Inequality in the Impact of the Coronavirus Shock: Evidence from Real Time Surveys

Abi Adams-Prassl, Teodora Boneva, Marta Golin, and Christopher Rauh*

August 5, 2020

Abstract

We present real time survey evidence from the UK, US and Germany showing that the immediate labor market impacts of Covid-19 differ considerably across countries. Employees in Germany, which has a well-established short-time work scheme, are substantially less likely to be affected by the crisis. Within countries, the impacts are highly unequal and exacerbate existing inequalities. Workers in alternative work arrangements and who can only do a small share of tasks from home are more likely to have lost their jobs and suffered falls in earnings. Women and less educated workers are more affected by the crisis.

JEL: J21, J22, J24, J33, J63

Keywords: Recessions, Inequality, Labor market, Job loss, Furlough, Short-time work, Coronavirus, Covid-19, Working from home, Gender gap

*Adams-Prassl: University of Oxford (email: abi.adams@economics.ox.ac.uk). Boneva: University of Zurich (email: teodora.boneva@econ.uzh.ch). Golin: University of Oxford (email: marta.golin@nuffield.ox.ac.uk). Rauh: University of Cambridge, Trinity College Cambridge (email: cr542@cam.ac.uk). Ethics approval was obtained from the Central University Research Ethics Committee (CUREC) of the University of Oxford: ECONCIA20-21-09. We thank Toke Aidt and Hamish Low for valuable feedback. We are grateful to the Economic and Social Research Council (UKRI grant number ES/V004042/1), the University of Oxford, the University of Zurich, the Keynes Fund, and the Cambridge INET for generous financial support, and Marlis Schneider for excellent research assistance.

1 Introduction

The Covid-19 outbreak has caused severe disruptions to labor supply in many countries around the world, bringing whole economies grinding to a halt. As a result, individuals are suffering large and immediate losses in terms of income and employment. Different public policies are put in place to buffer the economic consequences of the shock. Obtaining a better understanding of the distribution of impacts of the Covid-19 crisis is crucial for designing policy responses that target those individuals who have been most affected by the crisis. In this paper, we provide evidence from real time surveys conducted in the US, the UK and Germany in March and April 2020. We examine which workers were most likely to lose their jobs, be furloughed or on short-time work, reduce their hours, and experience a decrease in their earnings. Our focus lies on documenting cross-country differences as well as understanding which job characteristics allow individuals to buffer the shock of the crisis.

The impacts of the Covid-19 crisis are large and unequal within and across countries. There are several key results that emerge from our study. First, we find staggering cross-country differences in the labor market impacts of the Covid-19 epidemic. By early April, 20% and 17% of individuals in work at the onset of the pandemic lost their jobs in the US and the UK, respectively, compared to only 5% in Germany. The countries differ in the labor market policies that were introduced or extended in response to the crisis. Germany has a well-established short-time work (STW) scheme and we find that 34% of employees in work at the onset of the pandemic have been asked to reduce their hours to benefit from this scheme. Furloughing has been relatively prevalent in the UK but not as prevalent in the US; 36% and 25% of employees in the UK and US respectively report having being furloughed in their main job. Though it might be too early to claim that the "German economic miracle" witnessed during the Great Recession (Rinne and Zimmermann, 2012) is repeating itself, we find that the shock has been much smaller for German workers thus far.

Second, there are striking differences in the impacts within countries depending on job and worker characteristics. In all three countries, workers who report that they can do a high share of tasks from home are substantially less likely to have lost their job. Moreover, we find large differences in job loss probabilities across industries and occupations, mostly owing to the fact that the average percentage of tasks workers can do from home varies substantially across industries and occupations. Interestingly, the percentage of tasks workers can do from home is a significant predictor of job loss, over and above what can be explained by industry, occupation or other job characteristics. In all three countries, employees on permanent contracts have been significantly less likely to lose their jobs compared to employees with temporary work arrangements.

Turning to individual differences in job loss probabilities, in the US and the UK there are marked differences between men and women and between people with and without university education. Women and workers without a college degree are significantly more likely to have lost their jobs. Remarkably, while occupation fixed effects and the percentage of tasks one can do from home can account for all of the gap in job loss between college-educated workers and workers without a college degree, this is not the case for the gender gap. The gender gap persists even once we control for these job characteristics, indicating that other factors play a role. This does not only contrast with usual recessions in which men tend to be more likely to lose their jobs.[1] It also stands in contrast with the results from Germany, where neither gender nor having a college degree significantly predict job loss. Turning to time use data, we note that amongst the population working from home, women spend significantly more time homeschooling and caring for children.

Individual outlooks on the future are bleak. The average perceived probability of losing one's job within the next months is 35% in the US and 31% in the UK. Even in Germany, where the share of workers who have lost their job already is much smaller than in the anglophone countries, the average perceived probability of losing one's job before August 2020 is 25%. Individuals are worried about being able to pay their usual bills and expenses. 47% in the US, 40% in the UK, and 32% in Germany already have struggled to pay their usual bills.

Our paper contributes to several strands of the literature. First, it contributes to the literature on the impact of economic downturns on labor market outcomes (e.g., Hoynes, Miller and Schalle 2012; Christiano, Eichenbaum and Trabandt 2015) and the importance of short-time work schemes to buffer economic shocks (e.g., Giupponi and Landais 2018; Cahuc, Kramarz and Nevoux 2018; Kopp and Siegenthaler 2018). Second, it closely relates to the literature on alternative work arrangements and the role of firms in providing workers insurance against shocks to labor demand (Malcomson 1999; Koustas 2018; Mas and Pallais 2020). We show that firms are sheltering permanent workers more than those on temporary contracts. Third, our paper contributes to the economics literature documenting the immediate impact of the Covid-19 pandemic.

[1] See, for instance, Hoynes, Miller and Schalle (2012) and Bredemeier, Juessen and Winkler (2017).

Research using real time data has studied the relationship between the outbreak and stock returns and volatility (Alfaro et al. 2020; Baker et al. 2020*a*), subjective uncertainty in business expectations surveys (Baker et al. 2020*b*), business closures (Bartik et al. 2020), worries regarding the aggregate economy (Fetzer et al. 2020), household spending (Baker et al. 2020*c*; Carvalho et al. 2020), and labor market impacts in specific countries relying on administrative data (Cajner et al. 2020), data from businesses (Chetty et al. 2020), job ads (Kahn, Lange and Wiczer 2020), public survey data (e.g. Benzeval et al. 2020; Coibion, Gorodnichenko and Weber 2020), and own data collected through survey agencies (Bick and Blandin 2020; von Gaudecker et al. 2020). Other research using data collected before the crisis has discussed channels through which the current crisis may affect workers differently depending on their gender and occupation (Alon et al. 2020; Dingel and Neiman 2020; Mongey and Weinberg 2020). We provide real time evidence on the effect of the pandemic on labor market outcomes in three major economies. Moreover, our survey is tailored to capture elements specific to the Covid-19 recession such as furloughing and short-time work.

2 Data

We use real-time survey data collected as part of the COVID Inequality Project to study the labor market impacts of the pandemic.[2] The analyses presented in this paper are primarily based on data collected between April 9-14 in the US ($N = 4,000$), UK ($N = 4,931$) and Germany ($N = 4,002$).[3] We also provide additional insights using survey data collected between March 24-26 for which we only have information for the US ($N = 4,003$) and the UK ($N = 3,974$). To be eligible to participate in the study, participants had to be at least 18 years old and report having engaged in any paid work during the previous 12 months. To ensure that results are comparable across waves and countries, we chose to draw independent study samples for each wave/country using the same sampling methodology. More specifically, we used quota-based sampling to ensure that the samples are representative in terms of region in each country. Appendix Tables C.1 to C.3 show the distribution of respondents across regions and the comparison to the

[2]The surveys were conducted by a professional survey company. All participants were part of the company's online panel and participated in the survey online using their computers, tablets or mobile phones. The survey was scripted in Qualtrics. The median time to complete the survey was about 10 minutes.

[3]All dates refer to the year 2020. The results presented in this paper are based on the April wave of the survey, unless stated otherwise.

national distribution of individuals across the different regions.

Comparison to CPS, LFS and SOEP data: Appendix Tables C.4 to C.6 compare the characteristics of the April samples to nationally representative statistics from the Current Population Survey (CPS) for the US, the Labor Force Survey (LFS) for the UK, and the Socio-Economic Panel (SOEP) for Germany. The sample distributions are comparable in terms of occupations and industries, although some categories (e.g. "Computer and Mathematical" occupations) are over-represented. In terms of individual characteristics, women and workers with a university degree are over-represented. While there are some differences between our data and the nationally representative statistics, we note that our results are robust to re-weighting the sample using survey weights.[4]

Survey design: We collect detailed information on respondents' work arrangements and work history. Importantly, the data allow us to make two key distinctions. First, we can distinguish between workers who kept their jobs and workers who lost their jobs in the recent crisis. Second, we explicitly ask employees to report whether they have been furloughed (US&UK) or put on STW (Germany). Taken together, this information allows us to distinguish between three different groups of employees: those who are still regularly employed (i.e. not on furlough or STW), furloughed (US&UK) or on STW (Germany), and employees who were laid off. This distinction is important given the recent policy responses to the crisis (see Section 3).

The data include information on a range of individual (e.g. age, gender, education) and job characteristics (e.g. occupation, industry). To study the importance of workers' ability to work from home, we elicit information on the percentage of tasks workers could do from home (0-100%). The data further include information on respondents' net earnings in the previous months, as well as on the number of hours worked in a typical week in February and April. Appendix A provides more details on the survey design, while Appendix B includes the questionnaire.

Sample: To study the impact of the coronavirus crisis on the labor market, we limit the analysis to workers who are still in work in April or lost their job in the previous month due to the coronavirus outbreak. Individuals who did not have a job at the onset of the pandemic are not included in any of the analyses.

[4]To calibrate the weights, we use an iterative proportional fitting (or raking) procedure (Deville and Särndal, 1992; Kolenikov, 2014) to ensure that the distributions of gender, education, age, occupation, industry and region in our samples match those of the economically active population in each respective country.

3 Context

Given the speed at which events unfolded, it is important to situate our study into the existing context. In all three countries, the first Covid-19 cases were confirmed towards the end of January and the first deaths in the beginning of March. The countries differed, however, in the intensity and speed at which lockdown measures and public policies were introduced.[5] Germany announced the first nationwide social distancing measures on March 12th, closed schools on March 16th and announced a nationwide lockdown on March 22nd. In the UK, a nationwide lockdown was announced on March 23rd, and schools were also closed from that date. In the US, national emergency was declared on March 13th. There was a substantial degree of heterogeneity across US states with regard to the introduction of lockdown measures. California was the first to issue state-wide stay-at-home orders, which took effect on March 19th. The majority of US states followed, and by the time of our April data collection 40 US states had introduced similar lockdown measures.[6] In all three countries, visits to retail spaces and workplaces started dropping sharply on March 18th (Appendix Figure D.2).

