High-Pressure, High-Paying Jobs?
Online Appendix

Markus Nagler* Johannes Rincke† Erwin Winkler‡

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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

A Appendix

A.1 Sample descriptives of survey data

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 as described in the main text. 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.

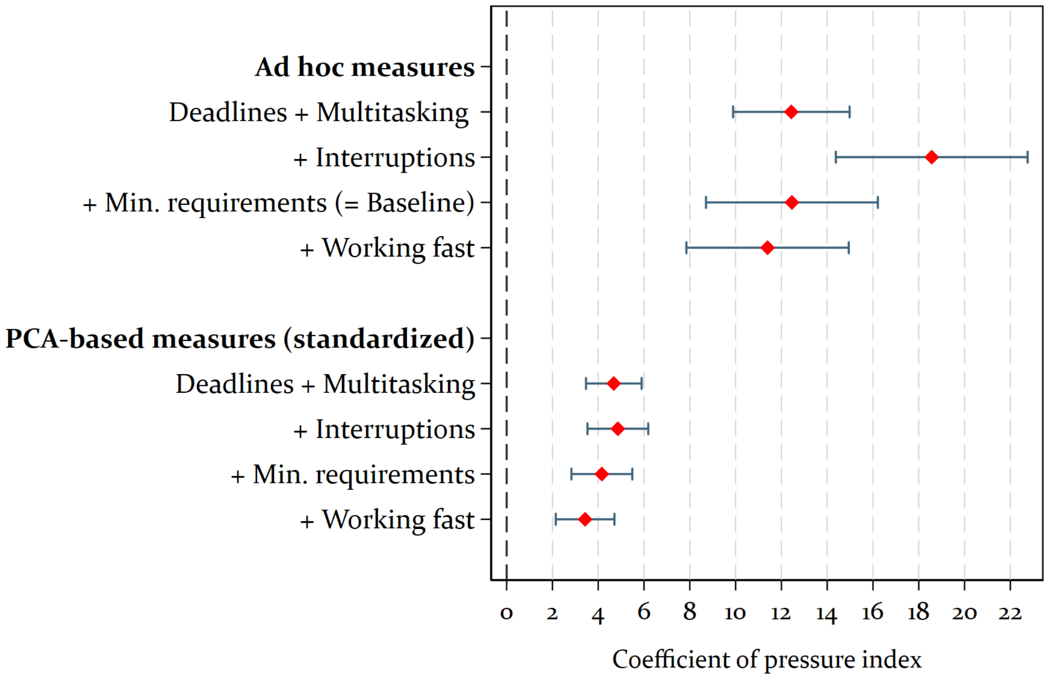
A.2 Alternative definitions of work pressure

Table A.2: Principal Component Analysis of Work Pressure Variables

	Comp 1	Comp 2	Comp 3	Comp 4
Deadlines	0.57	0.19	-0.39	-0.70
Multitasking	0.52	-0.35	0.77	-0.10
Minimum requirements	0.34	0.83	0.20	0.39
Interruptions	0.53	-0.38	-0.46	0.60
Eigenvalue	1.66	0.99	0.71	0.66
Proportion explained	0.41	0.25	0.18	0.16

Note: The table shows the results of a principle component analysis based on the four pressure variables (Deadlines, Multitasking, Minimum requirements, Interruptions) in categorical form (4='often', 3='sometimes', 2='seldom', 1='never'). The columns show the loadings of the 1st, 2nd, 3rd and 4th principal component, respectively. The last two rows show the eigenvalues and the share of the variation explained by the respective principal components. We use the first principal component, which explains 41% of the variation in the original variables, as a data-driven index of work pressure. The correlation between this index and our baseline index is 0.87.

Figure A.1: High-pressure jobs: Earnings premium for alternative definitions of work pressure



Note: This figure shows the coefficients of a regression of 100x log monthly earnings on different versions of the high pressure index. The upper part of the panel uses different combinations of questions in the 2018 BiBB data as the pressure index. The lower part of the panel uses the first component of a PCA-based pressure index, normalized to mean zero and standard deviation one. 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.

A.3 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.[1] 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.[2] 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.3 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

[1]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.

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

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 1a in the main text). Column (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.[3]

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 the paper 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 necessarly 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

[3]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.

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.

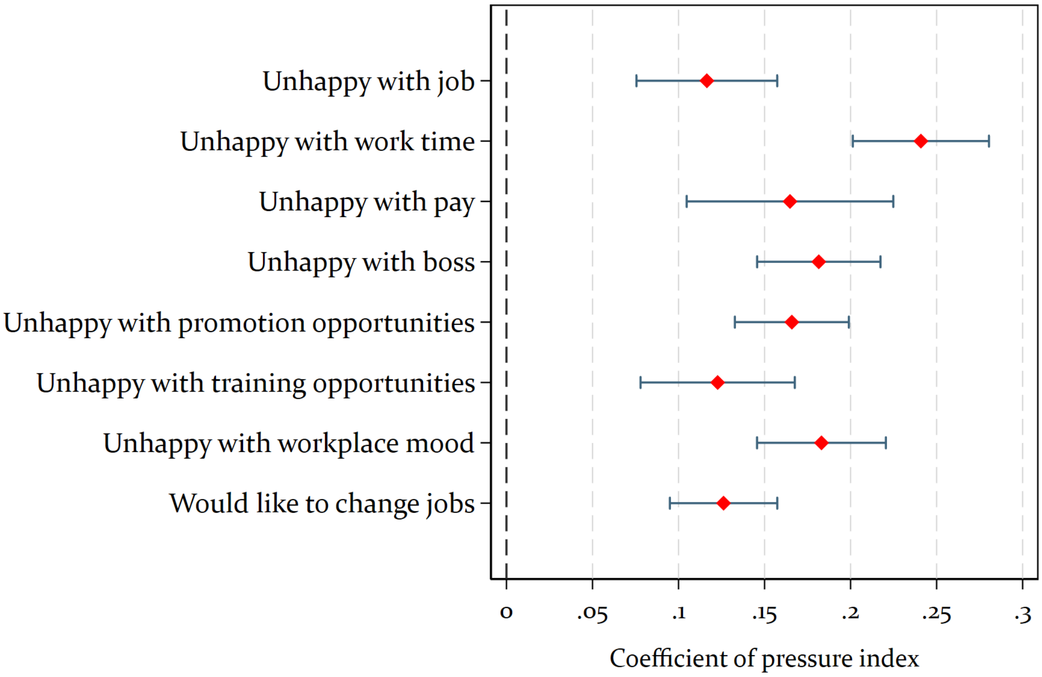
In summary, this analysis shows that workers in high-pressure jobs face several disamenities in their work even conditional on occupation and industry. Standard labor market theories of compensating wage differentials (Rosen, 1986) would predict that this leads to higher compensation for these workers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

