# High-Pressure, High-Paying Jobs?*

Markus Nagler† Johannes Rincke‡ Erwin Winkler§

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**Abstract**

Work-related stress has reportedly increased over time. Using worker-level survey and experimental data, we investigate the labor market consequences of work pressure. We build a measure of pressure strongly associated with adverse health outcomes and show that pressure comes with a sizable earnings premium, reflecting workers' willingness-to-pay to avoid pressure. As expected, we do not find a premium among civil servants who face strong labor market frictions. Our

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†University of Erlangen-Nuremberg, CESifo, and LASER; markus.nagler@fau.de

‡University of Erlangen-Nuremberg and CESifo; johannes.rincke@fau.de

§University of Erlangen-Nuremberg and LASER; erwin.winkler@fau.de

experimental evidence is consistent with workers sorting into high-pressure jobs and with a sizable market-level compensating differential. Differences in the prevalence and valuation of work pressure explain substantial shares of wage inequality.

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"Well, Yegor, it's hard work not sleeping, isn't it?"
"One's got to put up with it! It's part of our work, you see. In a gentleman's house it's easier; but then here one makes more."
Leo Tolstoy: *Anna Karenina*, Part 4, Chapter 14

# 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). Both in Europe and in the United States, a majority of workers reports working under high pressure or commonly experiencing high work stress (EU-OSHA, 2013; Maestas et al., 2017). Correspondingly, there is a public discussion about adverse health outcomes related to pressure and 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). Both in Europe and the United States, the societal consequences of work pressure therefore seem large, with Goh et al. (2016) estimating that in the United States 120,000 excess deaths per year and 5-8% of total national healthcare expenditures stem from workplace stressors.

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

In light of this discussion, several questions emerge on the labor market consequences of work-related stress and work pressure. For instance, are workers compensated for work pressure in the form of higher wages, as predicted by the theory of compensating wage differentials (Rosen, 1986)? This would imply that firms encounter higher labor costs if they organize work such that pressure rises. Do workers sort into high-pressure jobs based on their tolerance for this disamenity, as predicted by theory? And do differences in work pressure between workers and jobs contribute to, or explain, earnings inequalities in the labor market? Given these relevant questions, there is surprisingly little evidence on the economic consequences of work pressure.

In this paper, we study the labor market consequences of work pressure. To inform these complex questions, we use several approaches. We start by exploiting rich survey data to estimate wage premia in high-pressure jobs in Germany. These analyses highlight the economic relevance of our research question and provide suggestive evidence on compensating differentials for work pressure. In our main approach, we conduct a stated-choice experiment with German employees. Exploiting these data, we can cleanly estimate workers' willingness-to-pay (WTP) 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 German employment surveys in which workers provide a detailed account about the characteristics of their workplace, the exact nature of their job, as well as information on health outcomes (e.g., Spitz-Oener, 2006; Gathmann and Schönberg, 2010). 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 validate 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 conditional on demographic and narrow occupation controls. Using a random forest algorithm, we show that our pressure index is the most important variable predicting adverse health outcomes among a large set of demographic and job variables. In addition, while work pressure is prevalent across all 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 earnings by about 12 percent and an increase in hourly wages by about 6 percent. We also investigate whether these premia are consistent with theories of compensating differentials (Rosen, 1986). Most importantly, 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 (Bonhomme and Jolivet, 2009). In line with this reasoning, civil servants who face high work pressure report higher work hours on average, but do not receive an earnings premium. Overall, our findings based on the survey data reinforce the notion that work pressure is an economically important job amenity.

[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.

In light of the well-known difficulties when estimating compensating differentials from observational data, we complement the evidence from survey data with a stated-choice experiment that identifies workers' willingness-to-pay (WTP) to avoid work pressure. The sample consists of more than 3,300 German employees and is representative of the German workforce in key dimensions. Since the experiment allows us to cleanly identify the WTP to avoid pressure in the workplace (holding fixed other job characteristics, such as hours, firm characteristics, or tasks), we consider it our main approach. Following Maestas et al. (2023), we 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 amenities, such as working from home or paid days off, and anchor job attributes around the respondents' current job. Besides identifying the WTP to avoid work pressure, the experiment also allows us to provide evidence on the extent to which workers sort into high- and low-pressure jobs. In addition, following the conceptual work of Rosen (1986), we use the experimental data to bound the market-level compensating wage differential to avoid high pressure.[3] Finally, we use the experiment to provide evidence on the inequality implications of work pressure.

Our 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. Since any specific measure of work pressure will necessarily only cover parts of what workers perceive as pressure, this is likely a lower bound on workers' true valuation to avoid work pressure. Respondents' average WTP to avoid work pressure is similar to German workers' WTP to work from home and larger than their

[3]This rests on the idea that the compensating differential reflects the WTP to avoid the disamenity of the *marginal* worker (i.e., the worker who is just indifferent between this job or an alternative job without the disamenity). Her WTP is bound by the WTP of *inframarginal* workers.

WTP for flexible schedules, but lower than their WTP to avoid commutes of 30 minutes or more, for example (Nagler et al., 2022).

