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WP 26/20

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October 2026

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The Most Vulnerable Suffer Most: How Fear of Unemployment Exacerbates the Mental Health Gradient

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October 14, 2026

Abstract

Labor market anxiety is a major driver of psychological distress, yet mean effects might obscure significant vulnerabilities among those with low psychological reserves. Therefore, this paper investigates how the impact of job insecurity varies across the mental health distribution. Using German longitudinal data and a quantile regression framework with non-additive fixed effects, we address the endogeneity of fear of job loss by exploiting exogenous firm-specific staff fluctuations as an instrumental variable. Consistent with susceptibility theories, we find that the psychological burden is highly heterogeneous. The estimated penalty is largest at the bottom of the Mental Component Summary (MCS) distribution, reaching 8.8 points at the 10th percentile, and remains substantial between the 20th and 50th percentiles, at approximately 5–6 points. By contrast, the impact is negligible among those with better mental health. We also demonstrate that standard additive quantile fixed effects models mask this gradient, underestimating the burden on vulnerable segments.

JEL codes: C26, J28, J63, I10, I14

Keywords: Mental Health; Job Insecurity; Workforce Reduction; Quantile Regression; Non-additive Fixed Effects

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1 Introduction

Unemployment is a persistent feature of the economic cycle, with costs that extend far beyond the individuals transitioning out of work. A significant externality is the psychological impact on those who remain employed. This fear of unemployment can manifest through various channels, from the emotional toll on survivors of mass layoffs to generalized anxiety driven by unstable macroeconomic conditions. When individuals witness peers losing jobs or observe economic downturns, the perceived stability of their own livelihood is threatened. The literature has established a robust negative relationship between job insecurity and mental health (e.g., Caroli and Godard (2016), Cottini and Ghinetti (2018), Green (2011), Johnston et al. (2020), Reichert and Tauchmann (2017), and Watson and Osberg (2018)). However, little is known about how this effect differs across different levels of the mental health distribution, while a focus on mean effects may obscure significant vulnerabilities especially among those with the lowest psychological reserves.

Individual responses to environmental stressors often vary based on a baseline of susceptibility. This phenomenon is central to several psychological frameworks. For example, the Diathesis-Stress Model (Zuckerman, 1999) attributes this variance to an interaction of inborn genetic factors and acquired life experiences, such as diseases, family environments, and adolescent peer interactions. Alternatively, the Cumulative Risk Model (Evans, 2003) suggests that the impact of a new stressor is determined by the total number of co-occurring risk factors. Unlike the Diathesis-Stress Model, which focuses on an interaction between a specific vulnerability and a specific trigger, this model views health outcomes as the result of a linear or exponential accumulation of stressors over time. Integrating these perspectives, we hypothesize that the psychological burden of job insecurity is non-uniform: daily contingencies may trigger episodes in high-risk individuals, while low-risk individuals may remain resilient to all but catastrophic events.

A major challenge in identifying the causal impact of self-perceived job insecurity on mental health is that individuals who perceive their jobs as insecure differ systematically from those who do not. Specifically, individuals with poorer mental health may be more prone to perceiving or reporting their jobs as insecure (reverse causality), or they may systematically sort into unstable employment sectors (selection bias). Beyond these sources of endogeneity, unobserved individual heterogeneity also presents a distinct empirical hurdle. In a panel quantile treatment effects setting, this issue becomes more pronounced as the standard additive fixed effects approaches used in the literature are prone to mask the true distribution of vulnerability, thereby altering the interpretation. To address these overlapping issues, we combine two methodological strategies. First, following Reichert and Tauchmann (2017), we use German Socio-Economic Panel (SOEP) data and exploit preceding-year firm-level staff reductions as an objective instrumental variable for subjective job insecurity. Second, we implement the Quantile Regression for Panel Data (QRPD) with non-

additive fixed effects estimator developed by Powell (2022).

This framework provides the structural flexibility needed to relax the restrictive assumption of additive fixed effects. Under this specification, an individual’s unobserved traits (such as resilience) enter the model only as a constant shift in the outcome. That is, these traits can explain why some individuals consistently report better or worse mental health than others, but they cannot alter how strongly individuals respond to changes in job insecurity. However, our theoretical framework suggests that psychological resources and other inherent characteristics may shape not only baseline mental health but also individuals’ responsiveness to job insecurity. Because these characteristics are inherently unobserved, they are represented econometrically through individual fixed effects. QRPD allows these fixed effects to enter the model non-additively, permitting psychological traits to moderate the impact of job insecurity. Furthermore, because the estimator identifies the impact on the structural outcome distribution rather than relative individual deviations, our estimates capture direct shifts in absolute mental health levels across the population. In other words, we estimate treatment effects on the outcome distribution that are unconditional with respect to unobserved individual heterogeneity while conditioning on observable characteristics and time.

To our knowledge, this study provides the first causal analysis of the heterogeneous impact of job insecurity across the mental health distribution¹ and represents an early adoption of non-additive fixed effects within the health economics literature. Although a small number of studies have employed Powell’s (2022) estimator, primarily for its technical advantages, such as delivering consistent estimates in short panels, accommodating endogenous regressors through instrumental variables, and estimating unconditional distributions in the presence of unobserved heterogeneity (e.g., Alexiou and Trachanas (2021, 2022), Baryshnikova and Pham (2019), and Zhang et al. (2022)), they have treated it primarily as a methodological tool for addressing econometric challenges. In contrast, we demonstrate that its non-separability property is not merely a computational convenience or an estimation strategy, but a theoretical necessity, as it enables the direct modeling of latent, time-invariant factors that govern heterogeneous responses to exogenous shocks.

Consistent with our hypotheses, we find that the impact of job insecurity is highly heterogeneous. We show that, in the model that imposes standard additive fixed effects, the mental health gradient largely disappears. However, by relaxing this assumption, we reveal that the psychological burden intensifies for individuals in the lower quantiles but diminishes toward zero for those in the upper tail. Our estimates show that job insecurity imposes a mental health penalty of approximately 8.8 points (0.88 standard deviations) on the Mental Component Summary (MCS) for those in

¹Reichert and Tauchmann (2017) as well as Johnston et al. (2020) actually address effect heterogeneity across the mental health distribution by conducting quantile regression analysis. However, these exercises are based on reduced-form models, which do not identify the effect of primary interest. Moreover, they do not account for individual unobserved heterogeneity when analyzing distributional effects.

the worst condition (10th percentile), while we estimate an effect between 5 and 6 points from the 20th percentile to the median. For the most resilient individuals above the 60th percentile of the mental health distribution, we estimate an effect of roughly 1.5 points, which is statistically indistinguishable from zero. This confirms that job insecurity is most damaging to those with the least psychological reserve and that average-based models fail to capture this concentrated burden.

The remainder of this paper is organized as follows. Section 2 describes the data, Section 3 details the identification strategy and the econometric approach, Section 4 presents the main results, followed by robustness tests in Section 5. Section 6 provides a discussion and concluding remarks.

2 Data and Descriptive Statistics

For our empirical analysis, we use longitudinal data from the German Socio-Economic Panel (SOEP), a representative household survey providing rich information on labor market transitions and individual well-being. We restrict our sample to working-age individuals (ages 18–65) employed in the private sector at the time of the survey. This restriction is necessary because the high degree of job security in the public sector attenuates the perceived risk of displacement, thereby masking the psychological response to workforce fluctuations. Similarly, self-employed individuals are excluded as they are not subject to involuntary dismissal.