Table A.3: 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 the paper. 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.4 High-pressure jobs: Job characteristics

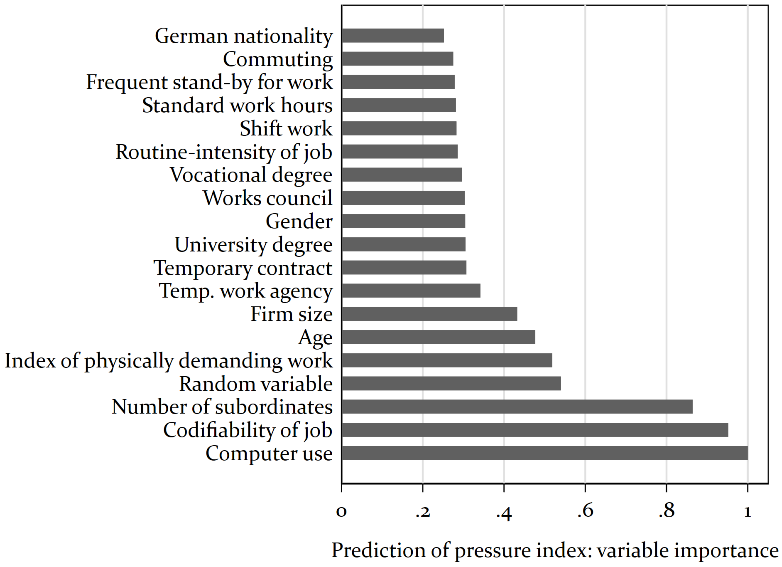
In this section of the Appendix, we further analyze what our work pressure index is capturing. First, we use regression and a random forest algorithm to predict our pressure index using a set of explanatory variables. Table A.4 shows that when we predict our main work pressure variable using the covariates 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. Some results, such as higher work pressure in routine jobs, are surprising, however. But note that this regression includes a large set of independent variables. Some of the predictors may additionally run into bad control problems, for example when jointly controlling for education and firm size or job tasks. To better understand the predictors of high work pressure, we use a random forest algorithm to predict our pressure index using a set of explanatory variables.

Figure A.3 shows the results of this exercise in the form of a variable importance plot.[4] As reference and to get a sense of which variables are truly predictive of high work pressure, we also include a random variable into the set of explanatory variables. Panel (a) of Figure A.3 shows that three variables perform better than the random variable in predicting work pressure: computer use, the number of subordinates, and the degree of codifiability of a job. A closer look at the sign of the correlation shows that computer use and the number of subordinates are positively correlated with pressure, suggesting that white-collar jobs and jobs which are higher up in the hierarchy ladder on average have higher degrees of work pressure. Somewhat surprisingly, a higher degree of codifiability is associated with higher levels of work pressure. However, this is driven exclusively by one item of our index, namely the existence of minimum requirements. Panel (b) of Figure A.3 shows that the importance of codifiability as a predictor of pressure drops substantially once we exclude minimum requirements from the index. Computer use and the number of subordinates remain the top predictors. Note that, at the same time, work pressure predicts both health outcomes and earnings and wage premia over and above these variables.

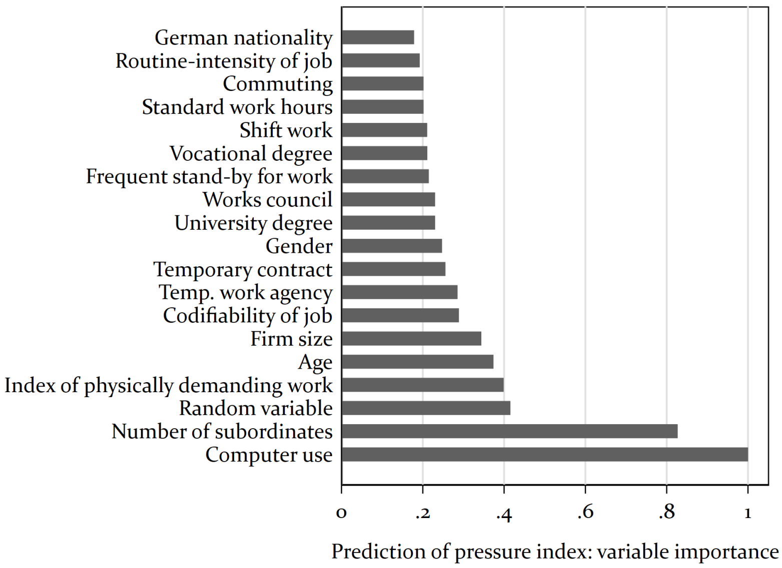
[4]The pressure index is residualized from 2-digit occupation and industry dummies and the results therefore reflect within-occupation and within-industry differences in work pressure, i.e., the variation we use in our main specification. The results without any residualization are very similar.