We find evidence for sorting into high-pressure jobs based on workers' valuation of this disamenity, a key prediction of Rosen (1986). Workers facing work pressure in their current jobs show a substantially lower WTP to avoid work pressure than workers who do not. We use these results to bound the market-level compensating differential and find 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. The relative magnitudes of these effects mirror the relative importance of both variables in predicting adverse health outcomes.

Finally, 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 37 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 33 log points. This corresponds to a decrease of almost 11%.[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 63 log points.

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

[4]This result mainly 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.

2007; Sorkin 2018; Lamadon et al. 2022; Taber and Vejlin 2020; Wissmann 2022; Lehmann 2023).[5] This literature has repeatedly acknowledged that estimating compensating differentials using observational data is difficult for a variety of reasons including search frictions, endogenous labor market matching, and lack of data on complete compensation packages including non-wage amenities (e.g., Brown, 1980; Bonhomme and Jolivet, 2009; Eriksson and Kristensen, 2014; Lavetti and Schmutte, 2018; Lavetti, 2020).[6] In current work, Sockin (2022) shows that amenities are typically positively correlated within firms and that high-amenity firms tend to pay more. 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. (2023) 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 lab evidence consistently suggests that individuals are averse against working under time pressure (Buser et al., 2022). In line with our analysis, the results in Sockin (2022) suggest that stress is one of the few amenities whose correlation with worker pay and worker satisfaction is in line with compensating

[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 stated choice experiment by Eriksson and Kristensen (2014), the field experiment by He et al. (2021) in China, and the combination of administrative labor market and experimental data to study compensating differentials for immoral work in Schneider et al. (2020).

differentials. A more sizable literature has investigated the health consequences of labor market developments.[8]

We contribute to these literature strands with a comprehensive analysis of the link between work pressure and labor market outcomes, combining evidence from detailed survey data and a choice experiment. Our study is the first to thoroughly investigate the role of work pressure for earnings and inequality. Given the relevance of work pressure in the labor market, we consider this an important contribution. Our estimates extend and incorporate recent findings in the small, but growing literature on work pressure. For instance, they are consistent with the willingness-to-pay of workers to avoid fast-paced work found by Maestas et al. (2023), with a positive link between stress and earnings in observational data (Sockin, 2022), and with individuals' aversion against time pressure (Buser et al., 2022). Relative to Maestas et al. (2023) and Sockin (2022), we provide a much more detailed picture about workers' willingness-to-pay to reduce work pressure and its role in the labor market. This is relevant since the economic implications of work pressure remain understudied. A further contribution relative to Maestas et al. (2023) lies in our extension of the measurement of work pressure. This is important since work pressure is subjective and any particular measure potentially understates the role of work pressure for earnings differences and thus compensation inequality.[9] Our validation exercises,

[8]Recent studies for example analyze the health effects of downsizing (Østhus, 2012; Ahammer et al., forthcoming) and the link between firm sales and worker health (Hummels et al., 2023). 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 or pay structure on health outcomes and stress (e.g., Åkerstedt et al., 2001; Cygan-Rehm and Wunder, 2018; Berniell and Bietenbeck, 2020; Dohmen et al., 2023).

[9]In line with this, Maestas et al. (2023) show that working at fast pace is more prevalent among low-earners than among high-earners, making it an element of work pressure that

especially the connection between our measure of work pressure and workers' (mental) health, add to the credibility of our results, but also demonstrate the importance of work pressure relative to other job amenities. We also contribute by providing an in-depth analysis of detailed observational datasets, including novel placebo analyses. At the same time, we believe that leveraging the experimental design of Maestas et al. (2023) is useful since it offers a benchmark against which our results can be interpreted. Relative to Buser et al. (2022), we provide extensive evidence on the labor market consequences of pressure. In particular, we offer an in-depth analysis of the inequality effects of work-related stress, showing that work pressure helps explain existing inequalities in the labor market. We also show that workers sort into jobs according to their aversion against work pressure and that this sorting pattern is consistent with substantial compensating wage differentials following Rosen (1986). Overall, using a variety of empirical approaches, our analysis consistently suggests that individuals are (to some extent) compensated for work stress and resulting health risks in the form of higher wages. We thus believe that our paper is complementary to recent work, especially to Maestas et al. (2023), and closes a gap in the literature regarding the role of work pressure in the labor market.

The remainder of this paper is structured as follows. In Section 2, we use observational data to study the link between work pressure, health and wages. In Section 3, we investigate the association between work pressure and wages using a stated-choice experiment. We also investigate sorting into high-pressure jobs and assess implications for compensation inequality. Section 4 concludes.

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contributes to compensation inequality, whereas work pressure and work stress more broadly likely explain compensation inequality, as is true both in Sockin (2022) and in our paper and as would be expected from theories of compensating differentials. In Maestas et al. (2023), work pressure also does not contribute much to compensation inequality, in contrast to our results and the broader public discussion about the role of work pressure in the labor market.

# 2 Work Pressure and the Labor Market: Observational Approaches

## 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) and cover 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. Since 1979, the survey has been conducted in seven waves. 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 to study the link between work pressure and labor market outcomes. 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.[10] This is important since it allows us to show that the link between 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

[10]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 (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

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 exploit the most recent survey wave of 2018 which provides the most comprehensive data.[11] We restrict attention to 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 7,825 observations.

