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Abstract

Work-related stress has reportedly increased over time. Using worker-level survey data, we build a measure of work pressure strongly associated with adverse health outcomes. In line with theories of compensating differentials, work pressure comes with a sizable earnings premium, even within narrowly defined occupations. As expected, we find no premium among civil servants who face strong labor market frictions. In complementary stated-choice experiments, we uncover a substantial willingness-to-pay to avoid work pressure. Our evidence is consistent with workers sorting into high- and low-pressure jobs. Differences in the prevalence and valuation of work pressure explain a substantial share of wage inequality.

JEL-Codes: I100, I310, J200, J310, J320, J810, M520.

Keywords: work pressure, compensating differentials, working conditions, wage inequality, health.

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1 Introduction

Workplace stress has been on the rise for decades. International workplace surveys, for instance by the polling company Gallup, show a rise in self-reported feelings of stress and worry over time (Gallup, 2022). Correspondingly, there is a public discussion about adverse health outcomes related to stress in the workplace, often attributed to aggregate trends such as technological change or globalization.[1] At the extreme, high-pressure jobs are suspected to have substantial adverse effects on workers' (mental) health and life expectancy (Kivimäki et al., 2018).

The theory of compensating wage differentials (Rosen, 1986) predicts that firms need to pay a compensating wage premium to workers if work-related stress is a disamenity. In theory, the rise of workplace stress should therefore have come with changes in the earnings structure that compensate (marginal) workers for the disamenity of working under increased pressure. Understanding to what extent work-related stress translates into higher earnings is therefore important from an economic policy perspective. Also, differences in workplace stress between workers and jobs may contribute to, or explain, existing earnings inequalities in the labor market.

In this paper, we study the labor market consequences of work-related pressure. We use two complementary approaches to do so. In a first approach, we exploit rich observational data to estimate wage premia in high-pressure jobs in Germany. In a second approach, we conduct a stated-choice experiment with a representative sample of German employees. Exploiting these data, we estimate workers' willingness-to-pay to avoid work pressure, study sorting into high-pressure jobs based on preferences, and analyze the contribution of differences in work pressure to wage inequality.

Our first approach relies on the German BIBB/BAuA employment surveys. In these surveys, workers provide a detailed account about the characteristics of their workplace, the exact nature of their job, as well as information on health outcomes, family outcomes, and job satisfaction (Rohrbach-Schmidt and Hall, 2020; Hall et al., 2020). The data come in 7 waves from 1979 to 2018 and are well-suited to study the connection between work pressure, wages, and other outcomes.

We conceptualize work pressure by building an index of whether workers often face tight deadlines or pressure to perform, often need to work on several important tasks at the same time (multitasking), are frequently interrupted in their work, and face minimum requirements of output. We test the validity of our measure by showing that workers employed in high-pressure jobs report worse health outcomes on a variety of margins. For example, they more often experience sleep problems and nervousness, even *within* narrowly defined occupations. While work pressure is prevalent across all

[1] See for example The Guardian (2020): "Career stress: the average age of burnout is now 32 – and home working is making it worse".

education and occupation groups, we show that work pressure as measured by our index is, on average, higher in more skill-intensive occupations in the upper hierarchy levels of firms.[2] Moreover, and in line with the notion that work-related stress has increased over time, our pressure index substantially increased in recent decades.

Exploiting the survey data, we show a sizable pay premium for high-pressure jobs. The link between work pressure and earnings holds within industries and occupations and is robust to the inclusion of a large set of controls including individual worker characteristics, firm and job characteristics, and even job task measures. According to our preferred specification, a switch from a zero-pressure to a high-pressure job within the same occupation goes along with an increase in monthly earnings by about 12 percent and an increase in hourly wages by about 6 percent.

We use complementary regressions to show that the observed earnings premia are consistent with theories of compensating differentials (Rosen, 1986). First, we contrast the results of our main sample of private sector workers with the results from a sample of civil servants for whom compensating differentials arguably play a much smaller role. This is because civil servants face largely fixed pay schedules and stronger labor market frictions, conditional on occupation and controls (Bonhomme and Jolivet, 2009). In line with this, civil servants who report high work pressure do not receive an earnings premium in our data, although they also report higher work hours on average, leading to lower hourly wages on average. Second, we use administrative panel data from the IAB Linked Personnel Panel (which allow us to run regressions using worker fixed-effects) to show that the lower bound for the compensating earnings differential is positive and significantly different from zero (Lavetti and Schmutte, 2018).[3]

In light of the well-known difficulties in estimating compensating differentials from observational data, we complement this approach with a stated-choice experiment among a representative set of over 3,300 German employees. In this second main approach, we follow Maestas et al. (2018) and let participants choose between hypothetical jobs that differ along job amenities as well as wages. We include measures of work pressure as well as other job attributes such as working from home or paid days off and anchor job options around the respondents' current job. This allows us to cleanly identify the willingness-to-pay (WTP) to avoid high pressure in the workplace. In addition, following the conceptual work of Rosen (1986), the experimental data

[2] Additionally, workers in high-pressure jobs are more likely to state that they are employed in firms that recently launched new production technologies and new information technologies. Workers in high-pressure jobs are also more likely to state that they are employed in firms that recently expanded, that recently outsourced parts of their production process to domestic and foreign suppliers, and that recently decreased their workforce.

[3] Since workers endogenously move towards better jobs offering both higher earnings and better amenities, and because of potential measurement error in the main explanatory variable, the fixed-effects regressions provide lower bounds.

allow us bound the compensating wage differential to avoid high pressure. The approach rests on the idea that the compensating differential reflects the WTP to avoid the disamenity of the *marginal* worker (i.e., the worker at the margin of this job or an alternative job without the disamenity). This is bound by the WTP of *inframarginal* workers. Finally, we provide evidence for the welfare and inequality implications of work pressure.

The experimental results show that employees have a sizable willingness-to-pay to avoid work pressure. On average, respondents are willing to forgo almost 10% of their wage to avoid frequent deadlines and around 6% to avoid frequent multitasking. The WTP is higher for female, older, less educated, and lower-earning individuals. In line with labor market sorting based on preferences for job amenities (Rosen, 1986), workers who report facing work pressure in their current jobs show a lower WTP to avoid work pressure than workers who do not. Our bounding exercise suggests that the compensating differential for frequent deadlines is between 5 and 11% of wages, while the compensating differential for frequent multitasking is between 4 and 8% of wages. Respondents' average WTP to avoid work pressure is similar to their WTP to work from home and larger than their WTP for flexible schedules, but lower than their WTP for additional paid days off or their WTP to avoid commutes of 30 minutes or more.

Importantly, the results from the experiment suggest that differences in work pressure between workers help explain existing wage inequalities, for example between high- and low-educated workers. The (hourly) wage gap between high- and low-educated workers amounts to around 40 log points in our sample. Taking into account the disamenity value of work pressure in current jobs, inequality between high- and low-educated workers shrinks to 35 log points. This corresponds to a decrease of almost 13%.[4] Similarly, once the disamenity value of work pressure is taken into account, inequality between workers at the 80th and workers at the 20th percentile of the hourly wage distribution decreases from 67 to 62 log points.

Our paper contributes to the literature on the role of non-wage job characteristics in the labor market. The theory of compensating wage differentials predicts that workers should be compensated for workplace disamenities such as job-related health risks (Rosen, 1986). A large literature investigates compensating wage differentials for non-wage job characteristics using observational data (e.g., Brown 1980; Duncan and Holmlund 1983; French and Dunlap 1998; Stern 2004; Villanueva 2007; Sorkin

[4]This result stems from two sources: First, low-educated workers are less likely than high-educated workers to report high pressure in their current job. Second, low-educated workers exhibit a higher willingness-to-pay to avoid work pressure, meaning that they attach a greater amenity value to low work pressure than high-educated workers.

2018; Lamadon et al. 2022; Schneider et al. 2020; Taber and Vejlin 2020).[5] Recently, Wissmann (2022) shows that German hospitality workers' daily earnings decreased after the introduction of smoking bans. This literature has repeatedly acknowledged that estimating compensating differentials using observational data is difficult for a variety of reasons including search frictions and endogenous labor market matching (e.g., Brown, 1980; Bonhomme and Jolivet, 2009; Lavetti and Schmutte, 2018; Lavetti, 2020).[6] Several recent papers therefore turn to choice experiments to estimate the trade-off between non-wage amenities and wages from the perspective of workers. Most importantly, Mas and Pallais (2017) and Maestas et al. (2018) estimate the willingness-to-pay of U.S. workers for alternative work arrangements and various non-wage characteristics of jobs using survey experiments.[7]

Our paper also contributes to the literature on health and labor market outcomes. A growing literature suggests that there is a tight connection between work stress and adverse health outcomes (e.g., Jamison et al., 2004; Nixon et al., 2011). Recent experimental evidence consistently suggests that individuals are averse against working under time pressure (Buser et al., 2022). A sizable literature has investigated the health consequences of labor market developments. Recent studies for example analyze the health effects of downsizing (Østhus, 2012; Ahammer et al., 2020) and the link between firm sales and worker health (Hummels et al., 2019). The literature also investigates the link between job loss and health outcomes (Sullivan and von Wachter, 2009; Kuhn et al., 2009; Browning and Heinesen, 2012), the health effects of adverse economic conditions (Ruhm, 2000, 2016; Pierce and Schott, 2020), and the more general impact of working hours on health outcomes (e.g., Åkerstedt et al., 2001; Cygan-Rehm and Wunder, 2018; Berniell and Bietenbeck, 2020).

We contribute to these literatures with a comprehensive analysis of the link between work-related pressure and labor market outcomes. The detailed nature of our data allows us to investigate this connection both between and within narrowly defined occupations. Our results suggest that individuals are (to some extent) compensated for work stress and resulting health risks in the form of higher wages. We provide evidence consistent with individuals actively selecting into high-paying, high-pressure jobs. Our experimental estimates are consistent with the willingness-to-pay of workers to reduce fast-paced work found by Maestas et al. (2018) and with individuals' aversion against time pressure (Buser et al., 2022). Relative to Maestas et al. (2018), we provide a much more detailed picture about workers' willingness-to-pay to reduce work-related stress.

[5]Most notably, there is a large literature estimating compensating wage differentials for risk of death (e.g., Viscusi and Aldy, 2003; Lavetti and Schmutte, 2018; Lavetti, 2020).

[6]These problems also include issues such as incomplete data to make jobs truly comparable, see, e.g., DiNardo and Pischke (1997).

[7]See also the field experiment by He et al. (2021) in China.

Relative to Buser et al. (2022), we provide evidence on the labor market consequences of time and work pressure. In particular, we provide an in-depth analysis of the inequality effects of work-related stress, showing that work pressure helps explaining existing inequalities in the labor market. We also contribute to the literature by using a variety of empirical approaches to isolate this compensating wage differential.

The remainder of this paper is structured as follows. In section 2, we analyze the link between work pressure, health and wages, and the development of work pressure over time, using observational data. In section 3, we investigate the association between work pressure and wages as well as the implications for inequality, using a stated-choice experiment. Section 4 concludes.

2 First Approach: Observational Data on Work Pressure and the Labor Market

2.1 Data, empirics, and a measure for work pressure

2.1.1 Data: The BIBB/BAuA employment surveys

We use the BIBB/BAuA employment surveys for the first part of our analysis. These surveys are carried out by the German Federal Institute for Vocational Education and Training (BIBB) in cooperation with the Federal Institute for Occupational Safety and Health (BAuA). The surveys contain a representative sample of one tenth of a percent of all individuals who are at least 15 years old and are working at least 10 hours per week. They were conducted in seven waves (1979, 1986, 1992, 1999, 2006, 2012, 2018), covering four decades (Rohrbach-Schmidt and Hall, 2020; Hall et al., 2020). We disregard the wave in 1992 since many questions that are relevant for our analysis were not asked. In the surveys, workers give a detailed account about their socioeconomic background, the characteristics of their workplace, the nature of the job and the tasks they are performing, as well as detailed information about their health status and their satisfaction with several aspects of their job. As in many other labor market datasets, a drawback of the data is that we can only observe earnings and hours and have to compute wages from this information. We thus mostly rely on earnings in our regressions.

The BIBB/BAuA employment surveys are particularly suitable for our research question. First, the nature of the data allows to analyze the link between workplace and job characteristics, earnings, and other worker outcomes between *and* within narrowly defined occupations.[8] This is important since it allows us to show that the link between

[8]For example, a focus on the within-occupation dimension is not possible in the commonly used O*NET data, which is based on surveys among experts about the characteristics of different occupations

work pressure, earnings, and other outcomes is present even within narrowly defined occupations. Second, the time dimension of the data enables us to analyze the change in work pressure in the German labor market over four decades, both between and within occupations and industries.

In the main analysis of our first approach, we focus on individuals aged between 20 and 60 and working at least 35 hours per week. We drop civil servants and self-employed individuals. With these restrictions, we end up with about 8,000 observations per wave. To study the link between work pressure, earnings, and other worker-level outcomes in detail, we focus on the most recent 2018 wave because it is the most comprehensive of all waves. The main results, however, also hold when we use the earlier waves instead.

2.1.2 Empirical specification

As a first approach, we estimate variants of the following specification using the 2018 wave:

$$y_i = \beta HighPressure_i + X_i' \gamma + \epsilon_i \tag{1}$$

The dependent variable y_i for worker i differs by analysis. In section 2.1.4, where we ask whether high work pressure is linked to health issues or lower job satisfaction, y_i reflects indicators for the worker's health status or job satisfaction, for example. In section 2.2, y_i denotes the log of worker's monthly earnings before taxes, work hours, or hourly wage. The coefficient of interest is β and denotes how worker outcomes differ between jobs of varying degrees of work pressure as defined by our main variable, which we define in the following section.

The vector X_i' controls for a variety of potential confounders. It contains a set of controls that we call "extended Mincer" controls, i.e., three education groups, a cubic term in age, gender, German nationality, and Nuts-2 region. In our preferred specifications, X_i' also contains a vector of 2-digit occupation dummies (KldB2010, similar to ISCO-08) and a vector of industry dummies (NACE-2). This for example takes into account permanent differences between jobs and industries, such as the degree of monopsony power.

In additional specifications, we also control for firm, job, and task characteristics such as firm size, the existence of a works council, employment by a temporary work agency, the number of subordinates (capturing the hierarchy level of a worker), commuting status, computer use, indicators whether the job has a high routine content

(Autor, 2013). A well-known limitation of the O*NET database is that experts tend to underestimate the change in job characteristics in an occupation over time. This, however, is not a problem in the BIBB/BAuA data, in which workers directly report the characteristics of their job and their workplace.

and a high codifiability, as well as an indicator for physical pressure.[9] Regressions employ sample weights and, in all specifications, standard errors are clustered at the 2-digit occupation level.

2.1.3 Definition of work pressure

We construct an index of work pressure based on the following four questions in the survey:

1. How often do you face tight deadlines and pressure to perform?
2. How often do you need to carry out several tasks at the same time?
3. How often are you being interrupted, for example by colleagues, telephone calls, bad material, or machine malfunctions?
4. How often do you face a minimum requirement, in terms of quantity or in terms of the time needed to carry out a task?

To answer these questions, survey participants have the choice between four options: 'often', 'sometimes', 'seldom', or 'never'. We create an index of work pressure for each worker i, which is given by the share of all questions (indexed by j) to which the individual responds with 'often':

$$HighPressure_i = \frac{\sum_j answer = often}{4} \tag{2}$$

$HighPressure_i$ can take values between 0 (if the individual does not answer 'often' to any of the questions) and 1 (if the individual answers 'often' to all four questions). As a robustness check, we also employ a binary indicator which takes on the value 1 if the individual answers 'often' to all four questions, and 0 otherwise.[10]

Our measure has several advantages over self-reported measures of feelings of stress. First, it relates to more objective elements of the job that respondents may not directly link to feeling stressed when asked about it. This comes with the advantage of being independent of social desirability issues around feeling stressed in the workplace. Second, it is consistently available since the first wave of the data in 1979, with

[9]This index contains for example indicators on whether workers need to lift heavy weights, need to work under cold, heat, moisture, and need to work with smoke or dust.

[10]In the earlier waves (1979, 1986, 1992, 1999), there is a fifth option 'always'. In these cases, we combine the categories 'often' and 'always'. All of our results are robust to different definitions of work pressure, though.

the exception of the 1992 wave.[11] Table A.1 in the Appendix provides descriptive statistics of the pressure variable(s) and other variables for all waves of the BIBB/BAuA employment surveys.

2.1.4 Is the index of work pressure a good proxy for workplace stress?

In this subsection, we show that our measure of work pressure is closely associated with workers' self-reported health outcomes, job satisfaction, and family outcomes. We also provide evidence that work pressure is high in workplaces or jobs where we would expect it to be high. Finally, we show that, in line with surveys and newspaper articles on workplace stress, our measure of work pressure has increased substantially since 1979, the earliest year for which we have data.