To buffer the labor market impacts of the pandemic, the countries introduced different policy measures. Germany, which already had one of the oldest and most comprehensive short-time work (STW) schemes, passed a law on March 13th, making the eligibility criteria for STW less stringent.[7] On March 20th, the UK government announced the Coronavirus Job Retention Scheme, which allowed firms to furlough workers. In contrast to the German STW scheme, furloughed workers are not allowed to undertake any work for their employer. In the US, where a similar furloughing scheme has been in place, the Coronavirus Aid, Relief, and Economic Security (CARES) Act was signed into law on March 27th. The CARES Act includes provisions to expand unemployment benefits to furloughed workers, gig workers, and freelancers, with unemployment benefits increased by $600 per week, as well as additional direct payments to families. Small businesses could obtain forgivable loans through the Payroll Protection Program (PPP). Germany and the UK also made provisions for the self-employed. On March 23rd, the German government agreed on an emergency assistance program to

[5] The timeline presented in Appendix Figure D.1 illustrates the exact timing of events.

[6] An overview of the different lockdown measures US states introduced (with corresponding dates) can be found on this website: `https://github.com/nytimes/Covid-19-data`.

[7] STW allows firms affected by temporary shocks to reduce their employees' hours instead of laying them off. Government subsidies pay short-time compensation to employees who reduce their hours (up to a cap).

support small businesses, freelancers and the solo self-employed, which was accessible immediately. On March 26th, the UK announced the Self-Employment Income Support Scheme which offered grants to self-employed workers not to be paid out before June.

The three countries we study do not only differ in their policy responses to the crisis. Most notably, there is also considerable variation in employment protection legislation (OECD 2020). The OECD Employment Protection Legislation (EPL) index, which summarizes core aspects of dismissal regulation such as procedural requirements and severance pay, is 0.09 in the US, 1.35 in the UK and 2.60 in Germany. Existing institutional differences are likely to have contributed to the large cross-country disparities in job loss we document in our study.

4 Results

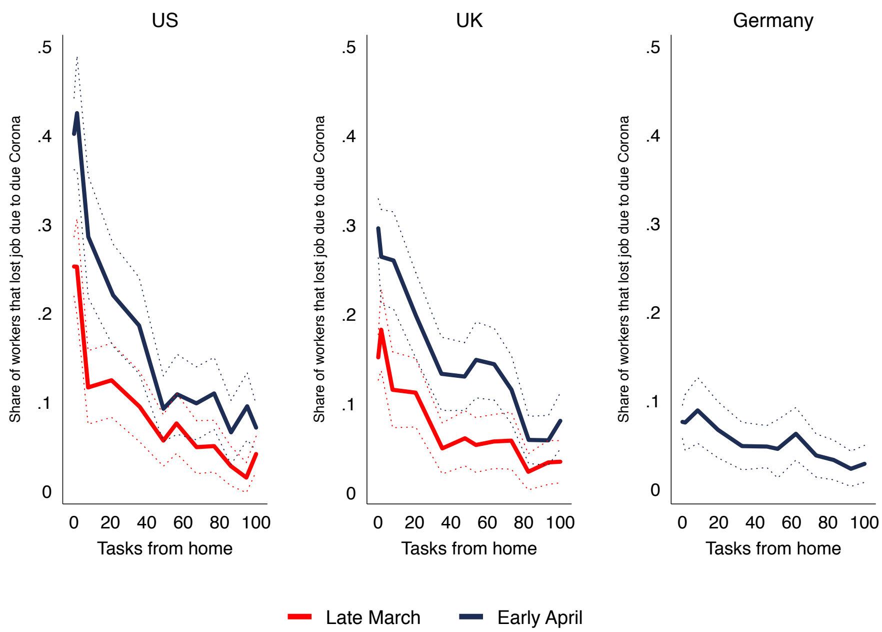
4.1 Job Loss

There are staggering cross-country differences in the percentage of workers who lost their jobs due to the Covid-19 pandemic. While 20% and 17% of US and UK workers lost their jobs by early April, the corresponding figure is 5% for Germany.[8] Within each country, the labor market impact of the pandemic was highly unequal. There are some notable similarities across countries in terms of who was most likely to be affected. In all waves and countries, there is a clear negative relationship between job loss and the ability to work from home (panel (a) of Figure 1). The most salient cross-country differences in job loss can be observed in the bottom part of the distribution. While more than 40% of workers who cannot work from home lost their jobs in the US by early April, the corresponding figure is below 10% in Germany. Panel (b) of Figure 1 displays the proportion of employees who lost their job by work arrangement. Again we observe a similar pattern in all three countries. Employees with permanent, salaried, fixed hour contracts were less likely to lose their jobs.

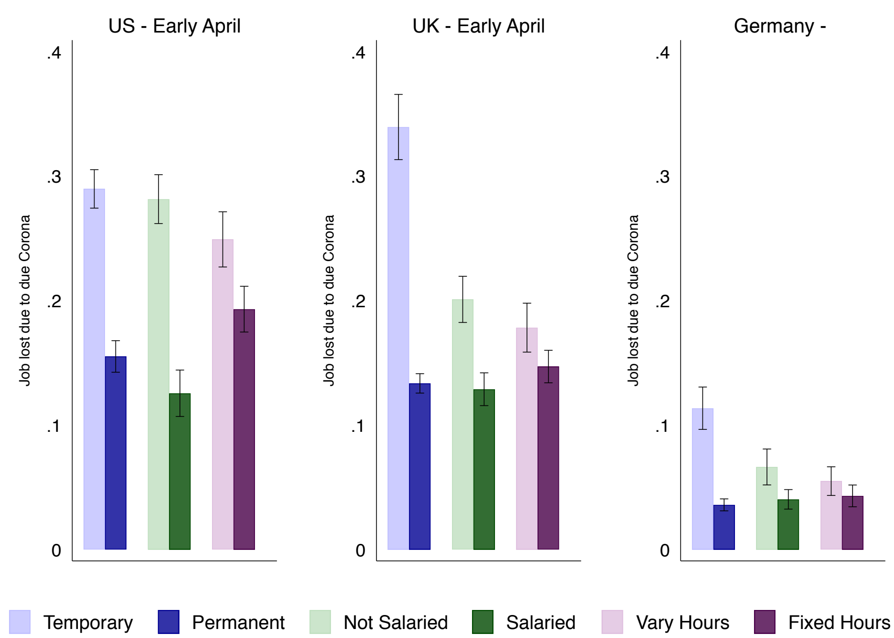
[8] We note that our results are broadly comparable to aggregate statistics obtained from other sources. For the US for example, data from the Household Survey show that in April 2020 total employment fell by 22.4 million, or around 14% of total employment in March 2020. Data from the Establishment Survey show a similar decline in total nonfarm employment, which was particularly concentrated in the leisure and hospitality sector (Bureau of Labor Statistics, 2020). Finally, Bick and Blandin (2020) find that 16.5% of workers in the US lost their jobs.

Figure 1: Job loss probability due to Covid-19 by percentage of tasks that can be done from home and work arrangement

(a) Job loss by percentage of tasks that can be done from home

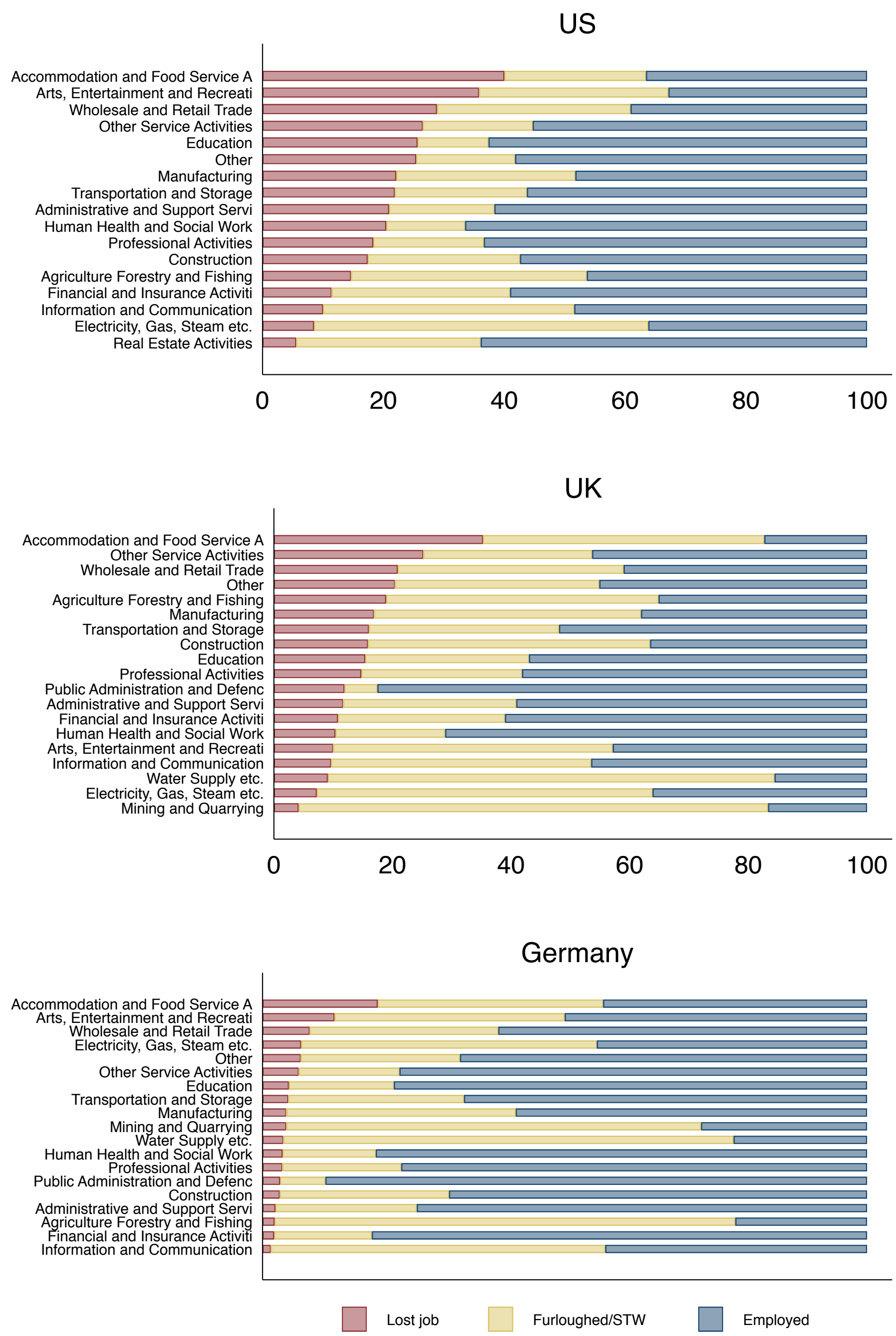


(b) Job loss by work arrangement



Notes: The dotted line in panel (a) and the thin black bars in (b) represent the 95% confidence intervals. The figures show the share of individuals who were in paid work four weeks before data collection that lost their job due to Covid-19.

Figure 2: Employment status by industry (early April)



Notes: The figure shows the share of workers who are employed (blue - right), furloughed for the US/UK or on STW for Germany (yellow - middle) or lost their job due to the Covid-19 crisis (red - left), by industry. The sample is restricted to employees (in their current or last job) only.

There are also large differences in job loss across industries and occupations.[9] Figure 2 presents the percentage of employees who lost their jobs, were furloughed (US&UK) or on STW (Germany), or still employed in early April. Employees in the 'Accommodation and Food Service Activities' industry were most likely to lose their jobs in all three countries. The 'Arts, Entertainment and Recreation' industry as well as the 'Wholesale and Retail Trade' industry were also considerably affected. Other industries such as 'Information and Communication' experienced lower declines. We also see sizeable differences in the percentage of workers furloughed or on STW. We investigate furloughing/STW in more detail in Section 4.3. Appendix Figure D.3 shows the large differences in job loss by occupation. Employees in 'Food Preparation and Serving' were substantially more likely to lose their jobs than employees in 'Computer and Mathematical' occupations.