2.1 Outcome Variable

We utilize the MCS as a mental health measure. The MCS is a validated metric for assessing mental health-related quality of life. It is derived from the SF-12 Health Survey (see Figure C1) and aggregates eight health dimensions, including vitality, social functioning, and emotional role limitations, into a single metric that ranges from 0 to 100. Higher values indicate better mental health status, and the metric is standardized to a mean of 50 and a standard deviation of 10. The MCS is a well-established index of mental health in both the economic literature (e.g., Cygan-Rehm et al. (2017), Marcus (2013), and Schiele and Schmitz (2016)) and psychotherapeutic outcomes research (e.g., Tarescavage and Ben-Porath (2014)). Its empirical validity is further supported by Salyers et al. (2000), who demonstrate its high internal consistency and strong reliability. By utilizing the MCS, we focus on impairments in everyday functioning rather than broad evaluative well-being. Our analysis is strictly limited to the MCS because discrete variables with limited unique values are poorly suited for the quantile framework. Quantile regressions face identification challenges with discrete outcomes due to the non-uniqueness of quantiles. This issue is exacerbated in the QRPD setting. Because the QRPD estimator identifies effects through within-individual variation and instrumental variables, it requires a continuous outcome with sufficient density to ensure convergence and to distinguish structural effects

at the distributional extremes. The SOEP has collected this variable biennially since 2002.

2.2 *Treatment Variable and Instrument*

The treatment variable is subjective job insecurity, captured by an annual survey question regarding employment stability concern (see Figure C2). Responses are measured on a three-point scale: "Not concerned at all", "Somewhat concerned", and "Very concerned." For the present analysis we transformed the original variable used by Reichert and Tauchmann (2017) into a binary indicator that takes the value of 1 if an individual reported low or high levels of fear, and the value of 0 if they reported no concerns². However, interpreting this indicator as a treatment variable conflicts with its inherently endogenous nature. A primary concern is reverse causality, meaning that an individual's deteriorating mental health leads to a more pessimistic perception of their environment, causing them to report higher job fear even when objective employment risks remain unchanged. Furthermore, unobserved traits like neuroticism or low resilience can simultaneously drive both poor mental health and a heightened sensitivity to job-related stressors. This is compounded by selection bias, as individuals with lower "health capital" may systematically sort into precarious sectors. Consequently, a direct regression of mental health on subjective insecurity would likely capture these confounders rather than the true structural impact of fear.

To address this endogeneity, we also follow the strategy of Reichert and Tauchmann (2017) by incorporating firm-level workforce reductions as an instrumental variable (IV) for subjective job insecurity. This variable is constructed from the answer to a survey question asking respondents whether their employer increased, decreased, or maintained the same number of employees during the 12 months preceding the interview (see Figure C3). We construct a binary indicator equal to one if the respondent's employer reduced its total headcount in the year prior to the interview. The measure captures only the extensive margin of workforce reductions. By focusing on aggregate firm-level shocks, we obtain a source of variation in job insecurity that is externally driven and distinct from an individual's idiosyncratic mental state or personal job performance. We discuss the validity of our instrument and potential concerns regarding the exclusion restriction in Section 3.1. Staff reduction was only collected in seven survey waves from 2002 to 2013, after which its collection was discontinued. Because the variable was not collected in 2006, one panel wave containing MCS and job insecurity information is excluded³.

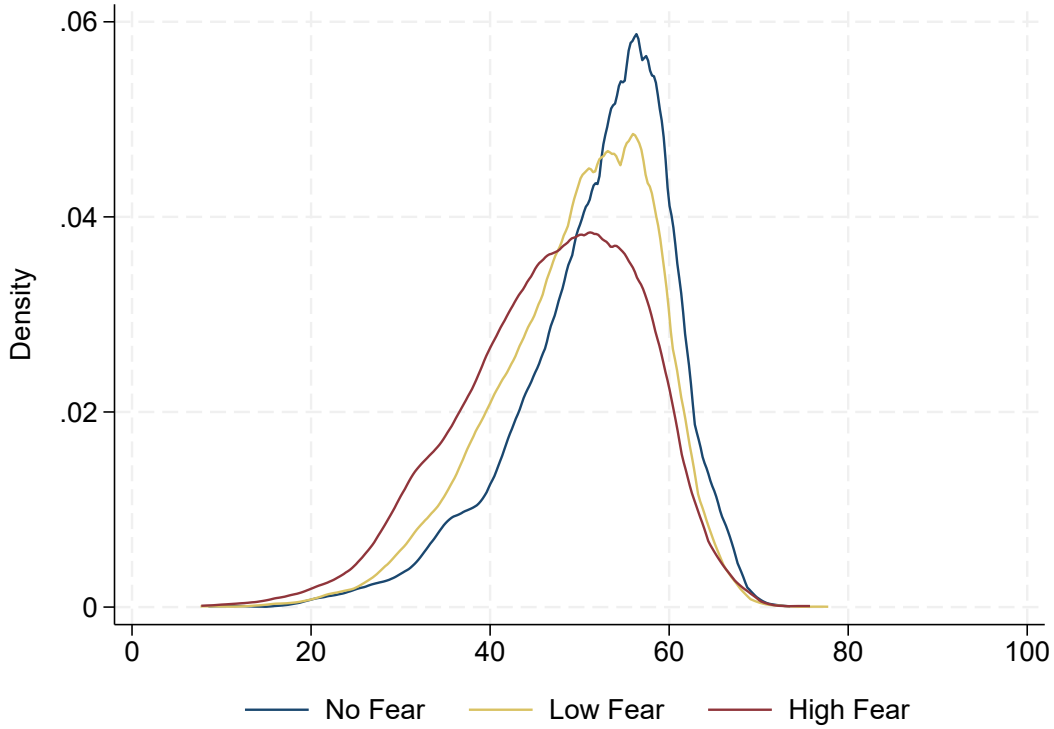
²Whereas Reichert and Tauchmann (2017), in a linear framework, employed a binary indicator for high job insecurity, we redefine our variable to capture any level of perceived risk. This adjustment is necessitated by the estimation difficulties associated with an Instrumental Variable-Fixed Effects Quantile Regression. Unlike a linear model, the quantile-based approach requires substantially more identifying variation across the entire distribution of the dependent variable. By adopting a broader definition of job insecurity, we maximize the number of within-individual transitions, which is essential to ensure model convergence and to achieve the statistical power necessary for identification.

³Table C1 in the Appendix summarizes the availability of core variables across all survey waves.

2.3 Descriptive Statistics

Figure 1 illustrates the density of the MCS stratified by levels of job insecurity. While the “No Fear” category exhibits a relatively tight distribution centered around higher mental health scores, the “Low Fear” category shifts the distribution to the left and increases the density in the lower tail. The “High Fear” category further shifts the distribution leftward, while also widening the lower tail even more. These patterns visually suggest that the impact of job insecurity is heterogeneous, with the most pronounced deterioration occurring among individuals already located at the lower end of the mental health distribution.

Figure 1: Density Distributions of the MCS by Subjective Job Insecurity



Notes: The figure illustrates the distribution of the Mental Component Summary (MCS) in our sample across three levels of subjective job insecurity: individuals reporting low, high, or no job insecurity. MCS scores are normalized to have a mean of 50 and a standard deviation of 10.