Figure A.3: Machine learning prediction of pressure index

(a) Baseline pressure index



(b) Excluding variable on minimum requirements from index



Note: The Figure shows the results of a machine learning exercise where we predict the work pressure index by demographic and job characteristics. The figure plots the variable importance measures. The pressure index is residualized from 2-digit occupation and industry dummies. 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.

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), however. 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.5 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.

We also investigate what other 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.[5] 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.

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

Table A.4: 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

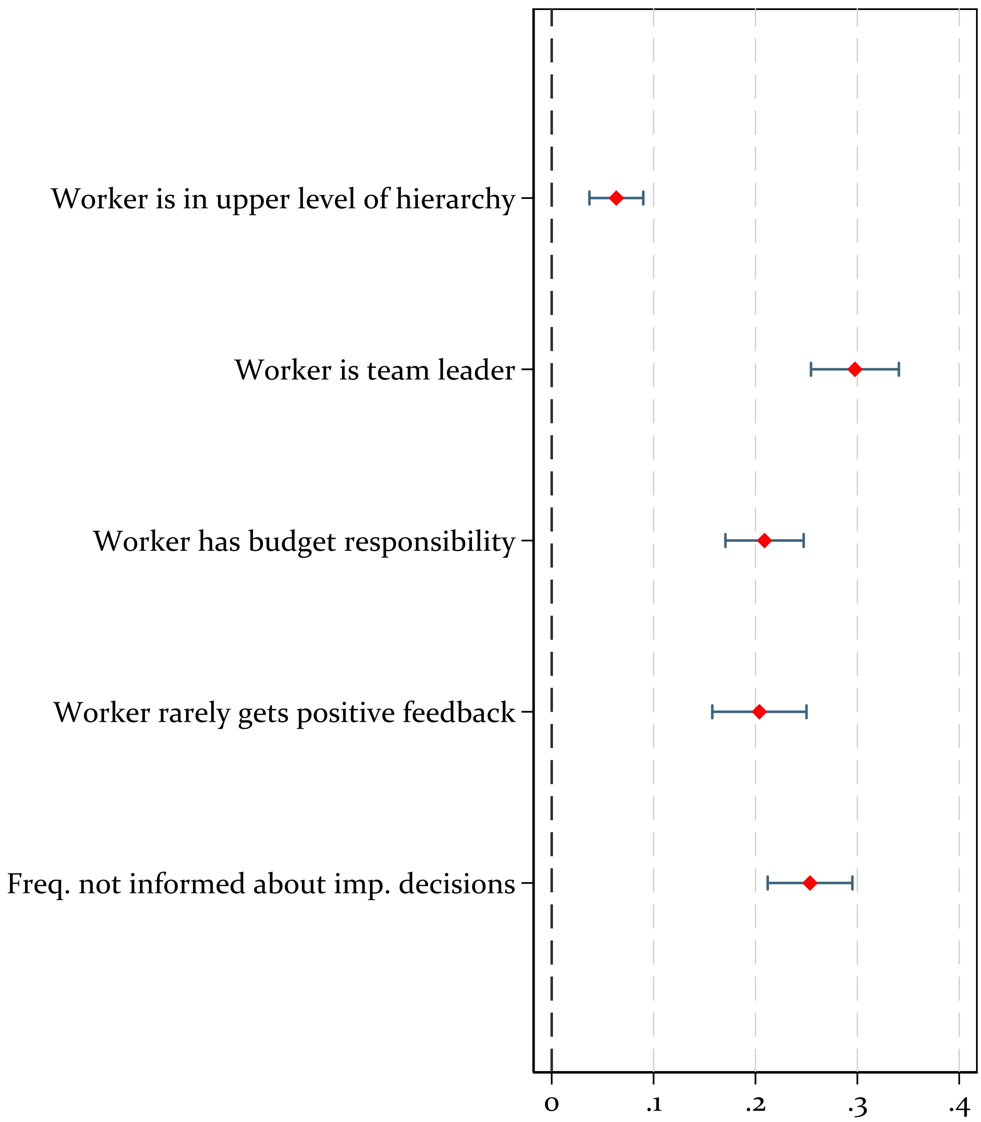
Note: This table shows the main predictors of work pressure, focusing on the 2018 wave. We use our work pressure index as the dependent variable. Extended Mincer controls include cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area besides the variables 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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.5: 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 main text.

