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Are they coming for us? Industrial Robots and the Mental Health of Workers*

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Abstract:

We investigate how an increase in the robot intensity (the ratio of industrial robots over employment) affects the self-reported mental health of workers in Germany. To do so, we combine individual mental health data from the German Socioeconomic Panel with the deliveries of robots to 21 German manufacturing sectors provided by the International Federation of Robotics for the period 2002-2014 (every two years). Controlling for a range of individual and sectoral characteristics, and employing individual-, time- and sectoral fixed effects, we find that an increase in robot intensity of 10% is associated with an average decrease of 0.59% of the average mental health standard deviation. This suggests that in a fast automating sector (i.e. rubber and plastics), where the robot intensity increased by approximately 2000%, mental health would have decreased by 118% of one standard deviation. This effect seems to be driven by job security fears of individuals working in non-interactive jobs and the fear of a decline in an individual's economic situation. Moreover, further sample divisions into low, middle and high occupational groups shows that the negative effects are affecting mostly the middle-level occupational group. Splitting the sample according to different age groups shows that the mental health of younger workers is the most vulnerable to an increase in automation. Results are also robust to instrumenting the stock of robots, and to different changes in the sample.

Keywords: Mental Health; Industrial Robots; Germany; Job Loss Fear; Job Polarization.
JEL codes: I10; O30 ; I31; J6

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1 Introduction

The automation trend encompasses the increased usage of industrial robots in production, digitization and the potential adoption of artificial intelligence. While the latter two are somewhat difficult to measure, the stock of robots is available from the International Federation of Robots (IFR). According to their data, in 1990 there were about 400,000 industrial robots worldwide, while this number grew to more than 2 million in 2017. In the last five years, the adoption of industrial robots has accelerated significantly (with an average worldwide growth rate of 11% in the last 5 years). Acemoglu and Restrepo (2017), Graetz and Michaels (2018) and Dauth et al. (2017), among others, have provided initial evidence that industrial robots are affecting the labor force in the United States, European countries and in Germany, respectively. Other studies such as Frey and Osborne (2017) and Arntz et al. (2017) estimate the replaceability of jobs either in an occupation-based approach or a task-based approach. Although both studies differ in the estimated percentage of replaceability (the estimates of Arntz et al. (2017) being more conservative), these numbers are non-negligible and have spiked the attention of the media and a growing body of literature. Some news articles portray a rather pessimistic picture of the impact of automation of workers, such as "The robots are coming for your job" (The Economist, 2018), "Automation and anxiety" (The Economist, 2016) or "Automation angst" (The Economist, 2015). A recent survey from the PEW Research Center (2017) shows that the prospect of further automation in the future is not well received by the U.S. population: 72% of the interviewed in the United States expressed their worry about the "future where robots and computers can do the jobs of many humans", while only 33% were enthusiastic about it.

The above sources have in common that they are particularly interested in the consequences of automation on labour market outcomes, such as wages or employment. However, to our knowledge, there is not much work being done on the impact of automation on the health of workers. There exists initial evidence that globalization, a trend somewhat comparable to automation, has a negative impact on the health of affected workers. McManus and Schaur (2016) show the effect of Chinese import competition on the physical health of workers while Colantone et al. (forthcoming) find that import competition (in general) has a negative effect on the mental health of workers in the United Kingdom. Similar effects appear to be affecting the German workforce, where offshoring has been found to impact the mental health of German workers negatively (Geishecker et al., 2012).

As import competition or offshoring are perceived to have comparable labour market effects as automation, this paper aims to provide further evidence on the implications of automation (represented here by adoption of industrial robots) on the mental health of German workers. Germany was among the earliest adopters of automation technologies and currently holds one of the highest stock of robots internationally. A German study by the Institute of Labor Economics (IZA) and the career-oriented networking site XING found that 12.6% of a representative sample of German workers "fear that their job surely or probably will be replaced by modern technology in the next 5 years". For males, this percentage increased to 16 % (IZA/XING, 2017). Although these numbers are significantly lower than the ones of the above cited PEW study for the U.S., they nonetheless reveal that at least certain parts of the workforce have an immediate fear of losing their job due to automation. Fear of losing their job and/or higher pressure to perform on the job could have an immediate impact on the well-being of workers, leading to increased stress, anxiety and other varieties of mental health issues. Furthermore, this stress could result in coping mechanisms such as increased work effort or longer working times, creating secondary stress effects that also could impact their mental health.

In what follows, we investigate how an increase in the amount of industrial robots over employment (the robot intensity) affects the self-reported mental health of workers in Germany. We combine mental health data of individuals from the German Socioeconomic Panel (SOEP), and the deliveries of robots to 21 German manufacturing sectors provided by the IFR for the time frame from 2002 to 2014 (every two years). In the next Section, we briefly discuss our data sources. In the following Section 3 we present the empirical strategy and the results of regressing the robot intensity in a sector on the mental health of individuals working in that sector. We split the sample along occupational and educational lines, and provide evidence that the proposed job polarization hypothesis (refer to Goos et al. (2014), for example) extends to the mental health dimension. Furthermore, splitting the sample into to different age groups shows that the mental health of younger workers is the most vulnerable to an increase in automation. Results are also robust to instrumenting the stock of robots in Germany with the robot stock of France, the United Kingdom, Spain, Italy, Norway and Finland (in a similar vein to Dauth et al. (2017)). In Section 4 we investigate the transmission channel of the observed effects. We test whether individuals experience higher job-loss fears, economic worries, work longer hours or are dissatisfied with their occupation. We end with a conclusion.

2 Data and methodology

We link individual, bi-yearly information on the mental health of individuals provided by the German Socio-Economic Panel (SOEP) with the stock of robots at the industry level. Therefore, all individuals within an industry are assigned with the a specific stock of robots for a given year[1]. The SOEP provides additional individual-level control variables. The third data source is the World Input Output Database - Socioeconomic Accounts (WIOD - SEA) which provides industry level statistics on employment and other sectoral statistics. All of these sources will be briefly described below. The time period of the study is between 2002 and 2014, where data is available for every even year.

2.1 SOEP

The (SOEP) is a longitudinal household survey provided by the DIW Berlin. It contains yearly answers from around 30 thousand respondents of approximately 11 thousand different households. It is a representative survey and includes information on different topics such as employment status, relationship status, satisfaction, fear, health, and personal and household income statistics. In 2002, the first set of health indicators entered the survey, which have been repeated since then every second year. Consequently, the sample for our analysis of mental health impacts of automation consists of 7 waves, from 2002 until 2014.

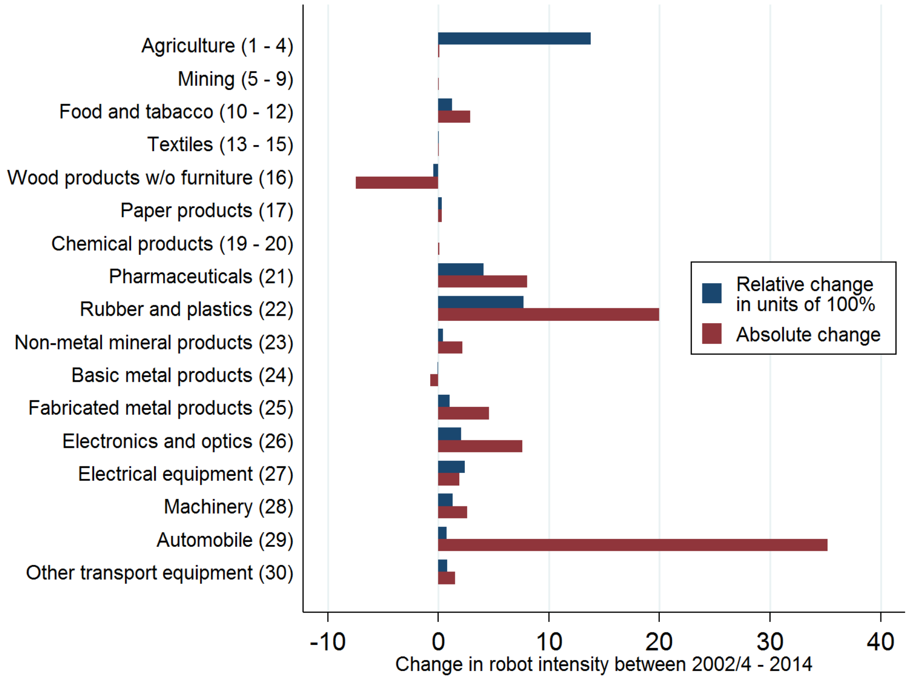
The mental health index in the SOEP is created by combining the answers to 12 health related questions [2] into 8 subcategories. See Table A.2 in the appendix for the matching between mental health related survey questions and subcategories (adopted from Hofmann and Mühlenweg (2018)). The subcategories are then combined into a single physical and mental index variable. This index variable is constructed to take values between 0 and 100, to have a mean of 50 and a standard deviation of 10 for the SOEP sample of 2004. A higher score means better mental health. The relevant mental health index variable is called *mcs* in the SOEP data set. For further information on the construction of the mental health index variable, refer to Anderson et al. (2007).

Additionally, in Section 3.2.4, we investigate the influence of the task-content of jobs on the impact of robot intensity on mental health. We link SOEP data with a compatible task-index, which was generously provided from Baumgarten et al. (2013).

[1] It would also be interesting to analyze what happens with the people that are unemployed and to assess whether automation contributed to this employment status, but this goes beyond the scope of the paper and will be left for future research.

[2] An approach based on the SF-12v2 approach, which is, for example, also used in the British Household Panel Survey (BHPS).

Figure 1: Changes in robot intensity



Y-axis shows a shortened sector description and sector codes based on NACE Rev. 2. Due to data availability, changes in sector 19 - 20, 21, 22, 26, 27 and 28 are from 2004 - 2014.