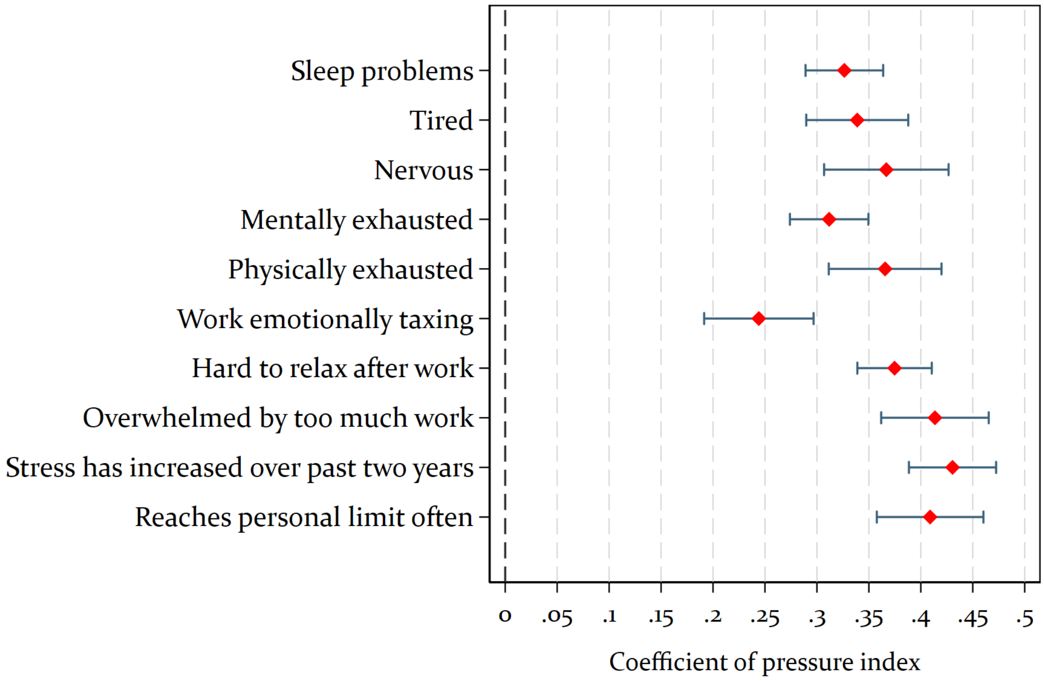
Measured work pressure predicts adverse health outcomes. We first analyze the connection between our measure and self-reported adverse health outcomes. The reason for this analysis is that the health economics literature suggests a tight connection between work stress and adverse health outcomes (e.g., Jamison et al., 2004; Nixon et al., 2011). We regress the respondents' answer to whether they suffer from a specific adverse health outcome on our work pressure index, conditioning on extended Mincer controls as well as 2-digit occupation and industry dummies.

Figure 1 shows the results from this analysis. Even conditional on a large set of control variables including workers' occupation, those who report higher work pressure as defined by our measure also suffer from more adverse health outcomes, including sleep problems, nervousness, finding work emotionally taxing, and being overwhelmed by too much work. This suggests that our measure indeed captures a work environment defined by a high degree of pressure. In Appendix A.2 we provide further results which suggest that our work pressure index is associated with a higher number of sick days, lower job satisfaction, and adverse family outcomes.

Work pressure is high in workplaces where we would expect it to be high. Next, we show that our work pressure variable does not merely capture worker skills, but that it is higher in jobs and firms where we would expect it to be higher. In Appendix Table A.3, we show that when we predict our main work pressure variable using the covariates in our baseline regressions, we find that on average, workers with a university degree are more likely to report high work pressure. Other worker characteristics such as gender and age do not predict work pressure once we condition on occupation and industry characteristics. Table A.4 in the Appendix shows that

[11] In general, we avoided questions which involve an emotional assessment of the job requirements. In the more recent waves, there is also a question about whether employees have to work very fast (cf. Maestas et al., 2018). We did not include this variable because it is not consistently available across waves. However, including this variable into the high pressure yields very similar results in the hedonic wage/earnings regressions (available upon request).

Figure 1: Link between pressure and health



Note: This figure shows the estimated link between our work pressure index and various self-reported health indicators, obtained from linear probability models. To estimate the coefficients, we use the respective health outcomes as the dependent variable. The dependent variable takes on the value of 1 if the respondent indicates that the respective health outcome (e.g., sleep problems) occurs often, and zero otherwise. The main explanatory variable is the work pressure index defined in equation 2. We include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of workplace area), 2-digit occupation and industry dummies. The bars represent 95% confidence bounds that allow for clustering at the 2-digit occupation level.

high-pressure jobs as defined by our measure are most likely found in occupations such as health care workers, doctors, journalists, and train drivers. Low-pressure jobs include painters, gardeners, and occupations in theology. These rankings suggest that our measure is both plausible and not mechanically related to skills since both high- and low-skilled occupations are among the jobs with the highest and lowest average pressure.

Next, in Appendix A.3 we show that workers in high-pressure jobs are more likely to be in the upper level of hierarchies and more likely to be a team leader and to have budget responsibility. High-pressure workers are also more likely to respond that they rarely receive positive feedback, that they are frequently not informed about important decisions, and that work stress has increased over the past two years.

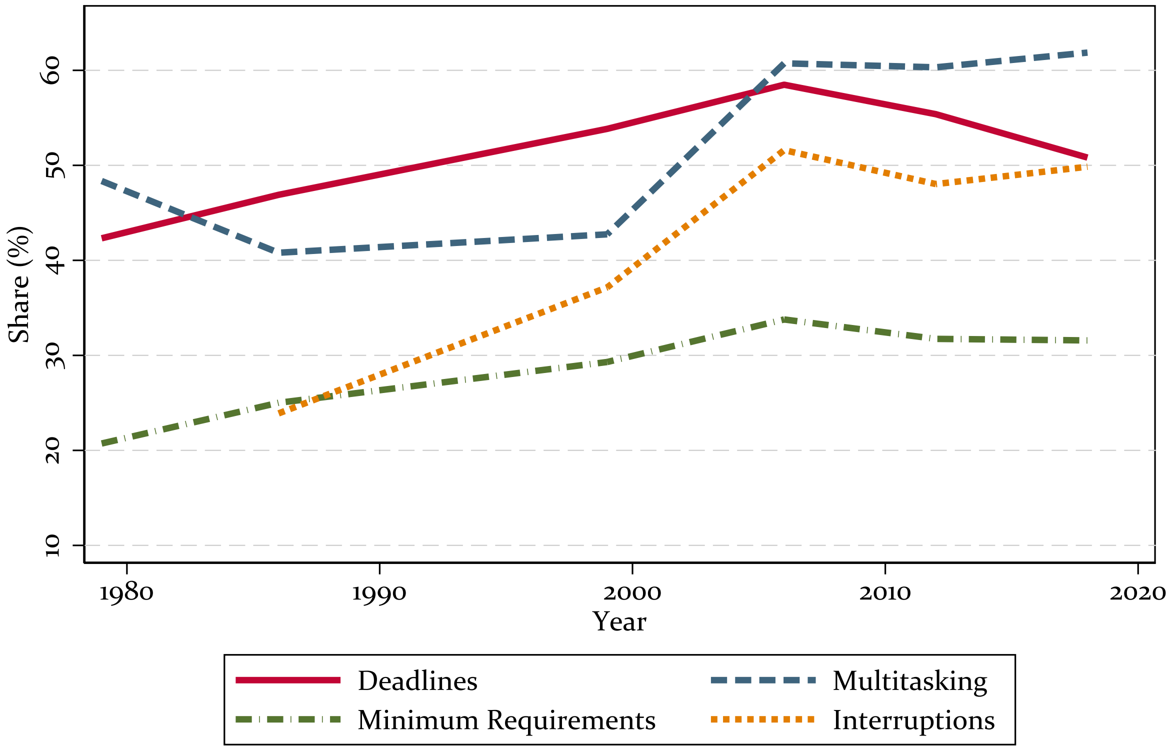
Finally, in Appendix A.4, we show that workers reporting high work pressure are significantly more likely to be employed by firms that have recently expanded, outsourced or displaced workers, or introduced new production technologies and computer programs. Thus, work pressure seems to be correlated with the secular labor market developments of the past decades that the literature has investigated more deeply (Acemoglu and Autor, 2011; Goldschmidt and Schmieder, 2017; Autor et al., 2020; Acemoglu and Restrepo, 2022).

Work pressure has increased over the past decades. To study the evolution of work pressure over time, we exploit the large time dimension of the data set and make use of all available waves between 1979 and 2018 (except for the 1992 wave), focusing on West Germany. Figure 2 provides evidence that work pressure in the German labor market has increased between 1979 and 2018. The figure shows the evolution over time of all four pressure variables separately. The increase in work pressure primarily occurred until the mid-2000s, leveling off afterwards (similar to, e.g., Lopes et al., 2014). All of the four pressure variables show a higher value in 2018 relative to 1979. For example, in 2018, more than 60% of respondents say that they need to perform multitasking often, as compared to less than 50% in 1979. In 2018, more than 50% of respondents indicate that they often experience tight deadlines and pressure to perform, compared to slightly above 40% in 1979. To our knowledge, this is the longest consistent and representative measurement of work stress over time in the literature. The observed increase is consistent with evidence from other surveys and with the general notion that work-related stress has increased over time (e.g., Gallup, 2022). The time trend is nearly identical once we include East German workers after Reunification (result available upon request), supporting the notion that the rise in work-related stress constitutes a secular trend.

To what extent is this trend driven by compositional changes in the workforce over time? In panel (a) of Appendix Figure A.1, we residualize the trend from education, gender, and age controls and show that the increase in work pressure is not exclusively driven by changes in the education, gender and age composition over time.[12] In panel (b) of Appendix Figure A.1, we additionally residualize the trend from 2-digit occupation dummies. It turns out that the trend is also not exclusively driven by changes in occupation composition. In other words, the observed rise in work pressure has occurred between *and* within occupation and demographic groups.

[12]For example, the raw increase in the minimum requirements variable in Figure 2 amounts to 11 p.p. After residualizing the trend from education, gender, and age controls, the increase still amounts to around 7.5 p.p.

Figure 2: High-pressure jobs: 1979-2018



Note: This figure shows the evolution over time of our four main work pressure variables. For each wave, the figure depicts the share of workers who indicate that often face tight deadlines (often need to engage in multitasking, often face minimum requirements, often are interrupted in their work). We use sample weights to compute the shares. Data source: BIBB/BAuA employment surveys 1979, 1986, 1999, 2006, 2012, 2018.

2.2 High-pressure, high-paying jobs?

2.2.1 Earnings differentials for high-pressure jobs

The theory of compensating differentials (Rosen, 1986) suggests that, if workers consider high pressure as a disamenity, they would choose a different job with lower pressure, ceteris paribus, if not compensated for high work pressure. Firms therefore need to pay a premium to high-pressure jobs in order to attract labor supply. In this section, we investigate whether there is a wage premium for high-pressure jobs, focusing on the most recent wave from the year 2018.

In Table 1, we show the relation between our work pressure variable, monthly earnings, (self-reported actual) work hours, and hourly wages. Panel (A) shows the estimated link between work pressure on monthly earnings. Column (1) shows that, absent any control variables, monthly earnings are higher for workers in high-pressure jobs. We control for several variables that we label "extended Mincer controls" in Column (2). These controls include education, a third-order polynomial for worker age, gender, whether workers are German, their NUTS-2 region, and urbanization of these regions. The estimated coefficient on our work pressure variable decreases only slightly, suggesting that it does not simply capture differences in labor market returns to education or experience or higher wages in some areas of the country.

We present our preferred specification in Column (3) where we control for 2-digit occupation and industry dummies. This specification accounts for potential bias from unobserved worker or firm heterogeneity between occupations and industries. It also accounts for the possibility that some occupations and some industries may inherently have higher work pressure and higher earnings, e.g., through different production processes. The estimated positive link between work pressure and monthly earnings becomes slightly smaller, but remains sizable and statistically significant. This means that there is a strong association between work pressure and monthly earnings *even within* occupations and industries. As an example, after having completed their educational training, lawyers face the decision between working in small, low-pressure family firms or, alternatively, in large-scale, high-pressure law firms which are engaged in high-stake litigation processes or in mergers between large international companies. According to the point estimate in Column (3), monthly earnings of workers in high-pressure jobs ($HighPressure_i = 1$) ceteris paribus on average are 12.5 log points higher than monthly earnings of workers in low-pressure jobs ($HighPressure_i = 0$). The implied earnings difference between a worker at the 25th percentile of work pressure ($HighPressure_i = 0.2$) and a worker at the 75th percentile ($HighPressure_i = 0.6$) equals around 5 log points.

In Column (4), we additionally control for firm and job characteristics. This specification includes variables on whether the firm has a works council, whether workers are employed through a temporary work agency, whether they commute, whether they are on a temporary contract, the number of subordinates of a worker, firm size quintile dummies, whether workers have standard work hours, whether they work in shifts, and whether they frequently need to work on stand-by. The connection between high work pressure and earnings is only slightly lower but still sizable and statistically significant. In Column (5), we additionally control for the exact tasks that workers perform, following the literature on task-biased technological change (Spitz-Oener, 2006; Autor, 2013). The impact of high work pressure on log earnings increases slightly again. Since we regard the variables in Columns (4) and (5) as potential outcomes of selecting into high-pressure, high-paying jobs, our preferred estimate is Column (3).[13]

[13]For example, a long commute, a job with high non-routine content, or employment at a large firm might be the result of selecting into a high-pressure, high-paying job, i.e., these variables might be endogenous controls. In an analysis of the returns to education in classical Mincer earnings regression, the occupation and industry dummies would represent bad controls since they are a result of educational

Panel (B) provides the same analysis for work hours. As expected, workers in high-pressure jobs on average work significantly longer hours. Does this drive the earnings premium entirely? To investigate this, we compute hourly wages from the earnings and the hours information. Panel (C) then presents the analysis for log hourly wages. There is a positive and statistically significant link between work pressure and hourly wages, with the exception of Column (4). The estimates in Panel (C) show that higher monthly earnings in high-pressure jobs are not solely driven by longer work hours, but a *wage* premium. In Appendix Figure A.6, we show the heterogeneity of the earnings estimates by age, gender, and education. The estimated earnings premium to high work pressure is positive for all sub-groups and slightly higher for above-median earnings, male, and high-educated workers.

In sum, the analysis in this section provides robust evidence that high-pressure jobs exhibit an earnings premium. Interestingly, this earnings premium holds even within occupations and industries. The earnings premium is driven by a higher number of work hours *and* a high hourly wage. A potential explanation of the estimated earnings premium to work pressure is that workers are compensated for the disamenity value of high-pressure jobs. However, alternative explanations such as convex returns to work hours may also explain our estimates (Goldin, 2014). In the following sections, we therefore further investigate the question whether the estimated earnings and wage premium is a compensation for work pressure.

investments. We argue that this problem does not arise in our context. By including these dummies, our estimation focuses on the link between work pressure and earnings or the link between work pressure on other outcomes *within* occupations and industries. This implies that we focus on the trade-off between earnings and non-monetary aspects of jobs that workers are facing after they have completed their education and their occupation-specific training, while at the same time controlling for unobserved heterogeneity at the occupation and industry level.

Table 1: High-pressure jobs: Earnings, wages, and work hours

	(1)	(2)	(3)	(4)	(5)
Panel A					
	Dep. Var.: 100x Ln(monthly earnings)				
High pressure	16.68***	13.98***	12.46***	9.37***	12.21***
	(3.33)	(2.10)	(1.92)	(2.07)	(1.86)
Adj. R2	0.01	0.33	0.43	0.49	0.52
Obs.	7825	7825	7825	7825	7825
Panel B					
	Dep. Var.: 100x Ln(work hours)				
High pressure	6.20***	6.43***	6.47***	6.58***	6.07***
	(0.79)	(0.75)	(0.74)	(0.68)	(0.73)
Adj. R2	0.02	0.08	0.14	0.17	0.17
Obs.	7825	7825	7825	7825	7825
Panel C					
	Dep. Var.: 100x Ln(hourly wage)				
High pressure	10.48***	7.55***	5.99***	2.79	6.13***
	(3.23)	(2.27)	(2.01)	(2.13)	(1.83)
Adj. R2	0.01	0.28	0.41	0.48	0.50
Obs.	7825	7825	7825	7825	7825
Extended Mincer controls	No	Yes	Yes	Yes	Yes
Occupation and industry dummies	No	No	Yes	Yes	Yes
Firm and job controls	No	No	No	Yes	Yes
Task controls	No	No	No	No	Yes

Note: This table shows the results of our main regressions using equation 1 using private sector workers, focusing on the 2018 wave. In Panel (A), we use 100*log monthly earnings as the dependent variable. In Panel (B), we use 100*log work hours. In Panel (C), we use 100*log hourly wage. Extended Mincer controls include education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area. Occupation dummies are 2-digit according to the Klassifikation der Berufe (KldB) 2010 (similar to ISCO-08). Industry dummies are 2-digit NACE dummies (Klassifikation der Wirtschaftszweige 2008). Firm and job controls include whether the firm has a works council, whether the worker is employed through a temporary employment agency, the number of subordinates of a worker, whether the worker commutes, whether she is on a temporary contract, five firm size bins, whether the worker has standard work hours, whether she works in shifts, and whether she frequently faces stand-by requirements. The task measures include dummies for routine tasks, codifiability of tasks, whether the worker uses a computer, and an index for the physical requirements in her work. Robust standard errors, allowing for clustering at the 2-digit occupation level, in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

2.2.2 Wage differentials for high-pressure jobs do not show up for civil servants

Our interpretation of the wage and earnings premia uncovered in the previous section as compensating differentials relies on the idea that (marginal) workers need to be compensated for disamenities of their job because they would otherwise change their jobs. However, it may also be the case that we are simply estimating unobserved differences in worker, firm, or match quality.