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

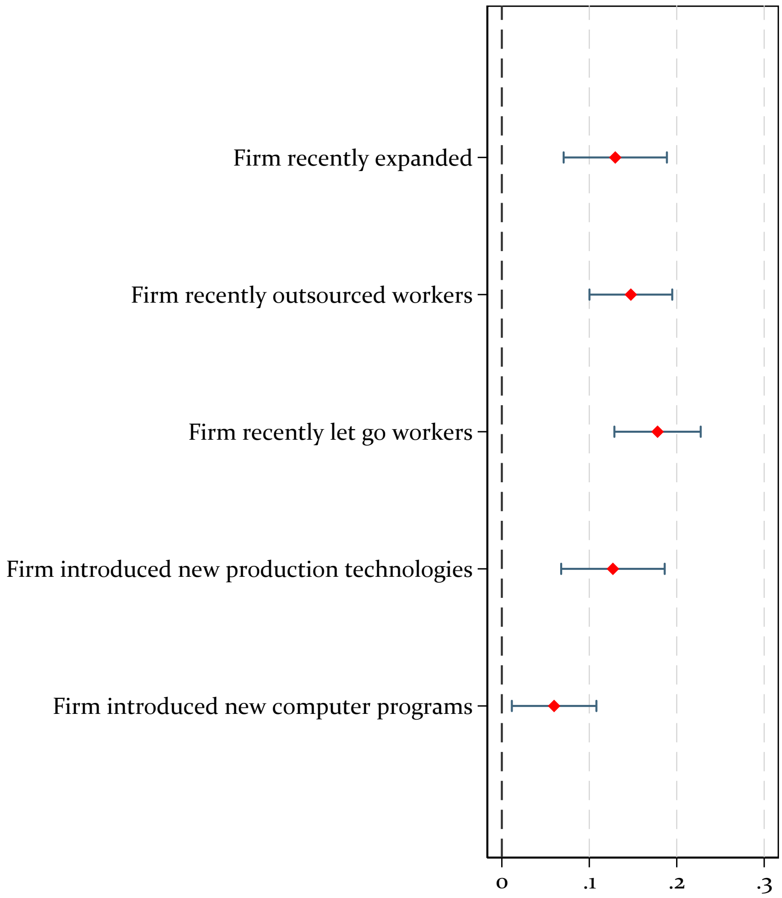


Note: This figure shows the estimated link between our work pressure index and various job characteristics, obtained from linear probability models. To estimate the coefficients, we use the respective job characteristic (reported by the worker) as the dependent variable. The main explanatory variable is the work pressure index defined in the paper. 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 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 the paper. 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.6 Work pressure over time

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 A.6 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.[6] 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 Figure A.7, 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.[7] In panel (b) of Figure A.7, 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.

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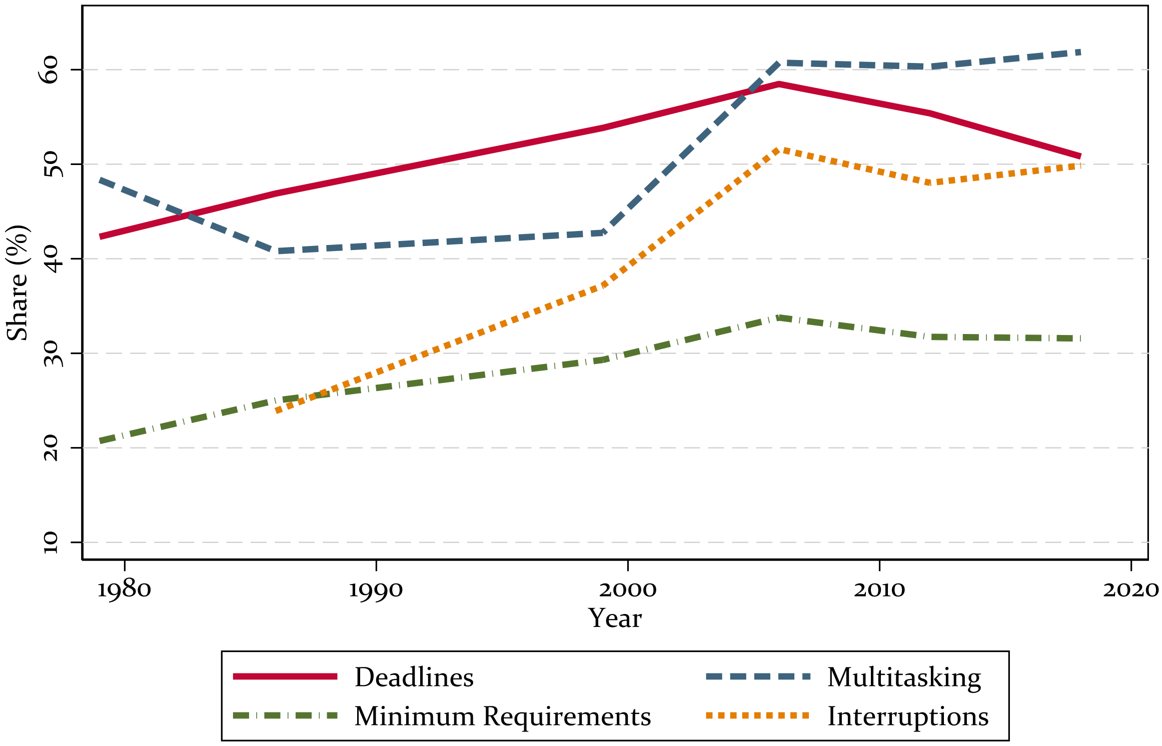
[6] In the more recent waves, there is also a question about whether employees have to work very fast (cf. Maestas et al., 2023). We did not include this variable when constructing our index of work pressure because it is not consistently available across waves. However, including this variable into the index yields very similar results in the hedonic wage/earnings regressions (see Figure A.1). In the earlier waves (1979, 1986, 1992, 1999), there is (in addition to the options 'often', 'sometimes', 'seldom', or 'never') a fifth response 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.

[7] For example, the raw increase in the minimum requirements variable in Figure A.6 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.