There are substantial differences in workers' ability to work from home both across as well as within industries and occupations (see Appendix Figures D.4 and D.5).[10] The mean share of tasks workers can do from home is lowest in the 'Accommodation and Food Service Activities' industry and highest in 'Information and Communication'. For occupations, the lowest average share can be observed in 'Food Preparation and Serving' while 'Computer and Mathematical' occupations have the highest share. In Appendix Figure D.6 we show that there is a strong relationship between the average share of tasks workers can do from home within a given industry and the percentage of workers who lost their jobs in that industry. The average share of tasks that can be done from home explains 66%, 44% and 24% of the variation in job loss across industries in the US, UK and Germany, respectively. For occupations, this relationship is similarly strong (Appendix Figure D.7). These patterns also hold for occupation-industry pairs.[11]

Table 1 (columns (1)-(3)) shows the results of linear probability models (LPM) in which we regress job loss on a range of job characteristics. Job loss is defined as a binary variable which equals one if the worker lost their job and zero otherwise. All

[9]We use NACE Rev. 2 codes to classify industries. Occupations are classified using O*NET SOC 2018 codes for the US&UK, and ISCO-08 codes for Germany. Differences in occupation classifications need to be kept in mind when comparing R^2 statistics across regressions with occupation fixed effects.

[10]In Adams-Prassl et al. (2020) we document that the variation within and across occupations and industries is remarkably consistent across countries and survey waves.

[11]Appendix Figure D.8 shows heatmaps of the average share of tasks that can be done from home by occupation (y-axis) and industry (x-axis), while Appendix Figure D.9 shows the share of jobs lost due to Covid-19. Comparing the two figures highlights that occupations in industries in which the average share of tasks that can be done from home is lower experienced larger declines in employment.

specifications control for region, occupation and industry fixed effects.[12] The share of tasks that can be done from home significantly predicts job loss over and above what can be explained by occupation and industry fixed effects, highlighting the importance of differences in the ability to work from home within occupations and industries. The results presented in this table also speak to the importance of contractual arrangements in sheltering workers form the economic downturn. Controlling for workers' ability to work from home and the occupation and industry they work in, we find that employees in less secure work arrangements are more likely to have lost their jobs. In all three countries, employees on permanent contracts were less likely to lose their jobs compared to employees on temporary contracts. Salaried employees were less likely to lose their jobs in the US and Germany compared to non-salaried employees. Finally, self-employed workers were more likely to lose their jobs in the US and the UK compared to employees.[13] The same patterns are found when using both waves for the US and the UK (Appendix Table D.1) or using survey weights in the analysis (Appendix Table D.2) which account for differences in gender, education, age, occupation, industry and region between our samples and nationally representative samples of the economically active population in each respective country.

Next we explore whether individuals' background characteristics and job characteristics relate to differences in job loss. We explore heterogeneity in job loss with respect to gender, education and age groups. Table 2 presents the results of an LPM in which we first regress job loss on individual characteristics only, and then add controls to account for job characteristics.[14] In the US and the UK, women were 6.5 percentage points (p.p.) and 4.8 p.p. more likely to lose their jobs. Differences in job characteristics between male and female workers can account for about half of the gender gap in job loss in both countries. We note, however, that a significant gender gap remains even once we control for job characteristics, suggesting that other factors we are not capturing in this regression play a role in driving the gender gaps.

[12]Region fixed effects refer to states for the US and Germany. For the UK, we include fixed effects for the nine regions of England, as well as Scotland, Wales and Northern Ireland.

[13]Note that the definition of job loss is the same for employees and self-employed workers (see Appendix A).

[14]Appendix Table D.3 presents weighted results. The results are robust to the use of weights.

Table 1: Job and earnings loss probability

	Job loss			Earnings loss		
	US	UK	DE	US	UK	DE
	(1)	(2)	(3)	(4)	(5)	(6)
Tasks from home	-0.2617***	-0.1917***	-0.0397***	-0.1328***	-0.0737***	-0.0202
	(0.0216)	(0.0195)	(0.0128)	(0.0303)	(0.0267)	(0.0233)
Self-Employed	-0.0996***	-0.0463*	0.0051	0.0224	0.0945**	0.0615*
	(0.0228)	(0.0257)	(0.0174)	(0.0320)	(0.0373)	(0.0322)
Permanent	-0.0659***	-0.1711***	-0.0546***	-0.0116	-0.0224	0.0030
	(0.0165)	(0.0205)	(0.0114)	(0.0233)	(0.0302)	(0.0210)
Salaried	-0.0632***	0.0110	-0.0193*	-0.0911***	-0.0455**	-0.0629***
	(0.0181)	(0.0154)	(0.0108)	(0.0248)	(0.0207)	(0.0197)
Fixed hours	0.0022	-0.0094	0.0035	-0.0714***	-0.1108***	-0.0927***
	(0.0164)	(0.0151)	(0.0097)	(0.0232)	(0.0203)	(0.0175)
Constant	0.4475***	0.2720***	0.1288***	0.3757***	0.3765***	0.2933***
	(0.0875)	(0.0667)	(0.0355)	(0.1208)	(0.0886)	(0.0645)
Observations	2995	3760	3354	2396	3111	3165
R^2	0.1600	0.1138	0.0654	0.1057	0.0890	0.0671
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable in Columns (1) - (3) is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. The dependent variable in Columns (4) - (6) is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. In Columns (4) - (6) the sample is restricted to those who were in work at the time of data collection. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table 2: Job loss probability - Individual characteristics

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0652***	0.0321**	0.0483***	0.0242*	0.0015	-0.0002
	(0.0151)	(0.0157)	(0.0124)	(0.0129)	(0.0077)	(0.0084)
University degree	-0.0789***	-0.0050	-0.0629***	-0.0070	-0.0130	0.0053
	(0.0151)	(0.0161)	(0.0123)	(0.0131)	(0.0086)	(0.0102)
30-39	-0.0325	-0.0043	0.0222	0.0304*	-0.0432***	-0.0186*
	(0.0201)	(0.0195)	(0.0156)	(0.0156)	(0.0097)	(0.0103)
40-49	-0.0286	-0.0087	0.0259	0.0229	-0.0343***	-0.0141
	(0.0214)	(0.0209)	(0.0171)	(0.0173)	(0.0115)	(0.0124)
50-59	0.0005	0.0171	0.0036	-0.0074	-0.0342***	-0.0204
	(0.0247)	(0.0241)	(0.0215)	(0.0216)	(0.0120)	(0.0127)
60+	0.0135	0.0111	0.0256	0.0111	0.0319	0.0290
	(0.0257)	(0.0253)	(0.0366)	(0.0359)	(0.0201)	(0.0207)
Tasks from home		-0.2574***		-0.1913***		-0.0400***
		(0.0219)		(0.0197)		(0.0131)
Self-employed		-0.1003***		-0.0477*		0.0059
		(0.0230)		(0.0260)		(0.0176)
Permanent		-0.0639***		-0.1720***		-0.0510***
		(0.0166)		(0.0206)		(0.0116)
Salaried		-0.0592***		0.0112		-0.0192*
		(0.0185)		(0.0156)		(0.0109)
Fixed hours		0.0018		-0.0123		0.0056
		(0.0165)		(0.0152)		(0.0097)
Constant	0.2371***	0.4311***	0.1191***	0.2454***	0.0860***	0.1320***
	(0.0689)	(0.0888)	(0.0253)	(0.0678)	(0.0132)	(0.0358)
Observations	3025	2995	3816	3760	3584	3354
R^2	0.0448	0.1618	0.0169	0.1161	0.0171	0.0679
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

In terms of education, we find that workers with a university degree were 7.9 p.p. and 6.3 p.p. less likely to lose their jobs in the US and the UK, respectively.[15] Once we account for job characteristics, we no longer find a significant difference in job loss between workers with/without a university degree. Workers with different levels of education sort into different types of jobs, and sorting is a likely explanation for the insignificant coefficient we find in the regressions controlling for job characteristics.[16] The results contrast with the results for Germany, where we do not find significant gender or education gaps in job loss. Turning to the age patterns in job loss, we find no association between age and job loss in the US and the UK. In Germany, younger workers seem to have been more likely to lose their jobs.

Once we control for differences in individual background characteristics, we still find similar differences in job loss by job characteristics. The share of tasks that can be done from home is still highly significant in all three countries, though the relationship is much steeper in the US (-0.26) and the UK (-0.19) than in Germany (-0.04).[17] The differences we find in job loss between employed and self-employed workers as well as between employees with different work arrangements are similar to the differences reported in Table 1.[18]

Why are women in the US and the UK more likely to lose their jobs than men? While we cannot provide a definite answer to this question, we provide suggestive evidence that differences in care responsibilities might play a role. When we additionally control for whether the respondent had to change their work patterns to care for others, the number of kids in the household and an interaction between the number of kids and the female dummy, we find that in the UK the coefficient on the interaction term is positive and significant (Appendix Table D.5), while the opposite seems to be true for Germany where we did not find a significant gender gap in job loss. The presence of care responsibilities is positively associated with job loss in both the US and Germany. We further provide evidence that childcare responsibilities are not shared equally between

[15] There might be other differences in education and/or skill levels across workers which are not captured by this classification. Workers with different types of skills may have been more/less affected independent of whether they had a university degree or not.

[16] As illustrated in Appendix Figures D.10 and D.11, university graduates tend to sort into occupations and industries in which a high share of tasks can be done from home.

[17] To illustrate the explanatory power of the working-from-home measure, we refer to Appendix Table D.4. Working from home alone can explain 10%, 6% and 1% of the variation in job loss for the US, UK and Germany, respectively.

[18] Appendix Figures D.12 and D.13 display the industry and occupation fixed effects from columns (2), (4) and (6) of Table 2 resembling the unconditional patterns in Figures 2 and D.3.

working parents who work from home. Mothers working from home spend considerably more time homeschooling and caring for children than fathers working from home (Appendix Figure D.14). This relationship also holds when we control for a broad range of individual and job characteristics (Appendix Table D.6).

At the time the April survey was conducted, there was high uncertainty about the speed at which the virus would be contained and the economy would rebound. Focusing on workers who had a job in early April, we find that in all three countries individual outlooks on the future are bleak. On average, those still in work perceive the likelihood of losing their job in the near future to be 35% and 31% in the US and the UK, and 25% in Germany. To shed light on what might be driving differences in perceptions about job loss, we elicited individual beliefs about the likelihood of social distancing measures being in place on August 1st. The average response to this question was 59% in the US, 62% in the UK, and 53% in Germany. Appendix Table D.7 presents the results from an LPM in which we regress perceptions about job loss on individual and job characteristics as well as perceptions about the likelihood of social distancing measures being in place in August. Younger workers and employees on less secure work contracts perceive the probability of losing their job to be higher. Women and workers who can do fewer tasks from home are more optimistic about their chance of keeping their job in the US and the UK. This stands in contrast to the realized experience of these groups so far, and might be explained by strong demand for work in 'essential sectors' (Kahn, Lange and Wiczer 2020). Finally, we find that individuals who believe social distancing measures will still be in place in August perceive the probability of losing their job to be significantly higher.