To further investigate this question, we use civil servants to run something akin to placebo regressions. Civil servants differ substantially in their job and work characteristics even within occupation and many have jobs with high work pressure.[14] As an example, a police officer or teacher in a high-pressure environment such as a low-income area in a large city is paid around the same as a police officer or teacher in the countryside. However, we would not expect them to receive similarly large compensating differentials because pay scales are largely fixed for civil servants and because frictions to changing jobs are much larger than in the private sector. For instance, civil servants typically have much fewer outside options than workers in most private sector occupations.[15] These are well-known circumstances that make a compensating differential unlikely to appear (see, e.g. Bonhomme and Jolivet, 2009).

Table 2 shows the results of these regressions. In line with our arguments, Panel (A) shows that monthly earnings of civil servants that report high work pressure are no different than monthly earnings of civil servants who do not. This is especially true conditional on occupation. Panels (B) and (C) illustrate the plausibility of using civil servants as the "placebo" group. In line with expectations, civil servants in high pressure jobs still report higher work hours. But since they are not compensated for this disamenity in their monthly earnings, they show lower hourly wages even conditional on a large set of individual, occupation, and job characteristics.

[14] Note that civil servants in Germany usually cannot choose where they start their first position, such that there is limited sorting into jobs.

[15] Note, for example, that there are only very few private schools in Germany and that private security services usually pay much lower (net) wages than the police does.

Table 2: "Placebo" regressions: Earnings, wages, and work hours of civil servants

	(1)	(2)	(3)	(4)	(5)
Panel A					
	Dep. Var.: 100x Ln(monthly earnings)				
High pressure	2.64	2.32	0.24	0.75	2.50
	(6.40)	(4.28)	(4.13)	(3.84)	(3.74)
Adj. R2	-0.00	0.43	0.46	0.48	0.49
Obs.	995	996	996	995	995
Panel B					
	Dep. Var.: 100x Ln(work hours)				
High pressure	7.61***	7.96***	7.70***	7.26***	6.76***
	(2.13)	(1.62)	(1.59)	(1.64)	(1.72)
Adj. R2	0.02	0.11	0.17	0.18	0.19
Obs.	995	996	996	995	995
Panel C					
	Dep. Var.: 100x Ln(hourly wage)				
High pressure	-4.97	-5.64	-7.45**	-6.51*	-4.26
	(5.84)	(3.59)	(3.44)	(3.34)	(2.98)
Adj. R2	0.00	0.41	0.44	0.46	0.48
Obs.	995	996	996	995	995
Extended Mincer controls	No	Yes	Yes	Yes	Yes
Occupation and industry dummies	No	No	Yes	Yes	Yes
Firm and job controls	No	No	No	Yes	Yes
Task controls	No	No	No	No	Yes

Note: This table shows the results of our main regressions using equation 1, but using civil servants instead of private sector workers. In Panel (A), we use 100*log monthly earnings as the dependent variable. In Panel (B), we use 100*log work hours. In Panel (C), we use 100*log hourly wage. Extended Mincer controls include education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area. Occupation dummies are 2-digit according to the Klassifikation der Berufe (KldB) 2010 (similar to ISCO-08). Industry dummies are 2-digit NACE dummies (Klassifikation der Wirtschaftszweige 2008). Firm and job controls include whether the firm has a works council, whether the worker is employed through a temporary employment agency, the number of subordinates of a worker, whether the worker commutes, whether she is on a temporary contract, five firm size bins, whether the worker has standard work hours, whether she works in shifts, and whether she frequently faces stand-by requirements. The task measures include dummies for routine tasks, codifiability of tasks, whether the worker uses a computer, and an index for the physical requirements in her work. Robust standard errors, allowing for clustering at the 2-digit occupation level, in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

2.2.3 Bounding the compensating differential using panel data

In Appendix A.6, we also use panel data to provide a lower bound for the compensating differential for work pressure. To this end, we leverage data from the Linked Personnel Panel, combined with administrative data on workers' earnings (LPP-ADIAB). The LPP-ADIAB is a worker- and establishment-level survey (carried out by the German Institute for Employment Research, IAB) that is linked to workers' social security data. In addition to demographic characteristics and information on personnel policies, the survey also includes questions on workers' perceptions of their jobs. This includes a question on whether workers often face tight deadlines over a longer time period or have to manage several important tasks at the same time. We estimate a standard earnings regressions with log earnings as dependent variable. The explanatory variables comprise our high pressure variable as well as controls for age (cubic), tenure, and occupational indicators (whether the worker supervises other workers, the number of subordinates, 2-digit industry and occupation fixed effects).

To bound the effect of work pressure on earnings, we also include worker fixed effects in our earnings regression. As argued by Lavetti and Schmutte (2018), workers move endogenously across jobs, generating a negative correlation between disamenities and wages across jobs within movers, the sample from which we identify the effect when including workers fixed effects. The reason is that, if low work pressure is a normal good, workers over time trade some of the higher earnings potential against (relatively) lower work pressure. In addition, within-person changes in perceived pressure may to some extent reflect measurement error, leading to attenuation bias. Thus, any significant positive effect of high pressure on earnings in such a regression to us would imply that the true compensating differential for high pressure is positive (and likely substantially larger).

In cross-sectional regressions analogous to the ones in the previous section, we again find a sizable positive earnings premium associated with work pressure. Importantly, when we include worker fixed effects, we still find a small, but statistically significant positive relationship between work pressure and earnings of around one percent.[16] Overall, this analysis shows that even in the severely downward biased worker fixed effects specification, there is a significant positive link between work pressure and earnings. In a next step, we turn to stated-choice experiments to provide further evidence on the role of compensating wage differentials for high work pressure in the labor market.

[16]Interestingly, the LPP contains one question on contractual work hours and one question on actual hours. We do not find any impact on contractual hours in the fixed effects specification, but a significant positive impact on actual hours. Results are available on request.

3 Second Approach: Willingness-to-Pay to Avoid Work Pressure in Choice Experiments

3.1 Experimental setup

The final piece of evidence regarding the interpretation of the estimated wage premium to work pressure as a compensating differential comes from stated-choice experiments. In these experiments, we vary work pressure along with wages across hypothetical jobs. The idea of the stated-choice method is to randomize job characteristics and observe the choices that individuals make when facing the trade-off between hypothetical jobs that differ in terms of wages and non-wage attributes. The resulting data allow us to identify the wage premium necessary to compensate workers for the presence of high-pressure job characteristic in those hypothetical choices.

Our pre-registered experimental setup follows Maestas et al. (2018), who use a survey experiment to estimate the willingness-to-pay of workers for alternative work arrangements and various non-wage characteristics of jobs.[17] Maestas et al. (2018) study 10 non-wage job attributes, including hours, schedule flexibility, physical job demands, and autonomy at work. The only attribute that captures work pressure in their experimental design is pace of work ("relaxed" vs. "fast-paced"). We adapt their experimental design to identify the willingness-to-pay to avoid high pressure in the workplace in Germany. We ran the experiment in July 2022 on a sample of over 3,300 German private-sector employees aged between 20 and 60. We recruited the subjects using the infrastructure of *Norstat*, a professional data collection agency.

We aim at estimating the willingness-to-pay to avoid jobs characterized by high pressure. For that purpose, we define two job attributes that capture work pressure. The first attribute captures the presence of deadlines, and the second refers to multitasking. When presenting the job attributes in the experiment, we use a wording that closely follows the wording of the respective survey questions discussed in the previous section. In both cases, the job attributes are defined by statements whether the respective high-pressure attribute would apply "frequently" or "occasionally."

In contrast to the survey items exploited in the previous section, we use only two measures characterizing hypothetical jobs as more or less stressful. This avoids that job profiles would be dominated by attributes capturing work pressure. We chose deadlines and multitasking as the two attributes for several reasons. First, these attributes show the highest independent correlation with earnings in our observational data. Second, information on deadlines and multitasking is available in both observational datasets we use. Third, we believe they are the clearest measures of work pressure among

[17] See the entry in the AEA RCT Registry, https://doi.org/10.1257/rct.9559.

the four elements of our survey-based pressure index. To enable comparisons with compensating differentials for non-wage job attributes unrelated to work pressure estimated in previous literature, we complement the job profiles by several further non-wage attributes. These are control over schedule, option to work from home, number of paid days off, commuting time, and hours. We provide an in-depth analysis of these elements, especially workers' willingness-to-pay to work from home, in Nagler et al. (2022).[18]

Each survey respondent completes a series of ten stated-choice experiments.[19] In each of these experiments, the task of the survey respondent is to select between two jobs, each defined by a randomly varying set of non-wage job characteristics, hours, and earnings.[20] For each respondent, we construct a baseline job profile that captures the characteristics of the respondent's current job. To obtain the baseline profile, we ask respondents to answer a survey about her current job characteristics immediately before participating in the experiments. Each survey item corresponds to one of the non-wage job attributes in the experiments. In Appendix Table A.9, we use these survey data to show that the cross-sectional link between work pressure and earnings is very similar to the association we found in our main observational data set.[21]

Starting from the respondents' individual baseline job profile, we construct hypothetical Job A and Job B by randomly selecting two non-wage attributes (including hours) to vary across the two jobs. All non-wage attributes not selected are identical across jobs A and B. For each of the two attributes selected to vary, we randomly choose corresponding attribute values for both jobs. To make sure that Job A and Job B actually vary in the selected attributes, we sequentially choose (for each selected attribute) the attribute values without replacement.[22]

[18]We pre-specified the attributes relating to work pressure and all other job attributes in the pre-analysis plan for the experiment.

[19]Appendix Figure A.8 shows a sample choice screen from the experiment.

[20]Hainmueller et al. (2015) show that such (forced choice) paired conjoint analyses perform remarkably well in predicting real world preferences for choice attributes.

[21]After the choice experiments, respondents additionally answered questions about their current health status. In Appendix Figure A.12, we show that there is a tight connection between frequent deadlines, frequent multitasking, and adverse health outcomes in our experimental sample.

[22]We use the following strategy to limit the variation in selected attributes. If hours are selected to vary, we add to the baseline weekly hours (determined to be the value from $\{15, 20, 25, \ldots, 55, 60\}$ that is closest to the stated hours) of each job a number randomly chosen from the set $\{-10, -5, 0, 5, 10\}$. Regarding paid days off, Bick et al. (2019) find that in their sample, US workers have around 10 days of annual leave on average. Instead, German workers have around 30 days of annual leave. We therefore set the baseline value to the value from $\{25, 30, 35\}$ that is closest to the number stated in the survey, and (if selected to vary) randomly choose from these values. If selected to vary, we randomly choose the commuting time from the set $\{15, 30, 45, 60\}$. Regarding options to telecommute, subjects choose in the survey between "none", "2 days per week", and "5 days per week". We set the baseline values correspondingly and (if selected to vary) randomly select from that set. The variation in all other non-wage attributes is binary (deadlines and multi-tasking: "frequently" vs. "occasionally"; control over schedule: "yes" vs. "no").

In addition to the two non-wage attributes that were selected to vary in a given experiment, the wage always varies between Job A and Job B. The wage randomization scheme ensures that the wages of both jobs are anchored at the respondent's actual hourly wage w. This is achieved by setting the wages of Job A and Job B as $\theta_A w$ and $\theta_B w$, respectively, where θ_A and θ_B follow a $N \sim (1, 0.01)$ distribution.[23] We truncate both weights to lie between 0.75 and 1.25. For each respondent, the wages are displayed in the unit in which the subject originally reported her earnings (hourly, monthly, or yearly) in the initial survey.[24]

We follow Maestas et al. (2018) and instruct respondents to assume that any job attributes not mentioned in the job profiles are identical across jobs. This minimizes the risk that choices are affected by differential perceptions regarding unspecified job characteristics. In addition to the series of 10 choice experiments, we include two further survey questions that allow us to differentiate between more and less attentive respondents. These attention check questions follow the "trick" questions in Maestas et al. (2018). 65.6% of respondents passed both attention checks.

3.2 Empirical specification

We estimate the willingness-to-pay to avoid high pressure job characteristics following Maestas et al. (2018). The approach assumes that respondents' observed choices (preference for either job A or job B) reflect a linear indirect utility function

$$V_{ijt} = \alpha + X'_{ijt}\beta + H'_{ijt}\theta + \delta \ln w_{ijt} + \epsilon_{ijt}, \tag{3}$$

where V_{ijt} denotes individual i's indirect utility from job j and choice pair t. X_{ijt} denotes the vector of non-wage job characteristics, H_{ijt} is a function of hours, and w_{ijt} is the wage rate. Using a logistic specification, we model the probability to select alternative j over alternative k as

$$P(V_{ijt} > V_{ikt}) = \frac{\exp[(X'_{ijt} - X'_{ikt})\beta + (H'_{ijt} - H'_{ikt})\theta + \delta(\ln w_{ijt} - \ln w_{ikt})]}{1 + \exp[(X'_{ijt} - X'_{ikt})\beta + (H'_{ijt} - H'_{ikt})\theta + \delta(\ln w_{ijt} - \ln w_{ikt})]}. \tag{4}$$

Workers are indifferent between a job not having attribute r at wage w and one that has attribute r and pays $w - WTP^r$ when

$$\delta \ln w = \beta^r + \delta \ln(w - WTP^r), \tag{5}$$

[23] 12.2% of the subjects stated in the survey that they were unable to accurately report their current (gross) income. For these subjects, we randomly chose an hourly baseline wage (in Euros) from the set 15, 16, . . . , 59, 60.

[24] We follow the strategy used by Maestas et al. (2018) to limit the number of job pairs in which one of the jobs dominates the other on all varying dimensions.

where the willingness-to-pay WTP^r for attributes may be negative for disamenities. Workers' WTP^r can thus be written as

$$WTP^r = w \left[1 - e^{\left(-\frac{\beta^r}{\delta} \right)} \right]. \tag{6}$$

We present our estimates in terms of $1 - e^{\left(-\frac{\beta^r}{\delta} \right)}$. This implies that, if attribute r is added to a job, utility-wise this is equivalent (in the case of $WTP^r < 0$) to a $100 \left(1 - e^{\left(-\frac{\beta^r}{\delta} \right)} \right)$ % wage decrease. We compute standard errors using the delta method, allowing for clustering at the respondent level.

3.3 Workers show substantial willingness-to-pay to avoid work pressure

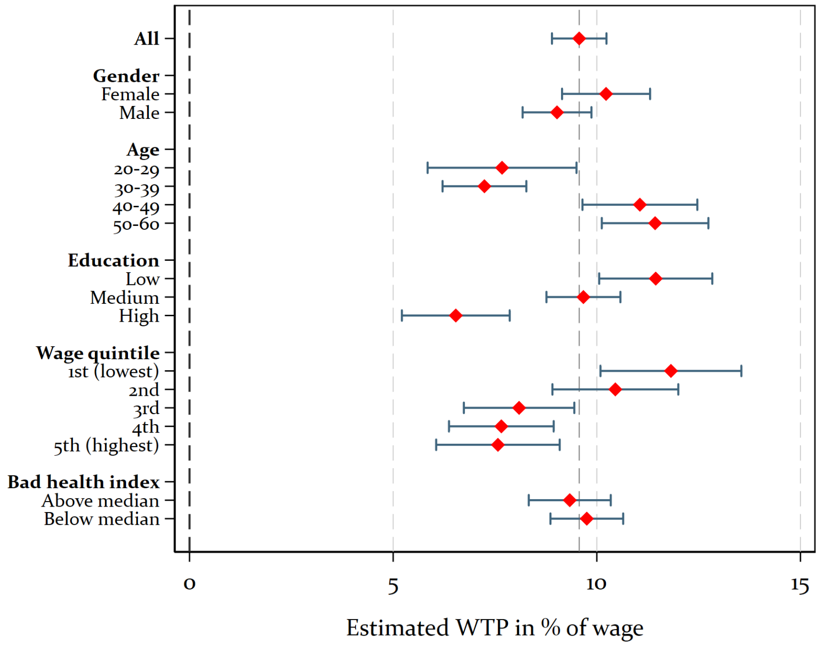
Figure 3 shows the willingness-to-pay in percent of workers' wages to avoid frequent tight deadlines and frequent multitasking. The first row of Panel (a) shows that, on average, workers are willing to accept a pay cut of 9.6 percent to avoid frequent tight deadlines. These results are in line with evidence by Buser et al. (2022) on time pressure aversion in experiments. Similarly, the first row of Panel (b) shows a willingness-to-pay of 7 percent to avoid frequent multitasking. Note that we always control for work hours. The results thus support the notion that workers perceive tight deadlines and multitasking as disamenities and therefore demand a wage premium in order to accept a job with high levels of work pressure.