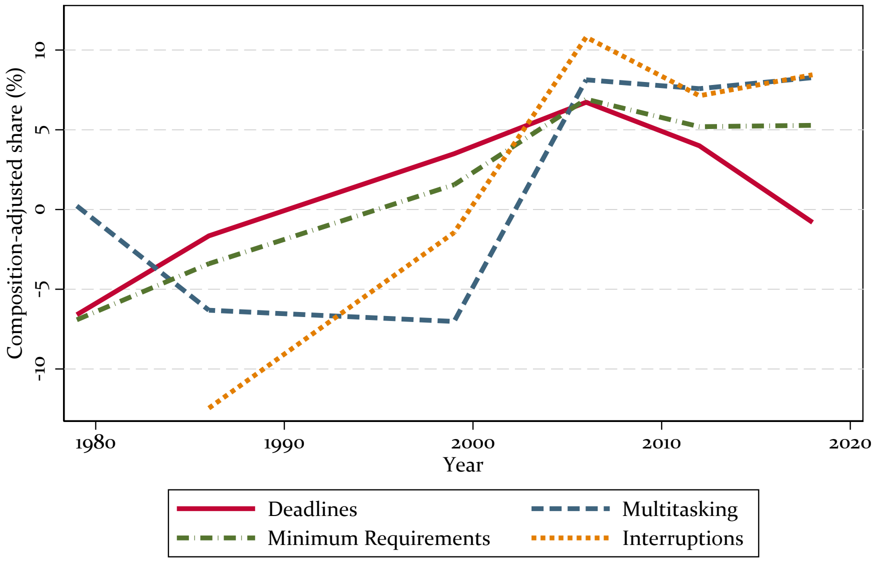
Figure A.6: High-pressure jobs: 1979-2018



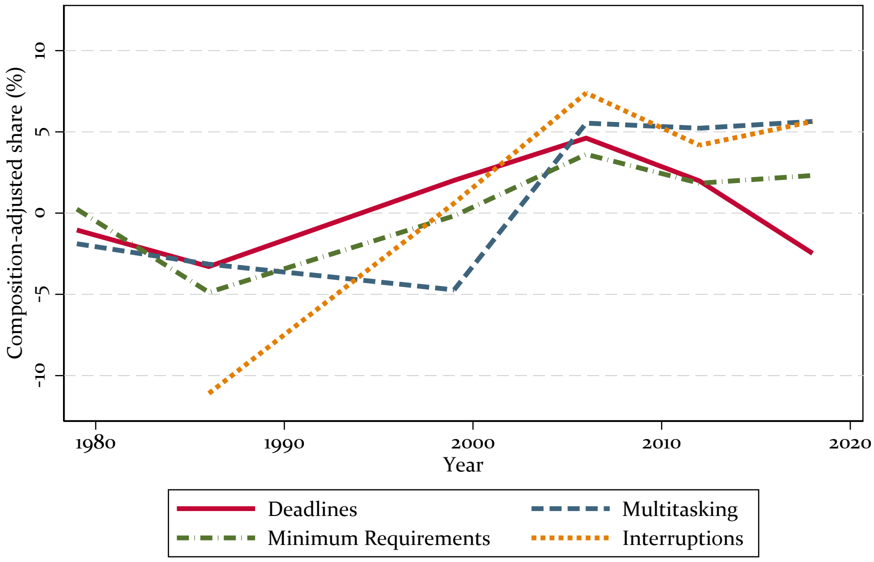
Note: This figure shows the evolution over time of our four main work pressure variables. For each wave, the figure depicts the share of workers who indicate that often face tight deadlines (often need to engage in multitasking, often face minimum requirements, often are interrupted in their work). We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

Figure A.7: Trends in pressure: accounting for composition

(a) Residualizing from age, education, gender



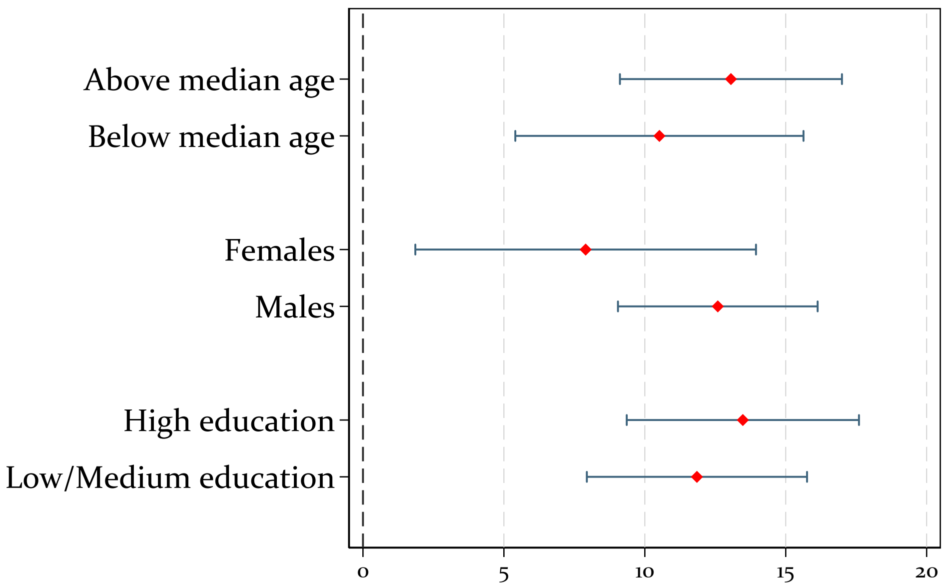
(b) Residualizing from age, education, gender, occupation



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.7 Further results on the earnings premium for high-pressure jobs

Figure A.8: High-pressure jobs: Heterogeneity of earnings effect



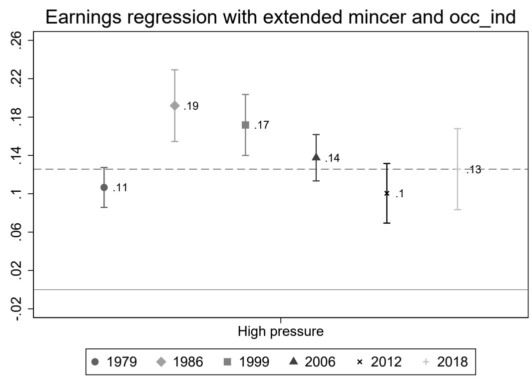
Note: This figure shows the coefficients of a regression of 100x log monthly earnings on the high pressure index, separately for different groups. We control for extended Mincer controls (education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place 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.6: High-pressure jobs: Earnings, wages, and work hours adjusting for 3-digit occupation dummies