### 2.1.2 Empirical specification

As a first approach, we use the 2018 survey data to estimate variants of the following specification:

$$y_i = \beta HighPressure_i + X_i'\gamma + \epsilon_i \quad (1)$$

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, $y_i$ 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 $\beta$ 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. Note, however, that here we use ordinal variables in a cardinal way.

The vector $X_i'$ controls for a variety of potential confounders. It contains a set of variables that we label "extended Mincer" controls, including education, a third-order polynomial for worker age, gender, whether workers are German, NUTS-2 region, and urbanization at municipality

not a problem in the BIBB/BAuA data, in which workers directly report the characteristics of their job and their workplace.

[11] Our main results hold when we use the earlier waves instead. See Figure A.9 in the Online Appendix.

level. In our preferred specifications, $X_i'$ also contains a vector of 2-digit occupation dummies (KldB2010, similar to ISCO-08; 45 dummy variables) and a vector of industry dummies (NACE-2; 21 dummy variables). This for example takes into account permanent differences between jobs and industries, such as the degree of monopsony power or the returns to hours worked (e.g., Bachmann et al., 2022; Denning et al., 2022).

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 and a high codifiability, as well as an indicator for physically demanding jobs.[12] Regressions employ sample weights. In all specifications, standard errors are clustered at the 2-digit occupation level.

#### 2.1.3 Definition of work pressure

Work pressure is a concept that is inherently difficult to measure. First, pressure and workplace stress are qualitative concepts that workers subjectively perceive to be present, but that are hard to define objectively. This comes with issues of social desirability bias when workers respond to direct questions about these perceptions, which may also change over time. Second, any specific measure of work pressure will necessarily only cover parts of what workers perceive as pressure since work pressure likely shows up in different forms across jobs.

Ideally, we would thus like to have a measure of work pressure that is less prone to social desirability bias, that is common to different jobs, and that plausibly measures important determinants of work pressure. To advance on these challenges, we construct an index of work pressure based on the following four questions in the survey:

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

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 a maximum time to carry out a given task?

We picked these four questions mainly because they meaningfully relate to work pressure (as we will show in the next section). Moreover, these survey items are consistently available since the first wave of our data, enabling us to study the long-term trend in our index. 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.

When answering the pressure-related 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 to which the individual responds with 'often'. $HighPressure_i$ can thus take values between 0 and 1.

Relative to self-reported measures of feelings of stress, we consider it an advantage that our index captures more objective elements of the job that respondents may not directly link to whether they experience feelings of workplace stress. Therefore, response behavior may be less prone to social desirability issues.

We document in the Appendix that our results are robust to various alternative ways of capturing different dimensions of work pressure. For instance, we use principal component analysis (PCA) to construct an alternative index of work pressure. Appendix Table A.2 shows that all four survey questions enter positively into the first principal component and have very similar loadings, suggesting that all four questions capture a similar variation in the data. The first principal component explains about 40% of the variation in the original variables and is strongly correlated with the baseline measure. Moreover, Appendix Figure A.1 documents that our main finding of a positive earnings premium for work pressure is robust to varying the number of survey items included when deriving the measure of pressure.

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

In this subsection, we validate our measure of work pressure. Most importantly, we show that our index is closely associated with workers' self-reported health outcomes. We also comment on further validation exercises that we relegated to the Online Appendix.

**Measured work pressure predicts adverse health outcomes.** To validate our measure of work pressure, we analyze its connection with self-reported 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).

In Panel (a) of Figure 1, 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. 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, finding work emotionally taxing, and being overwhelmed by too much work.

In Panel (b) of Figure 1, we validate our work pressure index using a machine learning algorithm. More specifically, we combine all the health outcomes from Panel (a) into a single index, using the first principal component of a PCA and then use a random forest algorithm to predict the health index by our work pressure index as well as by demographic and job characteristics. In Panel (b), we plot the variable importance of all included variables.[13]

[13]The random forest algorithm is a supervised machine learning method that fits a large number of individual decision trees. Each decision tree has the goal of minimizing the prediction error (mean squared error). For each decision tree, the algorithm draws a bootstrap sample

Strikingly, our work pressure index is by far the most important predictor of health outcomes. It is more important than demographic variables such as gender and age and more important than other job characteristics such as physical demands, shift work, or the codifiability of the job. When using the underlying variables instead of the index, frequent deadlines turn out to be the most important predictor of adverse health outcomes.[14] These results suggest that our index indeed captures work environments defined by a high degree of work pressure.

**Additional validations of the work pressure measure in the Appendix.** In the Appendix, we provide additional arguments in favor of our measure capturing work pressure. Online Appendix A.3 provides 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. Appendix A.4 analyzes how work pressure relates to job characteristics. For example, in Online Appendix Figure A.3, we use a random forest model to show that when we predict our main work pressure variable using the variables in our baseline regressions, we find that computer use and the number of subordinates are the top predictors. We also 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. Further analyses suggest 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. Table A.5 shows that, in line with expectations, high-pressure jobs are most likely found in occupations such as health care workers, doctors, journalists, and train

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and at each step, the algorithm randomly selects a subset of all available predictors. The final prediction is an aggregation of all individual decision trees. We randomly split the original data into a training and a test data set (50-50). Variable importance is a standard concept in machine learning and measures the extent to which a variable improves the prediction accuracy across all trees in the random forest.

