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Abstract

We use the most recent wave of the German Qualifications and Career Survey to reveal a substantial wage premium in a Mincer regression for workers performing their job from home. The premium accounts for more than 10% and persists within narrowly defined jobs as well as after controlling for workplace characteristics. In a next step, we provide evidence on substantial regional variation in the share of jobs that can be done from home in Germany. Our analysis reveals a strong, positive relation between the share of jobs with working from home opportunities and the mean worker income in a district. Assuming that jobs with the opportunity of remote work are more crisis proof, our results suggest that the COVID-19 pandemic might affect poorer regions to a greater extent. Hence, examining regional disparities is central for policy-makers in choosing economic policies to mitigate the consequences of this crisis.

JEL-Codes: H120, J310, J220, R100.

Keywords: working from home, COVID-19, regional disparities, home office, BIBB-BAuA.

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1 Introduction

Most countries show a substantial regional inequality in terms of wages and wealth. For Germany, Heise and Porzio (2019) report a persistent 26% real wage gap between the east and west.[1] A better understanding of the various sources of regional wage gaps is crucial to inform policy-makers and has been in the focus of recent research on the effects of shocks on local labor markets.[2] Here, we focus on the outbreak of the coronavirus as a shock that potentially affects regional labor markets to different degrees. In response to the pandemic, almost all countries adopted "stay at home" policies to contain the crisis. Working in strict accordance with social distancing is easier in jobs that can be carried out at home. Indeed, Alipour et al. (2020a) show for Germany that working from home (WFH) substantially reduces infection risks. However, this approach is not an option for every worker, particularly, if the job requires special equipment or personal proximity. Hence, the corona crisis is highly likely to affect workers differently. Moreover, if there are regional disparities in the share of jobs with the opportunity to work from home, the crisis could also have heterogeneous impacts on different regions within a country and increase regional inequalities.

In this paper, we use the latest wave of the German Qualifications and Career Survey (BIBB-BAuA) to investigate whether there is a systematical difference in wages between jobs with and without the opportunity to work from home.[3] Given that we plausibly assume that the recent crisis affects particularly jobs in which remote work is not possible, it is essential to determine whether those workers earned already lower wages before the crisis.[4] If so, the current crisis with all its job losses and income cuts through short-time allowances would further increase income inequality between workers.[5] Moreover, the crisis could also increase regional inequalities if the share of jobs that can be done from home is unequally distributed across a country. Given these concerns, we propose the following questions: Is there a wage premium for workers performing their work from home? What is the share of jobs that can be done from home in Germany and how does the share differ across NUTS2 districts in Germany? Finally, are there systematical differences in terms of average income across regions with high and low shares of WFH practices?

To tackle these questions, the BIBB-BAuA data are particularly suitable because they contain detailed information on occupation, earnings, as well as worker and workplace characteristics. Moreover, the data provides information on the region and industry, as well as some information on the employer. Most importantly, and in contrast to related studies such as Dingel and Neiman

[1] Dauth et al. (2018) present further facts about spatial wage disparities in Germany. Moretti (2011) documents that wage differences across regions are present in most countries.

[2] See, for instance the literature pioneered by Autor et al. (2013).

[3] The BIBB/BAuA Employment Survey was conducted between October 2017 and April 2018. Information is based on a random sample of 20,018 individuals working for at least 10 hours per week.

[4] We present evidence on this assumption in the following sections.

[5] In Germany, the short-time allowance is paid by the Federal Employment Agency and amounts to 60-67% of the former net wage rate depending on family status. In view of the COVID-19 pandemic, the short-time work allowance is being increased in stages for employees whose pay is reduced by at least half. Starting with the fourth month in which employees receive the short-time work allowance, it is raised to 70% (77% with children), and from the seventh month, it is raised to 80% (87% with children). Currently, the increase is scheduled to end by December 2021. Note that several employers have augmented the short-time allowance (depending on industry and underlying collective agreement).

(2020) or Mongey and Weinberg (2020), we observe workers' responses to survey questions that directly ask about the usage of working at home and the extent to which this is done by the worker. Given the fact that in the current crisis more employers allow their workforce to work from home, whenever this is possible, one might argue that the share of jobs with remote work opportunities is a lower bound and might be higher in the current crisis. To tackle this issue, the data further allows us to use a question where workers indicate whether their job is not at all suitable for working at home.

Our analysis provides particularly strong and robust evidence for a wage premium for workers with opportunities to work from home. The wage premium accounts for more than 10 percent in a rich Mincer type regression with a full set of worker and firm controls as well as fixed effects for industries, regions, detailed job classifications, and workplace characteristics such as activities, tools and skill requirements. Hence, workers who should be less affected by the COVID-19 crisis already had an advantage in terms of labor market outcomes before this crisis. This raises concerns that the current crisis is increasing the wage gap and contributing to a rising inequality if already less-privileged workers with jobs not suitable for working at home lose their jobs or suffer from income cuts through short-time allowance.[6]

To determine whether there are regional disparities, we compute the share of jobs with the opportunity to work from home across German NUTS2 districts. Here, a clear pattern emerges that indicates a low share of these jobs in Eastern Germany and a much higher share in urban areas of Western Germany. We further relate the share of workers using the option to work from home in a region to the mean worker earning. Here, we find a very strong, positive relation between these two measures. Noting that this is only a correlation, it nevertheless suggests that the current crisis could affect already-poorer regions more heavily because a lower share of workers can work from home there. In Germany, this effect could increase the already-existing inequality between the eastern and western parts.

Our analysis is mostly related to papers that study opportunities to work from home in light of the recent COVID-19 pandemic. Dingel and Neiman (2020) rely on US data and classify the feasibility to work from home using workers' responses to work context stemming from O*NET surveys. They find an overall share of 34% of US jobs eligible to be conducted at home and show disparities of this share across cities and industries. Mongey and Weinberg (2020) rely on the measure of Dingel and Neiman (2020) and compare characteristics of workers in the different types of occupations. They demonstrate that workers systematically differ across the types of occupations in many characteristics but they do not show a wage premium of WFH at the worker level. A recent study by Mergener (2020) documents the importance of specific individual tasks and illustrates that remote work is mainly an option for workers in jobs requiring cognitive and non-manual tasks. For German data, Alipour et al. (2020a) provide conditional correlations between WFH and worker characteristics showing that holding an academic degree, management responsibilities, as well as the usage of computers increases the opportunities to WFH. Similarly, Brynjolfsson et al. (2020)

[6] In Germany, short-time allowance protects many jobs and guarantees transfers to workers. Hence, in the absence of such an instrument, the potential wage gap would most likely be even higher.

show for US real-time data that workers in management or professional occupations are more likely to shift into remote work. Also relying on data from the US, Mongey and Weinberg (2020) study worker characteristics, demonstrating that workers without the opportunity for WFH are less likely to have a college degree, to be white, to be born in the US, and have lower levels of liquid assets. Whereas these papers emphasize the importance of workplace characteristics in determining the feasibility of WFH, we show that the wage premium survives even within jobs and after controlling for detailed workplace activities. Our main contribution is, then, to link these insights to persisting (regional) income inequality that could even become more pronounced in the recent crisis. Focusing on inequality distinguishes our analysis from most recent papers with few exceptions. Palomino et al. (2020) estimate the impact of social distancing on wage inequality. Indeed, their simulations reveal rising income inequality following a lockdown for all countries in their sample. Saltiel (2020) uses worker-level data from the STEP survey and documents a relatively low share of jobs that can be conducted at home in developing countries. Related to that, Gottlieb et al. (2020) demonstrate that the share of workers in urban areas who can work from home is clearly lower in poor countries. In contrast to our work, the focus in these studies is on heterogeneity between (developing) countries, whereas we focus on regional disparities that may exist even within a country. Finally, our paper is also related to Bloom et al. (2015), who found that home working led to a 13% performance increase and an increase in wages by 9.9%.

We structure our paper as follows: In Section 2, we define the main hypotheses to be tested in our empirical analysis. Section 3 provides a detailed description of the data. In Section 4, we show our main results for a worker-level analysis in Section 4.1 and a regional analysis in Section 4.2. Finally, Section 5 concludes and summarizes the main implications from our study.

2 Hypotheses

To guide our empirical analysis, we outline two main hypotheses, which we take to the data in the following sections. Our first hypothesis refers to a worker-level analysis and relates WFH to individual wages. In a second step, we take a spatial perspective and investigate the association between regional inequalities in the share of WFH jobs and income levels.

H1: *Workers with the opportunity to work from home earn higher wages.*

Our first hypothesis could reflect a productivity effect of WFH. Indeed, Bloom et al. (2015) document a causal effect of the opportunity to work from home on worker productivity. Using data from a Chinese travel agency, the authors reveal a 13% increase of performance. In a competitive labor market, this increase in productivity forces employers to respond by paying higher wages. As a rationale behind the increase in worker-level productivity, one could think of an improved morale while working at home. Moreover, workers might spend less time on less-productive activities such as chatting with colleagues or commuting. Higher wages could also be rationalized through the lens of an efficiency wage model à la Shapiro and Stiglitz (1984) where the employer-employee relationship is characterized by imperfect information. Workers decide upon their level of effort in the job, and firms are not able to adequately monitor their employees' efforts. Because effort is reducing the utility of workers, they have an incentive to shirk. Firms respond by paying higher wages because this raises the costs of those workers who are detected as shirking. Hence, when worker-level effort is not perfectly observable while WFH, higher wages help to reduce shirking in remote work. Another mechanism standing behind a potential wage premium could also be a selective granting of WFH opportunities to better and more reliable workers. During the recent COVID-19 crisis, however, it might be the case that rather than the reliability of a worker determining the opportunity for WFH it is the the characteristics of the occupation itself that determine such an opportunity. If job-specific tasks require personal proximity or special equipment, WFH is not an option even for the most reliable employees.