2.2 Robot Data

The International Federation of Robotics (IFR) is the only available source to retrieve information on the stock of industrial robots[3] employed in different countries and in different sectors. The IFR records the deliveries of robots and calculates the resulting stock of robots, assuming a complete depletion of the industrial robot after 12 years. In this paper, instead, we follow the standard economic literature and use the perpetual inventory method[4], assuming a yearly depreciation rate of 10%. Empirical results of using different depreciation rates (5 % and 15%) are available in Table 2. The IFR has it's own classification of sectors, which is based on the ISIC Rev. 4 classification. The SOEP provides the information in which sector an individual works according to the NACE Rev. 2 classification at the 2-digit level. Fortunately, the IFR and the SOEP classifications of sectors can be matched. The IFR-provided robot deliveries are in some cases only available from 2004. In other cases, only the 1-digit level deliveries are available, resulting in some 2-digit sectors in the SOEP to be combined into the next higher level. Table A.1 in the appendix provides information on the exact content of the sectors used in this study, the exact matching of sectors is available upon request.

[3] A "manipulating industrial robot (...) defined by ISO 8373 (is) an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications"Graetz and Michaels (2018); International Federation of Robotics (2012).

[4] Which means that the stock of robots ST_t in period t is given by the sum of the deliveries of robots DE_t in that period and the stock of robots of the previous period, ST_{t-1}, minus the depreciation rate δ times the stock of robots of period t, i.e. $\mathrm{ST}_t = \mathrm{DE}_t - \mathrm{ST}_{t-1} - \delta \cdot \mathrm{ST}_t$. Graetz and Michaels (2018) use the same method, also with a depreciation rate of 10%.

2.3 Sector Controls

2.3.1 The WIOD - SEA Database

When a sector employs an additional robot, the impact of this robot on workers should be assessed conditionally on the size of the sector. To control for the sector size, we divide the stock of robots by the employment of the respective sector (in units of thousands of employees), to construct the "robot intensity" of a sector. For this, data on the employment in each sector is needed. The World Input-Output Database (WIOD) provides in their "Socio-Economic Accounts" (SEA) 2016 release data on employment, gross values and prices of output, intermediate inputs and value added and compensation of capital and labour used in production for 56 industries in 43 countries for the years 2000 - 2014. The SEA itself is sourced by the World Input-Output tables, combined with employment data from Eurostat. The data is available at the 2-digit ISIC Rev. 4 level, which again can easily be matched to the definition of sectors used in this paper.

Figure 1 shows how the calculated robot intensity has changed in absolute and relative numbers from 2002/2 until 2014. Large differences between sectors are visible. The absolute change is biggest in the automobile sector, followed by the rubber and plastics sector, where the robot intensity increased by more than 20 robots per thousand employees.

2.3.2 Import Competition

Competition from abroad might pressure companies to try and reduce the costs of production, potentially leading to higher automation levels. Simultaneously, it might lead to a decrease in the mental health of workers as competitiveness both between companies and within companies increases. We therefore control for import competition to partial out this effect from the "pure effect" of industrial robots on mental health. This import competition variable should reflect the competition from abroad a domestic firm faces when selling one of their products on the domestic market. The purpose of the sold product can either be to be used as an intermediate input, or to be used as a final product. When this concept is applied to the sectoral level, it rephrases to the competition firms in sector S face by the sum of imported products originating from the corresponding (same) sector S in the respective exporting countries. This assumes that sectors produce unique bundles of products that are comparable between countries and therefore compete with each other. The "International Supply and Use Tables" from the WIOD for the years 2000 - 2014 provides the imported values of the product bundles tied to a domestic sector, so these can be summed up (over all exporting countries). This sum is defined as $\text{Imp}_{S,t}$ and the corresponding value of the product bundle a sector S produces as $\text{Dom}_{S,t}$. Then, the import competition in sector S in a specific year t is defined by the following equation:

$$\text{Import Competition}_{S,t} = \frac{\text{Imp}_{S,t}}{\text{Imp}_{S,t} + \text{Dom}_{S,t}} \tag{1}$$

Therefore, $\text{Import Competition}_{S,t}$ measures how much of the products of a sector S that are sold on the German market are imported, compared to the sales of this sector-specific product bundle.

3 Mental Health and Robot Intensity

3.1 Mental Health Identification Strategy

The mental health of workers depends on a plethora of factors. Naturally, not all of these factors are observable, consequently, they cannot be included in a regression model, and therefore enter the error term. If, however, some of these variables simultaneously affect the stock of robots or other independent variables, the estimated coefficients are not consistent. In order to minimize this threat, sectoral, time, and individual fixed-effects are included, as well as a wide array of time-changing sectoral and individual control variables. The following equation is estimated:

$$\mathrm{MH}_{t,i,S} = \beta_0 + \beta_1 \cdot \mathrm{RI}_{t,S} + \beta_2 \cdot \mathrm{X}^{\text{indv.}}_{t,i} + \beta_3 \cdot \mathrm{X}^{\text{sector}}_{t,S} + \eta_S + \tau_t + \mu_i + \epsilon_{t,i,S} \tag{2}$$

where $\mathrm{MH}_{t,i,S}$ is the mental health index score of individual i, measured at time t, who works in sector S, where the individual is exposed to the sector- and year-specific robot intensity $\mathrm{RI}_{t,S}$. $\mathrm{X}^{\text{indv.}}_{t,i}$ and $\mathrm{X}^{\text{sector}}_{t,S}$ are vectors of individual and sectoral control variables (respectively) and η_S, τ_t and μ_i are the various fixed effects.

The inclusion of time-changing individual covariates is a double-edged sword. On one hand, it decreases the risk of omitted variable bias. To see why, imagine a sector where employees experience a negative trend in work satisfaction. This could potentially influence their mental health, but also the decision of CEOs to replace the demotivated workers with robots. Leaving this variable out might introduce omitted variable bias into the model. As the work satisfaction of workers is time-changing, even individual fixed-effects can not solve this problem.

On the other hand, including independent variables such as work satisfaction creates the risk of simultaneity problems, because in this example, it is unclear if mental health causes better or worse work satisfaction, or work satisfaction causes better or worse mental health. Thus, throughout the paper, the analysis is done mostly twofold: first without any variables that could suffer from any obvious simultaneity problems (column (3) in Table 1), then with a richer set of individual control variables (column (5) in Table 1).

3.2 Empirical Results

In the following section, we present the results of the regression equation given by Eq. (2) under changing sets of controls and sample selections.

3.2.1 Main Results

Table 1 shows the results for the full sample, where the set of individual and sectoral control is increasing in size as the column-number increases. All regressions in panel A (OLS) and B (instrumental variable estimation) include individual, sectoral and time fixed effects. Therefore, all of the estimated regression parameters can be interpreted as the reaction of an individuals mental health index due to changes over time in the exposure to robot intensity or to other independent variables. In column (1) of panel A, it can be seen that changes in the logged robot intensity seem to have a significant negative effect on then mental health index score of workers in the respective sector. However, as discussed in section 3.1, this observed negative effect could be caused by confounding factors that influence robot intensity and mental health simultaneously. For example, poor competitiveness of a sector could result in an accelerating rate of automation as well as lower mental health.

Columns (2) and (3) add as controls the value of gross output and intermediate inputs, capital and labour compensation, the prices of gross output, intermediate inputs and value added, the number of persons engaged, the import competition of a sector (column (2)) and the size of the company where an individual works (column (3)). The set of covariates in column (3) is the broadest set of covariates that should not suffer from the suspected simultaneity problems. In model (3), the mental health of workers is observed to decrease by 0.00526 index score points for each additional percent of robot intensity. Although this change seems to be quite small, inspecting Fig. 1 shows that percentage changes over the sample length can be very high. For example, the robot intensity in the plastics sectors grew by 770.5% from 2004 until 2014. Therefore, our regression model would imply a decrease of $770.5 \cdot 0.00526 = 4.053$ mental health index points for an individual working for the whole time in that sector, which is equivalent to 44.25% of one standard deviation of the mental health index variable in that sector.

Column (4) includes a dummy variable that indicates if a person has changed the sector (and therefore their exposure to robots) in the last year. Changing the sector means naturally

Table 1: Robot intensity and mental health

Dependent Variable: Mental Health Index							
Regression:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: Fixed Effect Estimation						
log(Robot Intensity)	-0.520**	-0.564*	-0.526*	-0.525*	-0.650**	-0.670**	-0.626**
	(0.259)	(0.293)	(0.293)	(0.293)	(0.288)	(0.289)	(0.286)
Import Competition		-4.533	-5.778	-5.231	0.715	-0.258	1.802
		(9.451)	(9.533)	(9.556)	(9.448)	(9.572)	(9.449)
Size of company			-0.0613	-0.0620	-0.106	-0.122	-0.115
			(0.0701)	(0.0701)	(0.0730)	(0.0754)	(0.0742)
Changed Sector l.y.				-0.446	-0.492	-0.395	-0.398
				(0.346)	(0.335)	(0.338)	(0.336)
Actual working time					-0.0728***	-0.0743***	-0.0742***
					(0.0157)	(0.0164)	(0.0164)
Personal labour income					-0.0184	0.00762	0.00189
					(0.0501)	(0.0311)	(0.0326)
Index of physical health					-0.0525***	-0.0570***	-0.0645***
					(0.0186)	(0.0187)	(0.0185)
Some wor. job sec.						-1.229***	-0.952***
						(0.239)	(0.242)
Great wor. job sec.						-2.039***	-1.302***
						(0.371)	(0.386)
Some wor. own eco. dev.							-1.138***
							(0.252)
Great wor. own eco. dev.							-2.927***
							(0.404)
	Panel B: Instrumental Variable Estimation						
log(Robot Intensity)	-0.395	-0.879	-0.931*	-0.954*	-1.011*	-0.881	-0.791
	(0.371)	(0.556)	(0.554)	(0.554)	(0.547)	(0.558)	(0.548)
Kleibergen-Paap Wald rk F statistic	1139.08	1614.55	1612.48	1602.13	1523.72	1456.26	1451.78
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Add. sector controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Add. individual controls	No	No	No	No	Yes	Yes	Yes
Observations	12251	12251	12150	12150	11677	11449	11445
Number of individuals	5916	5916	5876	5876	5708	5619	5619
R-squared overall model	0.00129	0.00142	0.00121	0.00125	0.100	0.111	0.123

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Additional sector controls are: value of gross output, value of intermediate inputs, price of gross output, price of intermediate inputs, capital compensation, compensation of employees and persons engaged. Additional individual controls are: relationship status, personal income satisfaction, household income satisfaction, living standard satisfaction, health satisfaction, sleep satisfaction, work satisfaction, life satisfaction, life-in-5-years predicted satisfaction, worries about general economic development, body mass index, and body mass index squared. Exogenous instruments in panel B are the robot intensities of France, the UK, Italy, Spain, Norway and Finland.

changing the employer, which could influence an individuals mental health negatively or positively, creating the false impression that a change in the robot exposure led to a change in mental health. However, the dummy remains statistically insignificant throughout columns (4) - (7), and the significance of the coefficient of logged robot intensity remains unaffected by the inclusion.