Given the differences in the way the policies were administered, it is possible that workers who were laid off face a different probability of being rehired in the three different countries. While we cannot directly speak to this question because we do not observe respondents over time, we do have information on workers' perceptions of being rehired by the same employer. We do not find large cross-country differences in the perceived likelihood of returning to the same employer. The average perceived likelihood is 57% and 51% in the US and the UK, and 55% in Germany.

4.2 Earnings Loss

Many workers lost a substantial proportion of their income as a result of this recession. As in the Great Recession (Guvenen, Ozkan and Song 2014), the drop in earnings experienced by workers is not evenly spread across the initial earnings distribution. The percentage drop in earnings is greater at the bottom of the earnings distribution in all three countries (Appendix Figure D.15).[19] While it is not surprising that workers who lost their jobs experienced drops in income over this time period, one striking pattern in the data is that a very high proportion of workers who still had a job in April also experienced earnings losses. 35% (US), 29% (UK) and 20% (Germany) of respondents still in work in April report lower earnings in March (compared to Jan-Feb). Columns (4)-(6) of Table 1 show which job characteristics predict earnings losses for those still in work.[20] In the US and the UK, workers who can do fewer tasks from home are more likely to experience a drop in earnings. Self-employed workers were more likely to experience earnings losses in the UK and Germany. In all three countries, employees on salaried and fixed hour contracts were less likely to experience a decline in earnings. We further explore which individual characteristics predict earnings losses (Appendix Tables D.8 and D.9). We find no significant differences by gender. In the US, workers with a university degree were significantly less likely to experience earnings losses. In all three countries, we find evidence that younger workers were more likely to experience a decline in their income.

All respondents, irrespective of their current employment status, were further asked about their perceived likelihood of struggling to pay their usual bills and expenses in the near future (before August 1st). The average response to this question was 50% in the US, 45% in the UK, and 32% in Germany, indicating that many individuals think they will struggle financially.[21] Indeed, 47%, 40%, and 32% of individuals in the US, UK, and Germany report that they *already* struggle to pay their usual bills and expenses.

[19] To conduct this analysis, we compare individuals' net monthly income in March to their average net monthly income of January and February.

[20] Earnings loss is defined as a binary variable which takes on a value of one if net income in March is lower than the average net income of January and February.

[21] Appendix Figure D.16 displays the distribution of responses to this question separately for the US, UK and Germany.

4.3 Furloughing and Short-time Work

A prominent feature of the coronavirus crisis has been the introduction and increased use of furloughing and STW schemes. 25% (US), 36% (UK) and 34% (Germany) of employees in work at the onset of the pandemic report being furloughed or in STW in early April.[22] As with job loss, there is considerable variation in the percentage of workers furloughed or on STW across industries (Figure 2) and occupations (Appendix Figure D.3).

Appendix Tables D.10 and D.11 show the determinants of furlough in an LPM and a multinomial logit framework, respectively. Across all countries, workers on permanent contracts have been significantly more likely to be furloughed rather than laid off, and salaried workers have been significantly less likely to lose their job or be furloughed, when controlling for occupation, industry and background characteristics. The relationship between the ability to work from home and furloughing is less strong than that for job loss, with the exception of Germany. This is to be expected given that furloughed workers are not supposed to do any work for their employers under the US and UK schemes, while they can under the German scheme.[23] Turning to background characteristics, women are less likely to be on furlough in the US but more likely to be put on STW in Germany (controlling for job characteristics). We do not find significant differences in the likelihood of being on furlough between workers with/without a university degree, whereas across all countries older workers are significantly less likely to be on furlough or STW.

In the UK, employers can choose to top up the wage of their furloughed employees and 70% of respondents on furlough report that their employer offered to do so. However, 50% of employees in the UK were asked to take annual leave and 15% of them were asked to work while on furlough. In the US, 53% of furloughed employees lost their health insurance coverage. In Germany, we find a high correlation of 0.81 between the percentage of hours that employees were officially asked to work while on STW (51% on average) and the hours that they actually work (50% on average).

[22] In Germany, between early March and end of April, around 20% of the labor force applied for the STW scheme (Bundesagentur für Arbeit, 2020). In the UK, just under 4 million jobs were furloughed by April 23, 2020 and this figure rose to 6.3 million by May 3, 2020 and 9.4 million (or around a third of total employment) by July 12, 2020 (HMRC, 2020).

[23] In Appendix Table D.12 we present the R^2 from linear probability models of job loss and furloughing separately for each country, controlling for different sets of covariates. Across all countries, occupation fixed effects explain more of the variation in job loss compared to industry fixed effects, while the opposite holds true for a model of furloughing (see columns (1) and (2)). Contractual arrangement variables have similar explanatory power to industry fixed effects.

4.4 Hours Worked

Among those who still had a job in early April, we observe a stark decline in the number of hours worked. The average change in hours worked per week for those working non-zero hours (compared to a typical week in February) was 5 hours (US), 7 hours (UK) and 4 hours (Germany).[24] Figure 3 shows the average change in hours worked per week by industry, amongst workers who still have a job in early April. Across all industries there is large variation in the reduction in hours of those in paid work. Industries which require high in-person contact such as 'Education' or 'Art, Entertainment and Recreation' were disproportionately more affected. Industries that experienced the largest drop in hours also saw the largest share of workers laid off (Appendix Figure D.17). This is not a mechanical effect as the reduction in hours worked is calculated for those who are still working non-zero hours, so the change in hours only reflects the intensive but not the extensive margin. In Appendix Figures D.18 and D.19 we document similar patterns by occupation.

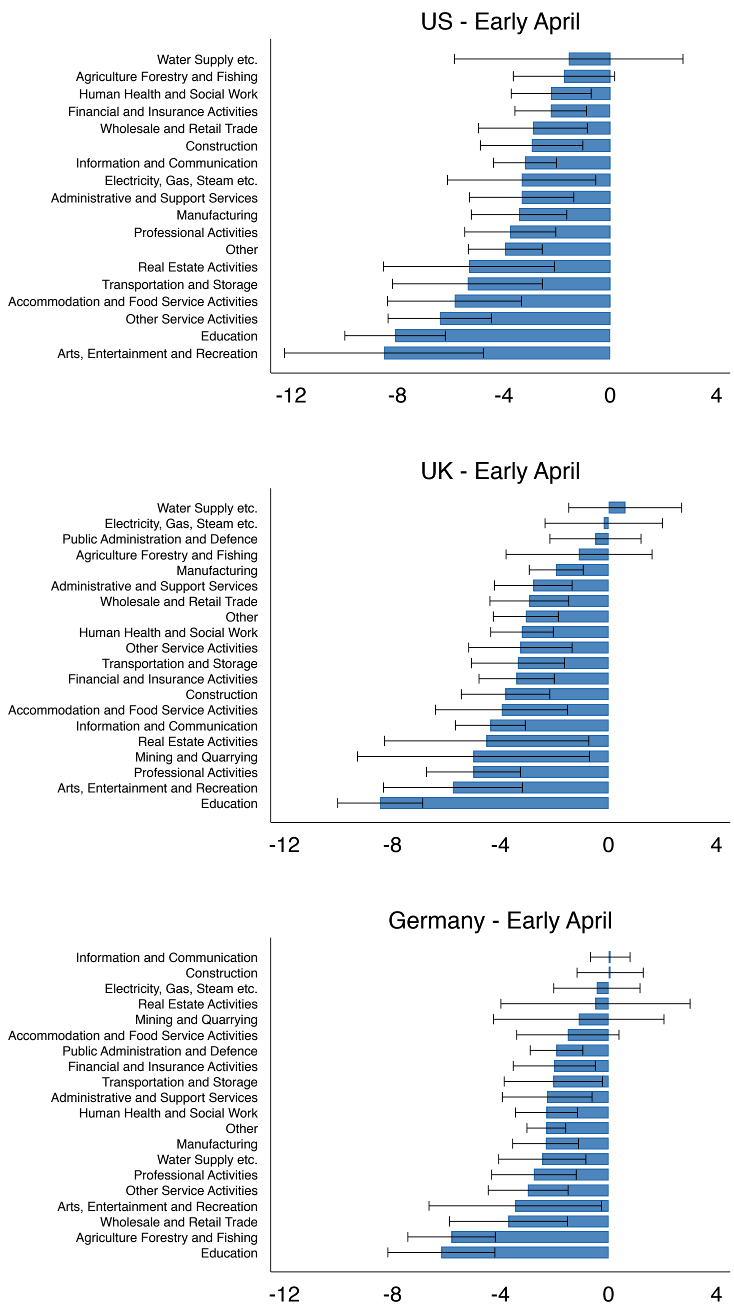
As explained in Section 3, different labor market policies were put in place in the three different countries to buffer the economic impact of the pandemic. Given the differences in the way these policies were administered, a broader question which emerges is whether the different policy responses mask actual cross-country differences (or similarities) in the impact of Covid-19 on the labor market. To shed more light on this question, we conduct an additional analysis which does not rely on how workers' status is defined. Instead, we study how hours worked changed between February and April for workers who had a job in February (irrespective of their current work status). The results are reported in Appendix Figure D.20. The figure shows the proportion of workers who reported working zero hours when surveyed in April (this includes people who lost their jobs), worked fewer (but positive) hours, the same, or more hours compared to a typical week in February, separately for each country. As illustrated by this graph, the lower job loss figures we find for Germany are not a mere artefact of how workers' status is defined in the different countries. In Germany, a much smaller share of workers who had a job in February worked zero hours in April, and a much higher share worked the same number of hours or more.[25] These patterns cannot be explained by labelling

[24]Similarly, Brewer, Gardiner and Handscomb (2020) find that the average change in hours worked for those in employment was 7 hours between early March and late April 2020.

[25]In Appendix Figure D.21 we limit the sample to the self-employed and split by median labor income in 2019. In all three countries, self-employed workers who had low earnings before the pandemic were considerably more likely to work zero hours in April. Low-wage gig workers, who are subsumed under that category, seem to be more affected compared to entrepreneurs with higher earnings.

differences across countries. We further illustrate the change in hours worked in all three countries in Appendix Figure D.22. Hours worked dropped considerably across the distribution of usual hours worked for the UK and the US, whereas for Germany a large proportion of workers worked the same number of hours in April as in a typical week in February.

Figure 3: Change in hours worked by industry



Notes: The thin black bars represent the 95% confidence intervals. The figure shows the change in hours worked between a usual work week in February and the last work week amongst those still working for the US (top), the UK (center) and Germany (bottom).

5 Conclusion

The Covid-19 crisis has had large impacts on the economy. The results from our study suggest that the impacts are unequally distributed. The percentage of tasks workers can do from home is highly predictive of job loss and so are individual work arrangements. Firms have played some role in smoothing the shock for permanent and salaried employees, and for those who usually work on fixed schedules.

In the US and UK, women and workers without a college degree are significantly more likely to have lost their jobs, while younger individuals are significantly more likely to experience a fall in their earnings. The outlook on the future is bleak with many workers expecting to lose their jobs in the near future.

Finally, we find large differences in the magnitude of the shock between the anglophone countries, the US and the UK, and Germany. The anglophone countries have seen much more employment ties cut. This might not only lead to an increase in the number of people suffering hardship at the moment, but it could also prove important for the period of economic recovery as match-specific human capital might be lost. The pandemic is likely to bring about a large reallocation of workers. Understanding the forces at work and how they interplay with institutional factors is of high policy importance.

References

Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh. 2020. "Work tasks that can be done from home: Evidence on the variation within and across occupations and industries." IZA Discussion Paper 13374.