[14]In unreported regressions, we also find that our work pressure variable is more important to predict adverse health outcomes than even industry or occupational fixed effects. The connection between pressure and health is very similar across demographic groups.

drivers. Low-pressure jobs include painters, gardeners, and occupations in theology. Appendix A.5 considers the link between work pressure and firm characteristics. We demonstrate that workers reporting high work pressure are 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). Finally, Online Appendix A.6 shows that our measure of work pressure has increased over the past decades, in line with a broad public debate reflecting common perceptions of increased workplace-related stress. We also show that this trend is neither merely driven by the demographic composition nor by the occupational composition of the workforce.

## 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. In this section, we use the 2018 wave of survey data to investigate whether there is a pay premium for high-pressure jobs.

Table 1 presents the results. Panel (A) shows the estimated link between work pressure on monthly earnings.[15] Column (1) shows that, absent any control variables, monthly earnings are higher for workers in high-pressure jobs. In Column (2), we include the "extended Mincer" controls (i.e., education, a third-order polynomial for worker age, gender, German nationality, NUTS-2 region, and urbanization at municipality level). The estimated coefficient on our work

[15] Earnings are what most papers in the literature using observational data have at hand, although the theory of compensating differentials would rather predict differences in *wages* to emerge in a frictionless labor market.

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.

In Column (3), we additionally 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 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.[16] 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.[17]

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

[16] Our results are similar when using 3-digit occupation dummies. See Online Appendix Table A.6.

[17] In Appendix Figure A.8, we show the heterogeneity of the earnings estimates by age, gender, and education. The estimated earnings premium for work pressure is positive and similar for all sub-groups, as expected from a model of compensating differentials. If anything, it is slightly higher for above-median earnings, male, and high-educated workers.

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 added in Columns (4) and (5) as potential outcomes of selecting into high-pressure, high-paying jobs, our preferred estimate is the one in Column (3).[18]

Panel (B) provides the same analysis for (self-reported actual) work hours. As expected, workers in high-pressure jobs on average work significantly longer hours. To investigate to what extent longer hours drive the earnings premium, we compute hourly wages from the earnings and the hours information. Panel (C) then presents the analysis for log hourly wages. The estimates vary a bit across specifications, but there is a positive and statistically significant link

[18]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 using a classical Mincer earnings regression, the occupation and industry dummies would represent bad controls since they are a result of educational 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.

between work pressure and hourly wages in all regressions, with the exception of Column (4).[19] Overall, the estimates in Panel (C) suggest that, in line with theories of compensating wage differentials, higher monthly earnings in high-pressure jobs are at least partly due to a *wage* premium.[20]

In sum, the analyses in this section provides evidence that high-pressure jobs exhibit a sizable earnings premium. Interestingly, this earnings premium holds even within occupations and industries. The evidence suggests that the earnings premium is driven by a higher number of work hours *and* a wage premium. One 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 addition, the estimates vary a bit across specifications, and may be prone to well-known issues with identification when investigating compensating differentials in observational data. In section 3, we therefore further investigate the question whether the estimated earnings and wage premium is a compensation for work pressure.

#### 2.2.2 No earnings differential for high-pressure jobs among 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.

[19]This insignificant result mainly stems from controlling for firm size. Since a feature of high-pressure jobs seems to be that they are more prevalent in larger firms, it is unclear whether one should control for firm size. In our stated-choice experiment below, we can cleanly separate worker preferences on work pressure from other wage determinants such as firm size.

[20]Our results are similar when we include part-time workers or when we focus on women only.

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. For instance, police officers or teachers working in a low-income area in a large city may experience much higher work pressure relative to public sector workers in the same occupation in an affluent suburb.[21] 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.[22] These are well-known circumstances that make a compensating differential unlikely to appear (see, e.g. Bonhomme and Jolivet, 2009).[23]

Table 2 shows the results of the respective 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.

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

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

[23]Note that civil servants may opt out of the public sector or switch jobs over time within the public sector. We would not observe this in our analysis due to the cross-sectional nature of our data.

# 3 Willingness-to-Pay to Avoid Work Pressure in Choice Experiments

Our analysis of observational data suggests that work pressure is an important job amenity associated with sizable earnings and wage differentials. While we showed that this wage differential plausibly reflects compensating differentials for work pressure, we acknowledge that well-known estimation issues around hedonic wage regressions may lead us to overstate the compensating differential for work pressure. We thus turn to stated-choice experiments to provide clean evidence on the workers' willingness-to-pay to avoid high work pressure, a key element of possible compensating wage differentials for high work pressure in the labor market.