Starting with the regression of column (5), the working time of the individual (including over-time hours), their personal labour income, an index of physical health[5], their body mass index, their relationship status, their satisfaction with their income, work, life, sleep, health and predicted life-in-5-years, and their worries about the general economic development are introduced into the regression. Although we would expect the results to suffer from simultaneity problems, the coefficient size of robot intensity remains fairly stable.[6]

Regressions (6) and (7) include some of the potential transmission channels. In fact, worries

[5] Which is constructed in a similar way as the mental health index, higher values mean better physical health.
[6] Adding these individual controls step-by-step does not change the results.

about job security and their own economic development[7] seem to be significantly negatively correlated with the mental health of individuals. Surprisingly, the coefficient of robot intensity remains largely unaffected by the inclusion of the suspected transmission channel.

In Panel B, robot intensity gets instrumented by the robot intensities[8] of France, the United Kingdom, Spain, Italy, Norway and Finland. In all regressions, the sign of the robot intensity is still negative, although coefficients become insignificant for regressions (1) - (2) and (6) - (7). In our preferred estimations (3) and (5), the instrumented robot intensity coefficient is significant.

Table 2: Robot intensity and mental health, robustness checks

Dependent Variable: Mental Health Index							
Regression:	(1) Baseline	(2) 2006 - 2010	(3) Excl. automotive	(4) Excl. mining and agr.	(5) 5% dep. rate	(6) 15% dep. rate	(7) Year trend
Corresp. Table 1:				(3)			
				Panel A: All genders			
Log(Robot intensity)	-0.526*	-1.854	-0.470	-0.582*	-0.560*	-0.499*	-0.528*
	(0.293)	(1.298)	(0.321)	(0.352)	(0.307)	(0.283)	(0.274)
Obs.	12,150	4,890	10,100	11,010	12,150	12,150	12,150
				Panel B: Males			
Log(Robot intensity)	-0.740**	-0.938**	-0.784**	-0.813*	-0.797**	-0.681**	-0.760**
	(0.343)	(0.401)	(0.383)	(0.417)	(0.361)	(0.331)	(0.322)
Observations	8,617	6,026	6,954	7,787	8,617	8,617	8,617
				Panel C: Females			
Log(Robot intensity)	-0.228	-0.399	0.0150	-0.211	-0.191	-0.276	-0.158
	(0.571)	(0.653)	(0.589)	(0.653)	(0.590)	(0.556)	(0.532)
Observations	3,533	2,395	3,146	3,223	3,533	3,533	3,533
Add. indiv. contr.	No	No	No	No	No	No	No
Corresp. Table 1:				(5)			
				Panel A: All genders			
Log(Robot intensity)	-0.650**	-0.900***	-0.604*	-0.656*	-0.677**	-0.625**	-0.699**
	(0.288)	(0.342)	(0.318)	(0.343)	(0.301)	(0.279)	(0.272)
Observations	11,677	8,074	9,673	10,654	11,677	11,677	11,677
				Panel B: Males			
Log(Robot intensity)	-0.861**	-1.133***	-0.930**	-0.830**	-0.906***	-0.809**	-0.951***
	(0.335)	(0.398)	(0.377)	(0.401)	(0.352)	(0.324)	(0.320)
Observations	8,323	5,804	6,690	7,574	8,323	8,323	8,323
				Panel C: Females			
Log(Robot intensity)	-0.282	-0.583	0.0601	-0.536	-0.273	-0.312	-0.220
	(0.584)	(0.656)	(0.603)	(0.660)	(0.603)	(0.568)	(0.543)
Observations	3,354	2,270	2,983	3,080	3,354	3,354	3,354
Add. indiv. contr.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Independent variables are the same as in column (3) and (5) of Table 1 respectively.

3.2.2 Robustness Checks

In Table 2, we test the robustness of the results from the main regression presented in Table 1. Table 2 is split into an upper and a lower part. The upper part follows the specification of column (3) from Table 1 in terms of control variables, whereas the lower part follows the column (5) specification. Column (1) in Table 2 simply replicates the baseline results from the main regressions for comparison. Column (2) removes the two earliest and latest waves of observations. Although the coefficient of robot intensity is no longer significant for the all-gender-sample, it

[7] The baseline for both variables is "no worries".

[8] Which are constructed exactly like the robot intensity of Germany.

remains strong and robust for the male-only sub-sample. Columns (3) and (4) exclude sectors which either have an exceptionally high or low robot intensity, for expample the automotive sector. The estimates in columns (5) and (6) show that coefficient sizes barely change when assuming alternative robot stock depreciation rates of either 5% or 15%. Finally, column (7) replaces the bi-yearly time dummies with a continuous linear time trend, which leaves the results largely unaffected.

A striking observation from Table 2 is that the effect of robot intensity on mental health is more robust and statistically significant for males across specifications and sub-samples. This is in line with Masayuki (2017) and Acemoglu and Restrepo (2017) (among others) who find that robots have affected men the most. The size of the coefficient is also higher for men than for females. A natural explanation for result could be that females often work in jobs that require more human to human interaction, which is perceived to be harder to replace by automation. In Table 5, we test the second part of this hypothesis. Finally, Table 2 has been replicated instrumenting the stock of robots as in the previous case. Results (which remain fairly unchanged) can be found in Table A.5 of the Appendix.

3.2.3 Educational and Occupational Effects

An often discussed dimension of job replacing trends is is their differential impact on different subgroups of society. As we have just discussed, it is evident from Table 2 that men are more affected than women. However, the literature is more concerned with the differential impact of automation or globalization on groups of varying "skill". The idea is that jobs that require a higher skill should be harder to replace. A more sophisticated hypothesis suggests that the job-replacing trend should be affecting the middle- income/skill group the most. Our understanding of this idea is that the probability that a job will be automated depends on both the cost of automating it (which depends on the nature of the task the job is associated with) and the cost of employing a human for this job. Since low skilled workers likely have a lower wage (also due to lower training requirements, see Feng and Graetz (forthcoming)), and higher skilled workers will likely have a job that is costly or impossible to automate, middle skilled workers are thought to be more affected be routine-biased technical change (automation) or offshoring, since they do more often easy-to-automate routine work (see, for example, Goos et al. (2014)).

Table 3 analyzes whether there are different effects by occupational and educational levels. In the upper part of the Table, we split the sample according to information on an individual's current job position, as contained in the variable *pgstib* of the SOEP. Jobs requiring no or only little vocational training or involve simple-to-do functions are sorted to the lowest occupational group. The middle group contains workers on a job that requires a completed vocational training degree or a high school diploma. The highest occupational group is formed by individuals that are self-employed, which are themselves employing workers or have jobs that require tertiary education. Table A.7 in the appendix provides the exact sorting of individuals into the groups. Panels (A) and (B) (in the upper part of the table) show a strong negative effect on the mental health for the medium-level occupations. The same can be found if we again switch the specification to include more individual control variables, as we have done before in the lower part of Table 2. This specification again corresponds to specification (5) of Table 1. While the already observed negative effect of robot intensity for the medium-occupation group stays the same in terms of size and significance, now the all-gender sample also shows a significantly negative coefficient for the high-occupation group. As before, there is no significant effect for females. Interestingly, the coefficient is at least twice as large for males than for the pooled sample. Overall, we take this as robust evidence that the mental health of workers engaged in the medium-level jobs is affected the most by the increase of industrial robots, providing new topics to the job polarization discussion.

Now we turn to the lower part of Table 3, where the sample is split according to the education an individual obtained. We constructed these educational groups by matching the highest educational degree obtained by individuals with educational groups as defined by the International

Table 3: Robot intensity and mental health (by occupation and skill groups)

Dependent Variable: Mental Health Index						
	Sample split according to occupation:					
Regression:	(1)	(2)	(3)	(4)	(5)	(6)
Occupational Group:	Low	Medium	High	Low	Medium	High
Corresp. Table 1:		(3)			(5)	
	Panel A: All genders					
log(Robot Intensity)	-0.144	-1.005**	-0.250	0.223	-1.113**	-0.969*
	(0.642)	(0.453)	(0.579)	(0.629)	(0.451)	(0.569)
Observations	3,205	5,112	2,965	3,093	4,979	2,829
	Panel B: Males					
log(Robot Intensity)	0.287	-2.332***	0.403	0.590	-2.460***	-0.201
	(1.386)	(0.761)	(0.876)	(1.277)	(0.774)	(0.864)
Observations	1,735	3,481	2,314	1,692	3,406	2,226
	Panel C: Females					
log(Robot Intensity)	1.007	-1.079	-0.0201	0.253	-1.141	-0.218
	(1.145)	(1.262)	(2.852)	(1.184)	(1.235)	(3.109)
Observations	1,288	1,375	449	1,226	1,328	425
	Sample split according to education:					
Regression:	(7)	(8)	(9)	(10)	(11)	(12)
Skill Group	Low	Medium	High	Low	Medium	High
	Panel D: All genders					
log(Robot Intensity)	-0.969	-0.582	-0.181	-0.819	-0.696*	-0.528
	(0.780)	(0.397)	(0.536)	(0.772)	(0.397)	(0.512)
Observations	1,635	7,098	3,241	1,569	6,806	3,133
	Panel E: Males					
log(Robot Intensity)	-1.583	-0.965	-0.442	-1.403	-1.153	-0.774
	(1.192)	(0.692)	(0.803)	(1.133)	(0.711)	(0.751)
Observations	975	4,597	2,379	947	4,447	2,304
	Panel F: Females					
log(Robot Intensity)	-1.784	0.551	1.382	-1.574	0.127	0.223
	(1.837)	(1.112)	(1.539)	(1.823)	(1.143)	(1.419)
Observations	535	2,086	703	507	1,972	680
Add. indiv. contr.	No	No	No	Yes	Yes	Yes

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Independent variables are the same as in column (3) and (5) of Table 1 respectively, accordingly columns (1) - (3) of this table include mostly sector controls and columns (4) - (6) additionally a set of individual controls.