After excluding observations with missing values, the final estimation sample is restricted to individuals who are observed in at least two of the 2002, 2004, 2008, 2010, and 2012 panel waves, as singletons do not provide the within-unit variation required for identification in a fixed effects (FE) framework. The resulting unbalanced panel consists of 22,770 person-year observations from 7,490 individuals. Table 1 summarizes the core outcome, treatment, and instrumental variables. The average MCS score in our sample is 50.15, with a standard deviation of 9.12. While the mean aligns closely with the standard population norm of 50, the standard deviation is slightly lower than the benchmark of 10. Regarding subjective job insecurity, 44% of observations report low concern, while 15% report high concern. Furthermore, 28% of the observations correspond to individuals whose employers experienced staff

reductions in the preceding 12 months. The relationship between staff reductions and subjective job insecurity is examined in detail in the next section (see Table 2). Summary statistics for the estimation sample as well as our control variables are reported in Table A1.

Table 1: Summary Statistics for Outcome, Treatment, and Instrumental Variables

	Mean	S.D.	Min	Max
Mental Component Summary (MCS)	50.15	9.12	7.65	77.77
Subjective Job Insecurity: Low	0.44	0.50	0	1
Subjective Job Insecurity: High	0.15	0.35	0	1
Staff Reduction	0.28	0.45	0	1

Notes: The estimation sample consists of 22,770 observations from 7,490 unique individuals. The analysis is restricted to private-sector employees aged 18 to 65 who appear in at least two of the following survey waves: 2002, 2004, 2008, 2010, and 2012. Further summary statistics for the estimation sample, including the control variables, are reported in Table A1.

3 Empirical Strategy

3.1 Identification

Instrument relevance is a key concern when relying on instrumental variables for identification. Table 2 confirms that exposure to firm-level staff reductions is strongly associated with elevated job insecurity. While only 19.4% of workers with no job insecurity experienced recent staff reductions, this exposure rises to 30.1% for those with low job insecurity and 45.5% for those with high job insecurity. First-stage diagnostics presented in Table 3 further support the relevance of the instrument, as the F -statistics substantially exceed conventional thresholds for weak-instrument identification, reaching 556.4 for the IV and 135.3 for the IVFE specification.

Table 2: Relevance of Firm-Level Staff Reductions for Subjective Job Insecurity

	Subjective Job Insecurity		
	No	Low	High
Staff Reduction	19.4%	30.1%	45.5%
N	9,449	9,977	3,344

Notes: Each column reports the conditional mean (in %) of firm-level staff reductions in the preceding 12 months given the reported level of subjective job insecurity.

To justify that workforce reductions only affect mental health through perceived job insecurity and not through other channels, such as increased workload or the distress of friends and colleagues losing their jobs, we rely on the extensive validation and

empirical testing established in Reichert and Tauchmann (2017). Most importantly, they conduct placebo analyses of public employees and civil servants, groups with very high dismissal protection, demonstrating that staff reductions have a negligible effect on mental health when the "fear" mechanism is structurally absent, even though these alternative channels should affect them as much as private-sector employees⁴. Furthermore, auxiliary regressions find no significant impact of workforce reductions on alternative mediators such as overtime hours or subjective work-related burdens like high time pressure. Finally, the negative health impact is shown to disappear for individuals with high subjective re-employment prospects, reinforcing the conclusion that the mechanism is driven by the fear of the consequences of job loss rather than the firm-level shock itself.

Reverse causality regarding the instrument remains an important concern, as workers with deteriorated mental health might be more likely to be aware of a staff reduction or to misinterpret unrelated turnover as a staff reduction. Our preferred specification includes individual fixed effects, which account for time-invariant individual characteristics that could influence both mental health and reporting behavior. However, these fixed effects cannot rule out time-varying reporting biases or generalized pessimism. Because our indicator captures only the extensive margin, any tendency to exaggerate a shock's severity (the intensive margin) does not bias event reporting. To examine potential misclassification, in Table B1 we regress both self-reported staff reductions and staff increases at time t on quartiles of two-year lagged mental health (MCS_{t-2}). We use this lag to capture a pre-existing mental health baseline that is less likely to be affected by contemporaneous labor market shocks. Across all lagged mental health quartiles, the coefficients are statistically insignificant for both staff reductions and staff increases. We continue by examining whether psychological vulnerability triggers generalized anxiety. To do so, in Table B2 we regress three alternative societal worries, concerns regarding the environment, global terrorism, and maintaining peace (see Figure C2), on the same mental health lag⁵. The estimated coefficients for all three concerns remain insignificant across all mental health quartiles, providing evidence that psychological vulnerability does not systematically inflate universal anxieties, thereby isolating our instrument from unobserved pessimism bias.

Beyond the validity of staff reduction as an instrument, our framework relies on the assumption that staff reductions are exogenous from the perspective of individual employees. While an individual's own performance might influence their specific risk of dismissal, a broad decline in a firm's total headcount is rarely driven by the idiosyncratic mental health or performance of a single worker. Moreover, as in conven-

⁴We also estimate a specification including these groups and find attenuated effects. See Table 5, Column 2.

⁵We focus on concerns about the environment, global terrorism, and maintaining peace because they are less likely to be directly related to individual socioeconomic circumstances than respondent-specific concerns such as worries about crime, euro stability, or immigration. For instance, concerns about crime may reflect unobserved spatial sorting, while concerns regarding euro stability may be associated with individual financial wealth and investment exposure.

tional fixed effects models, the QRPD framework allows for an arbitrary relationship between the instrument and unobserved individual fixed effects. Consequently, persistent worker sorting across firms does not threaten identification, provided that the remaining exogeneity assumptions hold.

3.2 *Baseline Linear Panel Estimation*

Our empirical analysis proceeds in two main steps. First, building on the identification strategy of Reichert and Tauchmann (2017), we establish a linear baseline by estimating average treatment effects. Second, we move beyond prior work by estimating the distributional impacts. To implement the first step, we estimate a fixed-effects two-stage least squares model. The first stage predicts subjective job insecurity using the exogenous firm-level staff reduction instrument alongside a set of covariates. The second stage then estimates the Mental Component Summary (MCS) using these predicted job insecurity values. Both stages incorporate individual fixed effects to account for time-invariant unobserved heterogeneity, such as latent personality traits, stable health predispositions, or ingrained labor market preferences. Year dummies capture common macroeconomic shocks. Among the time-varying controls⁶, we include marital status and household size. Age squared enters to accommodate the non-linear life-cycle patterns frequently observed in well-being studies. One-year lagged household gross labor income is included in the analysis to address potential bias resulting from reverse causality. Subjective employability prospects are captured using two indicators reflecting whether respondents perceive it as easy or difficult to find a new job, with “almost impossible” serving as the reference category⁷. We further account for job-specific characteristics, including tenure with the current employer and an indicator for having a temporary contract. Firm size is controlled for using a set of dummy variables distinguishing firms with fewer than five, five to 199, and 200 or more employees. We also control for occupation skill level using a four-category classification: skilled blue-collar and supervisory, lower-level white-collar, higher-level white-collar, and low-skilled blue-collar, with the latter serving as the reference category.