## 3.1 Experimental setup

In our 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 cleanly identify the wage premium necessary to compensate workers for the presence of high-pressure job characteristics (i.e., the compensating variation of workers). Importantly, the experiment allows us to vary job characteristics conditional on hours and other job or firm characteristics.[24]

Note that the compensating variation of workers is not the same as the market-level (compensating) differential and the two concepts do not have to line up in principle (Lehmann, 2023; Sockin, 2022). However, the former is a key component of the latter since without workers having a sizable willingness-to-pay to avoid this disamenity, we would not expect work

[24]In comparison to approaches using observational data, the experiment also allows us to control the environment to the extent that changes in specific amenities are not compensated through changes in other, unobserved amenities.

pressure to lead to compensating differentials in the first place (Lavetti, 2023). In addition, in the framework of Rosen (1986), workers sort on their compensating variation into jobs that differ along characteristics. Finally, workers' valuation of job characteristics is important to gauge overall compensation inequality in addition to wage inequality.

Our pre-registered experimental setup follows Maestas et al. (2023), who use a survey experiment to estimate the willingness-to-pay of workers for alternative work arrangements and various non-wage characteristics of jobs.[25] Maestas et al. (2023) study various 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.

Our main goal is to estimate 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."[26]

In contrast to the survey items exploited in the previous section, we use only two attributes characterizing hypothetical jobs as more or less stressful. We restrict ourselves to just two of these items in order to avoid that the job profiles would be dominated by attributes capturing

[25]See our entry in the AEA RCT Registry at `https://www.socialscienceregistry.org/trials/9559`.

[26]This reduction in potential categories again follows Maestas et al. (2023).

work pressure. We chose deadlines and multitasking as the two attributes capturing work pressure for two main reasons. First, these attributes show the highest independent correlation with earnings in our observational data. Second, we believe they are the most objective measures of work pressure among the four main elements of our survey-based pressure index.

Besides the two pressure-related items, we included in the job profiles several other non-wage attributes. We did this to make the jobs profiles more realistic, to avoid experimenter demand effects, and to enable comparisons with compensating differentials for non-wage job attributes unrelated to work pressure estimated in previous literature. The additional attributes are schedule flexibility, option to work from home, number of paid days off, commuting time, and hours. We provide an in-depth analysis of these dimensions, especially workers' willingness-to-pay to work from home, in Nagler et al. (2022).[27]

Each survey respondent completes a series of ten stated-choice experiments.[28] 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.[29] 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

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

[28]Appendix Figure A.10 shows a sample choice screen from the experiment. Appendix Tables A.7 and A.8 show descriptive statistics for the experimental sample.

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

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.[30]

Starting from the respondents' individual baseline job profile, we construct hypothetical Job A and Job B by randomly selecting two non-wage attributes (potentially 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.[31]

[30]After the choice experiments, respondents additionally answered questions about their current health status. In Appendix Figure A.11, we show that there is a tight connection between frequent deadlines, frequent multitasking, and adverse health outcomes in our experimental sample.

[31]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, there is a strong norm of 30 days in Germany, differently from the US. For instance, 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 (in minutes) 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 $\theta_A$ and $\theta_B$ follow a $N \sim (1, 0.01)$ distribution.[32] 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 reported her earnings when answering the survey (hourly, monthly, or yearly).[33]

We follow Maestas et al. (2023) 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. Almost 2/3 of respondents passed both attention checks. These respondents constitute our main estimation sample ($N =$ 2,168).

## 3.2 Empirical specification

We estimate the willingness-to-pay to avoid high pressure job characteristics following Maestas et al. (2023). The approach assumes that respondents' observed choices (preference for either job A or job B) reflect a linear indirect utility function

$$V_{ijt} = \alpha + X'_{ijt}\beta + H'_{ijt}\theta + \delta \ln w_{ijt} + \epsilon_{ijt}, \tag{2}$$

[32] 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.

[33] We follow the strategy used by Maestas et al. (2023) to limit the number of job pairs in which one of the jobs dominates the other on all varying dimensions.

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

$$P(V_{ijt} > V_{ikt}) = \frac{\exp[(X'_{ijt} - X'_{ikt})\beta + (H'_{ijt} - H'_{ikt})\theta + \delta(\ln w_{ijt} - \ln w_{ikt})]}{1 + \exp[(X'_{ijt} - X'_{ikt})\beta + (H'_{ijt} - H'_{ikt})\theta + \delta(\ln w_{ijt} - \ln w_{ikt})]}. \tag{3}$$

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

$$\delta \ln w = \beta^r + \delta \ln(w - WTP^r), \tag{4}$$

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

$$WTP^r = w\left[1 - e^{\left(-\frac{\beta^r}{\delta}\right)}\right]. \tag{5}$$

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 2 shows the willingness-to-pay in percent of workers' hourly 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 wage cut of 9.6 percent to avoid frequent tight deadlines. 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.[34]

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.[35]

Note that differences in WTP between demographic groups may also be due to systematic differences in the interpretation of scales in our experiment. In unreported regressions, we investigated whether the impact of pressure on health outcomes is similar across groups defined by gender, age, and education. We do not find systematic differences between groups in the predictive value of the response to the pressure variable for self-reported health outcomes, suggesting the absence of systematic differences in the interpretation of scales.

[34] Appendix Figure A.12 shows that our results are robust to including inattentive respondents.

[35] 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.