In the second part of our study, we focus on potential (regional) inequality effects of the recent COVID-19 crisis due to an unequal spread of WFH jobs across regions in Germany. As a direct consequence of the discussion on the wage premium of WFH jobs in **H1**, we expect that regions with a higher share of jobs with WFH opportunities are characterized by a higher average income.

H2: *Regions with a higher share of WFH jobs are characterized by a higher average income.*

With respect to rising regional inequality, differences in the share of WFH jobs may be problematic when the recent crisis affects WFH and No-WFH jobs to different degrees. Our underlying assumption is that WFH jobs are more crisis proof.[7] There is a widespread scientific consensus, that social distancing is essential to control the outbreak of the coronavirus. Policy-makers decided to lockdown entire industries and implemented strong regulations for sectors such as tourism or catering where direct personal contacts cannot be avoided. Those effects could propagate unequally across the country given that there are regional disparities in the share of WFH jobs.

3 Data

We use the most recent wave of the BIBB/BAuA Employment Survey, which was conducted between October 2017 and April 2018. It contains information from interviews on 20,018 individuals who report to work at least 10 hours per week.[8] The data set provides detailed information

[7] Recent research provides first evidence on the heterogeneous effects of the pandemic on WFH versus No-WFH jobs. Using real-time survey data, Adams-Prassl et al. (2020) show that there is a clear negative relationship between the percentage of tasks that can be carried out at home and job losses due to the Covid-19 pandemic. Barbieri et al. (2020) document for Italian data that workers who can operate from home have not been put under lockdown during the current crisis. For the Netherlands, von Gaudecker et al. (2020) show that workers in occupations that allow to work from home experienced much smaller declines in hours worked during the first months of the current crisis. Finally, we show in the following section that Germany recorded the largest increases in the number of unemployed people in occupations with the lowest WFH share.

[8] Previous waves and survey questions have been used in earlier research, for example by Acemoglu and Pischke (1998), Spitz-Oener (2006), Gathmann and Schönberg (2010), and Becker and Muendler (2015).

on worker characteristics, the income, industry, occupation, and workplace properties. What makes the data source especially suitable for our analysis is that the most recent wave includes questions on WFH practices. Specifically, workers are asked whether they work for their company—even if only occasionally—from home and how many hours per week they work from home on average. Furthermore, those workers who do not work from home are asked if their company would allow them to work at home temporarily or if WFH is not possible in their job. We use this information to construct three different measures: (*i*) WFH – an indicator variable equal to one if the respondent reports to work (occasionally) from home, (*ii*) WFH hours – the average number of hours per week WFH, and (*iii*) No-WFH – an indicator variable equal to one if the job cannot be performed from home.[9] Because the survey contains information if the hours worked from home are recognized as working time, we create two alternative measures: WFHr and WFH hours. These two measures only classify workers as WFH (and the respective hours per week) if those hours worked at home are fully or partially counted as working time.[10] In Table 1, we present summary statistics for these measures. Around 28% of respondents report to work (occasionally) from home, for an average of 6.58 hours per week. The numbers are lower (19% and 5.51, respectively) if only considering hours worked from home that are recognized as working time. 43% of the workers report that their job does not allow them to work from home.[11]

Table 1: Summary statistics for working from home in Germany

	Mean	Std. Deviation	Min.	Max	Observations
WFH	0.28	0.45	0	1	17827
WFH hours	6.58	7.01	1	60	4407
WFHr	0.19	0.39	0	1	16734
WFHr hours	5.51	7.02	0	60	4407
No-WFH	0.43	0.36	0	1	11351

Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017).

Whereas these measures are based on information collected in years prior to COVID-19, we first aim to provide some evidence that they nevertheless provide good information for WFH practices during the crisis. To do so, we examine the correlation between our WFH measures and appearance at the workplace during the lockdown in Germany. In Figure 1, we plot the share of WFH (and No-WFH) against the mobility trends for places of work provided by Google for the 16 different federal states in Germany during the peak of the lockdown.[12] As can be inferred from the left panel

[9]The corresponding questions in the survey read: (*i*) *Do you work for your company—even if only occasionally—from home?* (*ii*) *As a rule, how many hours per week do you work from home on average? This refers to hours actually worked, regardless of your standard working time.* (*iii*) *If your company would allow you to work at home temporarily, would you accept this offer?*

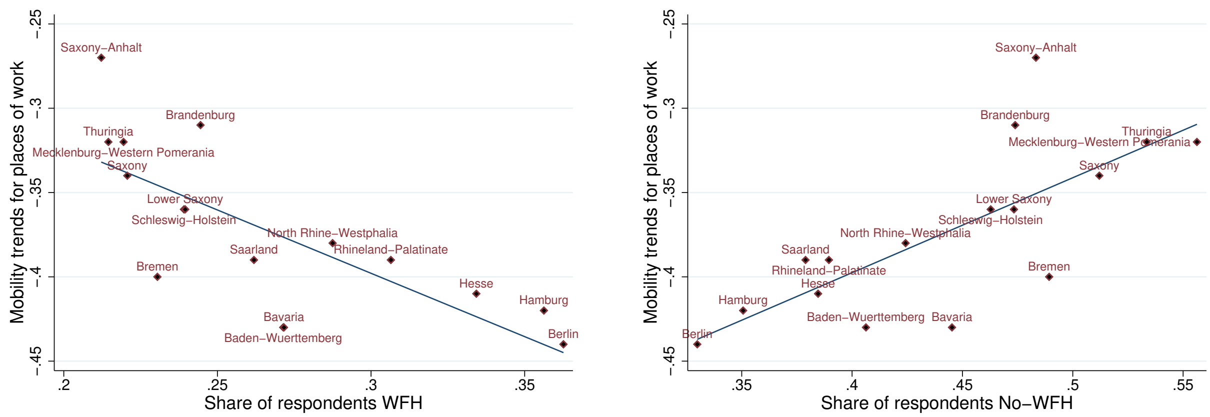
[10]Specifically, WFHr and WFHr hours are zero for those workers, for which our WFH and WFH hours measures are non zero, if hours worked from home are not at all counted as working time.

[11]We make use of a projection factor available in the data set which is based on the microcensus 2017, where weights are (among other things) calibrated at the federal state level. We also make use of this weighting factor whenever we aggregate our data (e.g., at the regional level) in the subsequent empirical analysis.

[12]Google prepared this report to provide information on the responses to social distancing guidance related to

of Figure 1, federal states with a higher share of WFH jobs experience a stronger decline in the mobility trend for places of work. Using our alternative measure No-WFH in the right panel, we see that those states with higher employment shares in jobs that cannot be performed from home experience a less-pronounced decline in the mobility trend for workplaces. Taking stock, Figure 1 provides some first indication that WFH practices vary at the regional level and that these measures are correlated with the appearance at the workplace in the current crisis.

Figure 1: Changes in mobility trend for workplaces and working from home



Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017) and Google mobility report.
Notes: The left panel plots the average WFH (an indicator variable equal to one if the respondent reports to work from home) against the change in mobility trend for places of work for the 16 federal states in Germany. The right panel plots the average No-WFH (an indicator variable equal to one if the job cannot be performed from home) against the change in mobility trend for places of work for the 16 federal states in Germany.

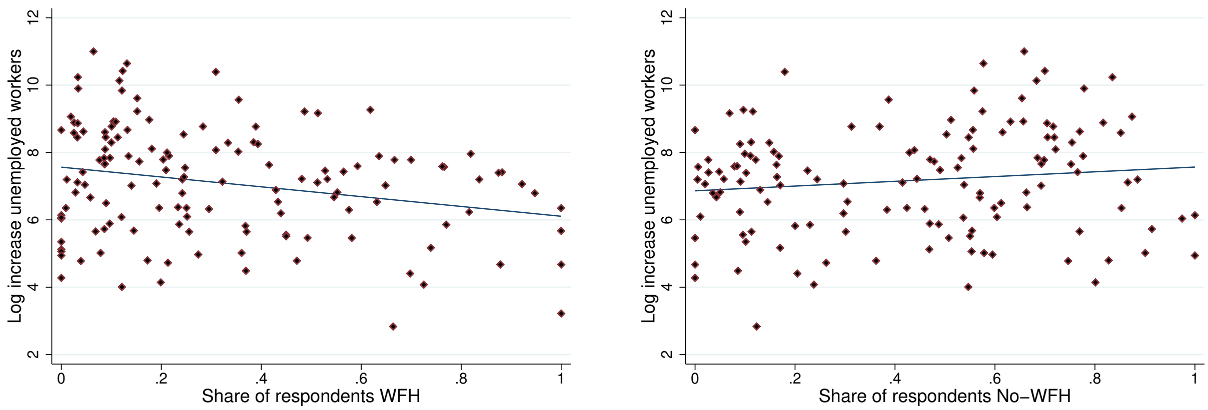
To further verify that our WFH variables measured in 2018 are linked to the current crisis, we investigate recent labor market developments. To do so, we analyze how they are correlated with changes in unemployment across occupations.[13] In Figure 2, we plot the share of WFH (and No-WFH) against the log increase in unemployment for different occupations between July 2020 and July 2019. As can be seen from the left panel, those occupations where workers are more likely to work from home experience a less-pronounced increase in unemployment rates. By making use of the No-WFH indicator (right panel), we observe that the increase in unemployment is more pronounced in those occupations where a higher share of workers reports that working from home is not possible. However, one important concern here is that short-time work absorbs the negative effect of the lockdown, implying that WFH practices are less reflected in adjustments in official unemployment statistics but are more linked to short-time work. Indeed, as investigated

COVID-19. Here, we use information for the first weeks of the shutdown on mobility trend changes for places of work on March 29, 2020, relative to a baseline value. As stated in the report, the number shows how visits at different places (here workplaces) changed compared to a baseline. Google calculated these changes compared to a baseline value, which is the median value, for the corresponding day of the week, during the 5-week period Jan 3–Feb 6.The full report and further details are available from `https://www.gstatic.com/covid19/mobility/2020-03-29_DE_Mobility_Report_en.pdf`.