3.3 *Quantile Regression for Panel Data with Non-Additive Fixed Effects*

To estimate the impact of job insecurity on the distribution of mental health, we employ the Quantile Regression for Panel Data (QRPD) with non-additive fixed

⁶Although a linear specification permits the inclusion of additional controls such as at the household-level, number of children and number of employed members, these variables introduce mild multicollinearity. While a linear model still produces estimates under these conditions, the lack of independent variation in our quantile framework renders the estimations computationally infeasible. We therefore adopt a more parsimonious specification to ensure model convergence in the subsequent quantile estimations.

⁷This measure is based on respondents’ answers to the following question: “If you lost your job today, would it be easy, difficult, or almost impossible for you to find a new job that is at least as good as your current one?”

effects estimator developed by Powell (2022). The choice of this estimator enables us to directly bridge the theoretical frameworks of susceptibility with the underlying econometrics. By design, traditional additive fixed effects (α_i) control for unobserved time-invariant traits only by shifting the intercept of the outcome equation ($Y_{it} - \alpha_i$). This imposes the restrictive assumption that the marginal effect of a shock is not systematically related to these unobserved traits, implying that a highly resilient agent reacts to job insecurity with the same intensity as a highly vulnerable one, differing only in their baseline levels. Because the QRPD framework does not explicitly estimate individual fixed effects, it maintains a non-separable disturbance term. This allows us to recover the structural, unconditional on fixed effects outcome distribution (Y_{it}) while still controlling for time-invariant unobserved heterogeneity. This distinction is critical for policy analysis. We are interested in how fear affects individuals who are actually at the bottom of the absolute mental health distribution, rather than merely those who are experiencing a negative shock relative to their own average.

3.3.1 *Structural Model and Estimation*

Following Powell (2022), we assume the following structural equation for the outcome MCS_{it} for individual i at time t :

$$MCS_{it} = D'_{it}\beta(U_{it}^*) \quad (1)$$

where D_{it} is the vector of regressors, including our main variable of interest, fear of unemployment, time-varying controls, and year fixed effects. U_{it}^* is a scalar disturbance term, normalized to $U_{it}^* \sim U(0, 1)$ representing the individual's rank in the conditional distribution of mental health. Crucially, unlike standard models where fixed effects are additive shifts, here the disturbance term is non-separable. We define $U_{it}^* = f(\alpha_i, \epsilon_{it})$, where α_i , as introduced above, represents time-invariant unobserved heterogeneity, and ϵ_{it} represents idiosyncratic shocks. In Powell's (2022) approach, the identification of the parameters $\beta(\tau)$ relies on the assumption of rank similarity. This assumption allows an individual's rank to fluctuate due to idiosyncratic shocks (ϵ_{it}), but requires that these changes are not systematically related to the treatment variable. In our context, this implies that while an individual's relative mental health may vary slightly day-to-day, their underlying 'resilience type' remains stable over the observed periods. The aforementioned specification implies that the marginal effect of fear on mental health, $\beta(U_{it}^*)$, is not constant across the population; rather, it varies according to the individual's position in the distribution of these unobserved characteristics.

Identification of the parameters $\beta(\tau)$ relies on a moment condition. To avoid incidental parameter bias from explicitly estimating the fixed effects, the approach leverages within-individual variation in the instrument to purge the unobserved heterogeneity. Specifically, utilizing the deviations of the instrument from its time-mean, $(Z_{it} - \bar{Z}_i)$, ensures that the variation is orthogonal to any time-invariant unobserved

heterogeneity. The parameter vector is then estimated by satisfying the sample analogue of the following GMM objective function:

$$E \left[\frac{1}{T} \sum_{t=1}^T (Z_{it} - \bar{Z}_i) \cdot \mathbb{1}(MCS_{it} \leq D'_{it} \beta(\tau)) \right] = 0 \quad (2)$$

where $\bar{Z}_i = \frac{1}{T} \sum_{t=1}^T Z_{it}$ represents the individual's average exposure to the instrument over the sample period. This condition implies that, for a given individual, periods with above-average instrument values are not systematically related to the likelihood of the outcome falling below the conditional quantile, except through the causal channel captured by $\beta(\tau)$ ⁸.

3.3.2 Computational Implementation

The objective function defined by this moment condition is non-convex and non-smooth, making standard derivative-based optimization methods unreliable. To address these computational challenges, Powell (2022) suggests employing an adaptive Markov Chain Monte Carlo (MCMC) optimization algorithm. Following the Quasi-Bayesian estimation approach of Chernozhukov and Hong (2003), we use the MCMC chain to explore the parameter space and minimize the GMM objective function. For our main specification (Table 4, Column 5) and the robustness and falsification tests (Table 5), we execute the algorithm with 1 million iterations. To ensure a chain reaches a stationary distribution, we discard the first 500,000 iterations as 'burn-in.' We also set the target acceptance rate to 0.3 to ensure that the final empirical value lands close to the theoretical optimal of 0.234. To mitigate autocorrelation between consecutive draws, we apply a thinning interval of 10, retaining only every 10th draw. This process yields a final sample of 50,000 independent draws for inference. Following Geyer (2011), we employ multiple randomized starting values to ensure the algorithm isolates the global minimum, while conducting a comprehensive suite of diagnostics⁹ to verify convergence. Point estimates reflect the means of the retained MCMC draws, with their standard deviations serving as standard errors.

4 Results

4.1 Average Effect of Job Insecurity on Mental Health

Before exploring the distributional heterogeneity, we establish the average causal effect of subjective job insecurity on mental health. Table 3 presents the estimates using linear models. Column 1 reports the pooled Ordinary Least Squares (OLS) estimates, indicating an average penalty of -2.95 points on the MCS for individuals

⁸See Powell (2022) for a thorough discussion.

⁹We use the community-contributed Stata module `qrpdmmcmc` (Kosheeva & Liatos, 2026) for the estimation of multiple chains and convergence assessment. The full set of diagnostic tests performed in this study corresponds precisely to those provided by this package.

reporting any level of job insecurity. However, this should be interpreted with caution, as it is likely subject to omitted variable bias due to the exclusion of time-invariant individual characteristics. When introducing individual fixed effects in Column 2, the coefficient shrinks to -1.26. A plausible explanation for this attenuation is that time-invariant unobserved heterogeneity, such as baseline psychological vulnerability or lower resilience, simultaneously depresses mental health and heightens the tendency to report job insecurity. By exploiting within-individual variation, the fixed effects model controls for these time-invariant unobserved characteristics.

Table 3: Average Impact of Job Insecurity on Mental Health (MCS)

	OLS	FE	IV	IVFE
	(1)	(2)	(3)	(4)
Job Insecurity	-2.95*** (0.13)	-1.26*** (0.15)	-6.57*** (0.83)	-4.49*** (1.60)
R^2 (within for FE)	0.045	0.009	—	—
Joint significance (p-value)	0.000	0.000	0.000	0.000
F -statistic on instrument	—	—	556.4	135.3
Individual FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	Yes	No	Yes	No
Covariates	Yes	Yes	Yes	Yes
N	22,770	22,770	22,770	22,770

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

However, the fixed effects model remains vulnerable to time-varying shocks. For instance, an unobserved temporary health shock, such as the sudden onset of a chronic illness or a family crisis, might simultaneously increase perceived job insecurity and worsen mental health. Column 3 implements the instrumental variable strategy to address these concerns. Upon doing so, the estimated average effect increases to -6.57 points. In our preferred IVFE specification (Column 4), which accounts for both time-varying shocks and stable unobserved traits, the average effect is -4.49 points. This substantial amplification in magnitude relative to the standard FE estimate (-1.26 points) suggests, for example, that the instrument corrects for measurement error in the self-reported insecurity variable, which conventionally attenuates OLS and FE coefficients toward zero. Alternatively, this larger estimate may reflect a Local Average Treatment Effect (LATE), capturing the impact specifically on "compliers", employees whose psychological distress is triggered by observable firm-level downsizing rather than generalized anxiety. Our results are also close to those reported by Reichert and Tauchmann (2017, p. 195), although the authors do not explicitly identify them as instrumental variable estimates. The moderate deviation between the results can be explained by the inclusion of one additional panel wave in the

present study and by the fact that Reichert and Tauchmann (2017) treat individuals who were moderately concerned differently from how they are treated in the present analysis (see Section 2.2).