Standard Classification of Education (ISCED).[9] The low-skill group consists of levels 0 - 2 of the ISCED-97, which refers to pre-primary, primary and lower secondary education. Levels 3 and 4 formed the middle-skill group, consisting of workers with upper secondary and post-secondary education. The highest group consists solely of workers with tertiary education. Unexpectedly, almost no statistically significant results are found. This seems to be stemming from the fact that the corollaries of robots adoption to the mental health of workers are more closely related to the job that workers are actually doing rather than their obtained educational level. Moreover, looking at the number of observations in both sample splits, there is no direct connection with the educational level and the skill-level of tasks that workers do.

3.2.4 Age groups

In Table 4, we follow Masayuki (2017) in dividing the sample into age groups. For comparability, we define our lowest age group the same way as in the Japanese study. The group of 20 to 29 year old individuals is the one fearing losing jobs to automation the most in Japan. In the

[9]We follow Geishecker et al. (2012) and Baumgarten et al. (2013).

Table 4: Robot intensity and mental health (by age group)

Dependent Variable: Mental Health Index					
Corresp. Table 1:			(3)		
Age groups	(1) 20-29	(2) 30-39	(3) 40-49	(4) 50-59	(5) 60+
			Panel A: All		
Log(Robot intensity)	-1.556***	0.256	0.0197	-0.0467	-0.666
	(0.506)	(0.386)	(0.294)	(0.364)	(0.761)
Observations	1,674	2,751	3,921	2,754	565
			Panel B: Males		
Log(Robot intensity)	-1.608***	0.239	0.385	-0.423	-0.788
	(0.487)	(0.405)	(0.387)	(0.431)	(0.809)
Observations	1,193	1,983	2,675	1,965	440
			Panel C: Females		
Log(Robot intensity)	-0.897	0.141	-0.638	1.137**	3.401
	(1.996)	(1.386)	(0.460)	(0.506)	(2.626)
Observations	481	768	1,246	789	125
Corresp. Table 1:			(5)		
			Panel D: All		
Log(Robot intensity)	-1.158**	0.402	-0.294	-0.0826	-1.409
	(0.512)	(0.407)	(0.294)	(0.365)	(0.886)
Observations	1,623	2,672	3,768	2,639	507
			Panel E: Males		
Log(Robot intensity)	-0.794	0.479	-0.0426	-0.561	-1.284
	(0.488)	(0.428)	(0.405)	(0.449)	(0.890)
Observations	1,156	1,937	2,589	1,893	399
			Panel F: Females		
Log(Robot intensity)	-2.611	-0.495	-0.709	1.394***	8.687**
	(1.748)	(1.123)	(0.432)	(0.522)	(4.067)
Observations	467	735	1,179	746	108

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Independent variables are the same as in column (3) and (5) of Table 1 respectively.

German case, as Table 4 shows, results are similar. Again, young men seem to be affected more negatively than same-aged women. Interestingly, we find a significant positive effect of automation for older females. Table A.6 in the Appendix shows that these results remain fairly the same when instrumenting the stock of robots.

3.2.5 Task-specific responses to automation

As we have seen in Table 3, the "skill" or educational level of an individual does not necessarily decide how affected he or she is by a higher exposure to robots. The actual job an individual is performing is more revealing. As Baumgarten et al. (2013) state it, "tasks are not synonymous with skills". Although the occupational groups as we defined them in Table 3 seem to somewhat capture an uneven impact of automation. However, the job descriptions that we used to construct those groups contain not much information about the actual task a person is performing in their job.

The SOEP provides more detailed occupational information contained in the variable *pgkldb92*, which codes individual occupations using the German Federal Statistical Offices classification of occupations. To link this information with the actual task content of the occupation, we follow Becker et al. (2013) and Baumgarten et al. (2013). Becker et al. (2013) use information provided by the German Qualification and Career Survey 1998/99 (BIBB-IAB work survey), where responding workers identified their occupation and the tools they use.[10] The authors then assigned each tool an either routine or non-routine, and additionally an interactive or non-interactive task-content. Non-routine tasks are non-repetitive tasks that require a higher degree of creative problem solving, and interactive tasks involve interaction and communication with other individuals (Becker et al., 2013). For example, the task tied to the tool "cash register" is labeled as a routine, but interactive task, because the task is repetitive, but involves interaction with customers. The exact mapping can be found in Table A1 in Appendix A of Becker et al. (2013). Baumgarten et al. (2013) apply this mapping to the classification of occupations used in the *pgkldb92* variable of the SOEP to identify the task content of each of the 2-digit-level occupations[11]. Following again Becker et al. (2013), they create an continuous index value for each of the occupations, that represents the average[12] number of all non-routine or interactive tasks in an occupation relative to the maximum of these averages across occupations, as given by the following equations:

$$\mathrm{NR}_k = \frac{\text{Average number of non-routine tasks in occupation } k}{\text{Maximum average number of non-routine tasks across all occupations}} \tag{3}$$

$$\mathrm{IA}_k = \frac{\text{Average number of interactive tasks in occupation } k}{\text{Maximum average number of interactive tasks across all occupations}} \tag{4}$$

(Baumgarten et al., 2013). Equations (3) and (4) produce index values NR_k and IA_k that vary between 0 and 1, where 1 represents the occupation that uses on average the most different non-routine or interactive tools in the sample, and 0 would represent an occupation with no non-routine or interactive tasks. That is, no respondent indicated to work with tools that are classified as non-routine or interactive.

However, as Baumgarten et al. (2013). point out, an occupation that uses a smaller amount of tools in general will have a lower index score by construction, even if all of the used tools qualify as non-routine or interactive. They accordingly propose a different denominator for the fractions in Equations (3) and (4):

$$\text{NR-Alt}_k = \frac{\text{Average number of non-routine tasks in occupation } k}{\text{Average number of total tasks in occupation } k} \tag{5}$$

$$\text{IA-Alt}_k = \frac{\text{Average number of interactive tasks in occupation } k}{\text{Average number of total tasks in occupation } k} \tag{6}$$

Here, even if only one task is performed on average in an occupation, if that task is a non-routine or an interactive one, the respective index score would be equal to 1. This would mean that the average respondent in this occupation is performing only non-routine or interactive tasks.

Table 5 presents the results of interacting the task-index values with our measure of robot intensity. The upper half (Panel A) shows the results for the whole sample, while the lower half (Panel B) presents the results for males only. The left half again follows column (3) from Table 1, while the right side repeats the exercise for column (5). The table is therefore split into 4 quadrants. The first two regressions in each quadrant (Columns (1), (2), (5) and (6)) include both the task index and the interaction between the task index and robot intensity. As we are still employing individual fixed effects, the values of the task index will only vary if an individual changes their occupation. Accordingly, it is no surprise that the coefficients of the task indices itself, without the interaction with robot intensity, are mostly insignificant. The later regressions in each quadrant (Columns (3), (4), (7) and (8)) therefore do not include the parent of the respective task index.

[10] And to a lesser degree, some tasks.

[11] Where some of the 2-digit-occupations are combined to counteract a lack of observations in the occupation-tool-task matching BIBB-IAB work survey.

[12] Average over respondents working in the respective occupation.

Table 5: Robot intensity and mental health (with interactions with tasks)

Dependent Variable: Mental Health Index								
Regression:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Corresp. Table 1:	(3)				(5)			
	Panel A: All genders							
log(Robot Intensity)	-0.679*	-0.821**	-0.572*	-0.626**	-0.754**	-0.740**	-0.672**	-0.695**
	(0.373)	(0.374)	(0.298)	(0.304)	(0.356)	(0.358)	(0.294)	(0.299)
NR	0.999				1.653			
	(3.707)				(3.530)			
log(Rob. Int.) · NR	-0.399		-0.292**		-0.487		-0.308**	
	(0.433)		(0.143)		(0.416)		(0.141)	
IA	-3.731				-3.811			
	(6.600)				(6.212)			
log(Rob. Int.) · IA	0.863		0.456**		0.832		0.417*	
	(0.768)		(0.223)		(0.730)		(0.216)	
NR-Alt.		-0.571				2.439		
		(8.543)				(8.017)		
log(Rob. Int.)		-0.0687		-0.136		-0.532		-0.264
· NR-Alt.		(1.003)		(0.345)		(0.953)		(0.341)
IA-Alt.		-12.84				-6.741		
		(10.02)				(9.524)		
log(Rob. Int.)		2.683**		1.183**		1.708		0.921*
· IA-Alt.		(1.344)		(0.523)		(1.295)		(0.518)
Observations	11815	11815	11815	11815	11353	11353	11353	11353
Add. indiv. contr.	no	no	no	no	yes	yes	yes	yes
	Panel B: Males							
log(Robot Intensity)	-0.904**	-0.976**	-0.840**	-0.863**	-0.967**	-0.922**	-0.937***	-0.931***
	(0.441)	(0.431)	(0.348)	(0.351)	(0.419)	(0.410)	(0.341)	(0.344)
NR	3.981				3.829			
	(4.291)				(4.112)			
log(Rob. Int.) · NR	-0.838*		-0.404**		-0.845*		-0.429***	
	(0.498)		(0.157)		(0.482)		(0.154)	
IA	-5.461				-4.491			
	(7.262)				(6.860)			
log(Rob. Int.) · IA	1.283		0.690***		1.160		0.675***	
	(0.863)		(0.260)		(0.821)		(0.253)	
NR-Alt.		8.208				9.069		
		(10.06)				(9.492)		
log(Rob. Int.)		-1.109		-0.196		-1.313		-0.310
· NR-Alt.		(1.166)		(0.389)		(1.116)		(0.379)
IA-Alt.		-18.43*				-11.40		
		(10.41)				(10.03)		
log(Rob. Int.)		3.653**		1.477**		2.547*		1.199**
· IA-Alt.		(1.508)		(0.616)		(1.470)		(0.611)
Observations	8356	8356	8356	8356	8069	8069	8069	8069
Add. indiv. contr.	no	no	no	no	yes	yes	yes	yes

Standard errors in parentheses, * p < 0.1, ** p < 0.05 and *** p < 0.01. Independent variables are the same as in column (3) and (5) of Table 1 respectively, accordingly columns (1) - (2) of this table include mostly sector controls and columns (5) - (8) additionally a set of individual controls.