[13] We use the most recent report "Arbeitsmarkt nach Berufen" from July 2020 from the Federal Employment Agency (BA) to obtain changes in unemployment for occupations at the three-digit level according to the classification KldB2010.

to significant extent in Alipour et al. (2020a), short-time work allowances reached a historic level during the pandemic and WFH effectively shields workers from short-time work in Germany.

Figure 2: Unemployment changes and working from home across occupations



Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017) and Employment Statistics of the Federal Employment Agency (BA).
Notes: The left panel plots the average WFH (an indicator variable equal to one if the respondent reports to work from home) against the log increase in number of unemployed workers for different occupations. The right panel plots the average No-WFH (an indicator variable equal to one if the job cannot be performed from home) against the log increase in number of unemployed workers for different occupations. Occupations are defined according to the three-digit KLDB2010 classification.

In the subsequent empirical analysis, we provide evidence for a wage premium for workers performing their job from home. To do so, we use information on hourly gross wages and several control variables, such as individual controls, plant-size, industry and occupation classification, regional information, and workplace characteristics. The hourly gross wage is computed by using information on the monthly gross wage and weekly working time agreed with the employer without overtime.[14] As an alternative, we follow Spitz-Oener (2008) and divide the midpoints (minimum for top interval) of 18 wage bracket intervals by monthly working hours. We use education (measured in years of schooling including training), age, experience (measured in years in employment using the workers age information and the years of education), gender, marriage, and migration as individual controls.[15]

Moreover, we use information on plant-size (classified into the following 7 categories: 1 to 4

[14] We use imputed wages for missing values and extreme values i.e., the 0.5 and 99.5 percentile, which are provided in the data set. Monthly working hours are computed as weekly working hours times 4.25. Notably, whereas in previous survey waves, respondents are asked about the time worked beyond normal working hours, this is not included in the recent survey. Hence, because monthly gross wages might include payments from overtime, overtime is not included in the working hours and could bias hourly gross wages.

[15] These variables are standard control variables in Mincer type regressions (see, for example, Table 1 on p. 506 in Spitz-Oener, 2008); however, they might slightly differ in the precise definition according to the data set. We follow the definitions from Becker and Muendler (2015), who combine different waves of the BIBB-BAuA surveys and define, among others, 15 time-consistent activities. In contrast to more recent studies (e.g., Card et al., 2013), the data set does not allow to include detailed firm (or plant) controls except for plant-size indicators (see below), fixed effects for workers and establishments, or any worker-firm match-specific controls.

Table 2: Summary statistics for individual controls used in Table 3

	Mean	Std. Deviation	Min.	Max	Observations
PANEL A – WFH					
log hourly gross wage	2.92	0.44	0.58	6.27	15530
log hourly gross wage (SO)	2.94	0.47	0.34	6.27	15530
Education	13.43	2.46	8.00	18.00	15530
Indic.: Female	0.46	0.50	0.00	1.00	15530
Indic.: Married	0.56	0.50	0.00	1.00	15530
Age	44.61	11.40	19.00	65.00	15530
Experience	26.17	12.04	0.00	50.67	15530
Indic.: Migrant	0.07	0.26	0.00	1.00	15530
Plantsize	4.38	1.71	1.00	7.00	15530
PANEL B – WFH hours					
log hourly gross wage	3.19	0.45	0.58	5.93	4010
log hourly gross wage (SO)	3.22	0.47	0.57	5.99	4010
Education	14.94	2.51	9.33	18.00	4010
Indic.: Female	0.44	0.50	0.00	1.00	4010
Indic.: Married	0.59	0.49	0.00	1.00	4010
Age	43.74	10.92	21.00	65.00	4010
Experience	23.80	11.42	0.00	48.67	4010
Indic.: Migrant	0.07	0.25	0.00	1.00	4010
Plantsize	4.68	1.77	1.00	7.00	4010
PANEL C – No-WFH					
log hourly gross wage	2.82	0.40	0.75	6.27	9720
log hourly gross wage (SO)	2.84	0.43	0.34	6.27	9720
Education	12.82	2.16	8.00	18.00	9720
Indic.: Female	0.46	0.50	0.00	1.00	9720
Indic.: Married	0.55	0.50	0.00	1.00	9720
Age	44.77	11.55	19.00	65.00	9720
Experience	26.94	12.16	0.00	50.67	9720
Indic.: Migrant	0.08	0.27	0.00	1.00	9720
Plant size	4.28	1.69	1.00	7.00	9720

Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017).

persons, 5 to 9, 10 to 49, 50 to 99, 100 to 499, 500 to 999, and 1000 or more persons). The industry classification is based on the NACE 1.1 for the European Communities and we distinguish between 61 different industries in our data. Regional information is based on the Nomenclature of Territorial Units for Statistics (NUTS2). For the job classification, we make use of the three-digit KldB-2010 information that allows us to distinguish between 157 different jobs. Finally, we aim to control for the workplace characteristics of jobs. We follow Becker and Muendler (2015) and construct 15 different activities: 1. Manufacture, Produce Goods; 2. Repair, Maintain; 3. Entertain, Accommodate, Prepare Foods; 4. Transport, Store, Dispatch; 5. Measure, Inspect, Control Quality; 6. Gather Information, Develop, Research, Construct; 7. Purchase, Procure, Sell; 8. Program a Computer; 9. Apply Legal Knowledge; 10. Consult and Inform; 11. Train, Teach, Instruct, Educate; 12. Nurse, Look After, Cure; 13. Advertise, Promote, Conduct Marketing and PR; 14. Organize, Plan, Prepare (others' work); 15. Oversee, Control Machinery and Technical Processes. Whereas these indicators describe *what* workers do in their job, we also construct measures on *how* workers perform their job. Therefore, we define indicators for the routineness and codifiability of jobs based on survey questions on repeated worksteps and work procedures. Moreover, we define skill requirements depending on the information about whether the job requires knowledge in specific areas: 1. legal; 2. project management; 3. medical or nursing; 4. mathematics, calculus, statistics; 5. German, written expression, spelling; 6. PC application programs; 7. technical knowledge; 8. commercial or business knowledge. Finally, we make use of an indicator for computer usage at the workplace. Whereas Table 2 provides summary statistics on demographic controls and plant size for three different samples used in the Mincer regressions in Table 3 below, Table A.5 in the Appendix provides summary statistics for the remaining indicators on workplace characteristics.

Dingel and Neiman (2020) emphasize the importance of job activities and requirements. They classify jobs with and without WFH opportunities based on occupation-specific descriptors from the US O*NET database. In subsection A.2 in the Appendix, we show predictions from a logistic regression at the individual level between our activities, performance, and skill requirements as well as our indicators for WFH practices (see Figures A.6 and A.7). This follows to a large extent the analysis in Alipour et al. (2020a), Alipour et al. (2020b), and Alipour et al. (2020c). Similar to these studies, we observe that the likelihood of WFH crucially depends on the composition of tasks within occupations.

As can be inferred from Tables 1 and 2, the number of observations for our subsequent empirical analysis varies according to the selection of dependent (and independent) variables. We focus our attention on individuals where the occupational status is "worker", "salaried employee", or "civil servant".[16] Using WFH as a measure for the extensive margin of working from home, we end up with the largest sample of 15,530 individuals. Only a fraction of those individuals is WFH. Hence, we arrive at a much smaller sample size of only 4,010 observations, when examining at the intensive margin (i.e., hours of WFH). Finally, the number of observations for our No-WFH indicator is 9,729, because the sample is restricted to those workers who do not report to work from home.

4 Empirics

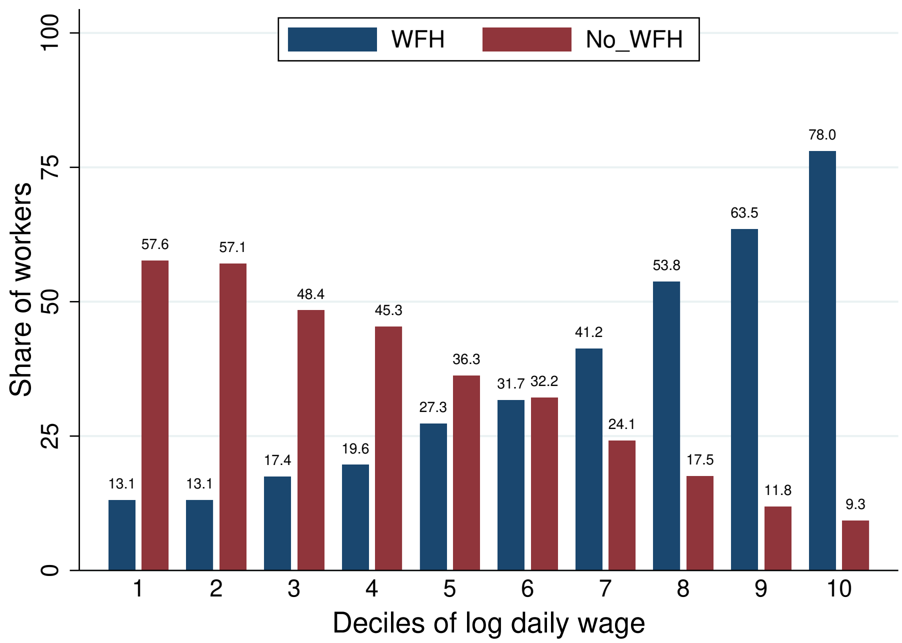
This section begins with a worker-level analysis to investigate wage differences between workers with and without the opportunity to work from home. In a second step, we analyze the regional variation in the opportunities to work from home in Germany and the respective relation to average wages in those regions.

