.014	0.106
male	-0.588^*	0.143	–	–
migrant	0.042	0.201	–	–
years of education	0.216	0.246	–	–
years of education^2	-0.514	0.890	–	–
married	0.025	0.189	-0.792^*	0.331
living with partner	1.496^*	0.201	1.685^*	0.333
household size	0.037	0.091	0.192	0.142
# of kids under 18	0.224^*	0.114	-0.276^+	0.164
# of employed persons in household	-0.045	0.102	-0.006	0.143
household income (lag)	0.223^*	0.021	0.041	0.038
occupation: blue-collar high skilled	0.355^+	0.208	0.306	0.324
white-collar low skilled	0.946^*	0.199	0.708^*	0.318
white-collar high skilled	1.954^*	0.248	1.532^*	0.412
tenure	0.064^*	0.008	–	–
mini job	-0.007	0.293	-0.713	0.494
midi job	0.251	0.361	0.299	0.371
temporary work contract	-0.055	0.275	0.265	0.307
side job	-0.088	0.268	0.447	0.358
firmsize: medium	-0.042	0.223	-0.121	0.351
large	0.323	0.234	0.171	0.410
year 2002	-0.252	0.175	0.697	0.738
year 2004	-1.150^*	0.169	-0.486	0.565
year 2008	-0.381^*	0.166	-0.055	0.225
constant	36.949^*	1.965	–	–
federal state indicators	included*		not included	
# of observations	18,591		18,591	
R^2 (within forFE)	0.251		0.101	
joint significance (p-value)	0.000		0.000	

Notes: *significant at 5%; +significant at 10%; robust standard errors reported. †Originally measured on a ten point scale; rescaled to have equal mean and equal variance as *MCS*.

Table A11: Estimated effects on *general life satisfaction*: **OLS vs. Ordered Probit**

	OLS		**Ordered Probit**		**Comparison of Estimates**	
	Est. Coef.	S.E.	Est. Coef.	S.E.	Coef. Ratio	Significance
dependent variable: *general life satisfaction (rescaled for OLS estimation)*						
staff reduction	−1.421*	0.153	−0.164*	0.018	8.675	✓
employability (lag): good	1.675*	0.210	0.178*	0.024	9.419	✓
moderate	2.668*	0.256	0.314*	0.030	8.483	✓
age	−0.648*	0.053	−0.076*	0.006	8.480	✓
age^2	0.667*	0.062	0.079*	0.007	8.436	✓
male	0.172	0.160	−0.003	0.019	−51.176	✗
migrant	0.552*	0.218	0.060*	0.026	9.129	✓
years of education	−0.109	0.273	−0.032	0.032	3.421	✗
years of education^2	0.518	0.991	0.125	0.117	4.155	✗
married	0.091	0.214	0.015	0.025	6.179	✗
living with partner	1.647*	0.228	0.179*	0.027	9.208	✓
household size	0.064	0.101	0.009	0.012	7.035	✗
# of kids under 18	0.175	0.127	0.021	0.015	8.216	✗
# of employed persons in household	0.008	0.113	−0.005	0.014	−1.631	✗
household income (lag)	0.276*	0.024	0.035*	0.003	7.806	✓
occupation: blue-collar high skilled	0.525*	0.227	0.063*	0.026	8.313	✓
white-collar low skilled	1.247*	0.218	0.133*	0.025	9.404	✓
white-collar high skilled	2.229*	0.274	0.258*	0.033	8.648	✓
tenure	0.067*	0.009	0.008*	0.001	8.615	✓
mini job	0.302	0.318	0.035	0.038	8.728	✗
midi job	0.155	0.403	0.030	0.047	5.088	✗
temporary work contract	−0.014	0.297	−0.002	0.035	7.040	✗
side job	−0.637*	0.301	−0.063+	0.034	10.155	
firmsize: medium	0.007	0.247	−0.001	0.029	−6.490	✗
large	0.357	0.260	0.038	0.031	9.354	✗
year 2002	−0.241	0.195	−0.037	0.023	6.589	✗
year 2004	−1.049*	0.187	−0.128*	0.022	8.167	✓
year 2008	−0.202	0.186	−0.030	0.022	6.681	✗
constant	61.763*	2.105	–	–		
federal state indicators	included*		included*			
threshold 1	–	–	−4.603*	0.261		
threshold 2	–	–	−4.360*	0.257		
threshold 3	–	–	−3.862*	0.254		
threshold 4	–	–	−3.432*	0.253		
threshold 5	–	–	−3.101*	0.253		
threshold 6	–	–	−2.539*	0.253		
threshold 7	–	–	−2.126*	0.253		
threshold 8	–	–	−1.408*	0.253		
threshold 9	–	–	−0.348	0.253		
threshold 10	–	–	0.487+	0.253		
# of observations	18,591		18,591			
R^2	0.074		–			
pseudo R^2	–		0.022			
joint significance (p-value)	0.000		0.000			
log-likelihood	–		–32360.2			

Notes: *significant at 5%; +significant at 10%; ✓ significant at 5% in either model; ✗ insignificant at 5% in either model.