4.2 *Distributional Effects of Job Insecurity on Mental Health*

The average treatment effects reported in Section 4.1 likely mask significant heterogeneity, as they do not account for varying levels of baseline susceptibility. To examine how the impact of labor market anxiety scales with individual vulnerability, we shift our focus to the outcome distribution. Table 4 presents the Quantile Treatment Effects (QTE) of job insecurity on mental health across five distinct specifications.

Column 1 presents a baseline estimation of the job insecurity effect across the mental health distribution using the Method of Moments Quantile Regression by Machado and Santos Silva (2019). We utilize the estimator primarily for comparison, as its location-scale framework represents a standard additive panel quantile approach that computationally permits the inclusion of additive fixed effects later on in Column 2. Notably, the median estimate of -2.80 points is nearly identical to the corresponding OLS mean estimate in Table 3. This alignment suggests that the "average" experience of a worker in the middle of the distribution is fairly representative of the sample's central tendency and is not being unduly skewed by extreme observations in the tails. However, even this relatively simple empirical model provides evidence in support of our hypotheses: the mean regression indeed masks significant heterogeneity, as the estimated penalty ranges from -1.86 points at the 90th percentile to -4.31 points at the 10th.

In Column 2, we incorporate individual additive fixed effects to control for time-invariant unobserved heterogeneity. Consistent with the average results in Table 3, the inclusion of these controls leads to a significant attenuation of the coefficients across the entire mental health distribution. As a result, the heterogeneity in the estimated impact largely disappears in this specification, as the difference in penalties between the 10th and 90th percentiles shrinks to only 0.47 points on the MCS scale. This compression empirically confirms that imposing an additive structure mechanically flattens the gradient, masking the differential responsiveness to shocks that we hypothesized. Once the additivity constraint is relaxed in Column 3, the gradient of vulnerability reappears: the estimated effect varies from -0.63 points at the 90th percentile to -2.04 points at the 10th. The difference between specifications 2 and 3 highlights the importance of accounting for non-additive unobserved heterogeneity in health-related contexts.

As a next step, we introduce our instrumental variable using the Generalized Quantile Regression¹⁰ (GQR) estimator developed by Powell (2020). This specifica-

¹⁰GQR is an estimator that utilizes "proneess" variables to identify an individual's rank within the conditional distribution of the outcome. The framework is suited for cross-sectional or pooled

Table 4: Quantile Treatment Effects of Job Insecurity on Mental Health (MCS)

	Quantile Regression	Additive FE	Non- Additive FE	IV	Non- Additive IVFE
	(1)	(2)	(3)	(4)	(5)
QTE					
0.1	-4.31*** (0.23)	-1.50** (0.59)	-2.04*** (0.26)	-8.81*** (0.54)	-8.78* (5.27)
0.2	-3.74*** (0.18)	-1.43*** (0.48)	-1.96*** (0.19)	-9.10*** (0.83)	-5.36** (2.10)
0.3	-3.35*** (0.15)	-1.42*** (0.46)	-1.76*** (0.18)	-8.06*** (0.53)	-5.96*** (1.12)
0.4	-3.06*** (0.13)	-1.34*** (0.39)	-1.29*** (0.15)	-7.65*** (0.53)	-5.05*** (1.08)
0.5	-2.80*** (0.12)	-1.25*** (0.41)	-1.13*** (0.11)	-7.33*** (0.43)	-5.37*** (1.01)
0.6	-2.57*** (0.11)	-1.16** (0.51)	-0.92*** (0.12)	-6.51*** (0.68)	-1.44 (1.38)
0.7	-2.34*** (0.11)	-1.11* (0.60)	-0.88*** (0.11)	-4.77*** (0.41)	-1.54 (2.26)
0.8	-2.11*** (0.11)	-1.09* (0.63)	-0.69*** (0.11)	-3.41*** (0.37)	-1.81 (2.88)
0.9	-1.86*** (0.12)	-1.03 (0.75)	-0.63*** (0.12)	-2.45*** (0.29)	—
Ind. FE	No	Yes	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	Yes	No	No	Yes	No
Covariates	Yes	Yes	Yes	Yes	Yes
<i>N</i>	22,770	22,770	22,770	22,770	22,770

Notes: Columns (1) and (2) use Method of Moments Quantile Regression (Machado & Santos Silva, 2019), with high-dimensional fixed effects handled via the absorption method (Rios-Avila et al., 2026). Columns (3) and (5) use Quantile Regression for Panel Data with non-additive fixed effects (Powell, 2022). Column (4) uses Generalized Quantile Regression (Powell, 2020). Columns (3)–(4)–(5) are estimated via adaptive Markov Chain Monte Carlo (MCMC). For Columns (3)–(4), MCMC parameters include 100,000 total draws, a 50,000-draw burn-in, and a thinning factor of 10, resulting in a final analytical sample of 5,000 draws. For Column (5), MCMC parameters include 1 million total draws, a 500,000-draw burn-in, and a thinning factor of 10, resulting in a final analytical sample of 50,000 draws. The estimate for the 90th percentile in Column (5) is omitted due to non-convergence. Standard errors are in parentheses. For Columns (3)–(4)–(5), standard errors represent the posterior standard deviation of the retained MCMC draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

tion allows us to address the endogeneity of job insecurity through our instrument in a pooled framework, omitting individual fixed effects for comparison. In line with

applications, and it is also capable of addressing endogeneity through the use of instrumental variables. In this context, QRPD can be viewed as a special case of GQR specifically adapted for panel data settings.

the mean estimates in Table 3, the introduction of the instrumental variable leads to a substantial increase in the magnitude of the estimated penalties across the entire distribution. While a pronounced gradient of vulnerability is present, ranging from -2.45 MCS points at the 90th percentile to -8.81 points at the 10th, the absence of individual fixed effects in this specification suggests these estimates may still be confounded by time-invariant unobserved heterogeneity.

Finally, the empirical model whose results are reported in Column 5 combines the non-additive fixed effects approach with our instrumental variable strategy. This allows for the identification of the structural effect of job insecurity under the maintained instrumental-variable assumptions while accounting for both time-invariant selection and time-varying endogeneity. The estimates reveal substantial heterogeneity across the mental health distribution. For individuals in the upper tail ($q \geq 0.6$), the estimated impact of job insecurity is approximately -1.50 points and remains statistically indistinguishable from zero, suggesting relatively limited mental health deterioration in response to perceived labor market threats. However, moving from the 60th percentile toward the median, the estimated effect more than triples, increasing from -1.44 points to -5.37 points. The negative impact continues to intensify further down the distribution, peaking at -8.78 points at the 10th percentile.