[16] Hence, we drop observations classified as "self-employed persons", "freelancer (in German: freiberuflich tätig)", "freelance collaborator (in German: freie Mitarbeiter/in)", "assisting family member", "target person, who cannot choose between worker and salaried employee", and "not specified", which account for 179 (79) observations with information on WFH (No-WFH).

4.1 Worker-level analysis

In Figure 3, we plot the share of workers reporting to WFH (blue) as well as the share of workers with No-WFH jobs (red) across the deciles of the (log) wage distribution. We infer a substantial heterogeneity in the possibilities to remote work across different income levels. Whereas WFH is mainly an option at higher income levels, No-WFH jobs are more likely at lower deciles of the wage distribution.

Figure 3: WFH across the wage distribution



Source: BIBB-BAuA 2018.

To test our first hypothesis **H1**, we regress the log gross daily wage on our indicator variables WFH, WFH hours, or No-WFH. Column 1 in Panel A of Table 3 reports the coefficient on WFH without using any controls. In columns 2 to 4, we then include controls for worker and firm characteristics, industry, and regional fixed effects. Thereby, we aim to control for income differences arising from heterogeneities in, for example, education or experience (worker controls), firm-size wage differences (firm controls), as well as industry or regional specificities (e.g., industry-wide collective bargaining agreements or urban productivity advantages). Even after including these controls, the wage premium remains significant and sizable. As emphasized in Dingel and Neiman (2020) and Mongey and Weinberg (2020), the feasibility to work from home depends on the job of a worker and the work context. In column 5, we therefore include fixed effects for three-digit occupation codes, and in column 6, we add 15 different indicators for activities that workers perform in their job. Moreover, the wage premium could simply reflect specific workplace characteristics and tools (see DiNardo and Pischke, 1997; Spitz-Oener, 2008). Hence, in column 7, we also control for the routineness and codifiability of a job, the skill requirements, and computer use. We observe that the wage premium remains significant at the 1% level and accounts for more than 10%, indicating a sizable wage premium for workers WFH within jobs and controlling for their work context.

In Panel B of Table 3, we examine the intensive margin of working from home. We restrict the sample to those workers that report to work from home and regress the log hourly gross wage on the average number of hours per week working from home (in logs), including from column to column the same set of controls as in Panel A. Throughout all columns, the coefficient on WFH hours is highly significant and positive indicating that workers who work from home to a larger extent also receive higher wages.

Table 3: Working from home and wage income

	Dependent variable: log gross hourly wage						
PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WFH	0.389***	0.238***	0.218***	0.211***	0.169***	0.131***	0.112***
	(0.00693)	(0.00654)	(0.00665)	(0.00654)	(0.00657)	(0.00661)	(0.00665)
Observations	15530	15530	15530	15530	15530	15530	15530
R-squared	0.169	0.388	0.425	0.448	0.503	0.528	0.537
PANEL B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log WFH hours	0.0805***	0.0464***	0.0436***	0.0431***	0.0277***	0.0237***	0.0233***
	(0.00674)	(0.00587)	(0.00598)	(0.00594)	(0.00603)	(0.00593)	(0.00587)
Observations	4010	4010	4010	4010	4010	4010	4010
R-squared	0.034	0.298	0.341	0.363	0.437	0.463	0.476
PANEL C	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No-WFH	-0.152***	-0.0985***	-0.0757***	-0.0702***	-0.0432***	-0.0246***	-0.0150**
	(0.00803)	(0.00728)	(0.00732)	(0.00718)	(0.00739)	(0.00729)	(0.00726)
Observations	9720	9720	9720	9720	9720	9720	9720
R-squared	0.036	0.264	0.322	0.356	0.423	0.452	0.466
Worker and firm controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	Yes	Yes	Yes	Yes
Occupation fixed effects	No	No	No	No	Yes	Yes	Yes
Activity controls	No	No	No	No	No	Yes	Yes
Performance and skill controls	No	No	No	No	No	No	Yes

Notes: The dependent variable in all columns and panels is the log hourly gross wage. In Panel A, WFH is an indicator variable equal to one if the respondent reports to work (occasionally) from home. In Panel B, WFH hours denotes the number of hours working from home (in logs). In Panel C, No-WFH is an indicator variable equal to one if the job cannot be performed from home. Worker and firm controls include education (in years of schooling), indicator variables for gender, married, migrant, age-squared, experience (-squared, -cubic and quartic), and plant-size indicators. Industry fixed effects are based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effects are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For details on the variable definitions, see Section 3.

A major concern with the results presented throughout Panels A and B of Table 3 is that WFH and WFH hours are choice variables and, thus, endogenous. As an alternative, we repeat the worker-level analysis by using information about whether the job is suitable for WFH or not. Clearly, the results obtained from regressions on the No-WFH indicator are obtained from a conditional sample because it only contains those workers who choose to not work from home. Nevertheless, the advantage of the No-WFH variable is that it might be less affected by the preferences of individuals on WFH practices. Moreover, this is important because not every worker is WFH in our data (before the COVID-19 outbreak) even though the job might be suitable for doing so. Panel C reveals that workers in those jobs that cannot be performed from home receive a negative wage premium (relative to those workers who do not work from home but have the possibility of doing so). The effect is significant throughout all specifications but less pronounced compared to our analysis in Panel A, indicating a wage discount of around 1 to 2%.[17]

In Section A.3 in the Appendix, we present further results on the positive (negative) wage premium for WFH (No-WFH) jobs. First, in Table A.6 we make use of our alternative wage measure, following the definition in Spitz-Oener (2008). The results are akin to the ones presented in the main text, with the only difference being that the estimated coefficient on No-WFH is not statistically different from zero in the most stringent specification (see column 7 in Panel C). Second, if we focus on our restrictive measures for WFH and No-WFH (see Table A.7), the results presented in Panel A and B of Table 3 remain unaffected by this sample modification. Third, we restrict the sample to full-time workers. Again, the results are to a large extent robust to this sample modification (see Table A.8). Only the estimated coefficient on No-WFH becomes insignificant in the most stringent specification.[18,19]

Finally, we do also present estimates from a quantile regression to investigate whether the relationship between WFH/No-WFH and wages is different along the conditional income distribution. In Table A.9, we report coefficients and standard errors for quantile regression estimates, namely the quantiles 0.1, 0.2,..., 0.9, and the OLS estimates, using the full model including all of our control variables akin to the last column 7 in Table 3. Here, a clear picture emerges. Examining WFH, we find that the returns to WFH are higher at higher points of the conditional wage distribution. Whereas the average (OLS) estimated coefficient is 0.112, the coefficient is only 0.09 for the first deciles and 0.14 for the highest decile of the conditional (log) wage distribution. Accordingly, when using No-WFH, we see that the penalty for not WFH is higher at lower points of the (conditional) wage distribution. The average discount for No-WFH in an OLS regression is -1.5%. In the quantile regression, the penalty at the first decile is -3.2%, whereas it becomes insignificant and, hence, not statistically different from zero for higher deciles of the (log) wage distribution.

[17]Whereas we focus our attention on the estimated coefficients on WFH, WFH hours and No-WFH in Table 3, we present a detailed regression output on worker controls for the most stringent specificiation in Table A.10 in the Appendix.

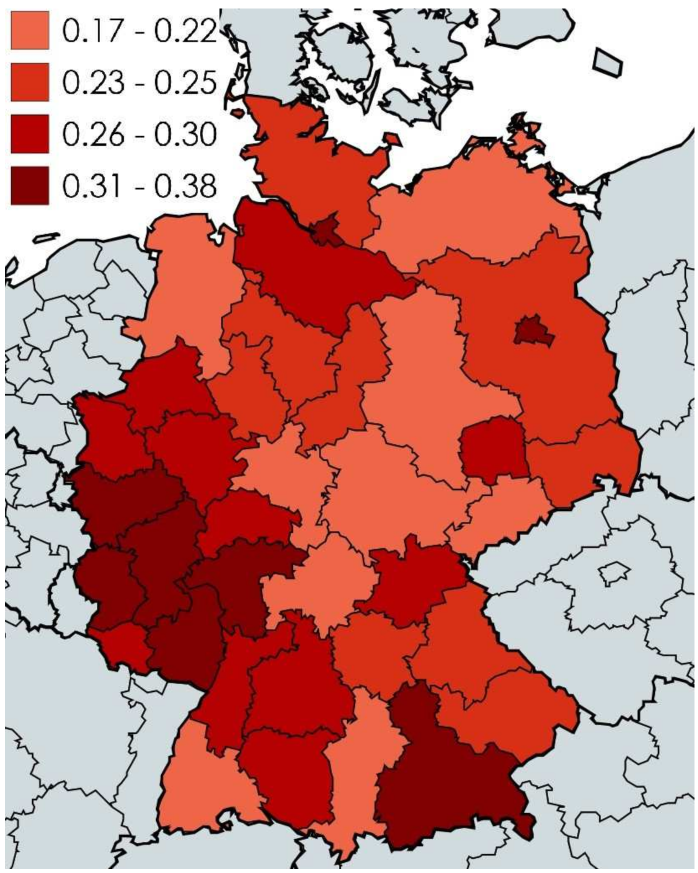
[18]We have also verified that the results presented in Table 3 remain unaffected from using the projection factor based on microcensus 2017.

[19]Because we cannot control for overtime when computing hourly wages (see footnote 14), we have also verified that the results presented in Table 3 remain unaffected when we restrict the sample to those workers who report not having any overtime.

4.2 Regional analysis

In a second step to our empirical analysis, we investigate the regional variation in WFH in further detail. Our data set provides regional information at the NUTS2-level for 38 districts in Germany. Because our worker-level analysis revealed a clear pattern indicating that workers with the opportunity to work from home earn a wage premium, we want to analyze the distribution of those jobs across regions. Finally, we are interested in the relationship between the share of jobs with WFH opportunities and the average wage, as motivated in **H2**, to infer the potential impact of COVID-19 on regional inequality in Germany arising from differences in WFH practices.