Alfaro, Laura, Anusha Chari, Andrew Greenland, and Peter Schott. 2020. "Aggregate and firm-level stock returns during pandemics in real time." National Bureau of Economic Research 26950.

Alon, Titan, Matthias Doepke, Jane Olmstead-Rumsey, and Michele Tertilt. 2020. "The impact of COVID-19 on gender equality." National Bureau of Economic Research 26947.

Baker, Scott, Nicholas Bloom, Steven Davis, Kyle Kost, Marco Sammon, and Tasaneeya Viratyosin. 2020*a*. "The unprecedented stock market impact of COVID-19." National Bureau of Economic Research 26945.

Baker, Scott R, Nicholas Bloom, Steven J Davis, and Stephen J Terry. 2020*b*. "Covid-induced economic uncertainty." National Bureau of Economic Research.

Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis. 2020*c*. "How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic." National Bureau of Economic Research 26949.

Bartik, Alexander W., Marianne Bertrand, Zoe B. Cullen, Edward L. Glaeser, Michael Luca, and Christopher T. Stanton. 2020. "How are small businesses adjusting to COVID-19? Early evidence from a survey." National Bureau of Economic Research 26989.

Benzeval, Michaela, Jonathan Burton, Thomas F Crossley, Paul Fisher, Annette Jäckle, Hamish Low, and Brendan Read. 2020. "The Idiosyncratic Impact of an Aggregate Shock: The Distributional Consequences of COVID-19." *Available at SSRN 3615691.*

Bick, Alexander, and Adam Blandin. 2020. "Real Time Labor Market Estimates-During the 2020 Coronavirus Outbreak." Mimeo.

Bredemeier, Christian, Falko Juessen, and Roland Winkler. 2017. "Mancessions, fiscal policy, and the gender composition of employment." *Economics Letters*, 158: 73–76.

Brewer, Mike, Laura Gardiner, and Karl Handscomb. 2020. "The truth will out - Understanding labour market statistics during the coronavirus crisis." The Resolution Foundation.

Bundesagentur für Arbeit. 2020. "Der Arbeitsmarkt im April 2020."

Bureau of Labor Statistics. 2020. "The Employment Situation - April 2020."

Cahuc, Pierre, Francis Kramarz, and Sandra Nevoux. 2018. "When short-time work works." CEPR Discussion Paper 4654-1530893226.

Cajner, Tomaz, Leland D Crane, Ryan A Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz. 2020. "The US labor market during the beginning of the pandemic recession." National Bureau of Economic Research.

Carvalho, Vasco. M., Juan R. Garcia, Stephen Hansen, Álvaro Ortiz, Tomasa Rodrigo, José V. Rodríguez Mora, and José Ruiz. 2020. "Tracking the COVID-19 Crisis with High-Resolution Transaction Data." Cambridge-INET Working Paper Series No: 2020/16.

Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team. 2020. "How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data." Working Paper.

Christiano, Lawrence J, Martin S Eichenbaum, and Mathias Trabandt. 2015. "Understanding the great recession." *American Economic Journal: Macroeconomics*, 7(1): 110–67.

Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber. 2020. "Labor markets during the COVID-19 crisis: A preliminary view." Becker Friedman Institute 41.

Deville, Jean-Claude, and Carl-Erik Särndal. 1992. "Calibration estimators in survey sampling." *Journal of the American Statistical Association*, 87(418): 376–382.

Dingel, Jonathan, and Brent Neiman. 2020. "How many jobs can be done at home?" National Bureau of Economic Research 26948.

Fetzer, Thiemo, Lukas Hensel, Johannes Hermle, and Chris Roth. 2020. "Coronavirus Perceptions and Economic Anxiety." *arXiv:2003.03848*.

Giupponi, Giulia, and Camille Landais. 2018. "Subsidizing labor hoarding in recessions: The employment & welfare effects of short time work."

Guvenen, Fatih, Serdar Ozkan, and Jae Song. 2014. "The nature of countercyclical income risk." *Journal of Political Economy*, 122(3): 621–660.

HMRC. 2020. "HMRC coronavirus (COVID-19) statistics." Figures retrieved from `https://www.gov.uk/government/collections/`

hmrc-coronavirus-covid-19-statistics.

Hoynes, Hilary, Douglas L. Miller, and Jessamyn Schalle. 2012. "Who suffers during recessions?" *Journal of Economic Perspectives*, 26(3): 27–48.

Kahn, Lisa B., Fabian Lange, and David Wiczer. 2020. "Labor Demand in the time of COVID-19: Evidence from vacancy postings and UI claims." Mimeo.

Kolenikov, Stanislav. 2014. "Calibrating survey data using iterative proportional fitting (raking)." *The Stata Journal*, 14(1): 22–59.

Kopp, Daniel, and Michael Siegenthaler. 2018. "Does short-time work prevent unemployment?" KOF Swiss Economic Institute, ETH Zurich 106.

Koustas, Dmitri. 2018. "Consumption insurance and multiple jobs: Evidence from rideshare drivers." *Unpublished working paper*.

Malcomson, James M. 1999. "Individual employment contracts." *Handbook of labor economics*, 3: 2291–2372.

Mas, Alexandre, and Amanda Pallais. 2020. "Alternative work arrangements." National Bureau of Economic Research.

Mongey, Simon, and Alex Weinberg. 2020. "Characteristics of workers in low work-from-home and high personal-proximity occupations." Working Paper.

OECD. 2020. *OECD Employment Outlook 2020: Worker Security and the COVID-19 Crisis.* OECD Publishing, Paris.

Office for National Statistics. 2019. "Estimates of the population for the UK, England and Wales, Scotland and Northern Ireland." Data retrieved from https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland.

Rinne, Ulf, and Klaus F Zimmermann. 2012. "Another economic miracle? The German labor market and the Great Recession." *IZA journal of labor policy*, 1(1): 3.

Statistische Ämter des Bundes und der Länder. 2018. "Fläche und Bevölkerung nach Ländern." Data retrieved from https://www.statistikportal.de/de/bevoelkerung/flaeche-und-bevoelkerung.

U.S. Census Bureau, Population Division. 2019. "Estimates of the Total Resident Population and Resident Population Age 18 Years and Older for the United States, States, and Puerto Rico: July 1, 2019 (SCPRC-EST2019-18+POP-RES)." Data retrieved from https://www.census.gov/newsroom/press-kits/2019/national-state-estimates.html.

von Gaudecker, Hans-Martin, Radost Holler, Lena Janys, Bettina Siflinger,

and Christian Zimpelmann. 2020. "Labour Supply in the Early Stages of the Covid-19 Pandemic: Empirical Evidence on Hours, Home Office, and Expectations." IZA Discussion Paper No. 13158.

A Survey Design

Work status and hours worked We collect detailed information on respondents' current work arrangements. We ask respondents to report how many jobs they have been working in over the past 7 days, either as employees or as self-employed. We made it explicit that individuals should count *all* jobs, including the ones in which they have been furloughed (US & UK) or on short-time work (Germany). Individuals who report not having a job are asked since when they have not had a job and whether their job loss was related to the coronavirus outbreak. Workers are classified as having lost their job in the recent crisis if they lost their job in the last four weeks and report 'definitely yes' or 'probably yes' to the question on whether their job loss was related to the coronavirus outbreak.[26] To study changes in the number of hours worked, we ask all respondents how many hours they worked in the previous week and how many hours they worked in a typical week in February.

Information on furloughing/STW To obtain a better understanding of the use of furloughing (US & UK) and STW schemes (Germany), we include questions on furloughing into the US & UK surveys, and questions on STW into the German survey. In the US and the UK, if respondents report being employed in their main job we ask them to report whether they have been furloughed, and, if yes, whether they have still been asked by their employer to do any work. In the UK, respondents provided us with additional information on whether their employer is topping up the government wage support, and whether they lost any annual leave entitlements. In the US, we additionally ask whether employees lost their health insurance coverage. In Germany, we ask employees whether they were on the STW scheme. We further ask respondents to state the official share of their usual hours that they are asked to work, and for the share of hours that they actually work.

Job characteristics Individuals who report having a job are asked detailed questions about their main job. First, they are asked whether they are employed or self-employed in this job. If they report being employed they are asked to provide more details on their employment. In particular, employees are asked to report whether they are on a permanent or temporary contract, whether their work schedule is fixed or flexible, and

[26]Note that the definition of job loss is the same for employees and self-employed workers, as it is based on the same information.

whether they are salaried or non-salaried, i.e. paid in a different way for their work (e.g. by the hour). All respondents with a job are further asked to provide information on the industry and occupation they work in. Occupations are classified using O*NET SOC 2018 codes for the US&UK, and ISCO-08 codes for Germany. Industries are classified using NACE Rev. 2 industry codes in all three countries. To study the importance of the ability to work from home, we ask all respondents what percentage of their tasks they could do from home. Answers are recorded using a slider ranging from 0-100%. To ease comprehension of this question, we provide participants with some examples. 'E.g. Andy is a waiter and cannot do any of his work from home (0%). Beth is a website designer and can do all her work from home (100%)'. Individuals who report not having a job are asked the same questions about their last job.

Income To obtain a clearer picture of the impacts of the crisis and the earnings lost, we ask all individuals in the early April survey wave to report their net monthly earnings from all sources for the months of January, February, and March. Throughout the paper, we define 'earnings loss' as a binary variable that takes a value of one if a respondent earned less in March 2020 compared to their average earnings over the months of January and February 2020. In addition, we ask respondents about their gross annual earnings in 2019. We also ask respondents to state whether they have already struggled to pay their usual bills or expenses.

Time use We ask respondents to report the time they spend on different activities on a typical working day over the past week. For individuals with children living in the household, we ask about the number of hours and minutes spent on active childcare and on homeschooling.

Expectations To obtain a better sense of how individuals think about their future, we ask respondents how likely they think it is that certain events will occur before August 1, 2020, on a 0-100% chance scale. Most notably, those include whether respondents think they will lose their job or shut their business (if self-employed), and have trouble paying their usual bills and expenses. To understand how long individuals think the crisis will last, we also ask individuals to report how likely they think it is that some form of social distancing measures will still be in place on August 1, 2020, using a 0-100% scale. Finally, former employees are asked how likely they think it is that their next job will be with their last employer.