In general, the interactiveness index (IA and IA-Alt.) interaction with robot intensity shows the expected sign: an increase of robot intensity over time in more interactive occupations seems to be associated with an positive response of mental health. For example, Column (4) suggests that an increase of robot intensity of 10% decreases average mental health of the full sample by -0.0625%, but increases mental health for those workers that have a fully interactive task, as measured by an alternative interactivity index of 1, by $-0.0625\% + 0.183\% = 0.12\%$. Apparently, interactiveness seems to be perceived as a shield against the prospect of being replaced by a robot.

Initially, we would have expected the same result for the non-routine task index (NR and NR-Alt.) interaction terms. Interestingly, they turn out to be exclusively negative in all regressions, meaning that for individuals with more non-routine tasks in their occupation, an increase in the robot intensity over time actually seemingly *decreases* their mental health. However, not all non-routine results are statistically significant. We interpret this as initial evidence that individuals perceive interactive tasks as harder to replace than non-routine tasks.

4 Mental Health and Robot Intensity: Transmission Channels

Its hard to believe that robots themselves directly decrease a general index of mental health. In this section, we therefore try to identify the underlying channels that link mental health with automation. As explained in the introduction, we assume that the observed effect for example in Table 1, is explained by an increase in the stress level of an individual, caused by either:

- an increased fear to lose their job due to being replaced, which could directly increase stress and anxiety levels;
- worrying that the individuals economic situation in the future might get worse, through expecting a lower wage due to a reassignment of tasks within their occupation;
- secondary stress effects through self-selected higher work effort or longer working hours employed as a coping tactic to counteract the above mentioned direct potential effects of automation.

In what follows, we use a similar regression equation as in the previous section:

$$\text{Transmission channel}_{t,i,S} = \beta_0 + \beta_1 \cdot \text{RI}_{t,S} + \beta_2 \cdot \text{X}^{\text{indv.}}_{t,i} + \beta_3 \cdot \text{X}^{\text{sector}}_{t,S} + \eta_S + \tau_t + \mu_i + \epsilon_{t,i,S} \quad (7)$$

where the dependent variable in no longer mental health, but one of the above mentioned transmission channels. We will use a largely unchanged set of individual and sector-specific control variables, as we will continue our practice to mainly use specifications (3) and (5) from Table 1. As a reminder: specification (3) contains mostly sector controls, to avoid the risk of simultaneity, whereas specification (5) includes also the larger set of individual controls, which should decrease the risk of omitted variables.

4.1 Empirical Results

4.1.1 Automation and Perceived Job Security

Table 6 shows the relationship between changes in robot intensity and the worries people experience about their job security.

The dependent variable here is the job security variable, which we already have seen as a control in columns (6) and (7) of Table 1. It is a categorical variable that takes the values ”no worries”, ”some worries” and ”great worries”. Because the related survey question is asked in every wave of the SOEP, the sample size increases compared to the regressions with mental health as the dependent variable. Columns (1) and (3) show results using logit fixed effects, (2) and (4) a linear probability model instrumented in the same way as in Table 1. Column (1) and (2) each correspond in their control vectors to the parsimonious specification (3) from Table 1, while the other columns follow specification (5).

We start with the full sample in Panel A. No statistically significant effects of automation on job-loss fear can be observed. We continue by acknowledging that the results from Table 3 suggest that there is large heterogeneity in the reaction of different genders and occupational groups on automation. We therefore split the sample again exactly as in Table 3. Panels B and C however show the neither the male nor female subgroup show any more significant results than the full sample. Furthermore, splitting the sample along occupational levels in Panels D, E and F does not show any differential job-loss fear due to higher robot exposure. Dividing the gender split into different levels of occupations, Panel G (column (2)) provides some evidence that an increase in robot intensity is associated with higher worries about the job security for men in the lowest occupational group.

Table 6: Transmission channel: robot intensity and job security (by occupations and genders)

Dependent Variable: Worries about job security				
Regression:	(1)	(2)	(3)	(4)
Model:	Logit FE	LPM IV	Logit FE	LPM IV
Corresp. Table 1:	(3)		(5)	
	Panel A: Full Sample			
log(Robot Intensity)	-0.0559	0.00771	-0.0394	0.00782
	(0.0854)	(0.0267)	(0.137)	(0.0272)
Observations	14191	26661	3753	10819
	Panel B: Men			
log(Robot Intensity)	-0.0974	0.0422	-0.0125	0.0367
	(0.102)	(0.0328)	(0.167)	(0.0337)
Observations	10379	18785	2751	7681
	Panel C: Females			
log(Robot Intensity)	0.0489	0.0736	-0.131	-0.231
	(0.0797)	(0.139)	(0.113)	(0.197)
Observations	8262	7791	3279	7065
	Panel D: Low Occupation			
log(Robot Intensity)	0.111	0.0654	0.0214	-0.0124
	(0.206)	(0.0551)	(0.401)	(0.0585)
Observations	2677	7348	595	2865
	Panel E: Medium Occupation			
log(Robot Intensity)	-0.0812	0.0118	-0.106	-0.0125
	(0.143)	(0.0421)	(0.233)	(0.0398)
Observations	5515	11264	1481	4669
	Panel F: High Occupation			
log(Robot Intensity)	-0.0521	-0.0144	0.0856	0.0916
	(0.175)	(0.0523)	(0.288)	(0.0616)
Observations	3566	6306	975	2601
	Panel G: Low Occupation Men			
log(Robot Intensity)	0.380	0.204**	0.629	0.0420
	(0.287)	(0.0845)	(0.512)	(0.0842)
Observations	1616	4284	352	1665
	Panel H: Medium Occupation Men			
log(Robot Intensity)	-0.254	0.0395	-0.425	0.00144
	(0.176)	(0.0525)	(0.315)	(0.0498)
Observations	3989	8056	1074	3355
	Panel I: High Occupation Men			
log(Robot Intensity)	-0.0434	0.00835	0.0191	0.0801
	(0.191)	(0.0546)	(0.321)	(0.0636)
Observations	3026	5284	837	2185
Add. indiv. contr.	No	No	Yes	Yes

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. The dependent variable is a factor variable of self-reported worries about job security, where the base value is "no worries about job security" and the two other values are "some worries" and "great worries". Independent variables are the same as in column (3) and (5) of Table 1 respectively, accordingly columns (1) and (2) of this table include mostly sector controls and columns (3) and (4) additionally a set of individual controls. The sample is split in panels D - I according to the occupational groups as in the upper part of Table 3. In the linear probability model, robot intensity is again instrumented as in Table 1.

Table 7: Transmission Channel: robot intensity and job security (with interactions with task-based indices of non-routine and interactive work)

Dependent Variable: Worries about job security						
Regression:	(1)	(2)	(3)	(4)	(5)	(6)
Model:	LPM	LPM	LPM IV	LPM IV	Logit	Logit
Corresp. Table 1:	(3)					
	Panel A: All genders					
log(Robot Intensity)	-0.0114	-0.0123	0.00883	0.00706	-0.0605	-0.0747
	(0.0191)	(0.0194)	(0.0213)	(0.0216)	(0.0868)	(0.0877)
log(Robot Intensity) · NR	0.0133*		0.0139*		0.0624*	
	(0.00725)		(0.00731)		(0.0341)	
log(Robot Intensity) · IA	-0.0218*		-0.0223*		-0.0605	
	(0.0117)		(0.0117)		(0.0540)	
log(Robot Intensity) · NR-Alt.		0.0223		0.0267		0.166*
		(0.0188)		(0.0191)		(0.0860)
log(Robot Intensity) · IA-Alt.		-0.0539*		-0.0545*		-0.130
		(0.0307)		(0.0318)		(0.120)
Observations	27810	27810	26310	26310	13978	13978
	Panel B: Males					
log(Robot Intensity)	-0.00970	-0.0117	0.0134	0.0110	-0.106	-0.116
	(0.0227)	(0.0230)	(0.0260)	(0.0263)	(0.104)	(0.105)
log(Robot Intensity) · NR	0.0167**		0.0149*		0.0662*	
	(0.00824)		(0.00831)		(0.0391)	
log(Robot Intensity) · IA	-0.0253*		-0.0228*		-0.0544	
	(0.0137)		(0.0136)		(0.0628)	
log(Robot Intensity) · NR-Alt.		0.0313		0.0308		0.179*
		(0.0214)		(0.0217)		(0.0985)
log(Robot Intensity) · IA-Alt.		-0.0588		-0.0512		-0.143
		(0.0367)		(0.0383)		(0.138)
Observations	19627	19627	18513	18513	10207	10207
Individual FE	yes	yes	yes	yes	yes	yes
Add. individual controls	no	no	no	no	no	no
Corresp. Table 1:	(5)					
	Panel C: All genders					
log(Robot Intensity)	-0.0195	-0.0222	0.00567	0.00224	-0.0593	-0.0743
	(0.0241)	(0.0247)	(0.0270)	(0.0276)	(0.135)	(0.138)
log(Robot Intensity) · NR	0.0117		0.00882		0.0829	
	(0.0111)		(0.0113)		(0.0585)	
log(Robot Intensity) · IA	-0.00493		-0.000777		-0.00712	
	(0.0183)		(0.0185)		(0.0909)	
log(Robot Intensity) · NR-Alt.		0.0413		0.0368		0.251*
		(0.0290)		(0.0301)		(0.151)
log(Robot Intensity) · IA-Alt.		-0.0220		-0.00887		-0.0433
		(0.0500)		(0.0526)		(0.226)
Observations	11326	11326	10685	10685	3846	3846
	Panel D: Males					
log(Robot Intensity)	-0.00500	-0.00693	0.0398	0.0373	-0.0439	-0.0381
	(0.0284)	(0.0290)	(0.0337)	(0.0343)	(0.167)	(0.169)
log(Robot Intensity) · NR	0.0171		0.0128		0.0911	
	(0.0129)		(0.0130)		(0.0665)	
log(Robot Intensity) · IA	-0.0234		-0.0173		-0.0212	
	(0.0221)		(0.0222)		(0.105)	
log(Robot Intensity) · NR-Alt.		0.0416		0.0338		0.252
		(0.0332)		(0.0344)		(0.175)
log(Robot Intensity) · IA-Alt.		-0.0697		-0.0491		-0.222
		(0.0629)		(0.0660)		(0.261)
Observations	8052	8052	7563	7563	2822	2822
Individual FE	yes	yes	yes	yes	yes	yes
Add. individual controls	yes	yes	yes	yes	yes	yes