Figure 4: Working from home in Germany

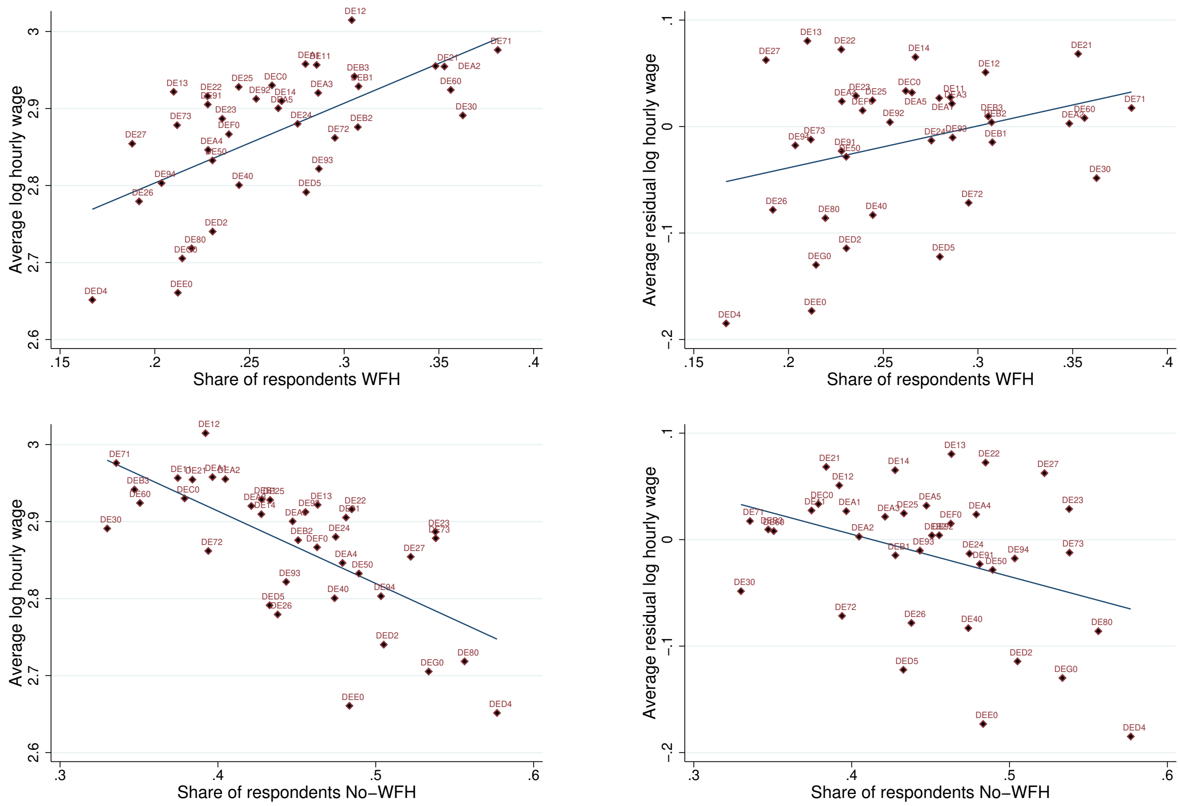


Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017).

Notes: The map illustrates the average share of workers who report to work (occasionally) from home for the 38 different NUTS2 regions in Germany.

Regional disparities We compute the (weighted) share of respondents working from home at the NUTS2 regional level and illustrate our results in Figure 4. Here, a darker color indicates a larger share of WFH jobs. The share of workers who report to work from home varies between 17 and 38 percent. Figure 4 reveals a clear pattern of a lower share of jobs with WFH opportunities in the eastern part of Germany, whereas this share is highest in urban areas around cities such as Darmstadt, Berlin, Hamburg, and Munich.[20]

Figure 5: Working from home and wages in Germany



Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017).
Notes: The upper left panel depicts the average of WFH and the average log hourly wage for 38 different NUTS2 regions in Germany. The upper right panel uses the average log residual wage after running a Mincer regression (see Section 4.1 for details). The lower left (right) panel depicts the average of No-WFH and the average log hourly wage (average log residual wage).

Opportunities to work from home and average wages As motivated throughout Sections 2 and 3, jobs with the opportunity to work from home are more crisis proof. Hence, regions might be prepared to varying degrees to take up the challenges of the recent crisis. In a final step, we therefore investigate the relationship between the share of WFH jobs and the average wage at the NUTS2 regional level. The upper panel in Figure 5 provides a clear picture of a positive relationship between the share of WFH jobs and the average wage rate. Districts with a higher share of jobs with the opportunity to work from home are characterized by a higher average wage rate. Notably,

[20]Table A.11 in the Appendix of this paper provides results for all NUTS2 districts in Germany used throughout the subsequent analysis, including the number of observations at the NUTS2 level.

this relationship holds true after controlling for observables to explain wage differences. Whereas the upper left-hand side contains the average log hourly wage on the y-axis, the panel on the upper right-hand side uses average residuals from a Mincer regression with a significantly large set of controls.[21] Notably, the lower panel of Figure 5 makes use of the No-WFH variable, which captures jobs that cannot be performed from home. In the light of the recent crisis, this robustness check is important because the actual share of home work opportunities could be higher than it was the case when the survey was conducted. Hence, it is particularly comforting for our analysis that the clear picture remains the same, with a negative relationship between the average wage and the share of jobs that definitely cannot be performed from home.

As reported in Table A.11 in the Appendix, the sample size at the NUTS2 level ranges between 97 observations in the statistical region Trier and 1419 observations in Upper Bavaria. To address potential concerns with respect to the representativeness, we conduct two robustness checks. First, we perform the same analysis at the more aggregate federal state level because the projection factor provided in the data set is constructed to ensure a high degree of representativeness at the federal state level. Figure A.8 in Appendix A.4, shows the same result of a positive relationship between the share of WFH-jobs and the average income at the state level. In particular, new federal states of the former German Democratic Republic are characterized by a low share of WFH-jobs and a low average income. As a second robustness check, we use an alternative measure for the WFH potential at the NUTS2 level. Rather than using our direct survey question, we rely on estimates provided in recent work by Fadinger and Schymik (2020). Figure A.9 in Appendix A.4 provides the same clear pattern of a higher average income in NUTS2 regions with a higher WFH potential.[22]

5 Conclusion

In this paper, we investigated the relationship between opportunities for WFH and wages at both individual and regional levels. Using the latest wave of the German Qualifications and Career Survey, our analysis revealed that WFH is mainly an opportunity for high-income workers. Whereas in the top decile of the wage distribution, almost 80% of workers use the option of WFH, the respective share accounts for only 13% in the lowest decile. In a detailed Mincer regression with a significantly large set of controls, we revealed a clear and stable wage premium for jobs with the option of WFH. The premium accounts for more than 10% and persists within narrowly defined jobs as well as after controlling for workplace characteristics. In a second step, we analyzed regional disparities in the opportunities of remote work in Germany. Our analysis provided clear evidence that districts with a low share of WFH jobs are also characterized by a lower average income. In particular, we

[21] The controls in the Mincer regression are akin to the ones used in the most parsimonious specification of Table 3 in column 7, but excluding region fixed effects.

[22] Finally, we also checked for spatial autocorrelation in the data across the 38 NUTS2 regions in Germany. To do so, we compute Moran's I statistic to test for global spatial autocorrelation by making use of the STATA command MORANSI provided by Kondo (2018). The Moran's I is -0.02510 for WFH and 0.00746 for No-WFH; however, both are not statistically significant (the reported p-values are 0.96507 and 0.43328, respectively). However, we do detect spatial autocorrelation when examining average (log) hourly wages. The corresponding Moran's I is 0.09759 and is significant at the 1% level (p-value is 0.00417).

documented a low share of WFH jobs in the new federal states of the former German Democratic Republic.

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A Appendix

A.1 Description of variables and further descriptive statistics

Table A.4: Description of variables used in Mincer regression

	Dependent variable
log hourly gross wage	Natural logarithm of gross hourly wage of an individual
log hourly gross wage (SO)	Following Spitz-Oener (2008), variable values are midpoints of the wage bracket intervals
	Variables of interest
WFH	Indicator variable equal to one if the respondent reports to work (occasionally) from home
No-WFH	Indicator variable equal to one if the job cannot be performed from home
WFH hours	Average number of hours per week working from home
WFHr	Is zero, if WFH is non-zero, but hours worked from home not count as working time
WFHr hours	Is zero, if WFH hours is non-zero, but hours worked from home not count as working time
	Control variables
Education	Education in years (schooling and training)
Age	Age in years
Age2	Age in years squared
Experience	Potential labor force experience (Age-Education-5)
Experience2/100	Potential labor force experience (squared)
Experience3/10000	Potential labor force experience (cubic)
Experience4/1000000	Potential labor force experience (quartic)
Female	Indicator variable equal to one if individual is female
Married	Indicator variable equal to one if individual is married
Migrant	Indicator variable equal to one if individual with migration background

Notes: In addition, we include 7 plant-size indicators as well as industry fixed effects based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effects are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For further details on variable definitions see Section 3.