## 3.4 Do workers sort into high-pressure jobs based on preferences?

Sorting on workers' compensating variation is a central prediction of the model of compensating differentials under worker heterogeneity (Rosen, 1986). In a next step, we therefore investigate whether workers sort into high-pressure jobs, based on their willingness-to-pay to avoid this disamenity. Figure 3 shows that, in line with the Rosen model, 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.13, we show that this result is more pronounced for workers who are arguably less constrained by frictions (i.e., more educated workers and workers with substantial labor market experience, measured by age $> 40$). We also show that the result holds within education levels.[36]

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.[37] In line with this, Buser et al. (2022) find that measures of time pressure aversion elicited in an experiment predict stated career preferences.[38] The extent to which high observed

[36]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.

[37]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).

[38]These differences could also stem from systematic differences in interpreting scales in the experiment between these groups. We would argue, however, that this source and direction of bias is unlikely in our setting. To see our argument, suppose it was true that our results would merely reflect differences in the interpretation of scales between workers with and without high job pressure. We would then expect workers who are more sensitive to work pressure as measured by our index to report it more often. At the same time, if a worker is more sensitive to work pressure, we would also expect her to have a higher willingness-to-pay to avoid it, all else

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.

The evidence on sorting also allows to bound the market-level compensating differential if we are willing to take theory at face value. The idea is that the market-level compensating differential reflects the willingness-to-pay of the *marginal worker* to avoid the disamenitiy. Under sorting, the WTP of this marginal worker is bound by the WTP of *inframarginal workers*. That is, the average willingness-to-pay to avoid high work pressure of workers who sorted into such jobs is lower than the willingness-to-pay of the marginal worker who is just indifferent between the high-paying, high-pressure job and the low-paying, low-pressure alternative. In contrast, the average willingness-to-pay of workers who sorted out of high-pressure jobs is higher than the willingness-to-pay of the marginal worker.[39]

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 Online Appendix Table A.9). Taken at face value, this analysis would suggest that the hedonic wage regressions understate the true compensating differential for frequent deadlines, while getting the compensating differential for multitasking about right.

Note that labor market frictions may prevent efficient sorting. At the extreme, this may lead to the situation where the market-level compensating differential is below its frictionless efficient level when workers in high-pressure jobs cannot leave these. In this case, this analysis would

equal. This would work against sorting, whereas in our data, the willingness-to-pay to avoid work pressure is lower among workers reporting high pressure.

[39]In the model of Rosen (1986), $E(Z|D=1) < \Delta W < E(Z|D=0)$, where $Z$ is workers' compensating variation, $D$ is a binary indicator of the disamenity, and $\Delta W$ is the market-level compensating differential. See Figure 12.2 on page 649 in Rosen (1986).

show that even under existing sorting, workers in high-pressure jobs dislike this disamenity to a sizable extent, suggesting substantial welfare losses in the absence of compensating differentials.

## 3.5 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 2 suggests that low-educated and low-earning workers exhibit a higher WTP to avoid 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 build on Equation (5) and compute the log compensation value (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. $\beta^D$ and $\beta^M$ are the corresponding estimated marginal utilities. We allow these marginal utilites (and therefore also the amenity value of low pressure) to differ between worker groups (education and wage quintiles, respectively). Additionally, to incorporate the effects of worker sorting, we allow the marginal utilities to differ depending on whether a worker is currently employed in a job with frequent deadlines or multitasking, or not. We compute standard errors by performing a block bootstrap with 200 replications (by respondent).

Figure 4 shows the results from this analysis. The upper part of the figure shows the level of inequality between high- and low-educated workers. The gap in hourly wages between these two groups amounts to 37 log points. Once we factor in the amenity value of low work pressure, the gap shrinks to around 33 log points. This means that the (dis-)amenity value of (high) low work pressure explains around 11% of the wage differences between high- and low-educated workers, holding other job attributes constant. The bottom part of Figure 4 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 is a job characteristic that many workers face. As a result, there is an ongoing public debate about potential adverse effects of work-related pressure and stress on workers and societies. At the same time, the labor market effects of work pressure are not well understood. Against this backdrop, we provide a detailed analysis of the role of work pressure in the labor market leveraging a variety of approaches. 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 substantial trade-off between higher earnings and lower work pressure. In light of this trade-off, workers sort into high-pressure and low-pressure jobs based on the individual disamenity value that they attach to 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.

Summing up, our analysis suggests that individuals are (at least to some extent) compensated for work stress and resulting health risks in the form of higher wages. This is a novel perspective in the public debate about pressure in the workplace that so far has mainly focused on the resulting adverse health outcomes of workers. A final welfare assessment is beyond the scope of our paper, since our approaches do not allow us to judge whether or not the labor market fully compensates workers for the disutility of work pressure.