B Questionnaire

Employment status and hours worked

How many jobs, where self-employment activity counts as a job, did you have in February 2020? Please think of any work you did other than completing surveys. If you were furloughed from a job, please count this as a job.
Many people work as employees, where they have an employment contract with an employer, or in self-employment. There is a lot of variation in self-employment, some people might be selling goods or services in their own business, or working through a digital platform such as Uber or Upwork. In addition to working a regular job for an employer, sometimes people do other things to earn money. These activities also count as self-employment. [None, 1, 2, 3 or more]

[If worked at least one job in February] *Think about a typical week in February for you at work (in all of your jobs). How many hours did you work in a typical week in February?* [Answers in 5-hour increments, from 0 to "More than 55 hours"]

How many jobs, where self-employment activity counts as a job, have you had last week? Please think of any work you did other than completing surveys. If you were furloughed from a job, please count this as a job.
Many people work as employees, where they have an employment contract with an employer, or in self-employment. There is a lot of variation in self-employment, some people might be selling goods or services in their own business, or working through a digital platform such as Uber or Upwork. In addition to working a regular job for an employer, sometimes people do other things to earn money. These activities also count as self-employment. [None, 1, 2, 3 or more]

[If worked at least one job last week] *Now think about all the work you did last week (in all of your jobs). How many hours did you work last week?* [Answers in 5-hour increments, from 0 to "More than 55 hours"]

[If reports working zero jobs last week] *Please think about your last job. In your last job, were you working as an employee or self-employed?* [Employee, Self-employed]

[If reports working at least one job last week] *In your main job, that is the job that you usually spend the most time working in, are you working as an employee or self-employed?* [Employee, Self-employed]

[For current employees] *Have you been furloughed?*[27] [Yes, No]

[If reports working zero jobs last week] *For how long have you not had a job?* [Recorded in weeks/months]

[If reports working zero jobs last week] *If you lost your job recently, do you think this was related to the coronavirus outbreak?* [Answers on 5-item scale, from "Definitely yes" to "Definitely no", with additional option "I did not lose my job recently"]

Income

Which category represents your total individual annual income (before taxes) in 2019? This should include money from all jobs, net income from a business or farm, and any rent, pensions, dividends, interest, social security payments or other money income you received. [Answers on 12-point scale, from "Less than $10,000" to "$150,000 or more"]

Please think about your earnings from all your jobs over the last few months. After tax, how much did you approximately earn in the following months? [Number in local currency for January 2020, February 2020 and March 2020]

Job characteristics: Questions phrased to refer to main or last job, depending on the respondent's employment status.

What sort of occupation best describes this job? [O*NET SOC 2018 major groups for US and UK; ISCO-08 major groups for Germany]

What category best describes the industry you work in? [NACE Rev. 2 industry classification]

[For current or former employees] *Do you have a permanent contract?* [Yes, No]

[27] For Germany, we asked whether you have been on short-time work.

[For current or former employees] *Is your job salaried or how do you get paid?* [Salaried, Hourly, Paid by the job, Commission or tips only, Other]

[For current or former employees] *Are the number of hours you work fixed or do they vary?* [Fixed, Vary - I choose how many hours I work, Vary - My employer decides how many hours I work but I am guaranteed some work each week, Vary - I am an on-call worker]

In your job, what percentage of the tasks could you do from home? Examples: Andy is a waiter and cannot do any of his work from home (0%). Beth is a website designer and can do all her work from home (100%). [Answer on 0-100 slider]

Time use
Please think about last week and the time you spent on various activities. On a typical working day, how many hours did you spend... [Answers in hours and minutes]

- *... outside your home for work?*
- *... outside your home for leisure?*
- *... working from home?*
- *... home-schooling children?*
- *... actively caring for children (other than home-schooling)?*

Expectations
On a scale of 0-100%, how likely do you think it is that some form of social distancing measures will be in force in your state [country] on 1st August 2020?
On a scale of 0-100%, how likely are the following scenarios to occur before 1st August 2020?

- *I will lose my job or shut my business if self-employed*
- *I will have troubles paying my usual bills and expenses*

[For former employees] *On a scale of 0-100%, how likely do you think it is that your next job will be with your last employer?*

C Comparison with nationally representative data

Table C.1: Distribution of respondents across regions - UK

Region	National	March	April
Scotland	8.42	8.48	8.54
Northern Ireland	2.76	2.57	2.80
Wales	4.79	4.83	4.87
North East	4.06	4.08	4.12
North West	11.00	11.02	11.11
Yorkshire and the Humber	8.24	8.28	8.34
West Midlands	8.80	8.86	8.92
East Midlands	7.27	7.32	7.38
South West	8.59	8.63	8.70
South East	13.70	13.79	13.87
East of England	9.29	8.91	8.03
Greater London	13.15	13.24	13.32
Observations		3974	4931

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above. Data source: Office for National Statistics (2019).

Table C.2: Distribution of respondents across area codes - US

Region	National	March	April
Area code 0	7.40	7.39	7.40
Area code 1	10.33	10.32	10.32
Area code 2	10.04	10.04	10.05
Area code 3	14.41	14.41	14.40
Area code 4	10.02	10.02	10.03
Area code 5	5.25	5.25	5.25
Area code 6	7.17	7.17	7.18
Area code 7	11.94	11.94	11.95
Area code 8	7.13	7.12	7.13
Area code 9	16.30	16.34	16.30
Observations		4003	4000

Notes: National figures refer to the latest available estimates for the population of residents aged 18 or above. Data source: U.S. Census Bureau, Population Division (2019).

Table C.3: Distribution of respondents across states - Germany

Region	National	April
Baden-Württemberg	13.33	13.29
Bayern	15.75	15.74
Berlin	4.39	4.40
Brandenburg	3.03	3.02
Bremen	0.82	0.82
Hamburg	2.22	2.22
Hessen	7.55	7.55
Mecklenburg-Vorpommern	1.94	1.97
Niedersachsen	9.62	9.62
Nordrhein-Westfalen	21.60	21.59
Rheinland-Pfalz	4.92	4.92
Saarland	1.19	1.20
Sachsen	4.91	4.90
Sachsen-Anhalt	2.66	2.65
Schleswig-Holstein	3.49	3.50
Thüringen	2.58	2.60
Observations		4002

Notes: National figures refer to the latest available estimates for the population of residents. Data source: Statistische Ämter des Bundes und der Länder (2018).

Table C.4: Demographics of the population and surveys

	US		UK		DE	
	CPS	April	LFS	April	SOEP	April
Female	0.480	0.582	0.471	0.552	0.479	0.475
University	0.394	0.494	0.361	0.488	0.272	0.287
<30	0.234	0.255	0.222	0.281	0.171	0.398
30-39	0.225	0.264	0.232	0.333	0.210	0.284
40-49	0.201	0.215	0.220	0.238	0.209	0.146
50-59	0.197	0.136	0.220	0.114	0.267	0.132
60+	0.143	0.130	0.105	0.033	0.144	0.040

Notes: The table shows the mean demographic characteristics of economically active individuals in our April samples, as well as nationally representative samples, for the US, UK and Germany. For the US, we use the February 2020 monthly CPS data, for the UK the 2019 LFS data, and for Germany the 2018 SOEP data as a benchmark.

Table C.5: Distribution across occupations of the population and surveys

	US CPS	US April	UK LFS	UK April	DE	DE SOEP	DE April
Management	0.092	0.114	0.146	0.102	Management	0.050	0.116
Business and Financial Operations	0.060	0.087	0.068	0.089	Academic	0.199	0.110
Computer and Mathematical	0.038	0.073	0.030	0.065	Technician, comparable non-tech.	0.248	0.155
Architecture and Engineering	0.022	0.019	0.032	0.030	Office and administration	0.095	0.190
Life, Physical, and Social Science	0.011	0.023	0.018	0.020	Service and retail	0.152	0.190
Community and Social Service	0.018	0.019	0.019	0.023	Farming, fishing, and forestry	0.011	0.019
Legal	0.011	0.018	0.010	0.016	Craftsmen and women	0.095	0.077
Educational Instruction and Library	0.063	0.078	0.072	0.085	Mechanical	0.061	0.027
Arts, Design, Entertainment, Sports, Media	0.023	0.035	0.027	0.039	Auxiliary	0.085	0.103
Healthcare Practitioners and Technical	0.064	0.043	0.052	0.038	Military	0.003	0.012
Healthcare Support	0.033	0.045	0.015	0.042			
Protective Service*	0.021	0.011	0.024	0.014			
Food Preparation and Serving	0.055	0.072	0.036	0.073			
Building, Grounds Cleaning, Maintenance	0.029	0.016	0.032	0.017			
Personal Care and Service	0.026	0.051	0.043	0.026			
Sales and Related	0.100	0.101	0.072	0.101			
Office and Administrative Support	0.109	0.074	0.129	0.105			
Farming, Fishing, and Forestry	0.008	0.010	0.012	0.004			
Construction and Extraction	0.056	0.032	0.044	0.023			
Installation, Maintenance, and Repair	0.031	0.019	0.022	0.013			
Production	0.050	0.032	0.038	0.041			
Transportation and Material Moving	0.080	0.029	0.059	0.034			

Notes: The table shows the breakdown by occupation of economically active individuals in our April samples, as well as nationally representative samples, for the US, UK and Germany. For the US, we use the February 2020 monthly CPS data, for the UK the 2019 LFS data, and for Germany the 2018 SOEP data as a benchmark. For the UK, we match UK SOC 2010 codes to O*NET SOC 2018 codes by first matching the UK codes to the ISCO-08 codes and then onto O*NET SOC 2018 codes for major groups. (*) Includes Military occupations, which the CPS data does not record among its occupation codes.

Table C.6: Distribution across industries of the population and surveys

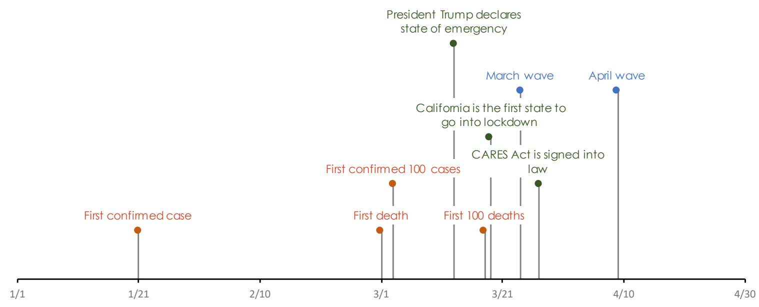
	US		UK		DE	
	CPS	April	LFS	April	SOEP	April
Agriculture, forestry and fishing	0.016	0.022	0.011	0.012	0.011	0.037
Mining and quarrying	0.005	0.011	0.004	0.016	0.002	0.022
Manufacturing	0.095	0.082	0.092	0.089	0.198	0.090
Electricity, gas, air cond supply	0.095	0.082	0.092	0.089	0.198	0.090
Water supply, sewerage, waste	0.005	0.013	0.007	0.023	0.006	0.055
Construction	0.071	0.064	0.072	0.063	0.050	0.068
Wholesale, retail, repair of vehicle	0.130	0.073	0.122	0.092	0.114	0.052
Transport and storage	0.050	0.033	0.049	0.042	0.052	0.050
Accommodation and food services	0.071	0.067	0.053	0.059	0.036	0.050
Information and communication	0.018	0.083	0.043	0.066	0.039	0.125
Financial and insurance activities	0.049	0.067	0.040	0.062	0.032	0.036
Real estate activities	0.021	0.023	0.013	0.013	0.009	0.012
Prof, scientific, technical activ.	0.079	0.065	0.079	0.044	0.051	0.024
Admin and support services	0.035	0.043	0.047	0.048	0.045	0.032
Public admin and defence*	0.046	0.012	0.067	0.039	0.070	0.059
Education	0.094	0.103	0.105	0.120	0.079	0.046
Health and social work	0.141	0.081	0.136	0.090	0.152	0.096
Arts, entertainment and recreation	0.019	0.044	0.026	0.037	0.017	0.023
Other service activities	0.043	0.084	0.028	0.051	0.021	0.058
Households as employers	0.005	0.012	0.001	0.007	0.006	0.009

Notes: The table shows the breakdown by industry of economically active individuals in our April samples, as well as nationally representative samples, for the US, UK and Germany. For the US, we use the February 2020 monthly CPS data, for the UK the 2019 LFS data, and for Germany the 2018 SOEP data as a benchmark. The industry groups refer to the NACE Rev. 2 industry codes. For the US, we matched the Census Codes from the CPS into NACE Rev. 2 codes. (*) Includes “Extraterritorial organisations", which the CPS data does not record among the industry codes.