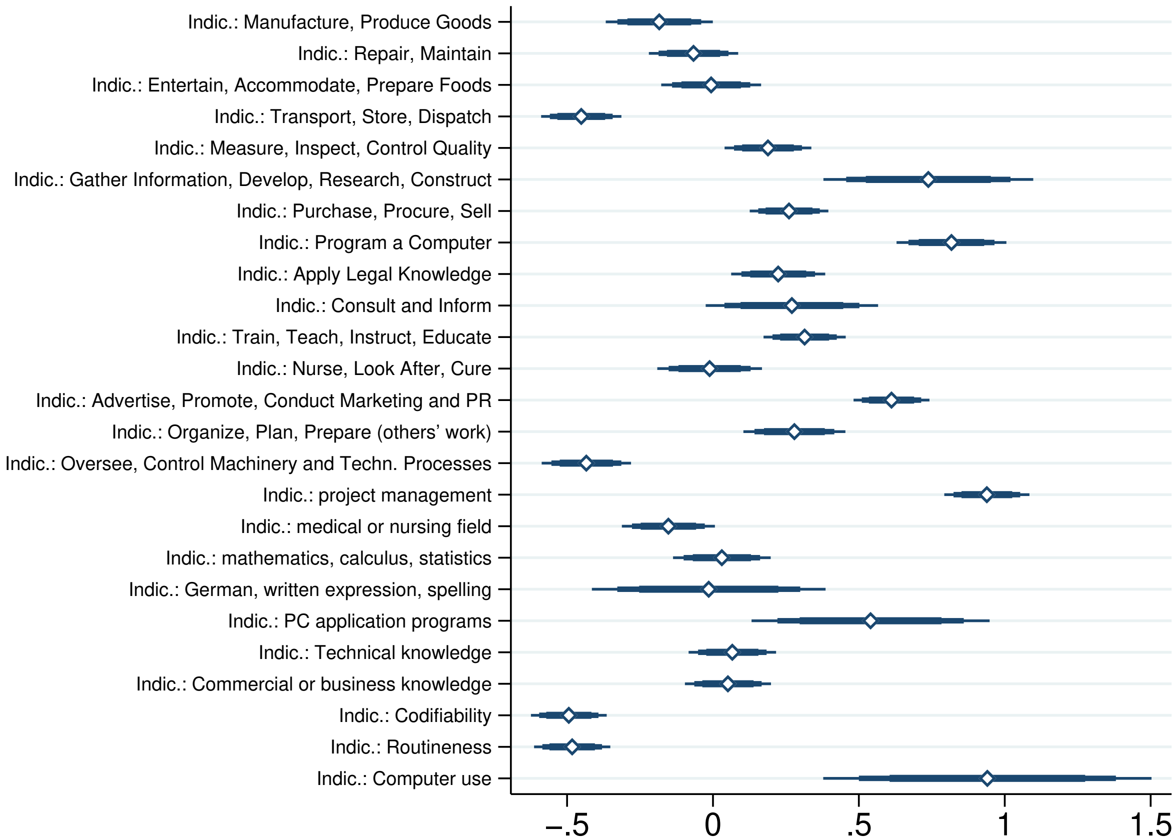
Table A.5: Descriptive statistics on indicators for workplace characteristics

	PANEL A		PANEL B		PANEL C	
Workplace characteristics	Mean	Std. Deviation	Mean	Std. Deviation	Mean	Std. Deviation
Manufacture, Produce Goods	0.23	0.42	0.16	0.37	0.26	0.44
Repair, Maintain	0.44	0.50	0.35	0.48	0.47	0.50
Entertain, Accommodate, Prepare Foods	0.19	0.39	0.18	0.39	0.19	0.39
Transport, Store, Dispatch	0.51	0.50	0.37	0.48	0.56	0.50
Measure, Inspect, Control Quality	0.73	0.44	0.76	0.42	0.72	0.45
Gather Information, Develop, Research, Construct	0.86	0.35	0.98	0.14	0.81	0.40
Purchase, Procure, Sell	0.43	0.50	0.53	0.50	0.39	0.49
Program a Computer	0.11	0.31	0.24	0.43	0.06	0.23
Apply Legal Knowledge	0.64	0.48	0.78	0.41	0.58	0.49
Consult and Inform	0.87	0.34	0.97	0.16	0.83	0.38
Train, Teach, Instruct, Educate	0.59	0.49	0.73	0.44	0.54	0.50
Nurse, Look After, Cure	0.23	0.42	0.22	0.41	0.23	0.42
Advertise, Promote, Conduct Marketing and PR	0.35	0.48	0.57	0.49	0.27	0.44
Organize, Plan, Prepare (others' work)	0.75	0.43	0.90	0.30	0.69	0.46
Oversee, Control Machinery and Techn. Processes	0.44	0.50	0.35	0.48	0.49	0.50
Legal knowledge	0.64	0.48	0.78	0.41	0.58	0.49
project management	0.48	0.50	0.81	0.40	0.36	0.48
medical or nursing field	0.30	0.46	0.27	0.44	0.30	0.46
mathematics, calculus, statistics	0.75	0.44	0.84	0.36	0.71	0.45
German, written expression, spelling	0.93	0.25	0.98	0.15	0.91	0.28
PC application programs	0.81	0.39	0.97	0.16	0.74	0.44
Technical knowledge	0.73	0.45	0.76	0.43	0.72	0.45
Commercial or business knowledge	0.55	0.50	0.75	0.43	0.48	0.50
Codifiability	0.52	0.50	0.34	0.47	0.59	0.49
Routineness	0.68	0.47	0.49	0.50	0.75	0.43
Computer use	0.86	0.35	0.99	0.11	0.81	0.39
Number of observations	15530		4010		9720	

Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017).

A.2 Working from home and workplace characteristics

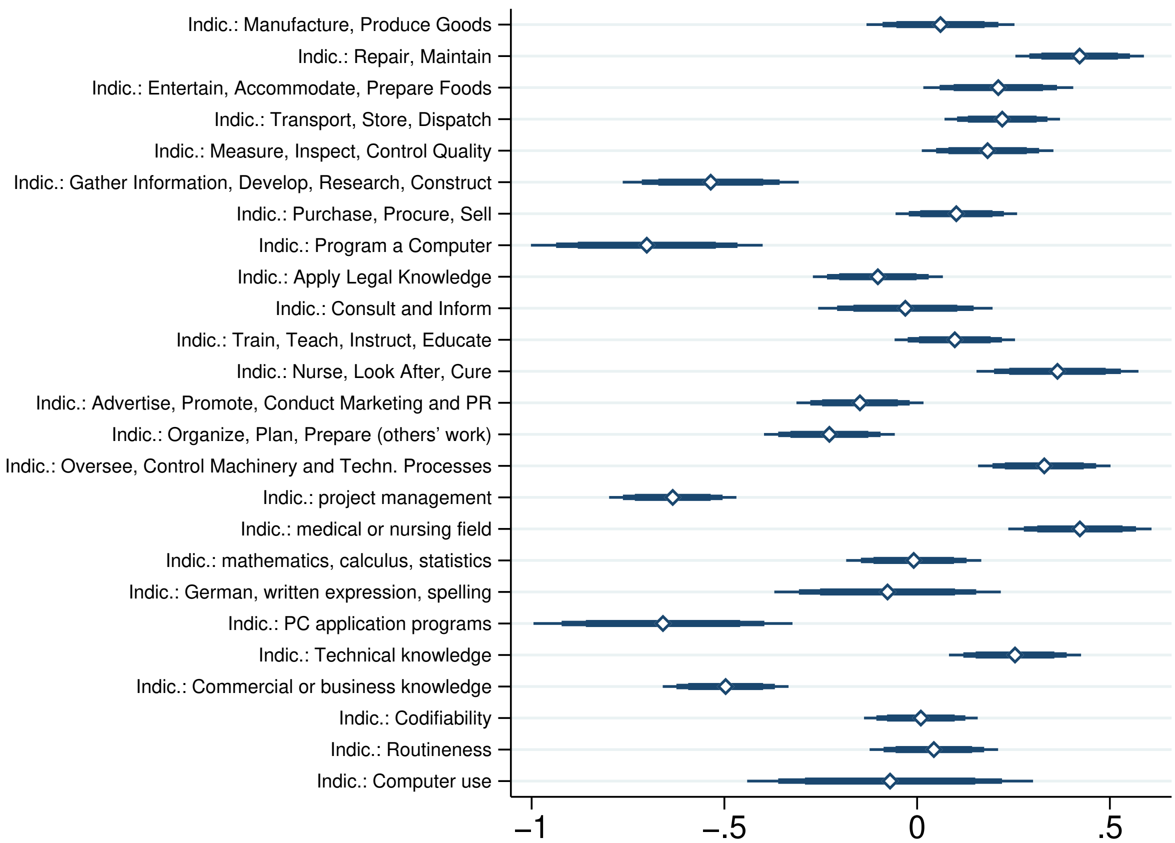
Figure A.6: WFH and workplace characteristics



Source: BIBB-BAuA (2018).

Notes: The figure shows the prediction from a logistic regression at the individual level. The dependent variable WFH is an indicator variable equal to one if the respondent reports to work (occasionally) from home. Indicators for workplace characteristics are described in Section 3. The number of observations is N = 17,827 and the Pseudo R-squared is 0.2419. Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals.

Figure A.7: No-WFH and workplace characteristics



Source: BIBB-BAuA (2018).

Notes: The figure shows the prediction from a logistic regression at the individual level. The dependent variable No-WFH is an indicator variable equal to one if the job cannot be performed from home. Indicators for workplace characteristics are described in Section 3. The number of observations is N = 11,351 and the Pseudo R-squared is 0.1546. Thick, medium, and thin lines represent the 99, 95, and 90 percent confidence intervals.