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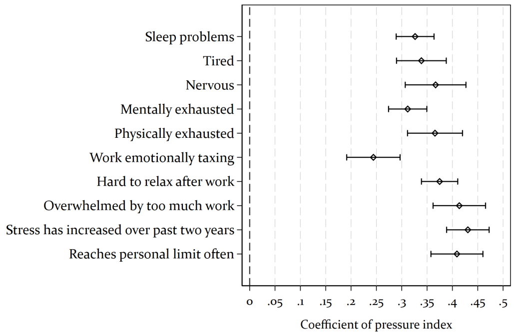
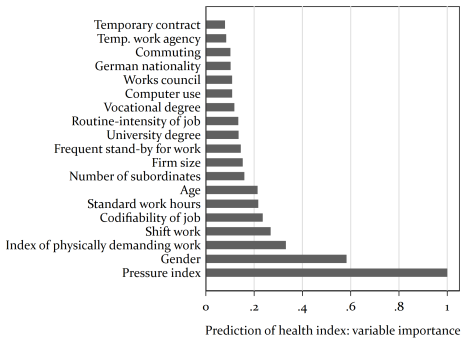
Figure 1: Link between work pressure index and health

(a) Pressure index and health outcomes



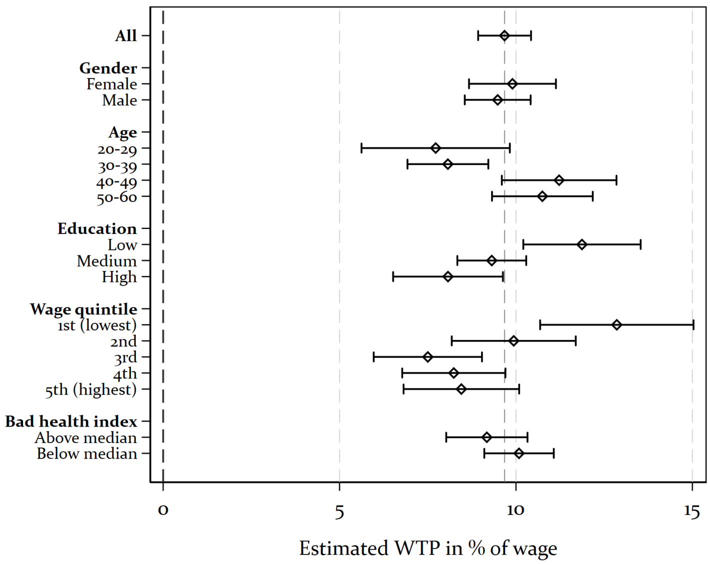

(b) Machine-learning prediction of health outcomes using random forest



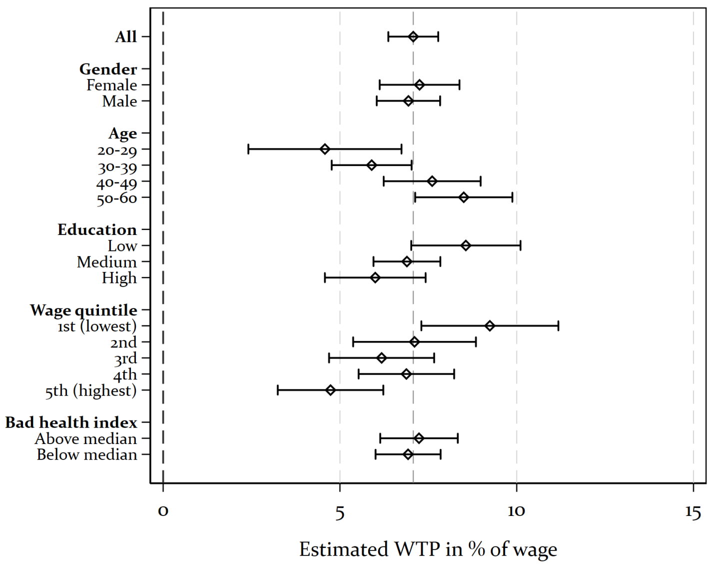

Note: This figure shows the link between our work pressure index and health outcomes. Panel (a) uses various self-reported health indicators as dependent variables. The dependent variable takes on the value of 1 if the respondent indicates that the respective health outcome (e.g., sleep problems) occurs often, and zero otherwise. The main explanatory variable is the work pressure index defined in the main text. 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. Panel (b) shows the results of a machine learning exercise where we predict a PCA-based health index by our pressure index as well as by demographic and job characteristics. The figure plots the variable importance measures. The random forest was run with 3,000 trees, a random selection of 4 variables at each step, and a minimum leaf size of 25 observations in each tree.