The estimate for the 90th percentile is omitted because the MCMC algorithm failed to converge, a common computational difficulty when estimating highly flexible models in the tails of the distribution. Even without considering this extreme of the distribution, the results reveal a clear pattern of effect heterogeneity, whereby the most vulnerable are hit hardest. The pronounced gradient within the estimated 10th–80th percentile range demonstrates that the “average” worker is a poor proxy for the broader population, as individuals exhibit substantially different degrees of vulnerability and responsiveness to economic shocks.

5 Robustness

To assess the validity of the estimated mental health gradient, we conduct a series of robustness, sensitivity, and alternative outcome tests. These tests examine whether the estimated effects are sensitive to the definition of job anxiety, and whether they are consistent with the hypothesized psychological channel of job insecurity, rather than reflecting unobserved trends or artifacts of the estimation procedure.

First, we evaluate the sensitivity of our baseline results to the treatment threshold. In our primary specification, the treatment indicator captures any level of perceived risk, grouping both low and high fear against a baseline of no concern. In Column 1 of Table 5, we implement a stricter definition where only individuals reporting high anxiety are classified as treated. Consequently, individuals experiencing low anxiety are shifted into the reference category alongside those with no job-related worries. Assuming that the psychological cost of labor market anxiety is non-linear and that a critical threshold of perceived threat is required to deplete coping reserves,

Table 5: Robustness, Sensitivity, and Alternative Outcome Tests

	Low/No Fear vs. High Fear (1)	Public Employees Included (2)	Dependent Variable: MCS_{t-2} (3)	Dependent Variable: PCS_t (4)	Dependent Variable: PCS_{t+2} (5)
IVFE	-4.79*** (1.69)	-4.35*** (1.52)	-1.29 (1.96)	-1.00 (1.29)	-0.01 (1.44)
QTE					
0.1	—	-9.93** (4.31)	-0.38 (2.46)	2.86 (3.43)	—
0.2	-9.20** (3.81)	-4.12** (2.07)	-0.32 (3.81)	-1.50 (2.50)	1.11 (2.23)
0.3	-7.38*** (2.76)	-4.61*** (1.01)	0.78 (2.68)	-3.01*** (0.88)	1.84 (2.15)
0.4	-6.89*** (1.34)	-4.76*** (0.78)	-1.34 (2.15)	-3.68*** (0.98)	-0.36 (1.38)
0.5	-5.01*** (1.07)	-5.76*** (1.21)	-2.10 (2.04)	-4.35** (2.14)	0.23 (1.34)
0.6	-2.20 (2.21)	-2.35 (2.07)	-2.22 (1.63)	-3.45* (1.78)	0.66 (1.53)
0.7	-2.46 (2.32)	-2.18 (2.27)	-2.23 (2.13)	0.59 (2.05)	-0.59 (1.83)
0.8	-4.83** (2.35)	-1.84 (2.68)	-2.84** (1.36)	1.01 (1.07)	-1.17 (1.51)
0.9	—	-1.94 (1.74)	—	1.54* (0.81)	—
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No
Covariates	Yes	Yes	Yes	Yes	Yes
N	22,770	26,026	16,346	22,770	19,018

Notes: All QTE estimates use the Quantile Regression for Panel Data with non-additive fixed effects (Powell, 2022). Estimations obtained via adaptive Markov Chain Monte Carlo (MCMC). MCMC parameters include 1 million total draws, a 500,000-draw burn-in, and a thinning factor of 10, resulting in a final analytical sample of 50,000 draws. Estimates for the 10th percentile in Columns (1) and (5) and for the 90th percentile in Columns (1), (3), and (5) are omitted due to non-convergence. Standard errors are in parentheses and they represent the posterior standard deviation of the retained MCMC draws. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

we hypothesize that isolating individuals with high levels of fear will reveal a more pronounced effect. Consistent with this hypothesis, the estimated average impact increases by 0.30 points in absolute terms, and the vulnerability gradient becomes more pronounced. At the 20th percentile, the mental health penalty intensifies to

-9.20 points (compared to -5.36 points in the baseline). The negative impact remains larger and statistically significant through the 50th percentile, before attenuating to an insignificant effect of approximately -2.50 points at the 60th and 70th percentiles, which is roughly 1 point larger in absolute terms than in our baseline specification. At the 80th percentile, we estimate a significant effect of -4.83 points. As this is the only instance of such a pronounced penalty in the upper tail across our entire analysis, we caution against a structural interpretation; this isolated estimate is likely a statistical anomaly rather than a meaningful economic response.

Afterwards, inspired by Reichert and Tauchmann (2017)¹¹, we conduct an attenuation test by augmenting the sample with 3,256 observations of public employees and civil servants. Given their institutional status and comparatively strong dismissal protection, job-loss fears are expected to be weaker for this group. As shown in Table 5, Column 2, the estimated coefficients at the lower quantiles in the combined sample (where the public sector accounts for 12.5% of observations) are in general smaller than in the private-sector baseline. Although we estimate an effect approximately 1 point larger than our baseline at the 10th percentile, estimations at the extreme tails should be interpreted with caution, as lower data density makes these regions highly sensitive to outliers and estimation variance. In contrast, coefficients at the upper quantiles remain small and statistically insignificant. This asymmetric attenuation is consistent with the interpretation that the estimated mental health effects in the private sector are driven by perceived job insecurity rather than general labor-market or sector-wide shocks.

Next, we address concerns regarding pre-existing trends and time-varying unobserved heterogeneity. We forward-date the treatment and examine the impact of job insecurity on mental health two years prior to the reported shock. If mental health were already on a differential downward trajectory prior to treatment, our main estimates could be confounded by anticipatory effects or negative selection. The results from this placebo test (Table 5, Column 3) show insignificant coefficients across most of the distribution. This lack of a lead effect among the most vulnerable individuals alleviates concerns about pre-trends driving the main results for this group, an implication that also aligns with the small and statistically insignificant estimated average effect. While we estimate a lead effect of -2.84 points at the 80th percentile, this isolated finding likely reflects sampling variability or heterogeneous anticipation effects rather than systematic pre-trends. Overall, the pattern provides limited evidence of differential pre-trends and is broadly consistent with the identifying assumption of no anticipatory effects in our main specification.

Finally, further evidence that the impact of job insecurity is concentrated in mental well-being is provided by examining physical health as an alternative outcome. In

¹¹We depart from the approach of Reichert and Tauchmann (2017) by not re-estimating the model exclusively for public employees and civil servants, as their inherent job security restricts the within-individual variation that, alongside the smaller sample size, is necessary for the QRPD estimator to converge.

Column 4 of Table 5, we re-estimate the model using the Physical Component Summary (PCS) scale¹². While chronic stress may eventually manifest in physiological symptoms, the immediate impact of labor market anxiety is expected to be primarily psychological. The results confirm that the impact of job insecurity on physical health in the short term is substantially smaller than its effect on mental health, particularly within the bottom three deciles. Interestingly, in the 90th percentile, we find a positive effect of 1.5 points, which may suggest a compensatory increase in health-conscious behaviors among the healthiest individuals. In the middle percentiles (40th-60th), the coefficients are just slightly smaller than those in our main model. To account for potentially delayed physiological responses, and in line with the existing literature (e.g., Schiele and Schmitz (2016)), we also examine the PCS score at $t + 2$ in order to capture effects that may require a longer gestation period to materialize. At this horizon (Table 5, Column 5), however, we find no significant effect on physical well-being, either in terms of distributional effects or in terms of a mean effect. Taken together, these findings suggest that physical health does not exhibit the pronounced gradient observed for mental health outcomes, reinforcing the conclusion that the primary consequences of subjective job insecurity are psychological rather than physical.