	Panel A				
	Dep. Var.: 100x Ln(monthly earnings)				
	(1)	(2)	(3)	(4)	(5)
High pressure	16.68***	13.98***	10.94***	8.17***	11.22***
	(3.09)	(1.82)	(1.75)	(1.78)	(1.71)
Adj. R2	0.01	0.33	0.47	0.52	0.55
Obs.	7825	7825	7825	7825	7825
	Panel B				
	Dep. Var.: 100x Ln(work hours)				
High pressure	6.20***	6.43***	6.39***	6.50***	5.97***
	(0.87)	(0.78)	(0.77)	(0.73)	(0.73)
Adj. R2	0.02	0.08	0.17	0.20	0.20
Obs.	7825	7825	7825	7825	7825
	Panel C				
	Dep. Var.: 100x Ln(hourly wage)				
High pressure	10.48***	7.55***	4.54**	1.67	5.24***
	(2.96)	(1.98)	(1.92)	(1.88)	(1.78)
Adj. R2	0.01	0.28	0.44	0.50	0.53
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

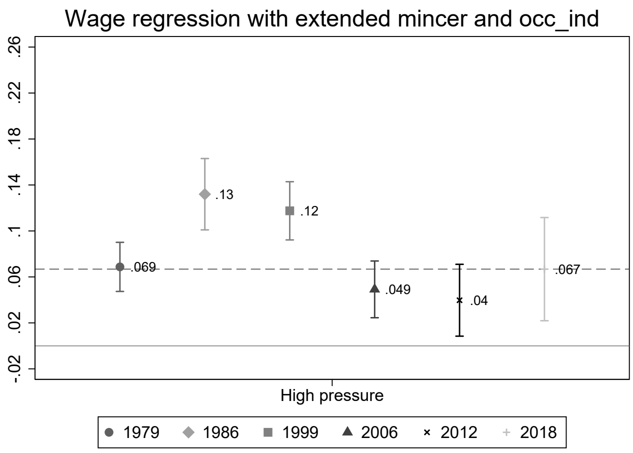
Note: This table shows the results of our main regressions using private sector workers, focusing on the 2018 wave. In Panel (A), we use 100*log monthly earnings as the dependent variable. In Panel (B), we use 100*log work hours. In Panel (C), we use 100*log hourly wage. Extended Mincer controls include education, gender, cubic age, a dummy for German nationality, NUTS-region of home, and population bins of work place area. Occupation dummies are 3-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 3-digit occupation level, in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Figure A.9: 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.8 Further information on the stated-preference experiment

Figure A.10: 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	0.17	0.17	0.17	0.19	0.19	0.12
Sometimes	0.61	0.61	0.62	0.61	0.60	0.64
Often	0.21	0.22	0.21	0.20	0.21	0.24
Frequent multitasking						
Never	0.09	0.08	0.10	0.11	0.10	0.06
Sometimes	0.55	0.54	0.56	0.57	0.56	0.53
Often	0.35	0.38	0.33	0.32	0.35	0.42
Working from home						
No WFH	0.65	0.68	0.63	0.80	0.71	0.32
WFH up to 2 days	0.19	0.17	0.21	0.11	0.16	0.38
WFH up to 5 days	0.16	0.14	0.17	0.09	0.13	0.30
Flexible schedule	0.37	0.33	0.41	0.29	0.31	0.63
Paid days off	28.70	28.33	29.01	28.60	28.61	29.06
Commuting time						
0-15 minutes	0.31	0.35	0.28	0.36	0.32	0.24
16-30 minutes	0.37	0.37	0.38	0.37	0.39	0.33
31-45 minutes	0.19	0.17	0.21	0.19	0.17	0.24
46-60 minutes	0.09	0.08	0.09	0.07	0.08	0.12
>60 minutes	0.04	0.03	0.05	0.02	0.03	0.08
Weekly work hours	36.84	33.54	39.56	36.88	36.05	38.85
Gross hourly wage	19.97	17.36	22.07	17.68	18.54	26.05

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, the number of attentive participants used for our estimation is 2,168. 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 45.2%. The share of low- (medium-, high-) educated is 24.7% (54.4%, 20.9%). In the last row, we exclude subjects who did not report a wage for their current job (10.6% 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	0.19	0.24	0.20	0.22	0.20	0.19	0.21	0.24	0.26
Sometimes	0.66	0.60	0.63	0.60	0.58	0.60	0.61	0.62	0.65
Never	0.15	0.16	0.17	0.19	0.22	0.21	0.18	0.14	0.09
Frequent multitasking									
Often	0.45	0.41	0.32	0.29	0.31	0.31	0.37	0.39	0.42
Sometimes	0.47	0.52	0.59	0.59	0.55	0.58	0.55	0.53	0.54
Never	0.08	0.07	0.09	0.12	0.14	0.11	0.08	0.08	0.04
Working from home									
No WFH	0.60	0.57	0.65	0.75	0.84	0.84	0.72	0.56	0.32
WFH up to 2 days	0.23	0.25	0.19	0.12	0.06	0.08	0.17	0.28	0.34
WFH up to 5 days	0.17	0.17	0.16	0.13	0.09	0.08	0.11	0.16	0.34
Flexible schedule	0.42	0.42	0.36	0.32	0.20	0.24	0.31	0.43	0.66
Paid days off	28.18	28.69	28.62	28.94	26.83	28.18	29.20	29.37	29.90
Commuting time									
0-15 minutes	0.26	0.30	0.33	0.32	0.40	0.35	0.32	0.28	0.20
16-30 minutes	0.41	0.39	0.37	0.35	0.32	0.42	0.38	0.42	0.35
31-45 minutes	0.20	0.19	0.17	0.20	0.17	0.14	0.18	0.19	0.26
46-60 minutes	0.11	0.08	0.09	0.08	0.07	0.07	0.07	0.09	0.12
>60 minutes	0.02	0.03	0.05	0.04	0.04	0.02	0.04	0.02	0.07
Weekly work hours	38.29	37.62	36.46	35.93	35.97	36.03	36.42	37.40	39.23
Gross hourly wage	18.45	20.55	20.27	19.63	11.09	14.04	17.20	21.09	34.20