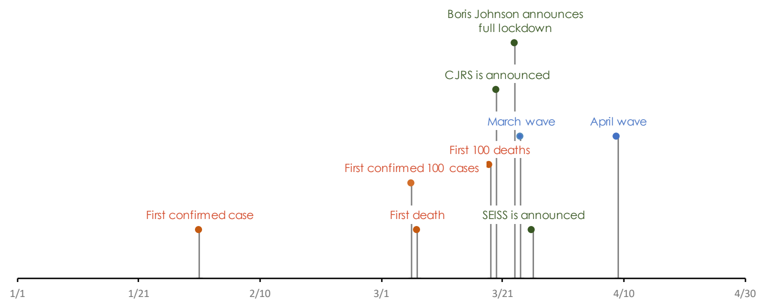
D Additional Tables and Figures

Figure D.1: Timeline of coronavirus outbreak and policy responses

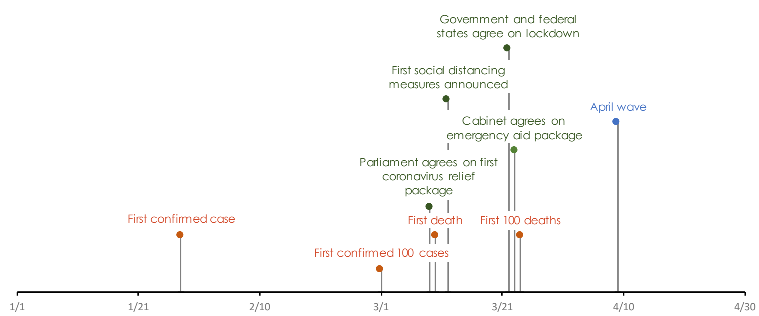
(a) US



(b) UK

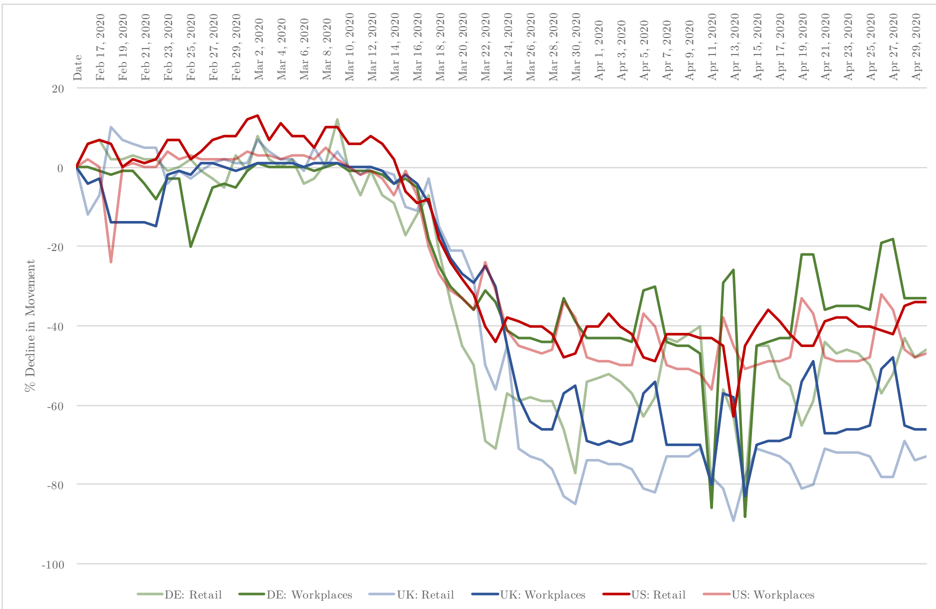


(c) Germany



Notes: This figure illustrates the exact timing of events with regard to the coronavirus outbreak (red) and the main policy responses (green) in (a) the US, (b) the UK, and (c) Germany. The dates when the surveys were launched are marked in blue.

Figure D.2: Change in community mobility



Notes: The figure shows the percentage change in retail and workplace mobility using data from the Google COVID-19 Community Mobility reports. Google uses anonymized location data provided by apps such as Google Maps to construct these measures. The retail trend shows the change in visitors at places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters. The workplaces trend shows how the number of visitors to workplaces has changed relative to the period before the pandemic.

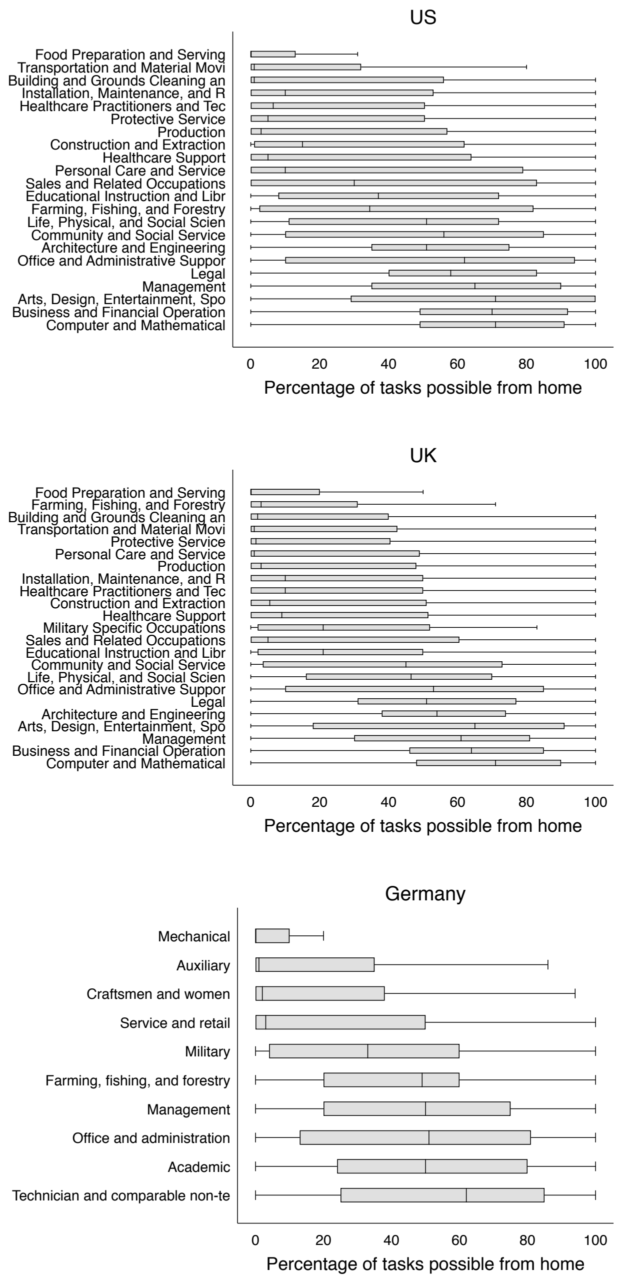
Figure D.3: Employment status by occupation (early April)

Notes: The figure shows the share of workers who are employed (blue - right), furloughed for the US/UK or on STW for Germany (yellow - middle) or lost their job due to the Covid-19 crisis (red - left), by occupation. The sample is restricted to employees (in their current or last job) only.

Figure D.4: Share of tasks that can be done from home by industry

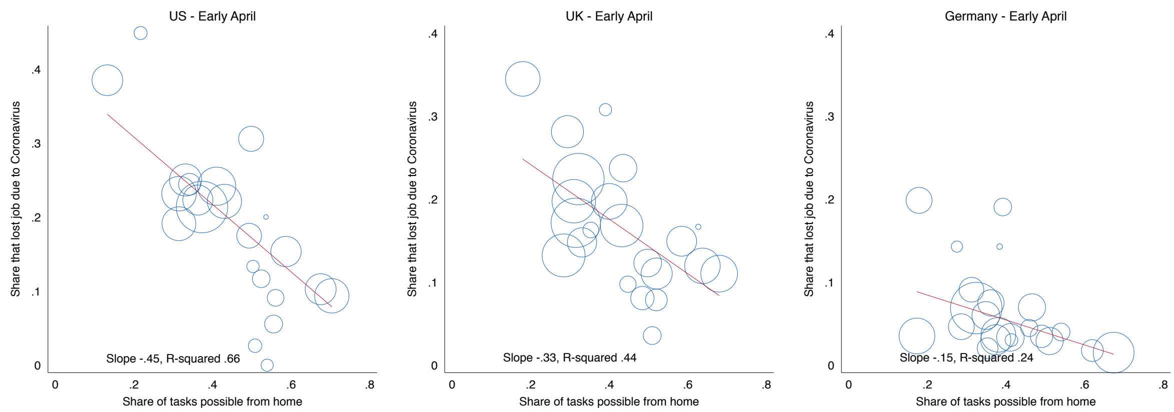
Notes: The figure shows box plots for the share of tasks that workers in each industry can do from home, separately for the US (left), UK (center) and Germany (right). The industries are ordered by the mean share of tasks that can be done from home. The gray boxes illustrate the 25^{th} to the 75^{th} percentile, the black line the median, and the whiskers are the values that are furthest away from the median on either side of the box, but are still within a distance of 1.5 times the interquartile range from the nearest quartile.

Figure D.5: Share of tasks that can be done from home by occupation



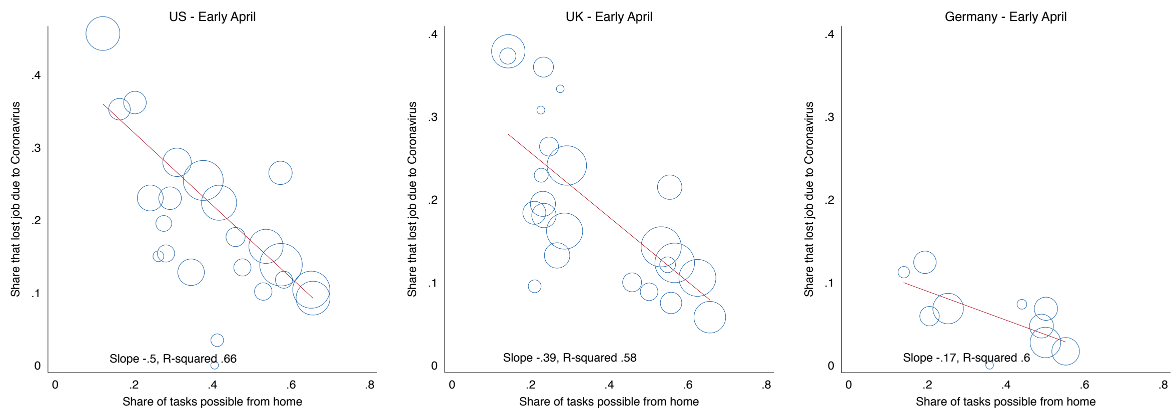
Notes: The figure shows box plots for the share of tasks that workers in each occupation can do from home, separately for the US (left), UK (center) and Germany (right). The occupations are ordered by the mean share of tasks that can be done from home. The gray boxes illustrate the 25^{th} to the 75^{th} percentile, the black line the median, and the whiskers are the values that are furthest away from the median on either side of the box, but are still within a distance of 1.5 times the interquartile range from the nearest quartile.