In both panels, we also show the heterogeneity in workers' willingness-to-pay to avoid job pressure across worker characteristics. The WTP estimates to avoid frequent tight deadlines and multitasking are slightly higher for females compared to males. In addition, the WTP estimates to avoid tight deadlines and multitasking is substantially higher for older and low-educated workers, and for those at the bottom of the wage distribution. For example, the WTP to avoid tight deadlines amounts to around 12% for workers with low levels of education (no university degree and no vocational degree), as compared to just above 6% for workers with high levels of education (university degree). In contrast, we do not find meaningful heterogeneities by self-reported health status.[25]

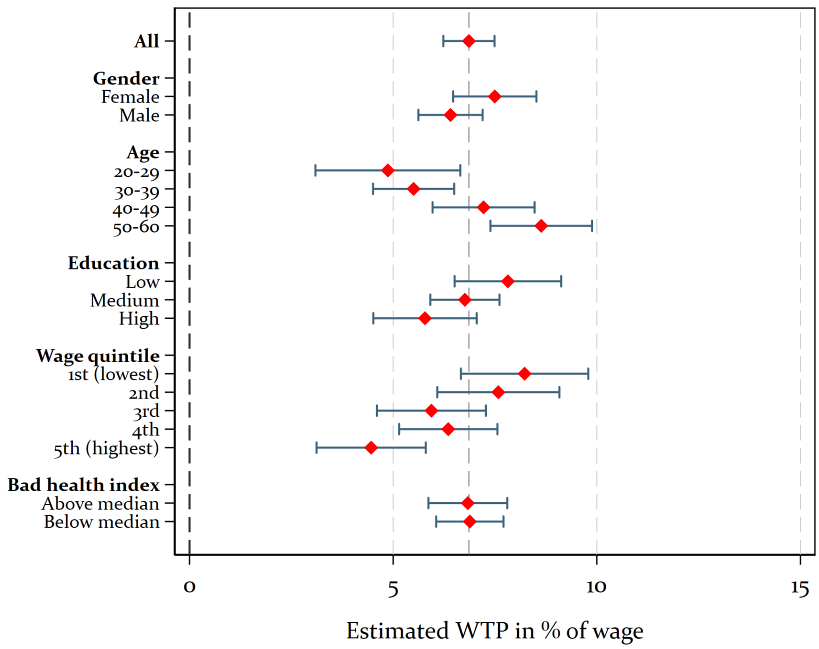
[25] This might be the result of two counteracting mechanisms. First, workers who currently suffer from health problems might have a higher WTP to reduce work pressure. Second, workers with a lower WTP to avoid work pressure are more likely to select into high-pressure jobs (see Section 3.4 on sorting) and, as a consequence, are more likely to experience health problems. See also Appendix Figure A.9 for more detailed results regarding heterogeneity by self-reported health status.

Figure 3: Workers' willingness-to-pay to avoid job pressure

(a) WTP to avoid frequent tight deadlines



(b) WTP to avoid frequent multitasking



Note: The figure shows the estimated willingness-to-pay to avoid frequent tight deadlines (Panel A) and frequent multitasking (Panel B). In each panel, the first row shows the average willingness-to-pay for all respondents in the sample. The following rows show the estimated WTP for several different sub-samples, by gender, age, education, wage quintile, and self-reported health status. The red diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the respondent level.

3.4 Sorting into high-pressure jobs based on preferences?

In a next step, we investigate worker sorting into high-pressure jobs, based on their willingness-to-pay. Figure 4 shows that, in line with theory (Rosen, 1986), workers who report the existence of frequent tight deadlines (frequent multitasking) in their current job show a lower willingness-to-pay to avoid this job attribute. In Appendix Figure A.11, we show that this result is more pronounced for older workers with substantial labor market experience (above age 40) and also holds within education levels.[26] A possible interpretation of this result is that workers (at least to some extent) actively select into or out of high-pressure jobs, trading wages against their individual disamenity value of high work pressure.[27] In line with this, Buser et al. (2022) find that experimentally elicited measures of time pressure aversion predict stated career preferences. The extent to which high observed work pressure actually reflects workers' preferences and the trade-off they are making between wages and work pressure are important ingredients to the policy discussion about work-related stress.

This analysis also allows to bound the "true" compensating differential if we are willing to take theory at face value. The idea is that the compensating differential reflects the willingness-to-pay for the marginal worker. Because of sorting, the WTP of this marginal worker is bound by the WTP of inframarginal workers. In our case, this would imply that the compensating differential for frequent deadlines is between 5% and 11% of wages, while the compensating differential for frequent multitasking is between 4% and 8% of wages. We can compare these bounds to the estimated compensating wage differentials in the experimental sample, stemming from conventional hedonic regressions (see Panel C in Appendix Table A.9). Taken at face value, this analysis would suggest that the hedonic wage regressions strongly understate the true compensating differential for frequent deadlines, while getting the compensating differential for multitasking about right.

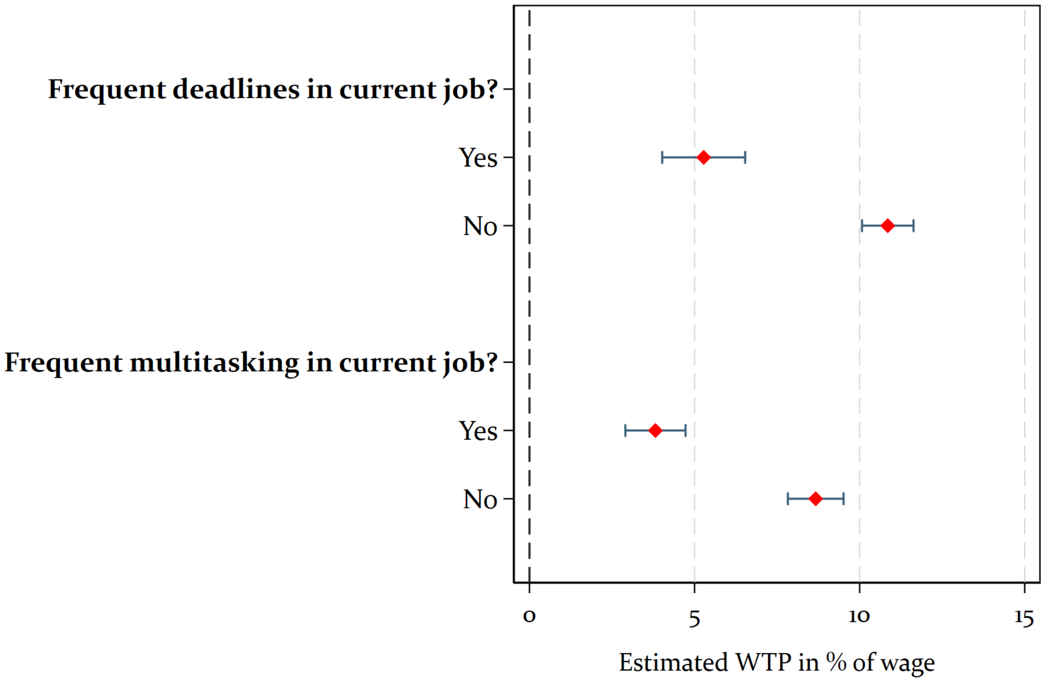
3.5 Putting the results into perspective

Comparison to other job characteristics. To benchmark our estimates, we included several other job attributes in the experiment. We report on these in a companion paper (Nagler et al., 2022), but replicate them below to compare workers' willingness-to-pay to avoid work pressure to other job amenities.

[26]In unreported regressions, we find that the results are always more pronounced for older than for younger workers, even when conditioning on education. In addition, male and female workers show similar sorting patterns. All results are available on request.

[27]Note that labor market frictions such as limited information on outside options (e.g., Jaeger et al., 2021) would work against finding differences in workers' willingness-to-pay to avoid the disamenity by their current job (Bonhomme and Jolivet, 2009).

Figure 4: Sorting: Workers' WTP to avoid pressure by own job characteristics

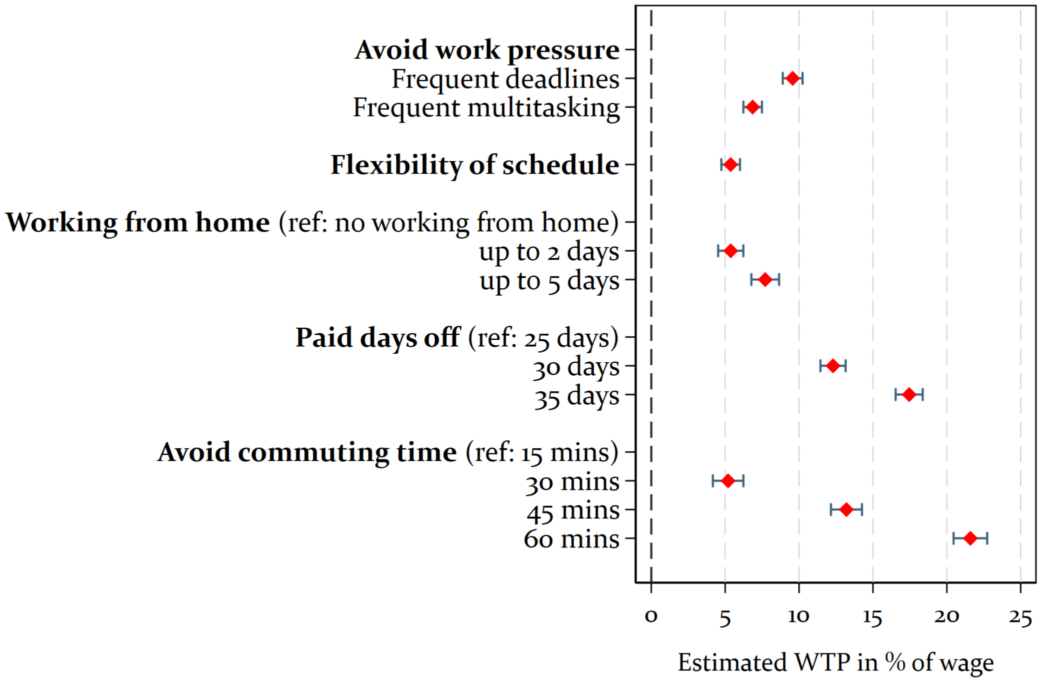


Note: This figure shows workers' estimated willingness-to-pay (WTP) to avoid work pressure, by own job characteristics. The first two rows show the estimated WTP depending on whether the respondent reported to have frequent tight deadlines in her current job or not. The last two rows show the estimated WTP depending on whether the respondent reported to have frequent multitasking in her current job or not. The red diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the respondent level.

Figure 5 shows the results from this analysis. We find that respondents' average WTP to avoid multitasking and to avoid deadlines is roughly the same as their WTP to work from home for up to 5 days, with the WTP to avoid multitasking being slightly lower and the WTP to avoid pressure being larger. Both are larger than respondents' WTP for up to 2 days of work from home or their WTP for flexible schedules. However, workers' WTP to avoid work pressure is lower than their WTP for 5 or 10 additional paid days off (relative to a baseline of 25) or their WTP to avoid commutes of 30 minutes or more (relative to a baseline of 15 minutes). In sum, these results suggest that differences in work pressure play an important role when workers are choosing between different jobs.

Work pressure and inequality. Finally, we investigate whether work pressure can explain some of the existing wage inequalities in the data. This is likely because high work pressure is more prevalent among high-educated and high-earning workers (see Appendix Tables A.7 and A.8). Additionally, the heterogeneity analysis in Figure 3 suggests that low-educated and low-earning workers exhibit a higher WTP to avoid

Figure 5: Workers' WTP to avoid work pressure compared to other job attributes



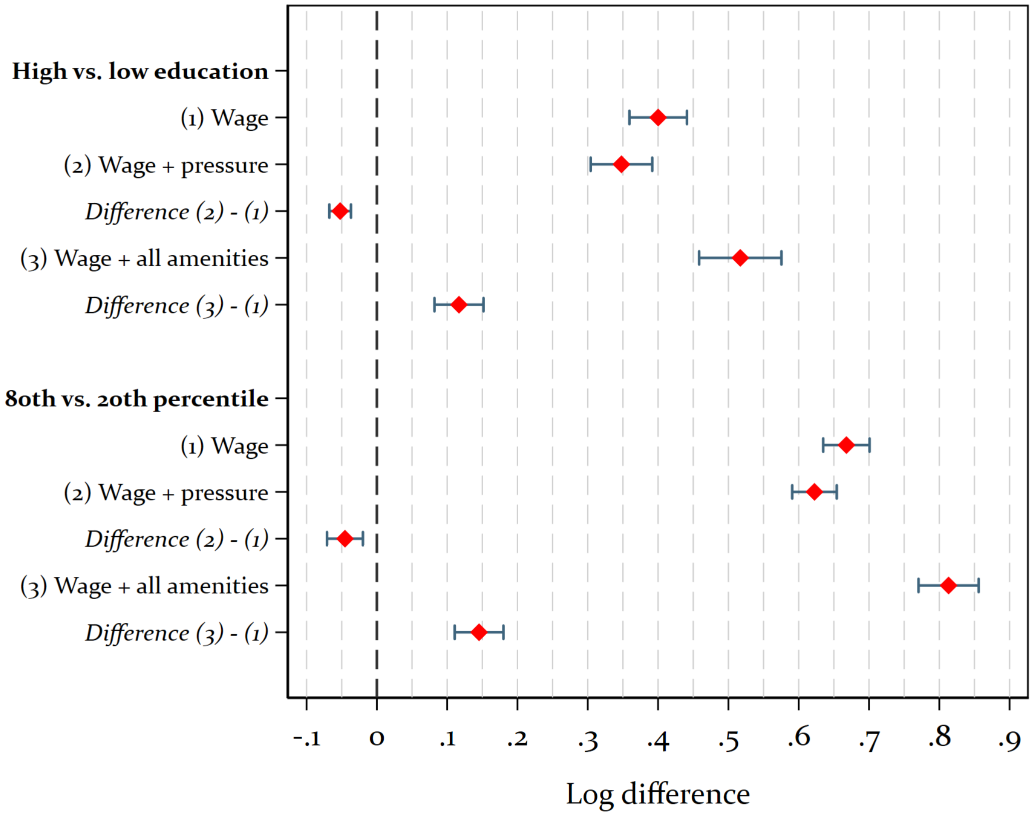
Note: This figure shows estimates of workers' willingness-to-pay for all job attributes included in the experiment. The first two rows show the estimated WTP to avoid frequent deadlines and frequent multitasking. The third line shows the estimated WTP for flexibility of schedule. The fourth and fifth lines show the WTP for working from home up to 2 days or up to 5 days (reference: no working from home), respectively. The next two rows show the WTP for 30 and 35 paid days off (reference: 25 paid days off), respectively. The last three rows show the WTP to avoid various (one-way) commuting times (reference: 15 minutes). The red diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the occupation level.

high work pressure, meaning that they attach a higher amenity value to low levels of work pressure, compared to high-educated and high-earning workers.

To study the implications for inequality, we compute the log compensation (i.e., wage plus the amenity value of low work pressure) for each worker as $ln\left[w + w\left[1 - e^{\left(-\frac{D\beta^D + M\beta^M}{\delta}\right)}\right]\right]$, where D (M) take on the value zero if deadlines (multitasking) occurs frequently in the current job and 1 otherwise. β^D and β^M are the corresponding estimated marginal utilities which we allow to differ between worker groups using the notation from Equation (6). We compute standard errors by performing a block bootstrap with 200 replications (by respondent).

Figure 6 shows the results from this analysis. The upper part of the figure shows the inequality between high- and low-educated workers. The gap in hourly wages between these two groups amounts to 40 log points. Once we factor in the amenity value of low work pressure, the gap shrinks to around 35 log points. This means that the (dis-)amenity value of (high) low work pressure explains around 13% of the

Figure 6: Implications of experimental estimates on compensation inequality



Note: The figure illustrates the implications of the experimental estimates for compensation inequality. The upper part of the figure focuses on inequality between high-educated workers (college degree) and low-educated workers (no college degree and no vocational degree). (1) depicts the difference in log hourly wages. (2) depicts the difference in log compensation (wage plus amenity value of low work pressure). (3) depicts the difference in log compensation (wage plus amenity value of all job attributes). The lower part of the figure shows the corresponding estimates for the difference between the 80th and the 20th percentile of the self-reported wage distribution. The red diamonds depict the point estimates. The bars reflect 95% confidence intervals which we obtain from 200 block (by respondent) bootstrap replications.

wage differences between high- and low-educated workers, holding other job attributes constant. In contrast, when we use our WTP estimates for all job amenities included in the experiment, the compensation inequality between high- and low-educated workers increases substantially to more than 50 log points. In other words, incorporating other job amenities included in the experiment exacerbates inequality relative to only considering earnings. The bottom part of Figure 6 shows that we reach a similar conclusion when analyzing inequality between the 80th and the 20th percentile of the (self-reported) wage distribution.