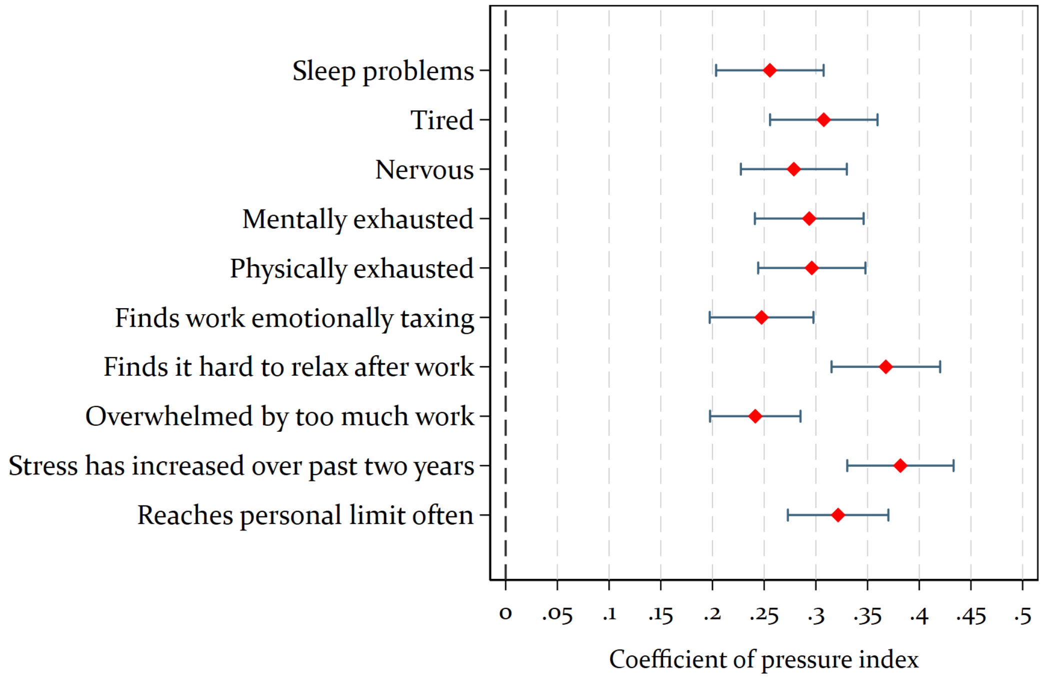
Note: The table shows descriptives on the participants' current job which we use as a baseline for the experiment. The number of participants who passed the attention checks is 2,168. The share of age groups 20-29 (30-39, 40-49, 50-60) is 9.9% (32.0%, 25.9%, 32.2%). In the last row, we exclude respondent where the hourly wage in the current job is missing (10.6% of attentive respondents).

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	18.62***	18.45***	15.96***			
	(2.99)	(2.56)	(2.31)			
Deadlines				6.64**	6.46**	7.41***
				(3.10)	(2.73)	(2.41)
Multitasking				11.51***	11.53***	8.46***
				(2.61)	(2.33)	(2.05)
Adj. R2	0.02	0.26	0.41	0.02	0.26	0.41
Panel B						
	Dep. Var.: 100x Ln(work hours)					
High pressure	10.43***	10.71***	9.15***			
	(1.41)	(1.32)	(1.30)			
Deadlines				4.46***	4.72***	4.69***
				(1.44)	(1.37)	(1.34)
Multitasking				5.83***	5.88***	4.48***
				(1.22)	(1.13)	(1.11)
Adj. R2	0.02	0.18	0.23	0.02	0.18	0.23
Panel C						
	Dep. Var.: 100x Ln(hourly wage)					
High pressure	9.08***	8.68***	7.45***			
	(2.41)	(2.12)	(1.91)			
Deadlines				2.18	1.86	2.84
				(2.43)	(2.16)	(1.89)
Multitasking				6.48***	6.41***	4.47***
				(2.04)	(1.89)	(1.65)
Adj. R2	0.01	0.19	0.35	0.01	0.19	0.35
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, respectively (reference: <30 days), and indicators for commuting time of 30, 45, 60, >60 minutes, respectively (reference: 15 minutes). Robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