Figure 2: Workers' willingness-to-pay to avoid job pressure

(a) WTP to avoid frequent tight deadlines

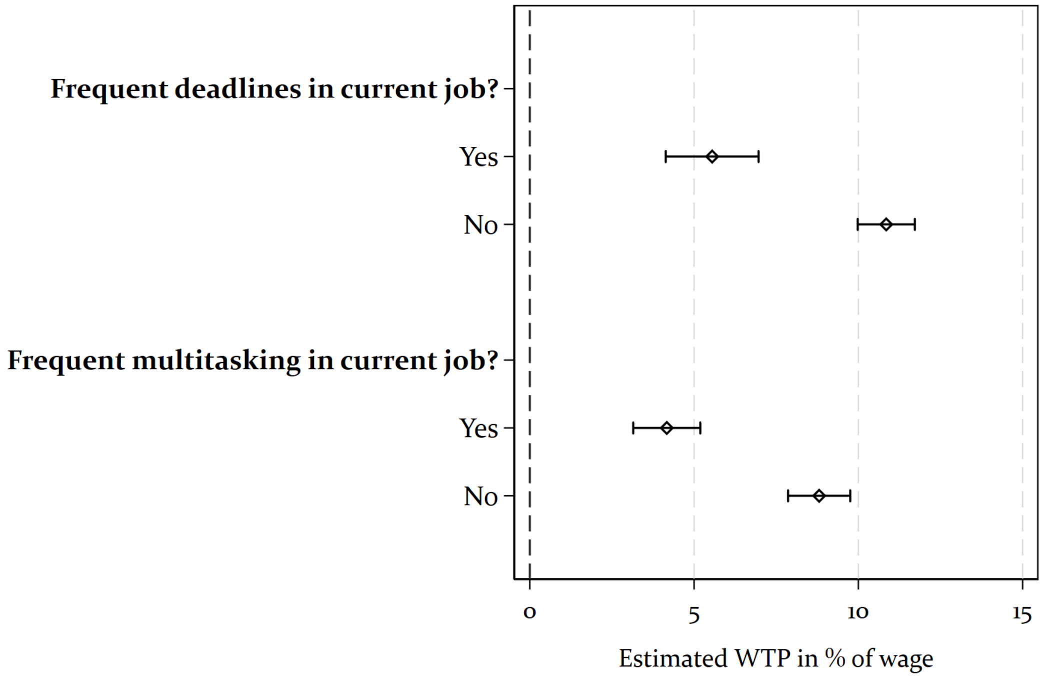



(b) WTP to avoid frequent multitasking



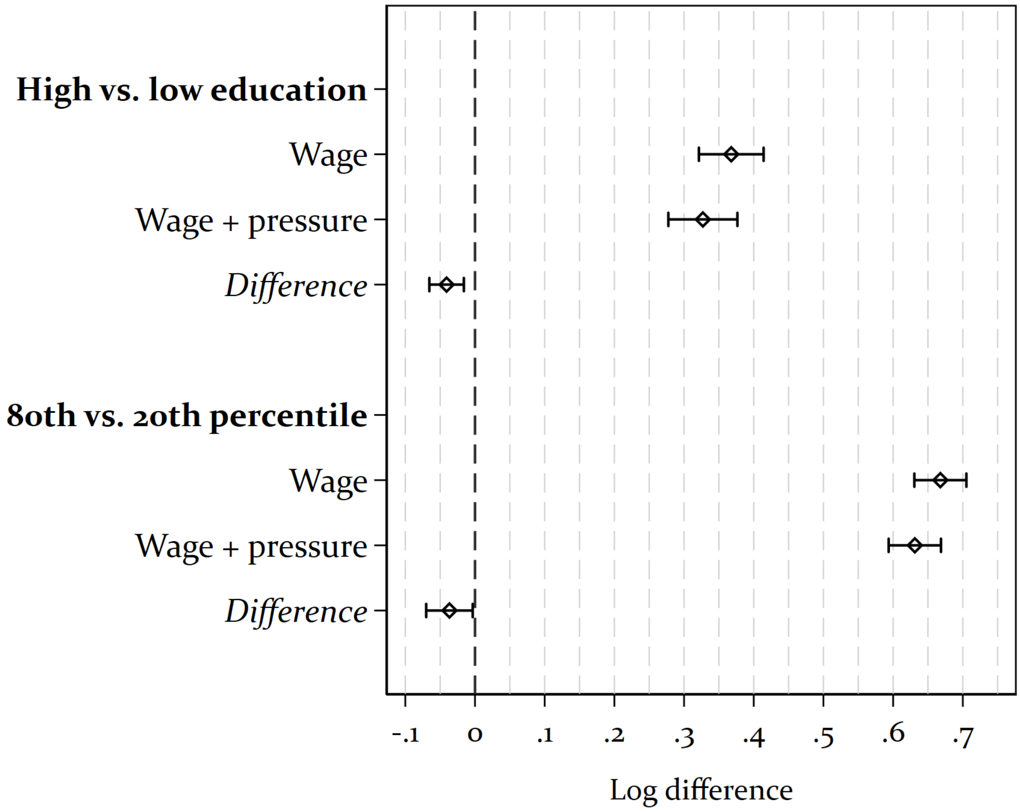

Note: The figure shows the estimated willingness-to-pay to avoid frequent tight deadlines (Panel A) and frequent multitasking (Panel B). In each panel, the first row shows the average willingness-to-pay for all respondents in the sample. The following rows show the estimated WTP for several different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

Figure 3: 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 hollow diamonds indicate point estimates, the bars reflect 95% confidence intervals where standard errors allow for clustering at the respondent level.

Figure 4: 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). Row (1) depicts the difference in log hourly wages. Row (2) depicts the difference in log compensation (wage plus amenity value of low work pressure). 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 hollow diamonds depict the point estimates. The bars reflect 95% confidence intervals which we obtain from 200 block (by respondent) bootstrap replications.

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

| | | | | | |
|---|---|---|---|---|---|
| | **Panel A** | | | | |
| | Dep. Var.: 100x Ln(monthly earnings) | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| 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 urbanization. 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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

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

| | | | | | |
|---|---|---|---|---|---|
| | Panel A | | | | |
| | Dep. Var.: 100x Ln(monthly earnings) | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| 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 urbanization. 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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.