A.3 Robustness regressions on wage premium

Table A.6: Working from home and wage income (alternative wage definition)

	Dependent variable: log gross hourly wage as in Spitz-Oener (2008)						
PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WFH	0.396***	0.241***	0.221***	0.214***	0.171***	0.131***	0.111***
	(0.00736)	(0.00699)	(0.00711)	(0.00701)	(0.00707)	(0.00712)	(0.00716)
Observations	15530	15530	15530	15530	15530	15530	15530
R-squared	0.157	0.372	0.409	0.430	0.483	0.508	0.518
PANEL B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log WFH hours	0.0821***	0.0473***	0.0450***	0.0447***	0.0295***	0.0254***	0.0250***
	(0.00705)	(0.00616)	(0.00627)	(0.00623)	(0.00634)	(0.00625)	(0.00619)
Observations	4010	4010	4010	4010	4010	4010	4010
R-squared	0.033	0.292	0.335	0.355	0.429	0.453	0.466
PANEL C	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No-WFH	-0.157***	-0.103***	-0.0771***	-0.0720***	-0.0433***	-0.0230***	-0.0128
	(0.00862)	(0.00786)	(0.00792)	(0.00780)	(0.00807)	(0.00796)	(0.00793)
Observations	9720	9720	9720	9720	9720	9720	9720
R-squared	0.033	0.252	0.308	0.338	0.401	0.432	0.445
Worker and firm controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	Yes	Yes	Yes	Yes
Occupation fixed effects	No	No	No	No	Yes	Yes	Yes
Activity controls	No	No	No	No	No	Yes	Yes
Performance and skill controls	No	No	No	No	No	No	Yes

Notes: The dependent variable in all columns and panels is the log hourly gross wage, following the definition in Spitz-Oener (2008). In Panel A, WFH is an indicator variable equal to one if the respondent reports to work (occasionally) from home. In Panel B, WFH hours denotes the number of hours working from home (in logs). In Panel C, No-WFH is an indicator variable equal to one if the job cannot be performed from home. Worker and firm controls include education (in years of schooling), indicator variables for gender, married, migrant, age-squared, experience (-squared, -cubic and quartic), and plant-size indicators. Industry fixed effects are based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effect are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For details on the variable definitions see Section 3.

Table A.7: Working from home and wage income (restrictive WFH measures)

	Dependent variable: log gross hourly wage						
PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WFHr	0.346***	0.193***	0.173***	0.163***	0.133***	0.100***	0.0823***
	(0.00805)	(0.00730)	(0.00733)	(0.00721)	(0.00714)	(0.00704)	(0.00704)
Observations	14620	14620	14620	14620	14620	14620	14620
R-squared	0.112	0.363	0.402	0.427	0.486	0.517	0.529
PANEL B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log WFHr hours	0.0688***	0.0378***	0.0360***	0.0350***	0.0239***	0.0198***	0.0201***
	(0.00764)	(0.00668)	(0.00681)	(0.00678)	(0.00692)	(0.00681)	(0.00674)
Observations	3035	3035	3035	3035	3035	3035	3035
R-squared	0.026	0.282	0.323	0.348	0.428	0.454	0.469
Worker and firm controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	Yes	Yes	Yes	Yes
Occupation fixed effects	No	No	No	No	Yes	Yes	Yes
Activity controls	No	No	No	No	No	Yes	Yes
Performance and skill controls	No	No	No	No	No	No	Yes

Notes: The dependent variable in all columns and panels is the log hourly gross wage. In Panel A, WFHr is an indicator variable equal to one if the respondent reports to work (occasionally) from home and hours worked at home are fully or partially counted as working time. In Panel B, WFHr hours denotes the number of hours worked at home and are fully or partially counted as working (in logs). Worker and firm controls include education (in years of schooling), indicator variables for gender, married, migrant, age-squared, experience (-squared, -cubic and quartic), and plant-size indicators. Industry fixed effects are based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effect are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For details on the variable definitions see Section 3.

Table A.8: Working from home and wage income (only full-time workers)

	Dependent variable: log gross hourly wage						
PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)
WFH	0.392***	0.241***	0.226***	0.217***	0.176***	0.139***	0.119***
	(0.00700)	(0.00657)	(0.00668)	(0.00654)	(0.00656)	(0.00659)	(0.00663)
Observations	13680	13680	13680	13680	13680	13680	13680
R-squared	0.186	0.409	0.446	0.473	0.528	0.553	0.563
PANEL B	(1)	(2)	(3)	(4)	(5)	(6)	(7)
log WFH hours	0.0715***	0.0414***	0.0401***	0.0394***	0.0291***	0.0259***	0.0254***
	(0.00670)	(0.00580)	(0.00588)	(0.00582)	(0.00590)	(0.00580)	(0.00575)
Observations	3625	3625	3625	3625	3625	3625	3625
R-squared	0.030	0.302	0.357	0.384	0.453	0.479	0.491
PANEL C	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No-WFH	-0.155***	-0.0964***	-0.0755***	-0.0679***	-0.0407***	-0.0203***	-0.0110
	(0.00822)	(0.00742)	(0.00744)	(0.00725)	(0.00742)	(0.00730)	(0.00726)
Observations	8478	8478	8478	8478	8478	8478	8478
R-squared	0.040	0.282	0.340	0.382	0.451	0.484	0.498
Worker and firm controls	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	Yes	Yes	Yes	Yes	Yes
Region fixed effects	No	No	No	Yes	Yes	Yes	Yes
Occupation fixed effects	No	No	No	No	Yes	Yes	Yes
Activity controls	No	No	No	No	No	Yes	Yes
Performance and skill controls	No	No	No	No	No	No	Yes

Notes: The dependent variable in all columns and panels is the log hourly gross wage. In Panel A, WFH is an indicator variable equal to one if the respondent reports to work (occasionally) from home. In Panel B, WFH hours denotes the number of hours working from home (in logs). In Panel C, No-WFH is an indicator variable equal to one if the job cannot be performed from home. Worker and firm controls include education (in years of schooling), indicator variables for gender, married, migrant, age-squared, experience (-squared, -cubic and quartic), and plant-size indicators. Industry fixed effects are based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effect are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For details on the variable definitions see Section 3. The sample is restricted to full-time workers, i.e. workers reporting to work at least 21 hours per week.

Table A.9: Working from home and wage income (quantile regressions)

	Dependent variable: log gross hourly wage	
	(1) WFH	(2) No-WFH
0.1	0.0927***	-0.0320**
	(0.0119)	(0.0144)
0.2	0.0920***	-0.0160*
	(0.00827)	(0.00967)
0.3	0.0945***	-0.0222**
	(0.00790)	(0.00890)
0.4	0.0969***	-0.0250***
	(0.00720)	(0.00801)
0.5	0.0999***	-0.0211**
	(0.00735)	(0.00833)
0.6	0.104***	-0.0163**
	(0.00750)	(0.00772)
0.7	0.120***	-0.0124
	(0.00776)	(0.00797)
0.8	0.122***	-0.0122
	(0.00765)	(0.00807)
0.9	0.136***	-0.0145
	(0.0104)	(0.0115)
OLS	0.112***	-0.0150**
	(0.00665)	(0.00726)
Worker and firm controls	Yes	Yes
Industry fixed effects	Yes	Yes
Region fixed effects	Yes	Yes
Occupation fixed effects	Yes	Yes
Activity controls	Yes	Yes
Performance and skill controls	Yes	Yes

Notes: The table shows estimates from a quantile regressions on WFH (column 1) and No-WFH (column 2) across the wage distribution (namely the quantiles 0.1,0.2,...,0.9), and the respective OLS estimates corresponding to the last column from Table 3. The dependent variable in all columns is the log hourly gross wage. In column 1, WFH is an indicator variable equal to one if the respondent reports to work (occasionally) from home. In column 2, No-WFH is an indicator variable equal to one if the job cannot be performed from home. Worker and firm controls include education (in years of schooling), indicator variables for gender, married, migrant, age-squared, experience (-squared, -cubic and quartic), and plant-size indicators. Industry fixed effects are based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effect are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For details on the variable definitions see Section 3. The regressions in column 1 and 2 are based on 15530 and 9720 observations, respectively.

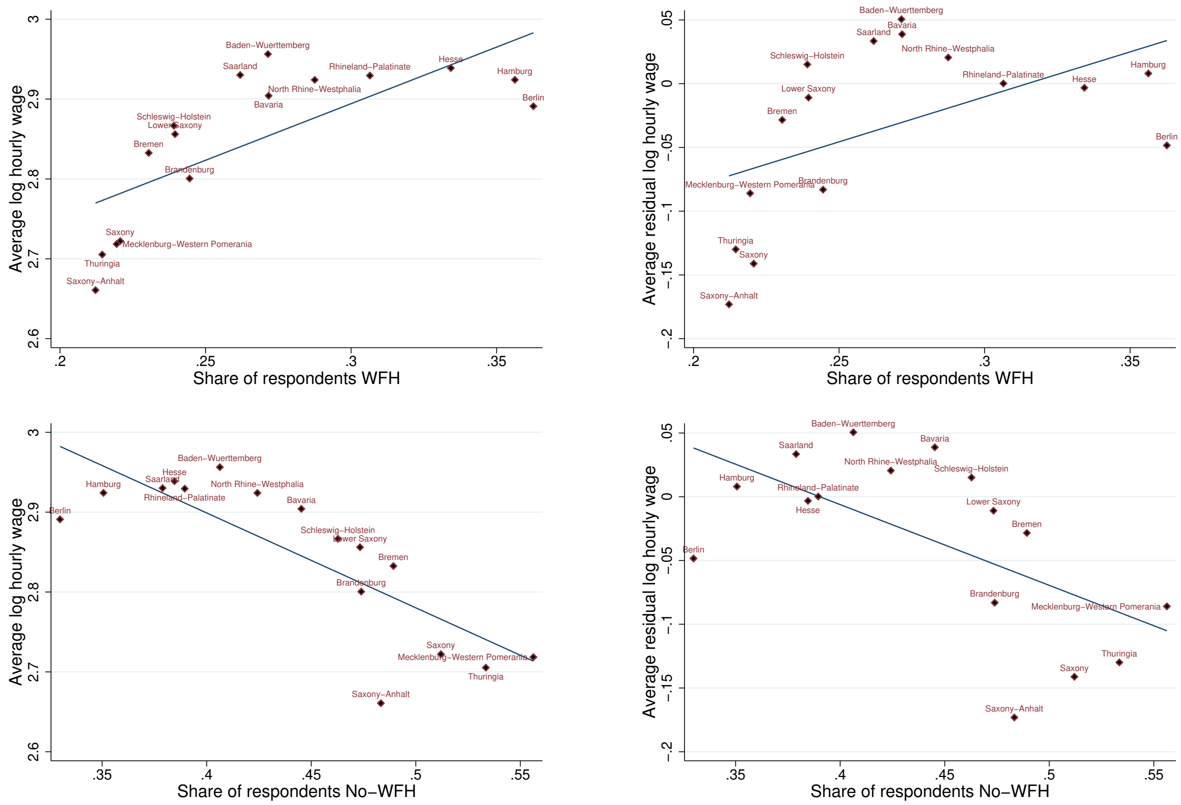
Table A.10: Working from home and wage income (detailed regression output)