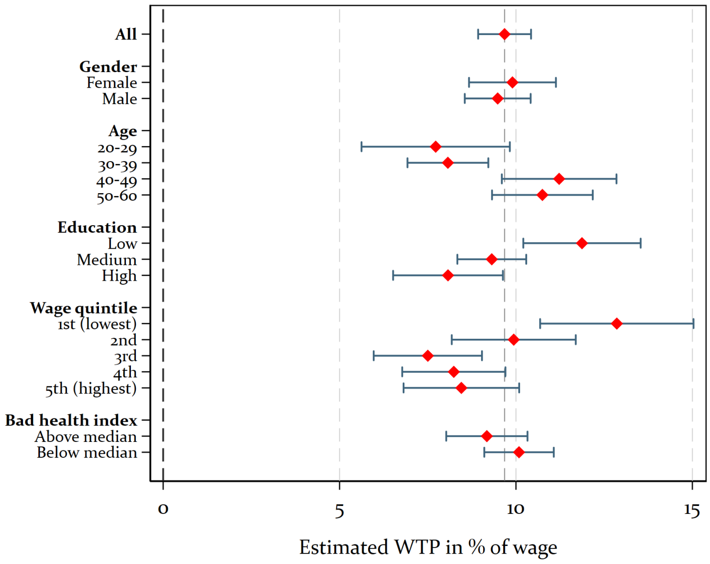
Figure A.11: High-pressure jobs and health outcomes in survey from experimental sample



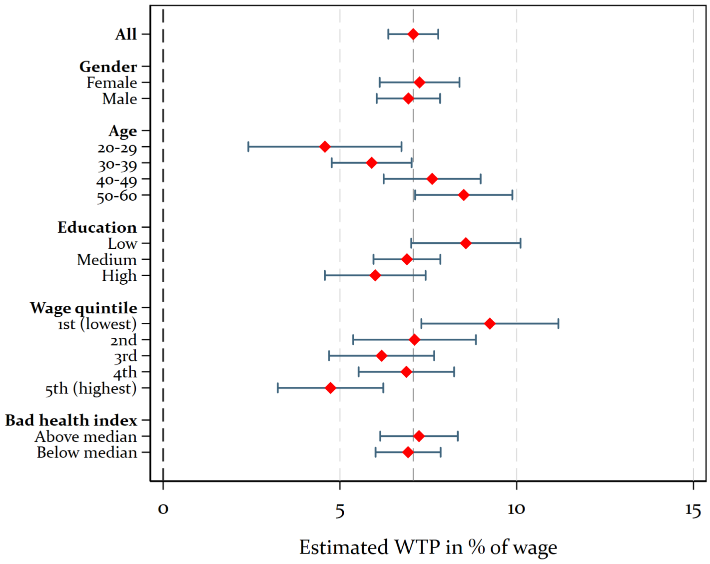
Note: Using data from the experimental sample, this figure shows the estimated link between our work pressure index and various self-reported health indicators, obtained from linear probability models. To estimate the coefficients, we use the respective health outcomes as the dependent variable. The dependent variable takes on the value of 1 if the respondent indicates 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 the paper. 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 allowing for clustering by respondent.

Figure A.12: Workers' willingness-to-pay to avoid work pressure including respondents who did not pass both attention checks

(a) WTP to avoid frequent tight deadlines



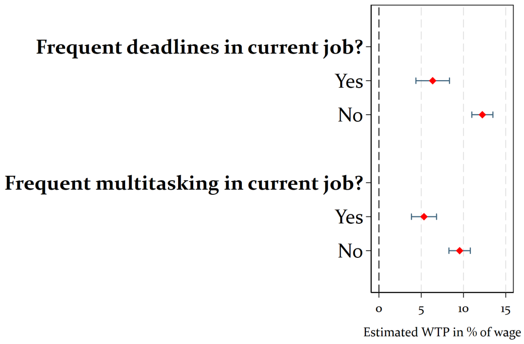
(b) WTP to avoid frequent multitasking



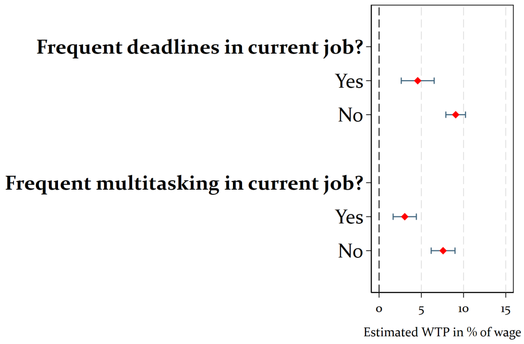
Note: Including the respondents who did not pass both attention checks, the figure shows the estimated willingness-to-pay to avoid frequent tight deadlines (Panel A) and frequent multitasking (Panel B). In each panel, the first row shows the average willingness-to-pay for all respondents in the sample. 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.

Figure A.13: Sorting: Workers' WTP to avoid pressure by own job characteristics by worker type

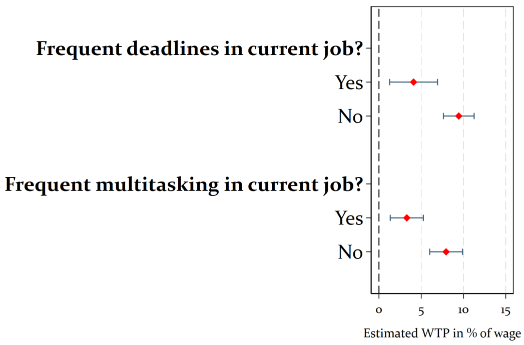
(a) Old



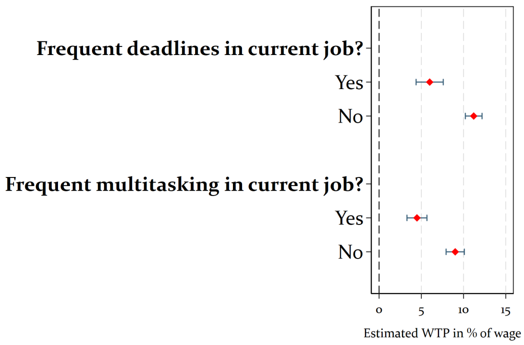
(b) Young



(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.

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