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. The dependent variable is a factor variable of self-reported worries about job security, where the base value is "no worries about job security" and the two other values are "some worries" and "great worries". Independent variables are the same as in column (3) and (5) of Table 1 respectively. In the IV linear probability model, robot intensity is again instrumented as in Table 1.

This stands in contrast to the negative effects of automation on mental health that could only be observed for the medium occupational group in Table 3. We conclude that for the whole sample as well as for the occupational and gender sub-samples, the fear of job-loss seems to not be a strong transmission channel that links automation to lower mental health. However, as we have seen, the average task-content of an occupation an individual is performing is more telling about the perceived impact of automation.

In Table 7, we still use the job-loss fear as a dependent variable, but we incorporate (as in Table 5) an interaction of the robot intensity and the non-routine and interactive index of tasks. We use Linear Probability models, both without (Columns 1 and 2) and with instruments for the robot intensity (Columns 3 and 4), and Logit models (Columns 5 and 6).

In Panel A (both genders), a job with more non-routine tasks in a sector with increasing robot intensity is related to more worries about job security. This somewhat surprising result is in line with Table 5, where higher robot intensity in more non-routine jobs seemed to decrease mental health. If one reverses this chain of thought, it means that workers with more routine tasks fear *less* about losing their job, and experience *increasing* mental health when automation intensifies.

On the other hand, the interaction between how interactive a job is and robot intensity shows a negative sign. Therefore, Panel A suggests that having a highly interactive task combined with increasing robot intensity will lead to less worries about the stability of the job. Individuals with interactive activities could perceive their position less likely to be automated in the environment they are working in.

Using the alternative measures of routine work and interactivity, the results for the non-routine interaction get weaker, while the estimated interactivity coefficients increase in size. As discussed above, we lean more towards using the alternative measures, which would suggest that while the interactivity of a job plays an important role in explaining the negative relationship between automation and job-loss fear, the non-routine task-content seems to be of lesser importance.

This evidence is mostly confirmed when restricting the sample to males only, as in Panel B. Panels C and D again replicate Panels A and B specification 5 of Table 1. While the signs of coefficients remain the same, coefficients are no longer statistically significant.

4.1.2 Automation and Worries about the Economic Situation of Individuals

Table 8 shows the results of repeating the same regressions as in Table 6 for the question whether individuals are worried about their own economic situation as the dependent variable. Panel A (full sample) shows that an increase in robot intensity in the sector is associated with more worries about the economic situation of people. Panel B shows the same for males in the Linear Probability Models and Panel C provides some mild evidence for females. When the occupational levels (Panels D - F) or the occupational plus levels genders (Panels G - I) are considered, no evidence is found.[13] We conclude that for the full sample, rising automation leads to economic worries. As we have seen in Column (7) of Table 1, economic worries seem to strongly related to worse individual mental health. Apparently, robot intensity leads to more economic worries, which in turn leads to lower mental health.

In the Appendix, Table A.8 shows the results of repeating these regressions while again interacting the robot intensity variable with the task content of an individuals occupation. In contrast to Table 7, the effect seems not to be differentiated significantly across different task groups. The sign of the estimates however remains consistent with the pattern observed before: interactivity seems to decrease the impact of automation on economic worries.

[13] The estimates for females did not show either any statistically significant relationship (not shown for brevity, but available upon request).

Table 8: Transmission channel: robot intensity and self-reported worries about their own economic situation (by occupations and genders)

Dependent Variable: Worries about own economic situation				
Regression:	(1)	(2)	(3)	(4)
Model:	Logit FE	LPM IV	Logit FE	LPM IV
Corresp. Table 1:	(3)		(5)	
	Panel A: Full Sample			
log(Robot Intensity)	0.207**	0.0442*	0.262	0.0522**
	(0.0947)	(0.0244)	(0.162)	(0.0245)
Observations	12392	27233	3384	11012
	Panel B: Men			
log(Robot Intensity)	0.145	0.0575*	0.220	0.0531*
	(0.112)	(0.0296)	(0.198)	(0.0305)
Observations	9115	19192	2558	7818
	Panel C: Females			
log(Robot Intensity)	0.327*	0.000508	0.383	0.0342
	(0.189)	(0.0447)	(0.341)	(0.0454)
Observations	3277	8041	826	3194
	Panel D: Low Skilled			
log(Robot Intensity)	0.0981	0.0635	0.0887	0.0484
	(0.238)	(0.0495)	(0.529)	(0.0514)
Observations	2117	7506	141	1852
	Panel E: Medium Skilled			
log(Robot Intensity)	0.0961	0.0424	0.225	0.0430
	(0.158)	(0.0380)	(0.269)	(0.0377)
Observations	881	3863	1286	4730
	Panel F: High Skilled			
log(Robot Intensity)	0.122	-0.00422	0.468	0.0736
	(0.181)	(0.0476)	(0.346)	(0.0536)
Observations	3504	6447	1008	2650
	Panel G: Low Skilled Men			
log(Robot Intensity)	0.0844	0.0832	-0.146	0.0620
	(0.306)	(0.0716)	(1.029)	(0.0713)
Observations	1194	4364	307	1692
	Panel H: Medium Skilled Men			
log(Robot Intensity)	-0.0302	0.0454	0.173	0.0494
	(0.194)	(0.0480)	(0.340)	(0.0492)
Observations	3428	8182	927	3404
	Panel I: High Skilled Men			
log(Robot Intensity)	0.0728	-0.00794	0.204	0.0312
	(0.199)	(0.0500)	(0.388)	(0.0571)
Observations	2965	5402	865	2225
Add. indiv. contr.	No	No	Yes	Yes

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. The dependent variable is a factor variable of self-reported worries about the workers own economic situation, where the base value is "no worries about own economic situation" and the two other values are "some worries" and "great worries". Independent variables are the same as in column (3) and (5) of Table 1 respectively, accordingly columns (1) - (4) of this table include mostly sector controls and columns (5) - (8) additionally a set of individual controls. The sample is split in panels D - I according to the occupational groups as in the upper part of Table 3. In the linear probability model, robot intensity is again instrumented as in Table 1.

Table 9: Transmission channel: robot intensity and the working time of individuals and the components of the mental health index

Regression:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Model:	FE	RE	IV FE	IV RE	FE	RE	IV FE	IV RE
Corresp. Table 1:	(3)				(5)			
	Panel A: actual working time							
log(Robot Intensity)	0.153	0.225	-0.240	-0.178	0.223	0.464**	-0.0167	0.263
	(0.233)	(0.155)	(0.320)	(0.299)	(0.279)	(0.227)	(0.315)	(0.284)
Observations	28283	28283	26798	26798	11672	11677	11017	11017
	Components of the index of mental health:							
	Panel B: mental health subcategory							
log(Robot Intensity)	-0.854***	-0.464*	-0.812**	-0.412	-0.928***	-0.512**	-0.912***	-0.399
	(0.302)	(0.247)	(0.406)	(0.340)	(0.289)	(0.239)	(0.338)	(0.276)
Observations	12150	12150	11441	11441	11672	11677	11017	11017
	Panel C: role emotional subcategory							
log(Robot Intensity)	-0.663	-0.324	-0.0145	0.100	-0.426	-0.279	-0.480	-0.350
	(0.497)	(0.446)	(0.627)	(0.571)	(0.301)	(0.225)	(0.346)	(0.269)
Observations	14017	14017	13267	13267	11672	11677	11017	11017
	Panel D: social functioning subcategory							
log(Robot Intensity)	-0.223	0.112	0.555	0.699	-0.0771	0.250	0.0724	0.395
	(0.490)	(0.446)	(0.634)	(0.572)	(0.301)	(0.233)	(0.339)	(0.273)
Observations	14017	14017	13267	13267	11672	11677	11017	11017
	Panel E: vitality subcategory							
log(Robot Intensity)	-0.144	0.0680	-0.188	0.130	-0.0726	0.0632	-0.332	-0.0201
	(0.491)	(0.444)	(0.651)	(0.582)	(0.306)	(0.248)	(0.363)	(0.291)
Observations	14017	14017	13267	13267	11672	11677	11017	11017
Add. indiv. contr.	No	No	No	No	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Independent variables are the same as in column (3) and (5) of Table 1 respectively, accordingly columns (1) - (4) of this table include mostly sector controls and columns (5) - (8) additionally a set of individual controls. In the IV models, robot intensity is again instrumented as in Table 1.