	Dependent variable: log gross hourly wage		
WFH	0.112***		
	(0.00665)		
log WFH hours		0.0233***	
		(0.00587)	
No-WFH			-0.0150**
			(0.00726)
Education	0.0242***	0.0342***	0.0236***
	(0.00522)	(0.0121)	(0.00668)
Indic.: Female	-0.119***	-0.123***	-0.0996***
	(0.00642)	(0.0130)	(0.00809)
Indic.: Married	0.0431***	0.0499***	0.0429***
	(0.00539)	(0.0117)	(0.00647)
Age^2	0.00862	0.00162	0.00496
	(0.00529)	(0.0123)	(0.00684)
Experience	0.0252***	0.0323*	0.0303***
	(0.00784)	(0.0173)	(0.00957)
Experience^2	-0.0964*	-0.116	-0.135**
	(0.0517)	(0.115)	(0.0620)
Experience^3	0.142	0.235	0.272
	(0.144)	(0.331)	(0.173)
Experience^4	-0.0884	-0.199	-0.214
	(0.139)	(0.328)	(0.165)
Indic.: Migrant	-0.0227**	-0.0329	-0.0256**
	(0.0101)	(0.0227)	(0.0119)
Observations	15530	4010	9720
R-squared	0.537	0.476	0.466
Worker and firm controls	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes
Occupation fixed effects	Yes	Yes	Yes
Activity controls	Yes	Yes	Yes
Performance and skill controls	Yes	Yes	Yes

Notes: The dependent variable in all columns is the log hourly gross wage and the regressions are akin to the last column from Table 3 for Panel A, B and C. In column 1, WFH is an indicator variable equal to one if the respondent reports to work (occasionally) from home. In columns 2, WFH hours denotes the number of hours working from home (in logs). In column 3, No-WFH is an indicator variable equal to one if the job cannot be performed from home. Worker and firm controls include education (in years of schooling), indicator variables for gender, married, migrant, age-squared, experience (-squared, -cubic and quartic), and plant-size indicators. Industry fixed effects are based on NACE 1.1. Region fixed effects are based on NUTS2. Occupation fixed effect are based on KldB-2010 classification. Activity controls include 15 different activities following the definition in Becker and Muendler (2015). Performance and skill controls include indicators for routineness, codifiability, 8 different skill requirements, and an indicator for computer use. For details on the variable definitions see Section 3. Note that regression output for age is dropped as it is controlled for via the variables experience and education, as experience is defined as age-education-5.

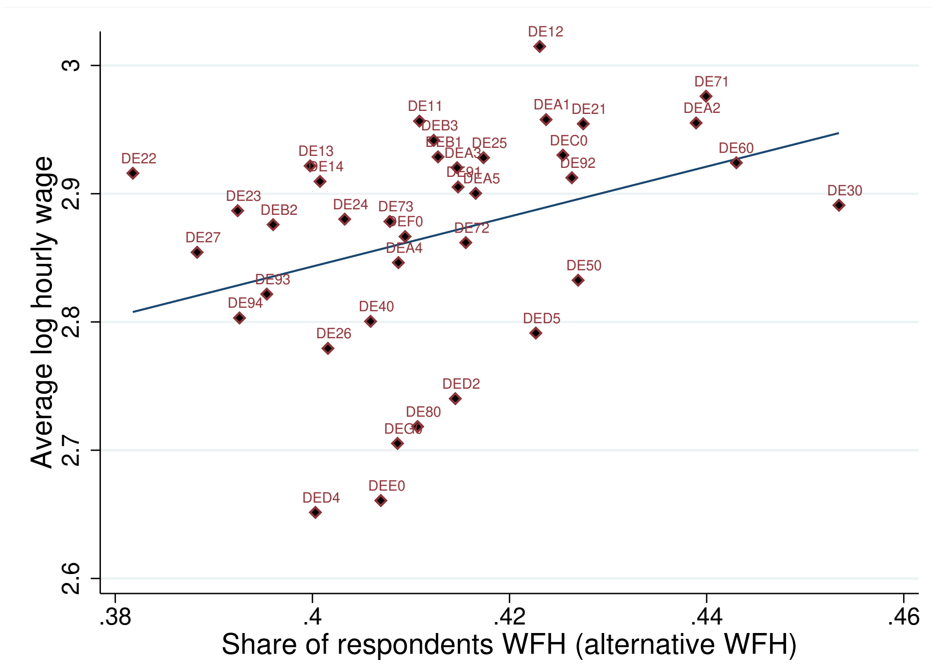
A.4 Further results on regional analysis

Figure A.8: Working from home and wages across federal states in Germany



Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017).
Notes: The upper left panel depicts the average of WFH and the average log hourly wage for the 16 federal states in Germany. The upper right panel uses the average log residual wage after running a mincer regression (see Section 4.2 for details). The lower left (right) panel depicts the average of No-WFH and the average log hourly wage (average log residual wage).

Figure A.9: Working from home and wages in Germany (alternative WFH measure)



Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017) and Fadinger and Schymik (2020).
Notes: The figure depicts the working from home potential from Fadinger and Schymik (2020) and the average log hourly wage (from the BIBB-BAUA 2018 sample) for 38 different NUTS2 regions in Germany.

Table A.11: Summary statistics for NUTS2 regions in Germany

NUTS2	NUTS2 Name	WFH	No-WFH	Wage	Residual wage	N(WFH)	N(No-WFH)
DEF0	Schleswig-Holstein	0.24	0.46	2.87	0.02	610	411
DE60	Hamburg	0.36	0.35	2.92	0.01	469	271
DE91	Statistical region Brunswick	0.23	0.48	2.91	-0.02	328	219
DE92	Statistical region Hanover	0.25	0.46	2.91	0	476	309
DE93	Statistical region Lueneburg	0.29	0.44	2.82	-0.01	356	222
DE94	Statistical region Weser-Ems	0.2	0.5	2.8	-0.02	502	350
DE50	Bremen	0.23	0.49	2.83	-0.03	145	87
DEA1	Duesseldorf	0.28	0.4	2.96	0.03	852	522
DEA2	Cologne	0.35	0.4	2.96	0	808	432
DEA3	Muenster	0.29	0.42	2.92	0.02	434	280
DEA4	Detmold	0.23	0.48	2.85	0.02	459	306
DEA5	Arnsberg	0.27	0.45	2.9	0.03	674	428
DE71	Darmstadt	0.38	0.34	2.98	0.02	843	464
DE72	Giessen	0.3	0.39	2.86	-0.07	195	120
DE73	Kassel	0.21	0.54	2.88	-0.01	230	158
DEB1	Statistical region Koblenz	0.31	0.43	2.93	-0.01	269	165
DEB2	Statistical region Trier	0.31	0.45	2.88	0	97	59
DEB3	Statistical region Rhine-Hesse-Palatinate	0.31	0.35	2.94	0.01	396	240
DE11	Stuttgart	0.29	0.37	2.96	0.03	778	469
DE12	Karlsruhe	0.3	0.39	3.01	0.05	580	342
DE13	Freiburg	0.21	0.46	2.92	0.08	418	290
DE14	Tuebingen	0.27	0.43	2.91	0.07	360	218
DE21	Upper Bavaria	0.35	0.38	2.95	0.07	1419	828
DE22	Lower Bavaria	0.23	0.48	2.92	0.07	308	207
DE23	Upper Palatinate	0.24	0.54	2.89	0.03	309	204
DE24	Upper Franconia	0.28	0.47	2.88	-0.01	276	183
DE25	Middle Franconia	0.24	0.43	2.93	0.02	507	323
DE26	Lower Franconia	0.19	0.44	2.78	-0.08	342	243
DE27	Swabia	0.19	0.52	2.85	0.06	495	344
DEC0	Saarland	0.26	0.38	2.93	0.03	187	124
DE30	Berlin	0.36	0.33	2.89	-0.05	1029	617
DE40	Brandenburg	0.24	0.47	2.8	-0.08	528	378
DE80	Mecklenburg-Western Pomerania	0.22	0.56	2.72	-0.09	328	229
DED4	Directorate region Chemnitz	0.17	0.58	2.65	-0.18	285	224
DED2	Directorate region Dresden	0.23	0.51	2.74	-0.11	375	261
DED5	Directorate region Leipzig	0.28	0.43	2.79	-0.12	240	158
DEE0	Saxony-Anhalt	0.21	0.48	2.66	-0.17	455	334
DEG0	Thuringia	0.21	0.53	2.71	-0.13	465	332

Source: BIBB-BAuA 2018 (projection factor based on microcensus 2017)

Notes: The table reports averages for WFH (an indicator variable equal to one if the respondent reports to work from home), No-WFH (an indicator variable equal to one if the job cannot be performed from home), log gross hourly wages, residual wages after running a Mincer regression (see Sections 4.2 for details), and the number of underlying observations - N(WFH) and N(No-WFH) - for the 38 different NUTS2 regions in Germany.