4 Conclusion

Work pressure has increased substantially during the past decades. This paper provides a detailed analysis of the role of work pressure in the labor market, using rich observational and experimental data. In light of an ongoing public discussion about work-related stress and its potential adverse effects on workers, it is crucial to understand to what extent different groups of workers are compensated in the form of a wage premium. Exploiting observational and experimental data, we provide several complementary pieces of evidence in favor of a quantitatively important compensating differential for work pressure.

Our analysis consistently suggests that, when choosing between different jobs, workers are facing a quantitatively important trade-off between higher earnings and lower work pressure. In light of this trade-off, workers are (at least partly) sorting into high-pressure and low-pressure jobs based on the disamenity value that they attach to high work pressure. The differential selection as well as the differential valuation of work pressure explains a non-negligible share of the existing earnings inequality between education groups and between wage percentile groups. This finding is of interest given the large and growing literature on the causes of earnings inequality.

In a broader perspective, labor markets in developed countries have undergone a substantial transformation during the last decades, driven to a large extent by technological progress and by globalization. The existing literature puts a very strong focus on employment, earnings, and earnings inequality. Potentially important non-wage factors, in contrast, have received less attention by researchers and policymakers.

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A Appendix

Table A.1: Sample descriptives: BIBB/BAuA employment surveys

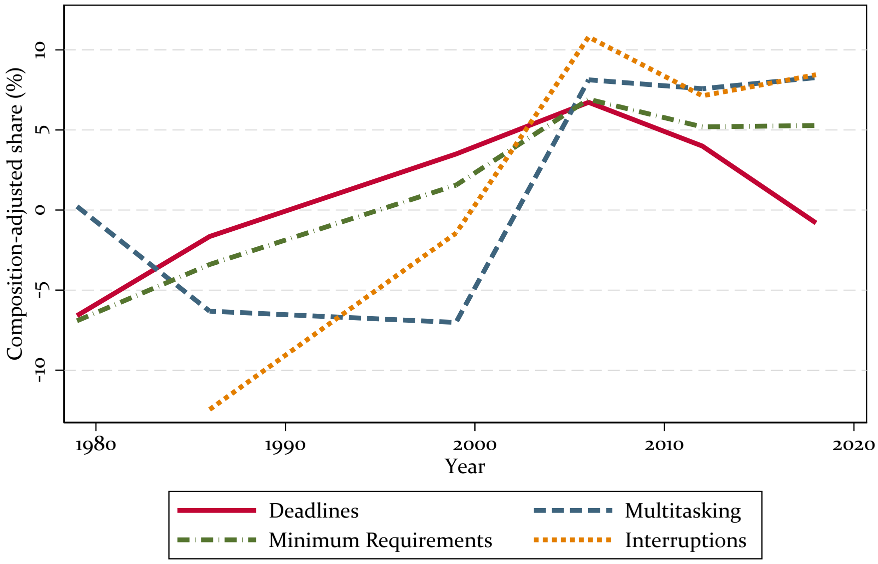
Wave	1979	1986	1999	2006	2012	2018
	(1)	(2)	(3)	(4)	(5)	(6)
	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd	mean/sd
Deadlines	0.42	0.47	0.54	0.58	0.55	0.51
	(0.49)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Multitasking	0.48	0.41	0.43	0.61	0.60	0.62
	(0.50)	(0.49)	(0.49)	(0.49)	(0.49)	(0.49)
Interruptions	.	0.24	0.37	0.52	0.48	0.50
	(.)	(0.43)	(0.48)	(0.50)	(0.50)	(0.50)
Minimum requirements	0.21	0.25	0.29	0.34	0.32	0.32
	(0.41)	(0.43)	(0.46)	(0.47)	(0.47)	(0.46)
High pressure index	.	0.34	0.41	0.51	0.49	0.49
	(.)	(0.28)	(0.31)	(0.31)	(0.31)	(0.31)
High education	0.05	0.06	0.10	0.18	0.19	0.23
	(0.22)	(0.23)	(0.30)	(0.39)	(0.39)	(0.42)
Medium education	0.82	0.71	0.76	0.73	0.73	0.67
	(0.38)	(0.45)	(0.43)	(0.44)	(0.44)	(0.47)
Low education	0.15	0.23	0.14	0.09	0.08	0.09
	(0.36)	(0.42)	(0.35)	(0.28)	(0.28)	(0.29)
Age	37.89	38.52	39.02	39.95	41.28	41.78
	(11.44)	(11.46)	(10.62)	(10.04)	(10.76)	(11.11)
Female	0.31	0.32	0.29	0.29	0.32	0.32
	(0.46)	(0.47)	(0.45)	(0.46)	(0.47)	(0.47)
Temporary contract	.	0.05	0.08	0.09	0.10	0.11
	(.)	(0.22)	(0.27)	(0.28)	(0.31)	(0.31)
Shift work	0.16	0.14	0.21	0.28	0.15	0.19
	(0.36)	(0.34)	(0.41)	(0.45)	(0.35)	(0.39)
Computer use	0.05	0.03	0.50	0.64	0.67	0.69
	(0.23)	(0.17)	(0.50)	(0.48)	(0.47)	(0.46)
Routine job	0.47	0.49	0.46	0.50	0.47	0.45
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Codifiable job	0.32	0.35	0.35	0.24	0.27	0.27
	(0.47)	(0.48)	(0.48)	(0.43)	(0.44)	(0.44)

Note: This table shows means (and, in parentheses, standard deviations) of some of our main variables across all waves in the BIBB/BAuA employment surveys. The High pressure index is computed according to 2. High education is equal to one if workers report having graduated from university or from a university of applied sciences. They are classified as medium education if they have another degree in secondary education or a completed apprenticeship/vocational degree. If they fall in neither category, they are coded as low educated.

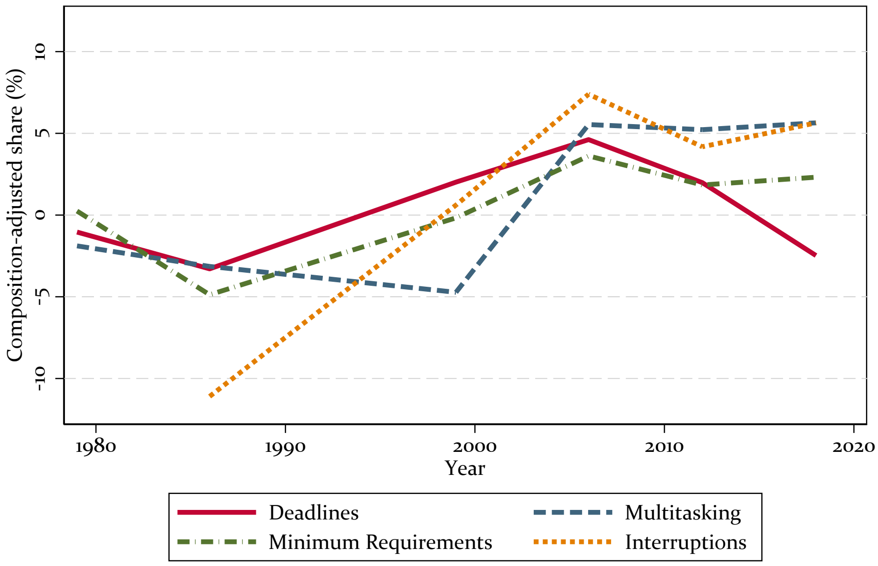
A.1 Time trend in work pressure: accounting for compositional changes

Figure A.1: Trends in pressure: accounting for composition

(a) Residualizing from age, education, gender



(b) Residualizing from age, education, gender, occupation



Note: In this figure, we account for compositional effects in the time trend of our work pressure variables. To this end, we pool all waves and residualize the work pressure variables from education, cubic age, and gender in Panel (a) and additionally from 2-digit occupation dummies in Panel (b).

A.2 Additional results on the link between work pressure, health outcomes, job satisfaction, and family outcomes

In this section of the Appendix, we provide additional results on the link between work pressure, health outcomes, job satisfaction, and family outcomes. To assess health outcomes, we build on two measures. First, we build a "bad health" index that aggregates all questions which we have considered in Figure 1 in the main text and normalize the aggregated response to have mean zero and standard deviation one among all respondents. The index mostly focuses on mental health outcomes. For example, the index contains replies to the questions whether workers often find it hard to sleep at night, whether they are nervous often, or whether they are mentally exhausted.[28] Higher values of the index correspond to worse health outcomes. Second, we use the number of sick days in the past 12 months as the dependent variable.

To assess workers' job satisfaction, we rely on two measures. First, we build a "job unhappiness" index that consists of questions regarding workers' unhappiness with specific job characteristics. For example, it aggregates questions on workers' unhappiness with their job in general, with their work time, their pay, and the general mood at their workplace.[29] Higher values of the index, which is again normalized to have mean zero and standard deviation one for the full sample, correspond to less job satisfaction. Second, we directly report the link between our pressure index and the likelihood of workers to respond that they would like to change their job.

To assess family outcomes, we again rely on two variables that measure distinct elements. First, we measure whether workers report being married. Second, we report the link between our pressure index and the likelihood that workers report having too little time for their family for work reasons. Additionally, we also show the link between the pressure index and indicators for having kids below age 18 that live in their household and indicators for being divorced or single.

Table A.2 shows the results of our analysis. According to the estimate in Column (1), workers in high-pressure jobs ($HighPressure_i = 1$) ceteris paribus on average have 1.27 standard deviations worse self-reported health outcomes than workers in low-pressure jobs ($HighPressure_i = 0$). The point estimate is highly statistically significant and is not driven by single elements of the index but reflects worse health outcomes on all dimensions that we use to construct the index (see Figure 1 in the main text). Column

[28]The remaining questions concern whether workers are often tired, whether they feel physically exhausted often, whether they find their work emotionally taxing, whether they often find it hard to relax, whether they often feel like they have too much work, and whether they often are taken to their personal limits.

[29]The remaining questions concern workers' unhappiness with their direct boss, with promotion opportunities, and with training opportunities.

(2) shows that workers in high-pressure jobs on average report around 2.8 more sick days in the 12 months before the survey than workers with low job pressure.[30]

Columns (3) and (4) show that workers with higher reported work pressure are more likely to state that they are unhappy with their job and are more likely to report wishing to change jobs. Again, the results in Column (3) are not driven by single elements of the index (see Appendix Figure A.2 which shows the detailed results for all items of the index). This result is interesting since in Section 2.2 we show that workers in high pressure jobs earn more conditional on observable characteristics, and usually wages are positively correlated with job satisfaction.

The results on job satisfaction in columns (3) and (4) point to the existence of considerable disamenities in high-pressure jobs. In the light of the theory of compensating wage differentials, these estimates suggest that not all workers in high-pressure jobs are fully compensated for the disamenities in these jobs, because otherwise there should not be any difference in job satisfaction between workers in high-pressure and workers in low-pressure jobs. Potential explanations are related to frictions which prohibit workers to fully adjust by switching between jobs with different degrees of work pressure. Ex ante, workers might not have full information on the nature and scale of disamenities attached to a high-pressure job. Ex post, workers who turn out to be unsatisfied with the combination of monetary and non-monetary aspects of their job might be partly locked in due to search frictions (Bonhomme and Jolivet, 2009) or due to the accumulation firm-specific or industry-specific human capital which would depreciate after leaving the initial firm or industry (Topel, 1991; Neal, 1995). An alternative explanation is that, when answering the question about their job satisfaction, respondents might not fully take into account that the wage premium they are earning serves as a compensation for the disamenities in their job. From the perspective of the respondent, the benchmark might be a (hypothetical) high-paying, low-pressure job and not necessarily a job which is feasible. Consequently, the low reported job satisfaction might reflect the worker's view about the disamenities attached to the high-pressure job rather than the worker's view about the combination of pay and disamenities.

Finally, Columns (5) and (6) show that workers in high-pressure jobs are not differentially likely to be married, but are more likely to report that they often do not have time for their families because of their work. In Appendix Figure A.3, we show that they are more likely to be divorced, and consequently, that they are less likely to be single (i.e., neither married nor divorced). Workers in high pressure jobs are also not more or less likely to have children below age 18 that live with them.

[30] We windsorize the number of sickdays at the 95th percentile to adjust for outliers. When we do not, the coefficient on work pressure is around 7. Results are available on request.

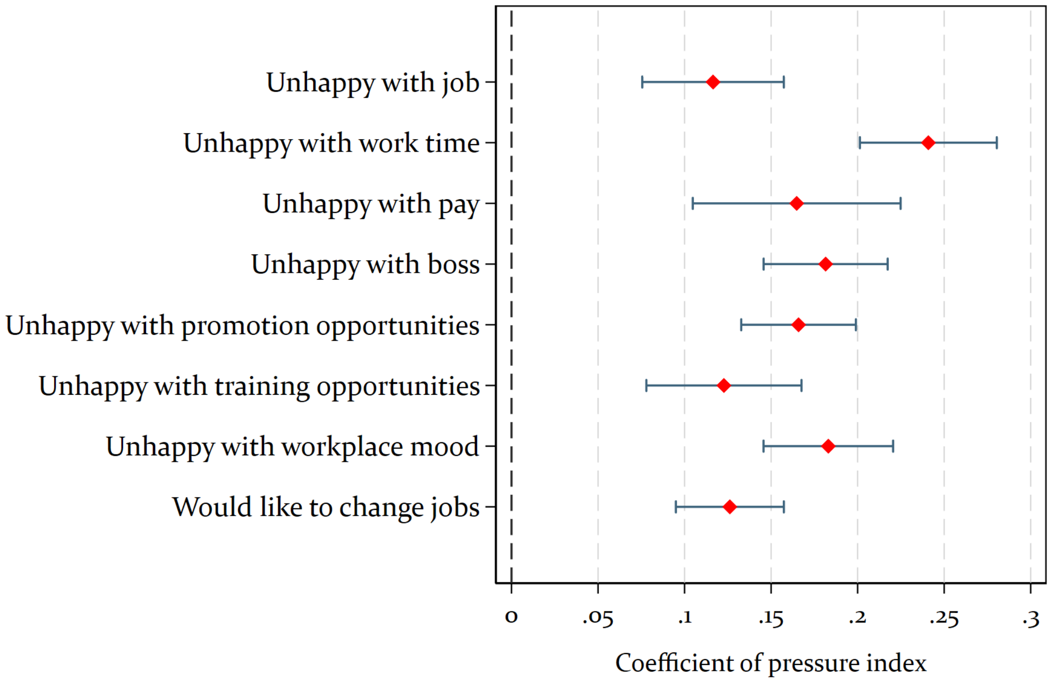
In summary, this analysis shows that workers in high-pressure jobs face several disamenities in their work even conditional on occupation and industry. Standard labor market theories of compensating wage differentials (Rosen, 1986) would predict that this leads to higher compensation for these workers to offset the disutility that these disamenities carry along for marginal workers.