6 Discussion and Conclusions

This paper investigates how the impact of job insecurity on mental health varies across the mental health distribution. Using German individual-level survey data from the SOEP, we utilize staff reductions as a source of exogenous variation. By employing a quantile regression estimator with non-additive fixed effects, we demonstrate that conventional mean regressions substantially underestimate the psychological burden among the most vulnerable segments of the workforce. While the effect is minimal at the upper end of the distribution (top 40%), we estimate a decline of approximately 5.4 points (0.54 standard deviations) at the median, and roughly 8.8 points (0.88 standard deviations) at the lower end of the mental health distribution. This gradient suggests that the psychological cost of job insecurity is not uniformly distributed but intensifies with individual susceptibility, consistent with cognitive scarcity theories which posit that individuals with fewer baseline resources are more susceptible to external shocks.

The study further argues for the necessity of non-additive fixed effects when researchers seek to account for unobserved heterogeneity in human behavior. Traditional additive fixed effects assume that unobserved traits, such as personal resilience,

¹²The PCS has the same properties as the MCS (a mean of 50 and a standard deviation of 10) and aggregates domains specific to physical health: physical functioning, role limitations due to physical health, bodily pain, and general health perceptions. Crucially for our test, the scoring algorithm ensures that the PCS and MCS are orthogonal by construction. In our sample, they remain virtually uncorrelated ($r = -0.06$), meaning these indices capture distinct, independent dimensions of well-being without mechanical spillover.

only shift a baseline without affecting the response to external shocks. By demeaning the data to remove these levels, researchers inadvertently mask the very heterogeneity they seek to study. Beyond structural susceptibility, several mechanisms may drive this, such as Allostatic Load Theory, suggesting chronic stressors cause physiological wear and tear, and Scarcity frameworks, where job fear consumes mental bandwidth already limited in individuals with pre-existing conditions.

Our results do not conflict with existing reduced-form distributional studies (Johnston et al., 2020; Reichert & Tauchmann, 2017). However, a direct comparison of structural estimates across quantiles is precluded, as causal distributional studies examining the specific impact of job insecurity on mental health do not exist. Therefore, we rely on average effects as a benchmark. Our estimate is close to that of Cottini and Ghinetti (2018), who use firm-level workforce changes as an instrument in a Danish panel. Using a broad measure of employment insecurity that combines job tenure, job status, and employability insecurity, they find that multidimensional insecurity reduces the Mental Health Index (MHI-5)¹³ by 5 points (0.41 standard deviations). Work in progress by Miele (2025), based on UK panel data, suggests that the anticipation of job loss emerges up to two years before the event and intensifies over time. The average impact on mental health in the year before the event is approximately 2.7 points (0.27 standard deviations) on the MCS, rising to around 2.9 points (0.29 standard deviations) once workers enter the mandatory 12-week notice period. Given our instrumental variable, we can interpret our estimates as the effect of exposure to firm-level workforce reductions among workers in firms undergoing, or at high risk of undergoing, economic distress. To some extent, this is comparable to Miele (2025), whose treatment group consists of individuals who ultimately experience job loss, implying that the anticipated shock is realized.

Beyond MCS estimates, Ahammer et al. (2025) examine objective health outcomes following firm downsizing using Austrian administrative records. Within 1.5 years of a mass layoff, survivors experience a 2.5% increase in drug prescriptions and a 13% increase in hospital days. Although the study focuses on firm downsizing rather than job insecurity directly, the fear of job loss can be identified as the primary mechanism driving these health declines. This translates to tangible economic costs, with sick leaves among the retained workforce rising by up to 18%. It is also informative to compare our estimates to the mental health impacts of actual job loss. Focusing on German studies using SOEP data and plant closures as a source of exogenous variation, Marcus (2013) finds that unemployment reduces mental health by 2.7 points of the MCS (0.27 standard deviations) for the affected individual and 1.8 points (0.18 standard deviations) for their partner. Schiele and Schmitz (2016) report an effect of 1.6 points (0.16 standard deviations) only at the 10th percentile of the MCS distribution. While this aligns with our qualitative finding of vulnerability at the

¹³Kelly et al. (2008) show a strong correlation between the MHI-5 and MCS ($r = 0.88$), suggesting that the two measures capture a similar underlying mental health domain, despite the relative simplicity of the MHI-5.

lower tail, their estimate’s more modest magnitude might partly reflect the inclusion of individuals who have already secured re-employment. Building on the average effects documented by Reichert and Tauchmann (2017), our results indicate that, at least in the lower mental health quantiles, the psychological penalty of job insecurity is not merely a precursor to unemployment but a substantial stressor in its own right.

To conclude, although our results highlight the severe psychological cost of job insecurity for the most vulnerable, they also underscore the limitations of a one-size-fits-all approach to workforce mental health. The stark divergence in outcomes, ranging from negligible impacts among the resilient to substantial declines for those with limited psychological reserves, demonstrates that policy interventions must move beyond broad-based financial safety nets. By recognizing the heterogeneity of vulnerability, policymakers and firm leaders can better target resources, such as proactive mental health support or specialized stress-management programs, toward employees at highest risk. Future research should also aim to further decompose these effects by integrating more granular data on individual cognitive and financial buffers, ultimately refining how we identify and protect those most susceptible to the pressures of an unstable labor market.

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Appendix

A Supplementary Descriptive Statistics

Table A1: Summary Statistics for the Main Estimation Sample

	Mean	S.D.	Min	Max
Physical Component Summary (PCS)	52.10	7.94	9.21	73.78
Age (years)	43.80	9.76	19	65
Age ² (years ² /100)	20.14	8.50	3.61	42.25
Male	0.57	0.50	0	1
Migrant	0.10	0.31	0	1
Years of education	12.52	2.51	7	18
Married	0.66	0.47	0	1
Living with partner	0.12	0.33	0	1
Household size	2.84	1.21	1	14
Number of kids under 18	0.63	0.91	0	9
Difficulty of finding new job:				
Easy	0.18	0.38	0	1
Difficult	0.64	0.48	0	1
Almost impossible	0.18	0.38	0	1
Tenure (years)	12.31	9.60	0	48.92
Mini- or Midi-job	0.03	0.16	0	1
Occupation:				
Low-Skilled Blue-Collar	0.12	0.33	0	1
Skilled Blue-Collar & Supervisory	0.21	0.41	0	1
Lower-Level White-Collar	0.43	0.50	0	1
Higher-Level White-Collar	0.23	0.42	0	1
Temporary work contract	0.04	0.19	0	1
Side job	0.04	0.18	0	1
Firm size:				
Less than 5 employees	0.07	0.26	0	1
5–199 employees	0.47	0.50	0	1
200 or more employees	0.46	0.50	0	1

Table A1: Summary Statistics for the Main Estimation Sample (Continued)

	Mean	S.D.	Min	Max
Lagged Gross HH labor income (in €1000, per month)	4.81	3.10	0	54.72
Year 2002	0.18	0.38	0	1
Year 2004	0.20	0.40	0	1
Year 2008	0.24	0.42	0	1
Year 2010	0.21	0.41	0	1
Year 2012	0.17	0.38	0	1

Notes: The table reports summary statistics for the main estimation sample. Summary statistics for the three core variables, MCS, job insecurity, and staff reduction, are reported in Table 1. The variables age², married, household size, difficulty of finding new job, tenure, occupation, temporary work contract, firm size, and lagged gross household labor income, alongside year dummies, enter directly into our fixed effects specifications.