Another aspect worthwhile investigating can be seen in Table 9, which concentrates on whether the working hours of an individual are affected by the changes in robot intensity, as well how robot intensity correlates with the different sub-components of the mental health index. Panel A shows that changes in robot intensity do not affect the actual working time of individuals. Accordingly, secondary stress effects stemming from increased working time seem not to be the cause for the observed decrease in mental health. It is however important to note that we only observe the extensive margin of work effort here. The intensive margin, or how much work-output a worker produces within on hour of working time, is unfortunately not part of the data provided by the SOEP. So while working hours seems unaffected, stress on the job might still be an important transmission channel of automation.

When assessing the impact of robot adoption on each different sub-component of the mental health index (Panels B - E), Panel B stands out. There is a strong and robust correlation with the sub-component of mental health of workers. Apparently, robot adoption does not affect the vitality, social functioning nor emotional state of an individual, but their "*(mental) work ability*" (as termed by Hofmann and Mühlenweg (2018)). Accordingly, more robots are strongly related to higher mental work ability impairment, leading to lower (potential) productivity at work either by doing less than wanted and/or or lower quality work, which could have further, unintended consequences the employing company, since it is directly affected by their employees work productivity. A correlation would have also been expected with the emotional balance variable, but it does not seem the case for the German workers.

Finally, Table A.9 in the Appendix shows how the adoption of robots is associated (or not) with work, life, life in 5 years, sleep and family life satisfaction. We do not find any evidence that more robots in the sector of employment generates any change in these satisfaction levels.

5 Conclusion

The increased use of robots in recent years has not been unnoticed in the media. Researchers have provided a large variety of studies on how likely human jobs will be replaced by robots (with varying results, but all agree on the fact that (some) jobs will be replaced). Given the fast adoption rate of robots in the world and especially in Germany, workers that do not directly get replaced experience nonetheless an increasing exposition to robots in their workplace.

The results from this paper show that robots do actually affect the mental health of workers, but they affect people in different ways. Men are more likely than women to see their mental health deteriorating, which is partially explained by higher potential for automation in the tasks performed by males. Furthermore, this paper shows that the perceived threat of automation is highest within the youngest cohort. Results also show that the employees with less interactive tasks are the ones fearing automation the most. These results are robust to different econometric methods and instrumenting the stock of robots. Weaker evidence suggests that non-routine tasks might be surprisingly more exposed to the risk of lower mental health due to automation, contrasting partly the conventional job polarization hypothesis.

Exploring the transmission channels by which robot adoption affects mental health, results show that the increased robot exposure has affected the worries about job security and the economic situation of workers, especially for individuals performing non-interactive tasks. Moreover, when decomposing the mental health variable into its sub-components, the (mental) work ability appears to strongly negatively correlated with increasing robot intensities. This suggests that an increased robot exposure leads to individuals feeling less productive, which in turn affects their overall mental health negatively.

This paper contributes to the slowly enlarging literature on how changes in production affect the health of workers. Although the estimates we presented in the paper are modest in size, they are nonetheless important. Companies should take into account the corollaries of the deepening of the use of new technologies on their workers, especially on their mental health. Public policy should also work hand-in-hand with the private sector to assure that workers are protected. Our results hint that there could actually be a "hidden cost of automation" for society.

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A Appendix

Table A.1: Overview of sectors

Sector	Description	Sector	Description
1 - 4	Crop and animal production, hunting	19 - 20	Manufacture of chemicals and chemical products
	Forestry and logging		Manufacture of coke
	Fishing and aquaculture		and refined petroleum products
5 - 9	Mining of coal and lignite, Mining of metal ores	21	Manufacture of pharmaceutical products
	Extraction of crude petroleum and natural gas	22	Manufacture of rubber and plastic products
	Other mining and quarrying	23	Manufacture of other
	Mining support service activities		non-metallic mineral products
10 - 12	Manufacture of food products	24	Manufacture of basic metals
	Manufacture of beverages	25	Manufacture of fabricated metal products,
	Manufacture of tobacco products		except machinery
13 - 15	Manufacture of textiles	26	Manufacture of computer,
	Manufacture of wearing apparel		electronic and optical products
	Manufacture of leather and related products	27	Manufacture of electrical equipment
16	Manufacture of wood and of products of wood	28	Manufacture of machinery and equipment
	and cork, except furniture	29	Manufacture of motor vehicles,
17	Manufacture of paper and paper products		trailers and semi-trailers
	Printing and reproduction of recorded media	30	Manufacture of other transport equipment

Table A.2: Mental Component Summary Scale

Questions	Subcomponent
During the last 4 weeks, how often did you feel energetic?	vitality subcategory
During the last 4 weeks, how often did you feel that due to physical or mental health problems you were limited that is, in contact with friends, acquaintances, or relatives?	social functioning subcategory
During the last 4 weeks, how often did you feel that due to mental health or emotional problems you achieved less than you wanted to at work or in everyday activities? During the last 4 weeks, how often did you feel that due to mental health or emotional problems, you carried out your work or everyday tasks less thoroughly than usual?	mental health subcategory
During the last 4 weeks, how often did you feel down and gloomy? During the last 4 weeks, how often did you feel calm and relaxed?	role emotional subcategory

Adapted from Hofmann and Mühlenweg (2018), who define the Mental Health subcategory as ”(mental) work ability”.

Table A.3: Summary Statistics (Specification (3) from Table 1)

Variable	Mean	Standard deviation	Min.	Max.	N
Mental health	50.87	8.9615	3.1072	79.4324	12150
Log(Robot intensity)	8.1412	2.1987	1.567	11.3201	12150
Value of gross output	135.3762	97.9704	11.005	338.061	12150
Value of intermediate inputs	91.1013	68.8128	6.375	238.613	12150
Capital compensation	15.5701	12.5215	0.629	47.272	12150
Compensation of employees of employees	27.4359	20.0461	3.726	63.231	12150
Price of gross output	125.832	66.5625	68.395	358.151	12150
Price of intermediate inputs	124.1328	63.1213	67.711	344.806	12150
Price of value added	128.5588	72.6584	72.476	382.514	12150
Persons engaged	0.6114	0.3269	0.061	1.129	12150
Import competition	0.2922	0.1348	0.1296	0.902	12150
Company Size	7.1942	2.7723	1	11	12150

Table A.4: Summary Statistics (Specification (5) from Table 1)

Variable	Mean	Standard deviation	Min.	Max.	N
Mental health	50.8416	8.9538	3.1072	79.4324	11677
Log(Robot intensity)	8.1826	2.1651	1.567	11.3201	11677
Value of gross output	136.5882	98.1804	11.005	338.061	11677
Value of intermediate inputs	91.9255	68.9822	6.375	238.613	11677
Capital compensation	15.7099	12.5537	0.629	47.272	11677
Compensation of employees of employees	27.72	20.0554	3.726	63.231	11677
Price of gross output	124.604	65.213	68.395	358.151	11677
Price of intermediate inputs	122.9808	61.8443	67.711	344.806	11677
Price of value added	127.2285	71.2559	72.476	382.514	11677
Persons engaged	0.6133	0.3278	0.061	1.129	11677
Import competition	0.2915	0.135	0.1296	0.902	11677
Changed sector last year	0.0987	0.2982	0	1	11677
Actual working time	40.6273	11.1274	1	80	11677
Company Size	7.2178	2.7377	1	11	11677
Personal labour income	1.7939	1.7002	0.022	99.999	11677
Relationship Status	1.7915	1.1271	1	8	11677
Satisfaction with income	0.7373	0.4401	0	1	11677
Worries on general economic development	1.1856	0.6342	0	2	11677
Satisfaction with household income	0.7356	0.441	0	1	11677
Satisfaction with living standards	0.938	0.2412	0	1	11677
Satisfaction with health	0.7912	0.4065	0	1	11677
Satisfaction with sleep	0.863	0.3439	0	1	11677
Satisfaction with work	0.8088	0.3933	0	1	11677
Satisfaction with life	0.8561	0.351	0	1	11677
Satisfaction with life in the next 5 years	0.9312	0.2531	0	1	11677
Body mass index	26.2288	4.2433	12.856	58.824	11677

Table A.5: Robot intensity and mental health (IV)

Dependent Variable: Mental Health Index							
	(1) Baseline	(2) 2006 - 2010	(3) Excl. automotive	(4) Excl. mining and agr.	(5) 5% dep. rate	(6) 15% dep. rate	(7) Year trend
Corresp. Table 1:	(3)						
	Panel A: All genders						
Log(Robot intensity)	-0.526*	-2.517	-0.744	-0.936**	-0.177	-0.809	-0.962**
	(0.284)	(1.701)	(0.462)	(0.460)	(5.241)	(3.493)	(0.414)
Obs.	8,865	3,323	6,447	7,610	8,110	8,110	11,310
	Panel B: Males						
Log(Robot intensity)	-1.294***	-1.683***	-1.332**	-1.333**	2.113	-2.200	-1.264***
	(0.481)	(0.591)	(0.559)	(0.539)	(6.628)	(4.621)	(0.486)
Obs.	5,901	4,225	4,527	5,529	5,901	5,901	8,020
	Panel C: Females						
Log(Robot intensity)	0.307	-0.00202	0.681	0.375	-2.634	1.690	0.000694
	(0.865)	(1.285)	(0.888)	(0.931)	(9.330)	(5.459)	(0.834)
Obs.	2,209	1,511	1,920	2,081	2,209	2,209	3,290
Add. indiv. contr.	No	No	No	No	No	No	No
Corresp. Table 1:	(5)						
	Panel A: All genders						
Log(Robot intensity)	-0.898**	-1.474***	-0.689	-0.942**	0.862	-2.224	-0.978**
	(0.406)	(0.511)	(0.460)	(0.456)	(5.081)	(3.429)	(0.407)
	7,764	5,469	6,144	7,329	7,764	7,764	10,890
	Panel B: Males						
Log(Robot intensity)	-1.284***	-1.786***	-1.292**	-1.396***	1.511	-4.616	-1.314***
	(0.473)	(0.577)	(0.549)	(0.526)	(6.450)	(4.511)	(0.472)
Obs.	5,678	5,395	4,335	5,352	5,678	5,678	7,764
	Panel C: Females						
Log(Robot intensity)	0.489	-0.0231	0.783	0.399	0.705	0.580	0.189
	(0.892)	(1.279)	(0.922)	(0.991)	(9.071)	(5.374)	(0.859)
Obs.	2,086	1,410	1,809	1,977	2,086	2,086	3,126
Add. indiv. contr.	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Independent variables are the same as in column (3) and (5) of Table 1 respectively.