Table A.2: High pressure jobs: Health, job satisfaction, and family outcomes

Dep. Var.:	Bad health		Unhappy with job		Family outcomes	
	Index	Sick days	Index	Change job	Married	No time for family
	(1)	(2)	(3)	(4)	(5)	(6)
High pressure	1.27***	3.29***	0.70***	0.13***	0.03	0.22***
	(0.06)	(0.92)	(0.06)	(0.02)	(0.02)	(0.03)
Mean dep.	-0.01	14.88	-0.01	0.19	0.51	0.18
Adj. R2	0.21	0.11	0.09	0.06	0.18	0.09
Obs.	7793	5110	7585	7694	7846	7823
Ext. Mincer	Yes	Yes	Yes	Yes	Yes	Yes
Occ. and ind. FE	Yes	Yes	Yes	Yes	Yes	Yes

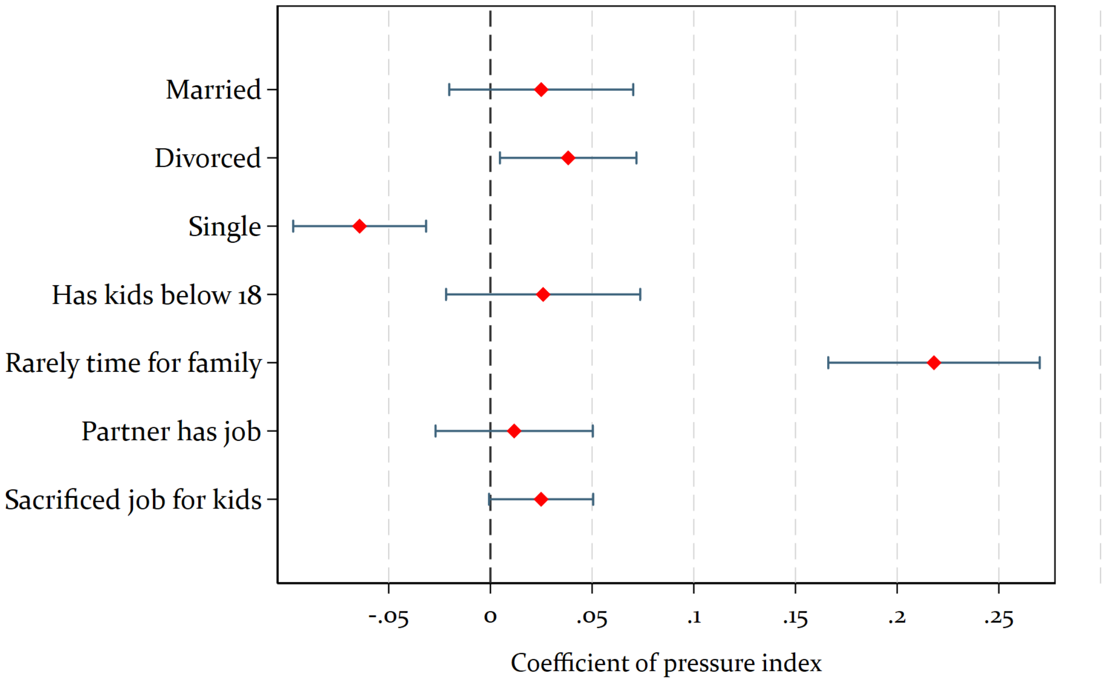
Note: This table shows further results on the link between work pressure, health outcomes, job satisfaction, and family outcomes. In column (1), we use an index of bad health outcomes as the dependent variable. The index aggregates several questions on workers' health outcomes and normalizes the aggregated response to have mean zero and standard deviation one among all respondents. The underlying variables include whether workers have trouble sleeping at night, whether they often feel tired, nervous, mentally exhausted, or physcially exhausted, whether they often find work taxing, whether they often find it hard to relax, whether they often feel overwhelmed by too much work, and whether they often feel like they are beyond their personal limits. In column (2), we use the number of sick days in the past 12 months as the dependent variable, windsorized at the 95th percentile. In column (3), we use an index of job unhappiness as the dependent variable that is again normalized to have mean zero and standard deviation one among all respondents. The underlying variables are whether workers feel unhappy with their job overall, with their worktime, with their pay, with their direct boss, with promotion opportunities, with training opportunities, and with the overall mood at their workplace. In column (4), we use as dependent variable the response to the question whether workers would like to change their job. In column (5), we use as dependent variable an indicator for being married. In column (6), we use as dependent variable the response to whether workers feel they often have too little time for family because of work. All regressions include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area). They also include 2-digit occupation dummies according to the Klassifikation der Berufe (KldB) 2010 as well as 2-digit NACE industry dummies (Klassifikation der Wirtschaftszweige 2008). Robust standard errors, allowing for clustering at the 2-digit occupation level, in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure A.2: Link between work pressure and job satisfaction



Note: This figure shows the estimated link between our work pressure index and various job satisfaction indicators, obtained from linear probability models. To estimate the coefficients, we use the respective job satisfaction indicator as the dependent variable. The main explanatory variable is the work pressure index defined in equation 2. We include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of workplace area), 2-digit occupation and industry dummies. The bars represent 95% confidence bounds that allow for clustering at the 2-digit occupation level.

Figure A.3: Link between work pressure and family outcomes



Note: This figure shows the estimated link between our work pressure index and various family outcomes, obtained from linear probability models. To estimate the coefficients, we use the respective family outcome as the dependent variable. The main explanatory variable is the work pressure index defined in equation 2. We include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of workplace area), 2-digit occupation and industry dummies. The bars represent 95% confidence bounds that allow for clustering at the 2-digit occupation level.

A.3 High-pressure jobs: Job characteristics

In this section of the Appendix, we further analyze what our work pressure index is capturing. First, in Table A.3, we predict the work pressure index using the covariates in our baseline regressions. We find that, on average, workers with a university degree report somewhat work higher pressure. Other worker characteristics such as gender and age do not predict work pressure once we condition on occupation and industry characteristics. The table also shows that larger firm size is a significant predictor of work pressure. Our main work pressure variable is also correlated with job tasks including whether a job consists of routine tasks, whether it is codifiable, its computer use, and whether the job is physically demanding.

We proceed by investigating what job characteristics are associated with high-pressure jobs in Figure A.4. In the first three rows, we regress indicators for the worker's position in the firm on our pressure index, conditioning on extended mincer controls as well as occupation and industry dummies.[31] Workers in high-pressure jobs are a bit more likely to be in the upper level of hierarchies and substantially more likely to be a team leader and to have budget responsibility. This is in line with what we would expect. The next three rows give a first glimpse of the work environments that workers in high-pressure jobs are facing. High-pressure workers are more likely to respond that they rarely receive positive feedback and that they are frequently not informed about important decisions.

While estimated work pressure thus likely differs between workers depending on their education, age, gender, or occupation, we still believe that the questions are asked in a skill-neutral way, i.e., the index should not be biased mechanically towards certain groups. For example, a worker with a vocational training degree might be confronted with tight deadlines or the need for multitasking just like a worker with a university degree. The need to work fast might in principle be present in very routine-intensive jobs just like in more complex non-routine-intensive jobs. To illustrate this, Table A.4 shows the professions with the highest and lowest average high-pressure index values. High-pressure jobs are most likely found in occupations such as health care workers, doctors, journalists, and train drivers. Low-pressure occupations include painters, gardeners, and occupations in theology. These rankings suggest that our measure is both plausible and not mechanically related to skills since both high- and low-skilled occupations are among the jobs with the highest and lowest average pressure.

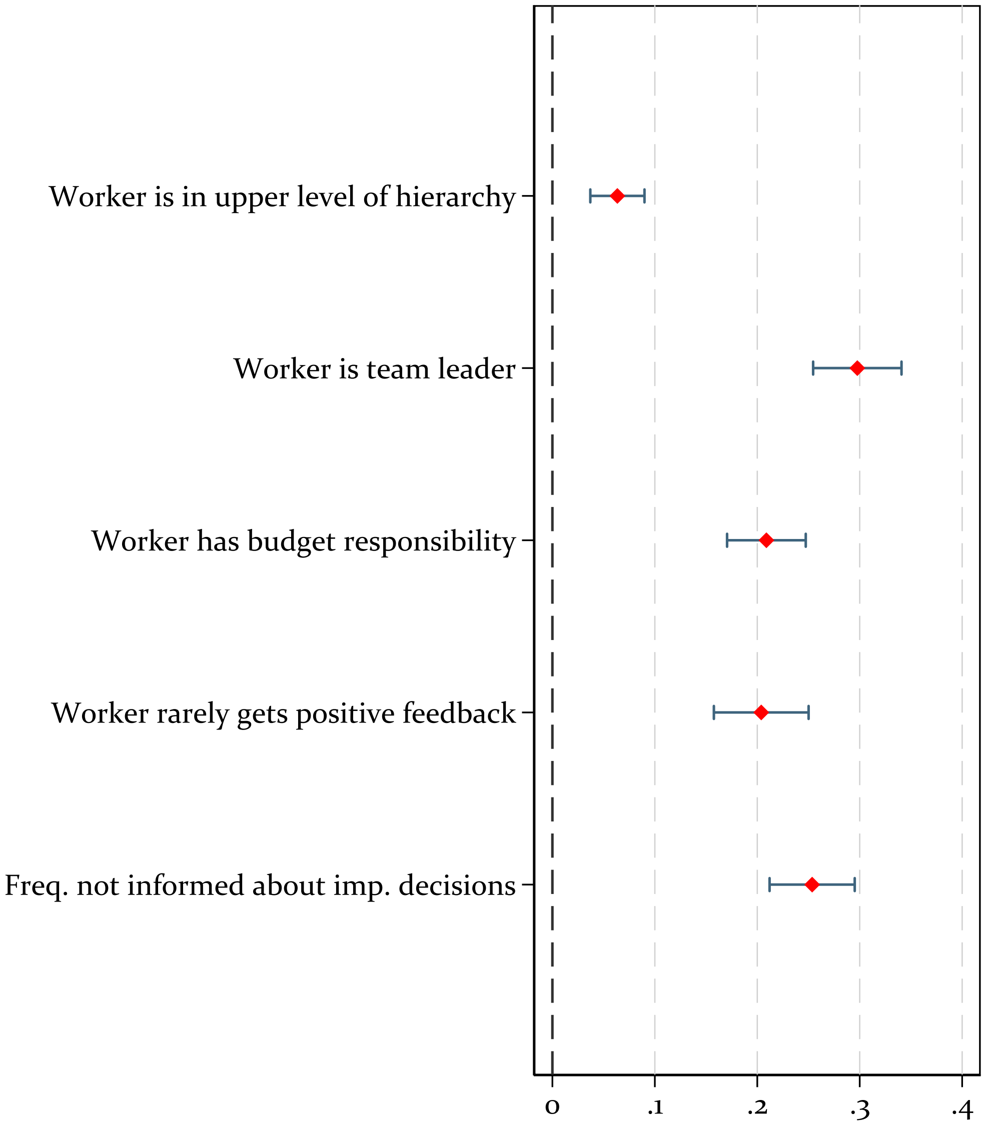
[31] All of these results are robust to excluding the occupation and industry dummies.

Table A.3: High-pressure jobs: Predictors

Dep. Var.:	Work Pressure			
	(1)	(2)	(3)	(4)
University	0.12	0.11	0.09	0.16**
	(0.13)	(0.11)	(0.11)	(0.06)
Vocational	0.11	0.10	0.07	0.11*
	(0.13)	(0.10)	(0.11)	(0.06)
Age	0.04	0.04	0.03	0.04
	(0.03)	(0.03)	(0.03)	(0.03)
Female	0.04**	0.01	0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.02)
Works council			0.01	0.01
			(0.01)	(0.01)
Temp. work agency			-0.10***	-0.09***
			(0.03)	(0.03)
Commuting			0.00	0.01
			(0.02)	(0.02)
Temp. contract			-0.05**	-0.04**
			(0.02)	(0.02)
5-49 employees			0.08***	0.07**
			(0.03)	(0.03)
50-249 employees			0.11***	0.10***
			(0.03)	(0.03)
250-999 employees			0.12***	0.10***
			(0.03)	(0.03)
$\geq$ 1,000 employees			0.13***	0.11***
			(0.03)	(0.03)
Standard work hours			-0.02	-0.02
			(0.02)	(0.02)
Shift work			0.02	-0.02
			(0.02)	(0.02)
Frequent stand-by for work			0.01	-0.01
			(0.01)	(0.01)
no. of subordinates			0.00	0.00
			(0.00)	(0.00)
Routine job				0.04***
				(0.01)
Codifiable job				0.10***
				(0.01)
Computer use				0.10***
				(0.01)
Index of physically demanding work				0.20***
				(0.03)
Mean dep.	0.50	0.50	0.50	0.50
Adj. R2	0.02	0.06	0.07	0.12
Obs.	7825	7825	7825	7825
Extended Mincer controls	Yes	Yes	Yes	Yes
Occupation and industry dummies	No	Yes	Yes	Yes

Note: This table shows the main predictors of work pressure, focusing on the 2018 wave. We use our work pressure index as the dependent variable. Extended Mincer controls include cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area besides the variables shown in the table. The left-out category for education are low education workers, i.e. those without vocational training or a college degree. Occupation dummies are 2-digit according to the Klassifikation der Berufe (KldB) 2010 (similar to ISCO-08). Industry dummies are 2-digit NACE dummies (Klassifikation der Wirtschaftszweige 2008). The left-out category for firm size is below 5 workers. Robust standard errors, allowing for clustering at the 2-digit occupation level, in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure A.4: High-pressure jobs: Job characteristics



Note: This figure shows the estimated link between our work pressure index and various job characteristics, obtained from linear probability models. To estimate the coefficients, we use the respective job characteristic (reported by the worker) as the dependent variable. The main explanatory variable is the work pressure index defined in equation 2. We include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of workplace area), 2-digit occupation and industry dummies. The bars represent 95% confidence bounds that allow for clustering at the 2-digit occupation level.

Table A.4: High- and low-pressure occupations

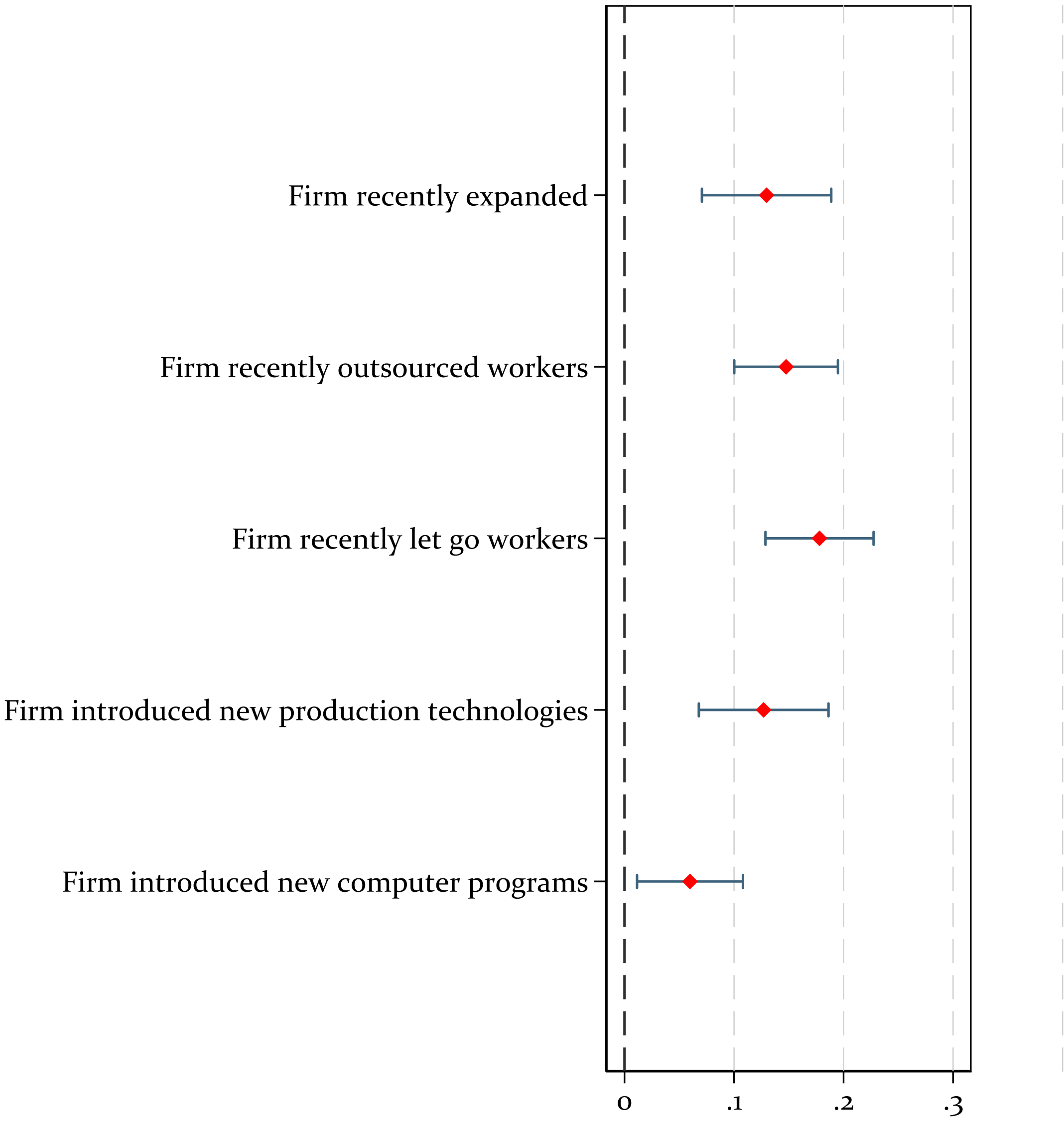
Panel A: Occupations with highest average pressure index	
Drivers of vehicles in railway traffic	.744
Occupations in geriatric care	.694
Occupations in editorial work and journalism	.662
Occupations in human medicine and dentistry	.658
Occupations in nursing, emergency medical services and obstetrics	.642
Panel B: Occupations with lowest average pressure index	
Painters and varnishers, plasterers, occupations in the waterproofing of buildings, preservation of structures and wooden building components	.329
Occupations in physical security, personal protection, fire protection and workplace safety	.346
Occupations in gardening	.346
Occupations in theology and church community work	.352
Occupations in wood-working and -processing	.37

Note: This table shows the 3-digit occupations according to the Klassifizierung der Berufe, 2010 Version (KldB2010, similar to ISCO-08) with the highest (Panel A) and lowest (Panel B) average value of pressure as defined in equation 2.

A.4 High-pressure jobs: Firm characteristics

There is a large literature in labor economics showing that during the last decades, the labor market has undergone secular changes including the computerization of workplaces and skill-biased technical change (Spitz-Oener, 2006; Acemoglu and Autor, 2011) as well as international and domestic outsourcing (Bernard et al., 2012; Hummels et al., 2014; Goldschmidt and Schmieder, 2017). In addition, there is a growing discussion about the role of highly productive and expanding "superstar firms" in the labor market (Autor et al., 2020). Against this backdrop, Figure A.5 demonstrates that high-pressure jobs coincide with variables capturing important secular trends, namely technological change and globalization. As can bee seen from Figure A.5, workers reporting high work pressure are significantly more likely to be employed by firms that have recently expanded, outsourced or displaced workers, or introduced new production technologies and computer programs. Note that the results on expansions and layoffs are not necessarily a contradiction, since firms might engage in automation and outsourcing to save labor costs and increase their productivity, while at the same time expanding in terms of sales or market shares.