B Validity of the Self-Reported Instrument

Table B1: Psychological Bias in Staff Fluctuation Reporting

	Staff Reduction (1)	Staff Reduction (2)	Staff Increase (3)	Staff Increase (4)
MCS_{t-2}	-0.0004 (0.001)	—	0.0006 (0.001)	—
Second MCS_{t-2} Quartile	—	-0.0024 (0.012)	—	0.0108 (0.011)
Third MCS_{t-2} Quartile	—	-0.0052 (0.012)	—	0.0093 (0.011)
Top MCS_{t-2} Quartile	—	-0.0177 (0.014)	—	0.0127 (0.013)
Within R^2	0.037	0.037	0.034	0.034
Joint significance (p-value)	0.000	0.000	0.000	0.000
Individual FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State FE	No	No	No	No
Covariates	Yes	Yes	Yes	Yes
N	16,346	16,346	16,346	16,346

Notes: In Columns (2) and (4), the bottom quartile of MCS_{t-2} serves as the baseline. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Falsification of Generalized Pessimism as a Confounding Mechanism

	Environmental Worries (1)	Worries about Peace (2)	Fear of Terrorism (3)
Second MCS_{t-2} Quartile	0.0033 (0.008)	0.0037 (0.009)	-0.0022 (0.011)
Third MCS_{t-2} Quartile	0.0031 (0.009)	-0.0007 (0.010)	-0.0079 (0.012)
Top MCS_{t-2} Quartile	-0.0084 (0.010)	0.0020 (0.011)	-0.0161 (0.013)
Within R^2	0.005	0.006	0.006
Joint significance (p-value)	0.000	0.000	0.001
Individual FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State FE	No	No	No
Covariates	Yes	Yes	Yes
N	16,333	16,336	13,222

Notes: The outcome variables are binary indicators equal to one if a respondent is somewhat or very concerned about the respective threat. See Figure C2 for the exact survey wording. The bottom quartile of MCS_{t-2} serves as the baseline. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

C SOEP Survey Questions

Table C1: Availability of Core Variables Across Survey Waves (2002 to 2012)

Variable	'02	'03	'04	'05	'06	'07	'08	'09	'10	'11	'12	Post-2012
Mental Component Summary (MCS)	✓		✓		✓		✓		✓		✓	Biennial
Subjective job insecurity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	Annual
Firm-level staff reductions	✓		✓				✓	✓	✓		✓	Discontinued after 2013

Notes: The table illustrates the availability of the core variables in the German Socio-Economic Panel (SOEP) survey waves. A checkmark indicates the variable was collected in the corresponding year. The Mental Component Summary (MCS) was collected for the first time in 2002. The collection of the firm-level staff reductions variable was discontinued after 2013.

Figure C1: SOEP Survey Questions on Health Outcomes (SF-12)

91. How would you describe your current health?

- Very good ☐
- Good..... ☐
- Satisfactory..... ☐
- Poor..... ☐
- Bad..... ☐

92. When you have to climb several flights of stairs on foot, does your health limit you greatly, somewhat, or not at all?

- Greatly..... ☐
- Somewhat ☐
- Not at all ☐

93. And what about other demanding everyday activities, such as when you have to lift something heavy or do something requiring physical mobility: Does your health limit you greatly, somewhat, or not at all?

- Greatly..... ☐
- Somewhat ☐
- Not at all ☐

94. During the last four weeks, how often did you:

Always Often Some- Almost Never
times never

- feel rushed or pressed for time? ☐ ☐ ☐ ☐ ☐
- feel down and gloomy? ☐ ☐ ☐ ☐ ☐
- feel calm and relaxed?..... ☐ ☐ ☐ ☐ ☐
- feel energetic? ☐ ☐ ☐ ☐ ☐
- have severe physical pain? ☐ ☐ ☐ ☐ ☐
- feel that due to physical health problems
 - you achieved less than you wanted to at work or in everyday activities? ☐ ☐ ☐ ☐ ☐
 - you were limited in some way at work or in everyday activities? ☐ ☐ ☐ ☐ ☐
- feel that due to mental health or emotional problems
 - you achieved less than you wanted to at work or in everyday activities? ☐ ☐ ☐ ☐ ☐
 - you carried out your work or everyday tasks less thoroughly than usual? ☐ ☐ ☐ ☐ ☐
- feel that due to physical or mental health problems you were limited socially, that is, in contact with friends, acquaintances, or relatives? ☐ ☐ ☐ ☐ ☐

Notes: This figure displays the English translation of Questions 91–94 from the 2012 individual questionnaire of the German Socio-Economic Panel (SOEP). These items comprise the standard SF-12 health survey instrument used to construct our dependent variables: the Mental Component Summary (MCS) and the Physical Component Summary (PCS). Source: TNS Infratest Sozialforschung (2013).

Figure C2: SOEP Survey Questions on Economic and Societal Worries

127. How concerned are you about the following issues?

	Very concerned	Somewhat concerned	Not concerned at all
The economy in general.....	☐	☐	☐
Your own economic situation.....	☐	☐	☐
The stability of the financial markets	☐	☐	☐
Your health	☐	☐	☐
Environmental protection.....	☐	☐	☐
The impacts of climate change.....	☐	☐	☐
Maintaining peace	☐	☐	☐
Global terrorism.....	☐	☐	☐
Crime in Germany	☐	☐	☐
Immigration to Germany.....	☐	☐	☐
Hostility towards foreigners or minorities in Germany	☐	☐	☐
Stability of the euro.....	☐	☐	☐
<i>If you are employed:</i>			
Your job security.....	☐	☐	☐

Or what else are you concerned about?

*Please
state:*

Notes: This figure displays the English translation of Question 127 from the 2012 individual questionnaire of the German Socio-Economic Panel (SOEP). The binary treatment indicator used in the primary specifications equals 1 if the respondent selected "Very concerned" or "Somewhat concerned," and 0 if "Not concerned at all". In the threshold sensitivity analysis (Table 5, Column 1), the treatment equals 1 strictly for "Very concerned," while "Somewhat concerned" is shifted into the reference category. The questions regarding environmental protection, maintaining peace, and global terrorism serve as the outcome variables for the falsification tests presented in Table B2. Source: TNS Infratest Sozialforschung (2013).

Figure C3: SOEP Survey Question on Firm-Level Staff Reductions

**36. How was it in the previous twelve months in the company where you currently work:
Has the number of employees increased, decreased, or remained the same?**

Increased.....	☐	
Decreased	☐	
No change	☐	Don't know ☐

Notes: This figure displays the English translation of Question 36 from the 2012 individual questionnaire of the German Socio-Economic Panel (SOEP). This item serves as the basis for our instrumental variable, capturing the extensive margin of workforce downsizing. The binary indicator Staff Reduction equals 1 if the respondent selected "Decreased," and 0 if they selected "Increased" or "No change". Responses indicating "Don't know" are treated as missing. Source: TNS Infratest Sozialforschung (2013).