Table A.6: Robot intensity and mental health (IV, by age group)

Dependent Variable: Mental Health Index					
Corresp. Table 1:			(3)		
	(1)	(2)	(3)	(4)	(5)
Age groups	20-29	30-39	40-49	50-59	60+
			Panel A: All		
Log(Robot intensity)	-6.368***	-0.104	-0.179	-2.828*	0.460
	(2.188)	(1.830)	(1.087)	(1.448)	(2.752)
Observations	1,674	2,751	3,921	2,754	565
			Panel B: Males		
Log(Robot intensity)	-4.838**	1.135	-0.376	-4.219***	-1.557
	(2.280)	(2.056)	(1.346)	(1.585)	(2.667)
Observations	1,193	1,983	2,675	1,965	440
			Panel C: Females		
Log(Robot intensity)	-7.907	-1.297	-0.245	2.183	16.12
	(8.424)	(4.011)	(2.446)	(4.028)	(22.44)
Observations	481	768	1,246	789	125
Corresp. Table 1:			(5)		
			Panel D: All		
Log(Robot intensity)	-6.013***	-1.211	-1.098	-2.448*	0.566
	(2.036)	(1.743)	(1.122)	(1.435)	(2.808)
Observations	1,623	2,672	3,768	2,639	507
			Panel E: Males		
Log(Robot intensity)	-3.319	0.389	-1.911	-4.019**	-1.076
	(2.065)	(1.981)	(1.372)	(1.607)	(2.417)
Observations	1,156	1,937	2,589	1,893	399
			Panel F: Females		
Log(Robot intensity)	-8.736	-4.120	0.140	2.933	-132.8***
	(8.794)	(3.767)	(2.576)	(4.567)	(5.17e-07)
Observations	467	735	1,179	746	108

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Independent variables are the same as in column (3) and (5) of Table 1 respectively.

Table A.7: Occupational grouping based on SOEP indicator *pgstib*

pgstib code	low group	pgstib code	high group
210	ungel. Arbeiter	250	Meister, Polier
220	angel. Arbeiter	330	Brigadier, Meister in der LW
310	Arbeiter in der Landwirtschaft	340	hoehere Leitungsfunkt. in der LW
520	Angest. mit einf. Taetigkeit	410	selbst. Landwirt
521	Angest.einf. Taet ohne Ausb.absch	411	selbst. Landwirt ohne Mitarbeiter
522	Angest.einf. Taet. mit Ausb.absch	412	selbst. Landwirt 1-9 Mitarbeiter
610	Beamte im einf. Dienst	413	selbst. Landwirt 10+ Mitarbeiter
		420	Freiberufler, Akad.
	middle group	421	Freiberufler, Akad. ohne Mitarbei
230	gelernte und Facharbeiter	422	Freiberufler, Akad., 1-9 Mitarbei
240	Vorarb., Kolonnenfuehrer	423	Freiberufler, Akad., 10+ Mitarbei
320	Facharbeiter in der Landwirtschaf	432	Sonst. Selbst., 1-9 Mitarbeiter
530	Angest.mit qual. Taetigkeit	433	Sonst. Selbst., 10+ Mitarbeiter
620	Beamte im mittleren Dienst	510	Industrie- und Werkmeister
630	Beamte im geh. Dienst	540	Angest., hochqual.Taetigkt.,Leitu
		550	Angest.mit umfassenden Fuehrungsa
		640	Beamte im hoeheren Dienst

Table A.8: Transmission Channel: robot intensity and worries about own economic situation (with interactions with task-based indices of non-routine and interactive work)

Dependent Variable: Worries about own economic situation						
Regression:	(1)	(2)	(3)	(4)	(5)	(6)
Model:	LPM	LPM	LPM IV	LPM IV	Logit	Logit
Corresp. Table 1:	(3)					
	Panel A: All genders					
log(Robot Intensity)	0.0214	0.0201	0.0492**	0.0479**	0.194**	0.206**
	(0.0170)	(0.0171)	(0.0192)	(0.0193)	(0.0965)	(0.0980)
log(Robot Intensity) · NR	0.00728		0.00612		0.0224	
	(0.00669)		(0.00670)		(0.0363)	
log(Robot Intensity) · IA	-0.0159		-0.0138		-0.0605	
	(0.0107)		(0.0107)		(0.0540)	
log(Robot Intensity) · NR-Alt.		0.00848		0.00638		0.166*
		(0.0172)		(0.0174)		(0.0860)
log(Robot Intensity) · IA-Alt.		-0.0283		-0.0224		-0.130
		(0.0251)		(0.0248)		(0.120)
Observations	28457	28457	26882	26882	12214	12214
	Panel B: Males					
log(Robot Intensity)	0.0105	0.00931	0.0422*	0.0409*	0.111	0.123
	(0.0200)	(0.0201)	(0.0225)	(0.0226)	(0.114)	(0.115)
log(Robot Intensity) · NR	0.00932		0.00777		0.0474	
	(0.00752)		(0.00756)		(0.0412)	
log(Robot Intensity) · IA	-0.00941		-0.00720		0.0150	
	(0.0122)		(0.0121)		(0.0682)	
log(Robot Intensity) · NR-Alt.		0.0157		0.0129		0.127
		(0.0192)		(0.0194)		(0.108)
log(Robot Intensity) · IA-Alt.		-0.0137		-0.00596		-0.0987
		(0.0276)		(0.0285)		(0.163)
Observations	20084	20084	18920	18920	8964	8964
Individual FE	yes	yes	yes	yes	yes	yes
Add. individual controls	no	no	no	no	no	no
Corresp. Table 1:	(5)					
	Panel C: All genders					
log(Robot Intensity)	0.0234	0.0261	0.0485**	0.0502**	0.228	0.230
	(0.0208)	(0.0211)	(0.0246)	(0.0248)	(0.161)	(0.165)
log(Robot Intensity) · NR	0.00846		0.00536		0.00232	
	(0.00966)		(0.00979)		(0.0648)	
log(Robot Intensity) · IA	-0.00489		-0.00204		0.0798	
	(0.0155)		(0.0155)		(0.107)	
log(Robot Intensity) · NR-Alt.		0.0251		0.0168		0.162
		(0.0243)		(0.0250)		(0.177)
log(Robot Intensity) · IA-Alt.		-0.0568*		-0.0407		-0.0628
		(0.0336)		(0.0340)		(0.271)
Observations	11558	11558	10884	10884	3468	3468
	Panel D: Males					
log(Robot Intensity)	0.0107	0.0137	0.0482	0.0508*	0.150	0.161
	(0.0254)	(0.0255)	(0.0308)	(0.0309)	(0.198)	(0.201)
log(Robot Intensity) · NR	0.0103		0.00691		0.0262	
	(0.0111)		(0.0112)		(0.0737)	
log(Robot Intensity) · IA	-0.00361		0.000339		0.123	
	(0.0185)		(0.0185)		(0.124)	
log(Robot Intensity) · NR-Alt.		0.0289		0.0210		0.223
		(0.0271)		(0.0281)		(0.202)
log(Robot Intensity) · IA-Alt.		-0.0523		-0.0403		0.0143
		(0.0394)		(0.0412)		(0.324)
Observations	8212	8212	7703	7703	2616	2616
Individual FE	yes	yes	yes	yes	yes	yes
Add. individual controls	yes	yes	yes	yes	yes	yes

Standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. The dependent variable is a factor variable of self-reported worries about the own economic situation or individuals, where the base value is “no worries” and the two other values are “some worries” and “great worries”. Independent variables are the same as in column (3) and (5) of Table 1 respectively. In the IV linear probability model, robot intensity is again instrumented as in Table 1.

Table A.9: Transmission channel: robot intensity and self-reported satisfactions

Regression:	(1)	(2)	(3)	(4)
Model:	Logit FE	Logit RE	Probit RE	LPM IV
Corresp. Table 1:	(3)			
	Dep. var.: satisfaction with work			
log(Robot Intensity)	0.0955	0.0911	0.0527	-0.00672
	(0.0911)	(0.0764)	(0.0473)	(0.0171)
Observations	11924	28889	28889	27321
	Dep. var.: satisfaction with life			
log(Robot Intensity)	0.0237	0.0310	0.0183	0.0150
	(0.104)	(0.0888)	(0.0540)	(0.0148)
Observations	9006	28905	28905	27321
	Dep. var.: satisfact. with life in 5 yrs.			
log(Robot Intensity)	-0.0794	-0.0550	-0.0235	0.0150
	(0.135)	(0.105)	(0.0589)	(0.0148)
Observations	7533	18680	18680	27321
	Dep. var.: satisfaction with sleep			
log(Robot Intensity)	-0.00800	0.152	0.0889	0.0150
	(0.214)	(0.184)	(0.106)	(0.0148)
Observations	9190	16297	16297	27321
	Dep. var.: satisfact. with family life			
log(Robot Intensity)	0.0996	0.181	0.0984	0.0150
	(0.211)	(0.160)	(0.0972)	(0.0148)
Observations	16495	19942	19942	27321
Add. indiv. contr.	No	No	No	No

Robust standard errors in parentheses, * $p < 0.1$, ** $p < 0.05$ and *** $p < 0.01$. Indedependent variables are the same as in column (3) of Table 1, including mostly control variables. Results for specification (5) from Table 1, including more individual control variables, are similar.