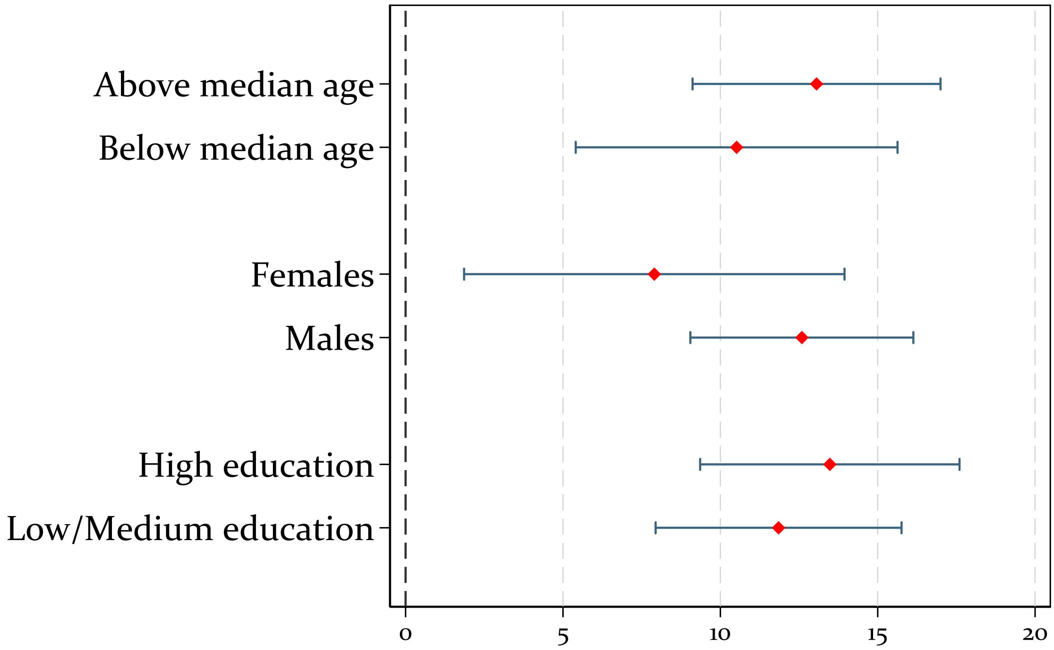
Figure A.5: High-pressure jobs: Firm characteristics



Note: This figure shows the estimated link between our work pressure index and various firm characteristics, obtained from linear probability models. To estimate the coefficients, we use the respective firm characteristic (reported by the worker) as the dependent variable. The main explanatory variable is the work pressure index defined in equation 2. We include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of workplace area), 2-digit occupation and industry dummies. The bars represent 95% confidence bounds that allow for clustering at the 2-digit occupation level.

A.5 Further results on the wage premium to high-pressure jobs

Figure A.6: High-pressure jobs: Heterogeneity of earnings effect



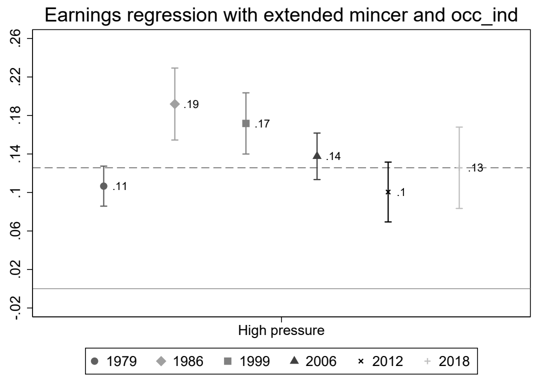
Note: This figure shows the coefficients of a regression of 100x log monthly earnings on the high pressure index, separately for different groups. We control for extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area) and 2-digit occupation and industry dummies (NACE-2). The bars represent 95% confidence bounds that allow for clustering at the occupation level.

Table A.5: Hedonic wage regressions with separate work pressure variables

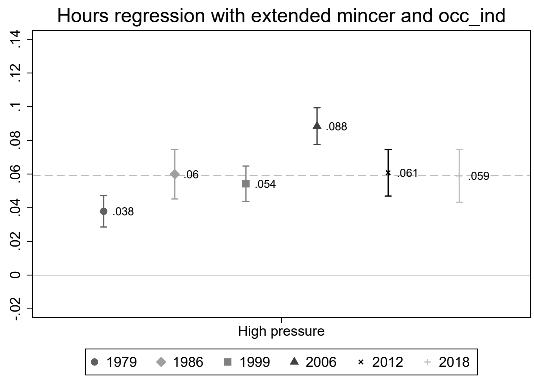
	(1)	(2)	(3)	(4)	(5)
Panel A					
	Dep. Var.: 100x Ln(monthly earnings)				
Deadlines	6.59***	3.60**	3.71***	3.91***	4.95***
	(2.43)	(1.58)	(1.16)	(1.07)	(1.08)
Multitasking	13.32***	8.67***	9.02***	7.88***	7.34***
	(2.32)	(1.34)	(1.09)	(1.11)	(1.06)
Interruptions	3.23**	5.19***	2.55**	0.55	0.42
	(1.39)	(1.08)	(1.14)	(1.08)	(0.88)
Minimum requirements	-9.60***	-5.05***	-4.17***	-4.30***	-1.59
	(1.87)	(1.37)	(1.25)	(1.27)	(1.25)
Panel B					
	Dep. Var.: 100x Ln(work hours)				
Deadlines	4.50***	4.37***	4.16***	4.02***	3.94***
	(0.49)	(0.47)	(0.45)	(0.44)	(0.45)
Multitasking	1.61***	1.67***	1.35***	1.44***	1.24***
	(0.39)	(0.39)	(0.39)	(0.37)	(0.38)
Interruptions	-0.10	0.26	0.89**	0.88***	0.57*
	(0.59)	(0.53)	(0.35)	(0.32)	(0.32)
Minimum requirements	-0.56	-0.60	-0.67	-0.48	-0.37
	(0.53)	(0.55)	(0.58)	(0.52)	(0.52)
Panel C					
	Dep. Var.: 100x Ln(hourly wage)				
Deadlines	2.09	-0.77	-0.45	-0.11	1.01
	(2.50)	(1.71)	(1.22)	(1.05)	(1.07)
Multitasking	11.71***	7.00***	7.68***	6.44***	6.10***
	(2.31)	(1.44)	(1.14)	(1.11)	(1.01)
Interruptions	3.33**	4.93***	1.66	-0.34	-0.15
	(1.62)	(1.36)	(1.18)	(1.16)	(0.96)
Minimum requirements	-9.04***	-4.45***	-3.50***	-3.83***	-1.22
	(1.93)	(1.47)	(1.17)	(1.21)	(1.20)
Extended Mincer controls	No	Yes	Yes	Yes	Yes
Occupation and industry dummies	No	No	Yes	Yes	Yes
Firm and job controls	No	No	No	Yes	Yes
Task controls	No	No	No	No	Yes

Note: The table shows the estimated link between all four single work pressure variables, earnings, hours, and wages. Robust standard errors, allowing for clustering at the 2-digit occupation level, in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure A.7: Link between work pressure, earnings, hours, and wages, by wave



(a) 100x Ln(monthly earnings)



(b) 100x Ln(work hours)

(c) 100x Ln(hourly wage)

Note: The figure shows the estimated link between work pressure, earnings, work hours, and hourly wages, separately for each wave in the BIBB/BAuA employment surveys. Regressions include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area) and 2-digit occupation and industry dummies (NACE-2). The bars represent 95% confidence bounds that allow for clustering at the occupation level. The horizontal dashed line reflects the point estimate of the 2018 wave for which we show results in more detail in the paper.

A.6 Using panel data to provide a lower bound on the compensating wage differential for work pressure

To further investigate whether there is a compensating differential for high pressure in the workplace, we leverage panel data from the IAB Institute for Employment Research to bound the effect of high pressure on wages. More specifically, we use data from the Linked Personnel Panel, combined with administrative data on workers' earnings (LPP-ADIAB). The LPP-ADIAB is a worker- and establishment-level survey carried out by the German Institute for Employment Research that is linked to workers' social security data. The first wave of the survey was carried out in 2012/2013, with subsequent waves in 2014/15, 2016/17 and 2018/19. Parts of the sample of workers are resurveyed, such that there is a panel dimension in the data. We use the procedure by Dauth and Eppelsheimer (2020) to clean the administrative earnings data. We only depart in including bonus payments for workers since we believe that parts of the compensating differentials for high pressure jobs are paid to workers through such payments. The IAB data do not include information on hours worked. Therefore, following the existing literature using these data, we focus on full-time employees and focus on daily wages, computed as total earnings divided by the number of days worked. Note that this data set neither contains civil servants nor self-employed individuals, since these do not pay social security contributions in Germany.

In addition to demographic characteristics and information on personnel policies, the survey also includes questions on workers' perceptions of their jobs. This includes a question on whether workers often face tight deadlines over a longer time period or have to manage several important tasks at the same time. While this combined question is not exactly identical to the questions in our main data set, it is very similar. We code workers as having high pressure if they reply that the statement applies "fully" or "mostly".

We estimate standard wage regressions with log daily wages as dependent variable. The explanatory variables comprise our high pressure variable, extended mincer controls (cubic age, 3 education groups, gender, tenure, German nationality), the number of subordinates to control for the hierarchy level, as well as 2-digit occupation and industry dummies, and dummies for survey year. To provide a lower bound for the compensating wage differential, we include worker fixed effects in our earnings regression in most specifications (in that case, the time-constant variables drop out of the specification).

There are two reasons why we believe that this provides a (severely biased) lower bound on the "true" compensating wage differential for work pressure. First, as argued by Lavetti and Schmutte (2018), workers move endogenously across jobs, generating a negative correlation between disamenities and wages across jobs within movers, the sample from which we identify the effect when including workers fixed effects. The reason is that both consumption and amenities are normal goods, which is why workers tend to move towards jobs offering more of both. Second, within-person changes in perceived pressure may to some extent reflect measurement error, leading to attenuation bias. Thus, any significant positive effect of high pressure on earnings in such a regression to us would imply that the true compensating differential for high pressure is positive and likely substantially larger.

In the administrative labor market data provided by the Institute for Employment Research, wages are top-coded at the contribution ceiling to social security. Following Card et al. (2013), we impute top-coded wages using a series of Tobit regression. This, however, is a problem for our fixed effects regressions. For workers with top-coded wages, changes in the measured wage over time reflect pure noise, stemming from the random component which is added to the wage during the imputation. We deal with this issue in two ways. First, we drop observations with a top-coded wage. Alternatively, we use the self-reported survey earnings information for workers with a top-coded wage.

Table A.6 shows the results from our analysis. Column (1) shows the pooled estimate of our high pressure variable on log earnings. In line with our main results, it is sizable and significantly different from zero.[32] All remaining columns include worker fixed effects. Columns (2) and (3) show that among the sample of non-censored observations, the link between high pressure and wages is positive and statistically significant, even when including worker fixed effects. It is larger in Column (3), where we restrict the sample to workers with at least three panel observations. We find the same pattern in Columns (4) and (5), where we use self-reported earnings for workers with a top-coded wage. Overall, this analysis shows that even in the severely downward-biased individual fixed effects specification, there is a significant positive link between high work pressure and wages.

[32] This result is qualitatively similar to the estimates when only using the questions on deadlines and on multitasking in our main data.

Table A.6: Worker fixed effects regressions: Linked Personnel Panel

Dep. Var.:	100 x Ln(daily wage)				
		Drop censored		Self-reported wage	
	(1)	(2)	(3)	(4)	(5)
High pressure	5.72***	0.60**	0.84**	0.62	0.74*
	(1.15)	(0.25)	(0.37)	(0.39)	(0.38)
Obs.	17,180	13,802	4,165	16,726	5,150
Worker FE	No	Yes	Yes	Yes	Yes
Restrict on >= 3 panel obs.	No	No	Yes	No	Yes

Note: This table shows the results of regressions of log daily wage on a variable reflecting high work pressure, controls for cubic age, 3 education groups, gender, tenure, German nationality, the number of subordinates, as well as 2-digit occupation and industry dummies, and year dummies. Column (1) shows pooled OLS regressions of all workers. Columns (2) and (3) include worker fixed effects in the regression and drop those observations where we can only impute earnings since they earn more than the social security contribution ceiling. In these columns, Column (3) restricts the sample to only contain workers with more than 2 panel observations. Columns (4) and (5) repeat these regressions but use workers' self-reported earnings instead of dropping them when their earnings are above the contributions cap. In the fixed-effects regressions, the time-invariant variables are dropped. The data stem from the IAB Linked Personnel Panel (LPP-ADIAB). Robust standard errors, allowing for clustering at 2-digit occupation level in column (1) and at worker level in columns (2)-(5), in parentheses. * p<0.10, ** p<0.05, *** p<0.01

A.7 Further information on the stated-preference experiment

Figure A.8: Screen design in choice experiment

	Job A	Job B
Work hours	40 hours per week	40 hours per week
Paid days off	30 days per year	30 days per year
Deadlines	often	often
Multitasking: Multiple important tasks at the same time	occasionally	often
Flexible schedule	no	no
Option to work from home	5 days per week	2 days per week
Mean commuting time to the workplace	45 minutes	45 minutes
Gross earnings	€ 5007 per month	€ 5685 per month

	Job A	Job B
Which job would you prefer?	○	○

Note: The figure shows an example of the choice screen in the experiment, translated to English. The experiment was conducted in German.

Table A.7: Descriptives of experimental sample (part 1)

	All	Females	Males	Education		
				Low	Medium	High
Frequent deadlines						
Never	0.18	0.17	0.18	0.20	0.18	0.11
Sometimes	0.60	0.60	0.61	0.59	0.61	0.61
Often	0.22	0.23	0.22	0.21	0.21	0.28
Frequent multitasking						
Never	0.09	0.08	0.10	0.11	0.10	0.05
Sometimes	0.56	0.54	0.57	0.57	0.56	0.52
Often	0.35	0.38	0.33	0.32	0.34	0.43
Working from home						
No WFH	0.68	0.71	0.65	0.82	0.73	0.33
WFH up to 2 days	0.18	0.16	0.20	0.10	0.16	0.38
WFH up to 5 days	0.14	0.12	0.15	0.08	0.11	0.29
Flexible schedule	0.36	0.31	0.40	0.27	0.32	0.61
Paid days off	28.65	28.31	28.94	28.52	28.59	29.02
Commuting time						
0-15 minutes	0.32	0.36	0.29	0.37	0.32	0.24
16-30 minutes	0.37	0.37	0.37	0.37	0.39	0.33
31-45 minutes	0.19	0.16	0.21	0.17	0.18	0.25
46-60 minutes	0.08	0.07	0.09	0.07	0.08	0.11
>60 minutes	0.04	0.03	0.05	0.03	0.03	0.07
Weekly work hours	36.92	33.61	39.77	36.54	36.47	38.72
Gross hourly wage	19.52	17.10	21.53	17.24	18.27	26.17

Note: This table shows descriptives on the subjects' current job. We use these job characteristics to construct a subject-specific baseline job profile for the experiment. The number of participants is 3,307. High-educated workers are those with a college degree. Medium-educated workers are those with a high-school degree or a vocational degree. The share of females is 46.3%. The share of low- (medium-, high-) educated is 31.0% (50.2%, 18.8%). In the last row, we exclude subjects who did not report a wage for their current job (12.2% of respondents).

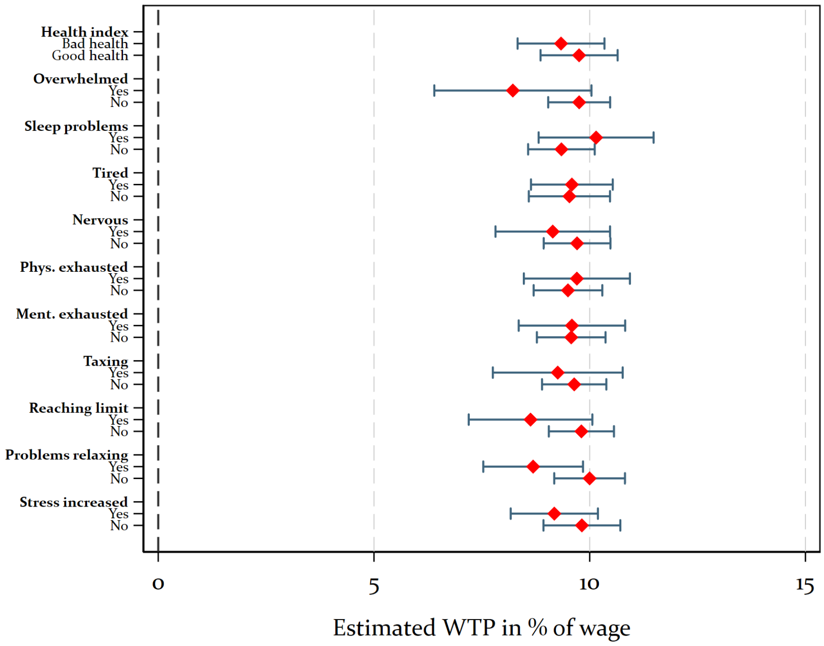
Table A.8: Descriptives of experimental sample (part 2)

	Age group				Hourly wage quintile (1st=lowest)				
	20-29	30-39	40-49	50-60	1st	2nd	3rd	4th	5th
Frequent deadlines									
Often	0.17	0.23	0.24	0.21	0.20	0.20	0.22	0.24	0.27
Sometimes	0.66	0.60	0.59	0.60	0.56	0.58	0.61	0.63	0.63
Never	0.17	0.17	0.17	0.19	0.24	0.21	0.16	0.13	0.10
Frequent multitasking									
Often	0.42	0.40	0.33	0.30	0.29	0.33	0.37	0.41	0.42
Sometimes	0.48	0.53	0.57	0.59	0.56	0.57	0.56	0.52	0.54
Never	0.10	0.07	0.09	0.11	0.14	0.10	0.08	0.07	0.04
Working from home									
No WFH	0.63	0.60	0.68	0.78	0.84	0.85	0.75	0.58	0.34
WFH up to 2 days	0.24	0.25	0.17	0.11	0.08	0.08	0.15	0.28	0.35
WFH up to 5 days	0.14	0.16	0.14	0.11	0.08	0.07	0.09	0.14	0.31
Flexible schedule	0.40	0.40	0.35	0.31	0.23	0.23	0.30	0.41	0.66
Paid days off	28.27	28.54	28.69	28.83	26.95	28.25	29.19	29.37	29.80
Commuting time									
0-15 minutes	0.28	0.31	0.33	0.34	0.39	0.36	0.32	0.29	0.21
16-30 minutes	0.39	0.39	0.37	0.35	0.35	0.39	0.38	0.41	0.36
31-45 minutes	0.21	0.19	0.18	0.19	0.15	0.15	0.20	0.19	0.26
46-60 minutes	0.10	0.08	0.09	0.08	0.07	0.08	0.06	0.08	0.11
>60 minutes	0.03	0.04	0.04	0.04	0.04	0.03	0.04	0.02	0.07
Weekly work hours	38.26	37.59	36.55	36.15	36.19	36.35	36.83	37.46	39.17
Gross hourly wage	18.56	20.27	19.87	18.82	11.07	14.02	17.19	21.11	34.41

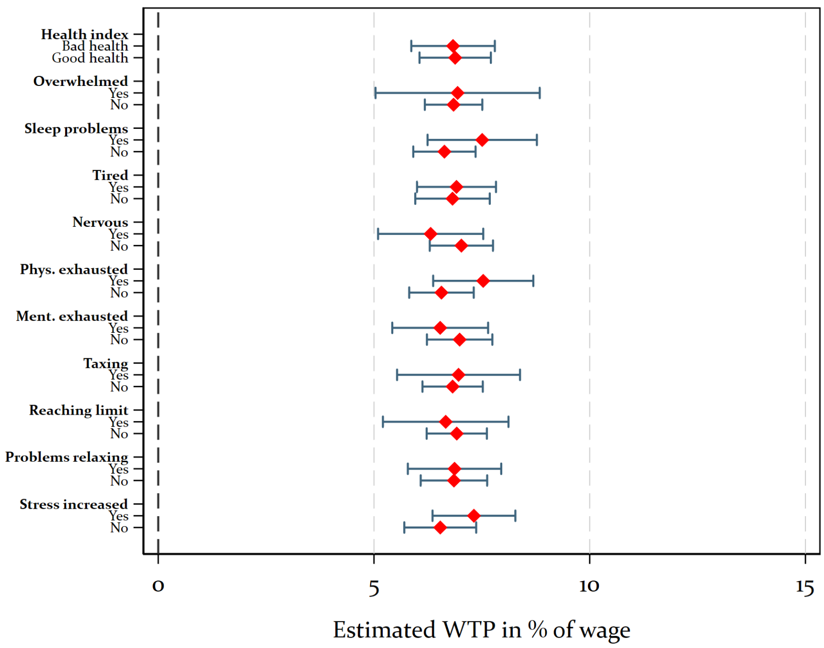
Note: The table shows descriptives on the participants' current job which we use as a baseline for the experiment. Number of participants is 3,307. The share of age groups 20-29 (30-39, 40-49, 50-60) is 9.9% (31.8%, 25.8%, 32.6%). In the last row, we exclude respondent where the hourly wage in the current job is missing (12.2% of respondents).

Figure A.9: Workers' willingness-to-pay to avoid job pressure by own health status

(a) WTP to avoid frequent tight deadlines



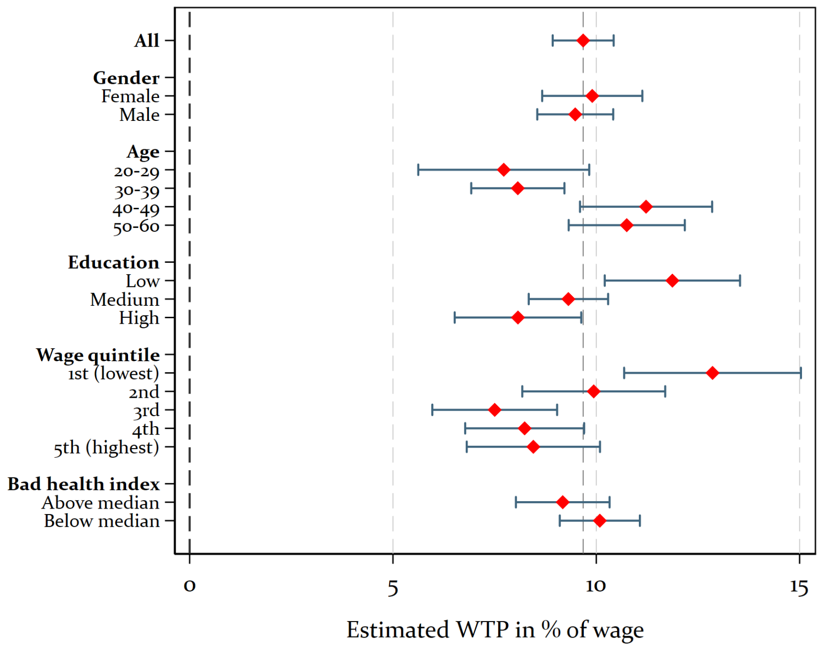
(b) WTP to avoid frequent multitasking



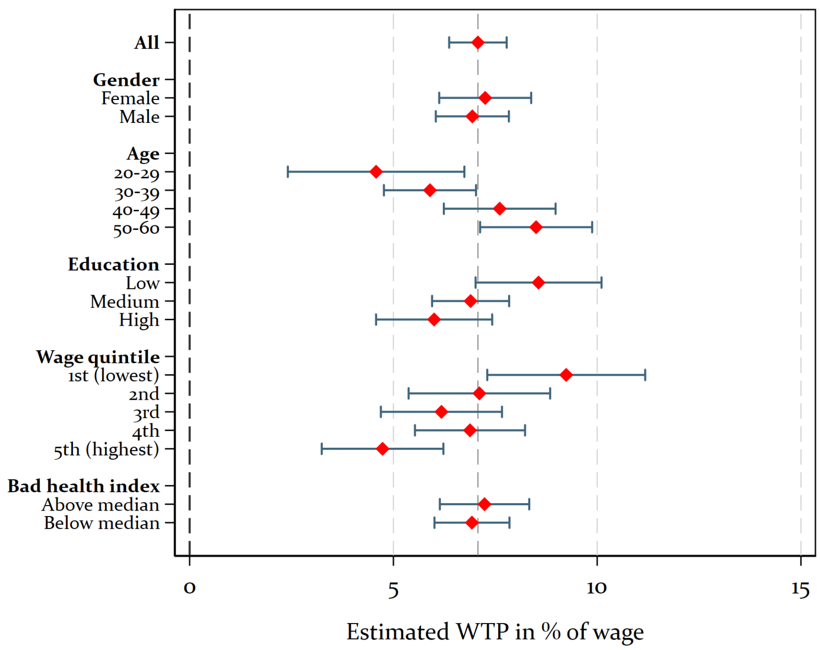
Note: The figure shows the estimated willingness-to-pay to avoid frequent tight deadlines (Panel A) and frequent multitasking (Panel B), separately for groups that differ in terms of their self-reported health status. Note that the questions about health are asked after completion of the choice experiment. To construct the health index used in the first row, we add up all variables in the subsequent rows and split the smaple at the median. The red diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the respondent level.

Figure A.10: Workers' willingness-to-pay to avoid work pressure among respondents who passed both attention checks

(a) WTP to avoid frequent tight deadlines



(b) WTP to avoid frequent multitasking



Note: Focusing on the respondents who passed both attention checks, the figure shows the estimated willingness-to-pay to avoid frequent tight deadlines (Panel A) and frequent multitasking (Panel B). In each panel, the first row shows the average willingness-to-pay for all respondents in the sample. The following rows show the estimated WTP for several different sub-samples, by gender, age, education, wage quintile, and self-reported health status. The red diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the respondent level.

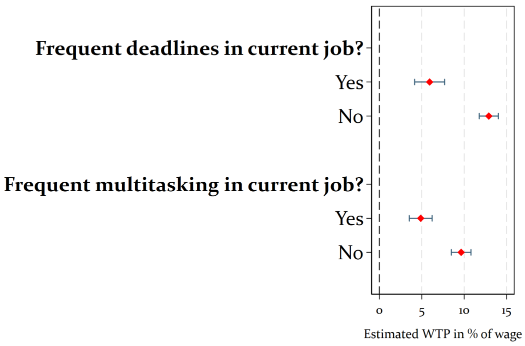
Table A.9: Earnings premium to high-pressure jobs in experimental sample

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A						
	Dep. Var.: 100x Ln(monthly earnings)					
High pressure	18.16***	17.03***	15.02***			
	(2.42)	(2.08)	(1.88)			
Deadlines				7.09***	5.75***	5.97***
				(2.43)	(2.14)	(1.90)
Multitasking				10.73***	10.83***	8.81***
				(2.08)	(1.86)	(1.65)
Adj. R2	0.02	0.25	0.39	0.02	0.25	0.39
Panel B						
	Dep. Var.: 100x Ln(work hours)					
High pressure	9.26***	9.87***	8.75***			
	(1.13)	(1.06)	(1.04)			
Deadlines				4.87***	4.93***	4.74***
				(1.16)	(1.07)	(1.06)
Multitasking				4.44***	4.93***	4.07***
				(1.00)	(0.92)	(0.90)
Adj. R2	0.02	0.18	0.22	0.02	0.18	0.22
Panel C						
	Dep. Var.: 100x Ln(hourly wage)					
High pressure	9.55***	7.88***	6.81***			
	(1.97)	(1.75)	(1.58)			
Deadlines				2.12	0.69	0.98
				(1.95)	(1.76)	(1.55)
Multitasking				6.97***	6.67***	5.45***
				(1.66)	(1.55)	(1.37)
Adj. R2	0.01	0.18	0.33	0.01	0.19	0.33
Mincer controls	No	Yes	Yes	No	Yes	Yes
Other job characteristics	No	No	Yes	No	No	Yes

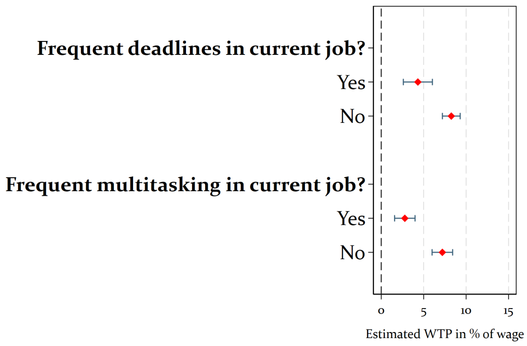
Note: Using data from the experimental sample (the survey conducted before the start of the choice experiment), this table shows the estimated link between work pressure, earnings, hours, and wages. Mincer controls include 3 education groups, 4 age groups, and gender. Other job characteristics include all job attributes included in the experiment: indicators for flexibility of schedule, option of working from home up to 2 days or up to 5 days, respectively (reference: no working from home possible), indicators for 30-34 or >35 days off, respecively (reference: <30 days), and indicators for commuting time of 30, 45, 60, >60 minutes, respectively (reference: 15 minutes). Robust standard errors, allowing for clustering at the 2-digit occupation level, in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure A.11: Sorting: Workers' WTP to avoid pressure by own job characteristics by worker type

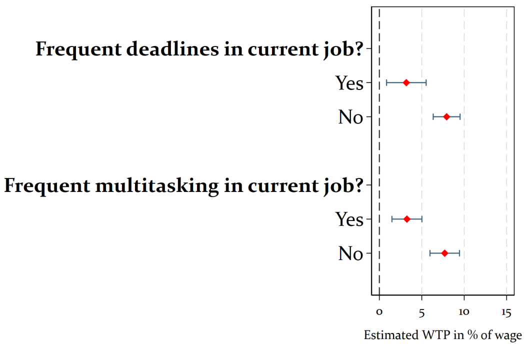
(a) Old



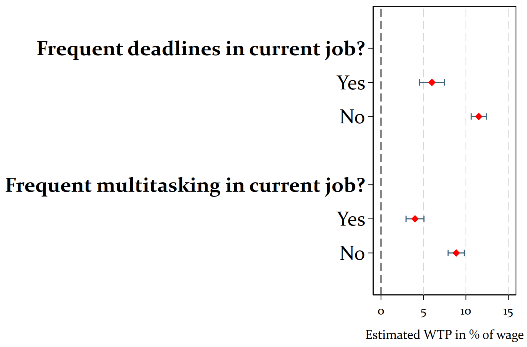
(b) Young



(c) High educated

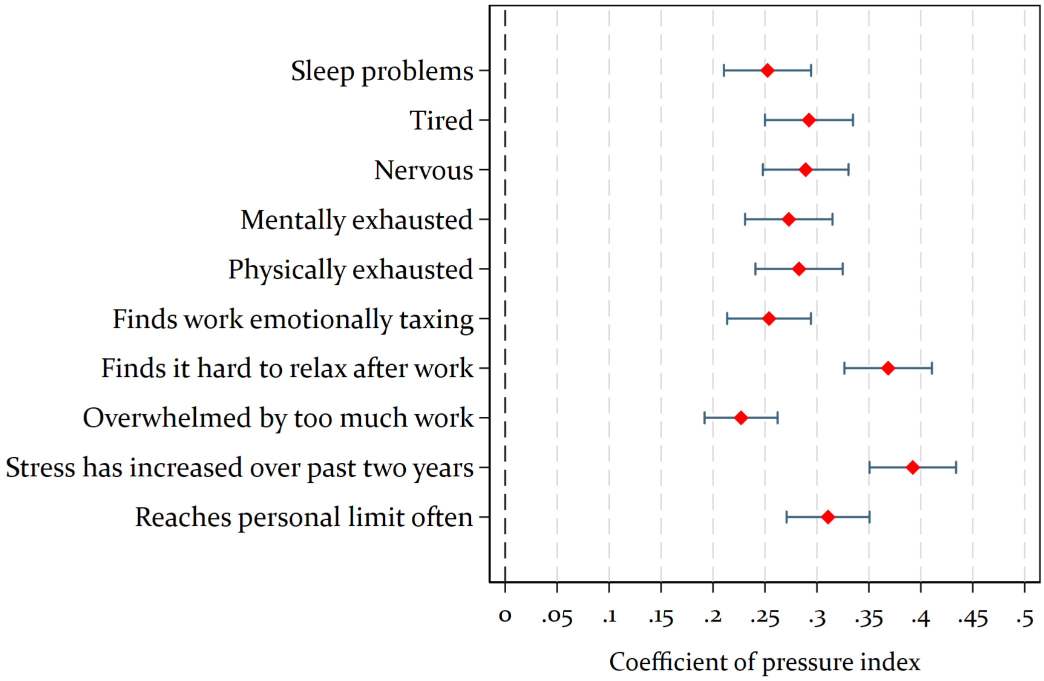


(d) Low or medium educated



This figure shows workers' estimated willingness-to-pay (WTP) to avoid work pressure, by own job characteristics and by worker type. Worker types are denoted in each subcaption. Old workers are those aged 40 and above, while young workers are aged below 40. High education is defined as having completed a tertiary degree, while medium or low education is defined as not having completed a tertiary degree. In each subfigure, the first two rows show the estimated WTP depending on whether the respondent reported to have frequent tight deadlines in her current job or not. The last two rows show the estimated WTP depending on whether the respondent reported to have frequent multitasking in her current job or not. The red diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the respondent level.

Figure A.12: High-pressure jobs and health outcomes in survey from experimental sample



Note: Using data from the experimental sample, this figure shows the estimated link between our work pressure index and various self-reported health indicators, obtained from linear probability models. To estimate the coefficients, we use the respective health outcomes as the dependent variable. The dependent variable takes on the value of 1 if the respondent idicates that the respective health outcome (e.g., sleep probems) occurs often, and zero otherwise. Note that the questions about health are asked after completion of the choice experiment. The main explanatory variable is the work pressure index defined in equation 2. We include extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of workplace area), 2-digit occupation and industry dummies. The bars represent 95% confidence bounds that allow for clustering at the 2-digit occupation level.