Figure D.6: Share of tasks that can be done from home versus job loss probability due to Covid-19 by industry



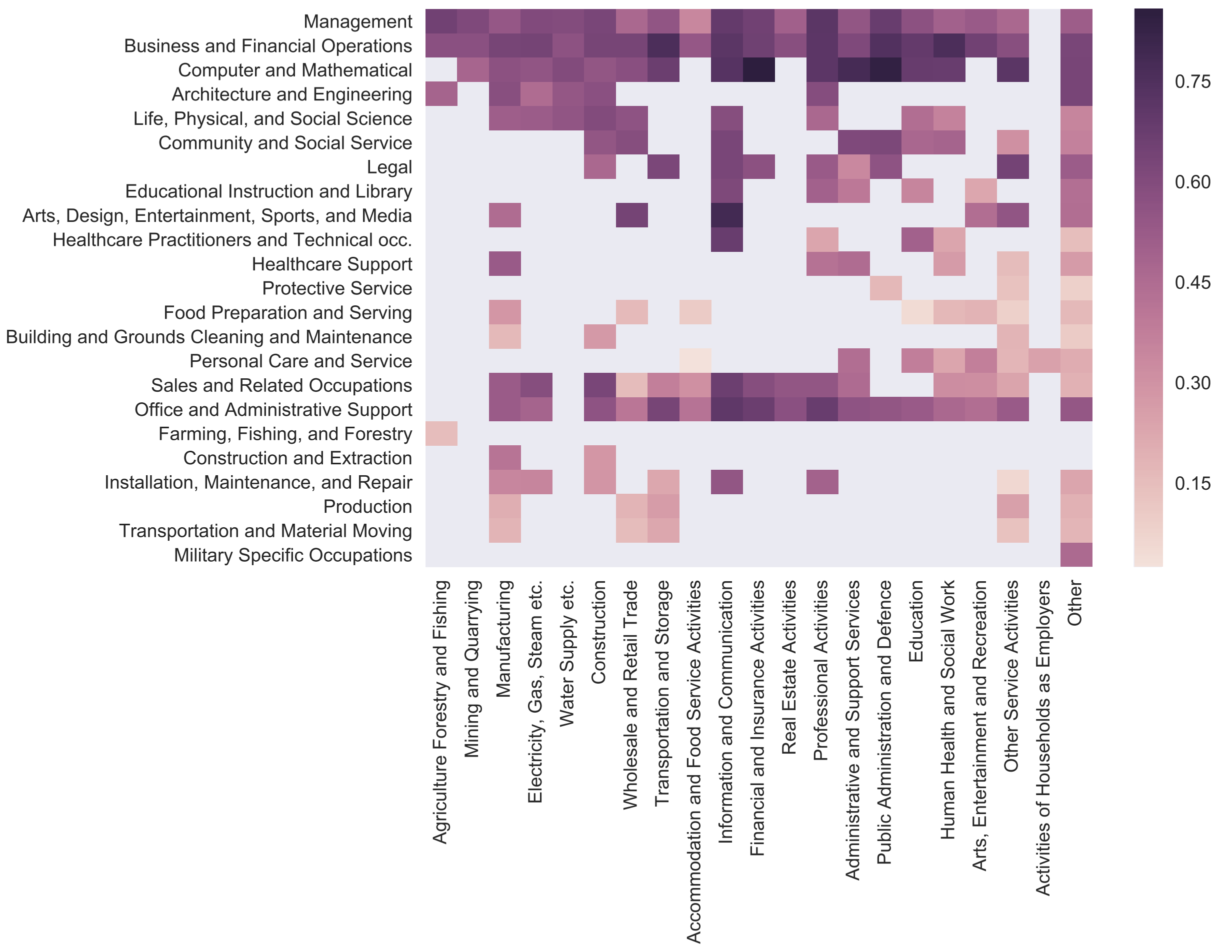
Notes: Each bubble represents an industry and the size is proportional to the number of observations we have for that industry. The figure shows the average share of tasks that can be done from home by industry on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure D.7: Share of tasks that can be done from home versus job loss probability due to Covid-19 by occupation



Notes: Each bubble represents an occupation and the size is proportional to the number of observations we have for that occupation. The figure shows the average share of tasks that can be done from home by occupation on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure D.8: Share of tasks that can be done from home by occupation-industry pairs

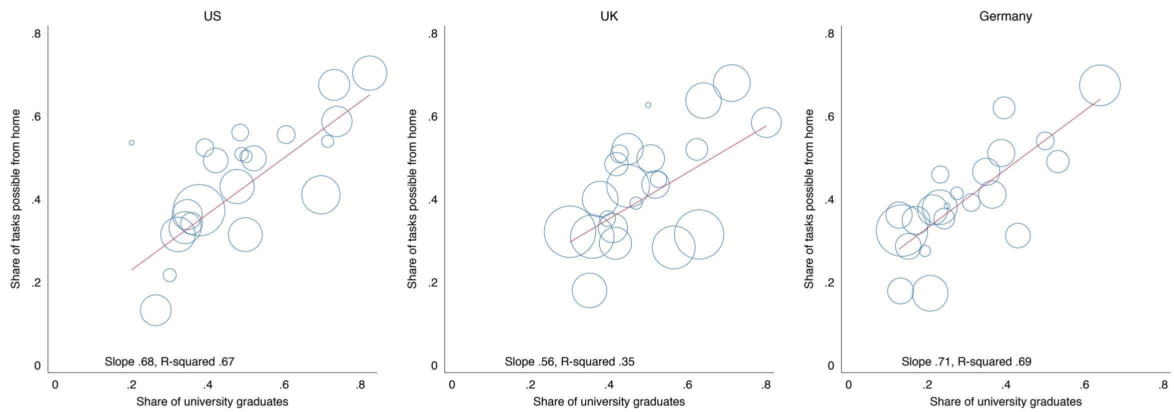


Notes: Joint data for US and UK from the April wave of the surveys. Cells with less than 10 observations are dropped. The darker the color of a cell, the higher the share of tasks that can be done from home. The legend on the right indicates the levels of the share of tasks that can be done from home.

Figure D.9: Jobs lost due to Coronavirus by occupation and industry

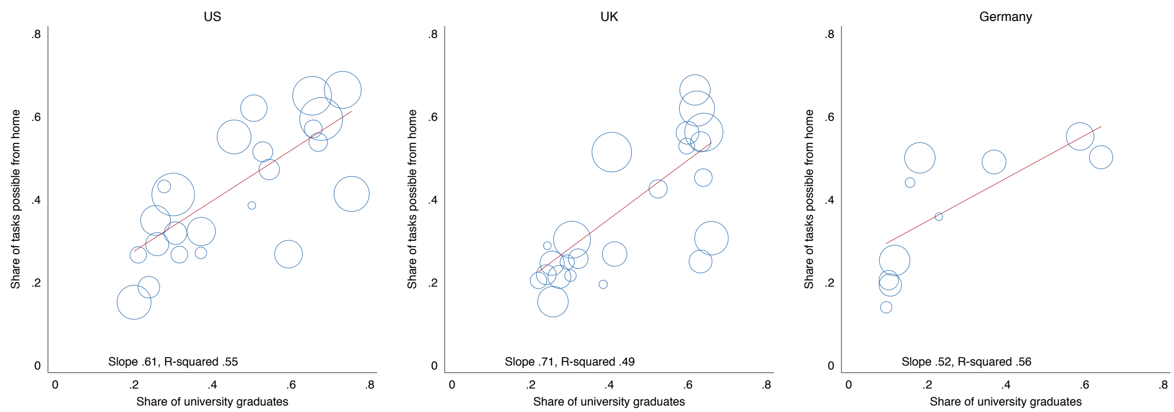
Notes: Joint data for US and UK from the April wave of the surveys. Cells with less than 10 observations are dropped. The darker the color of a cell, the higher the job-loss probability. The legend on the right indicates the levels of the job-loss probabilities.

Figure D.10: Share of workers with a university degree versus share of tasks that can be done from home by industry



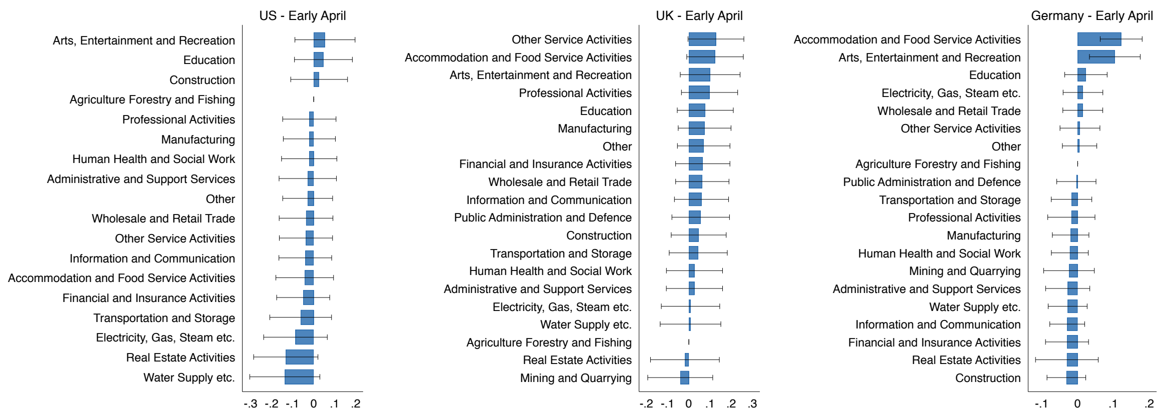
Notes: Each bubble represents an industry and the size is proportional to the number of observations we have for that industry. The figure shows the share of workers with a university degree by industry on the x-axis and the share of tasks that can be done from home on the y-axis.

Figure D.11: Share of workers with a university degree versus share of tasks that can be done from home by occupation



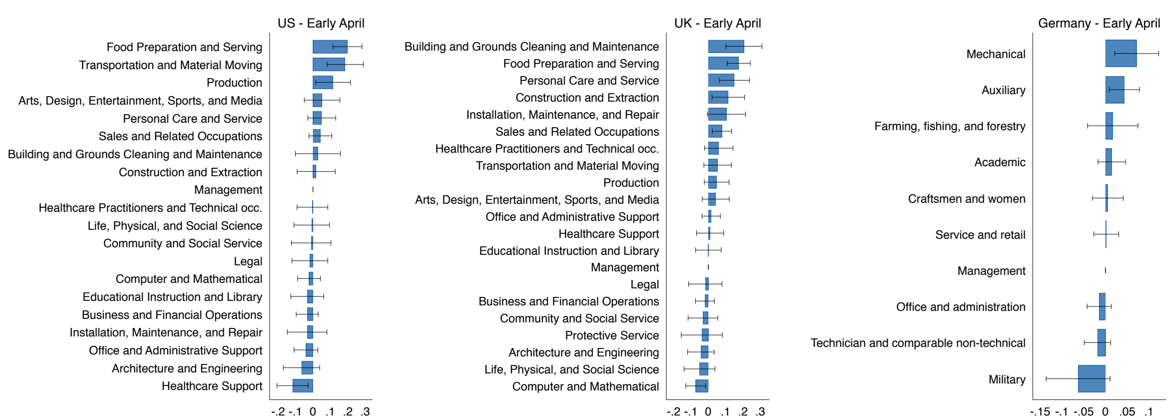
Notes: Each bubble represents an occupation and the size is proportional to the number of observations we have for that occupation. The figure shows the share of workers with a university degree by occupation on the x-axis and the share of tasks that can be done from home on the y-axis.

Figure D.12: Industry fixed effect for job loss



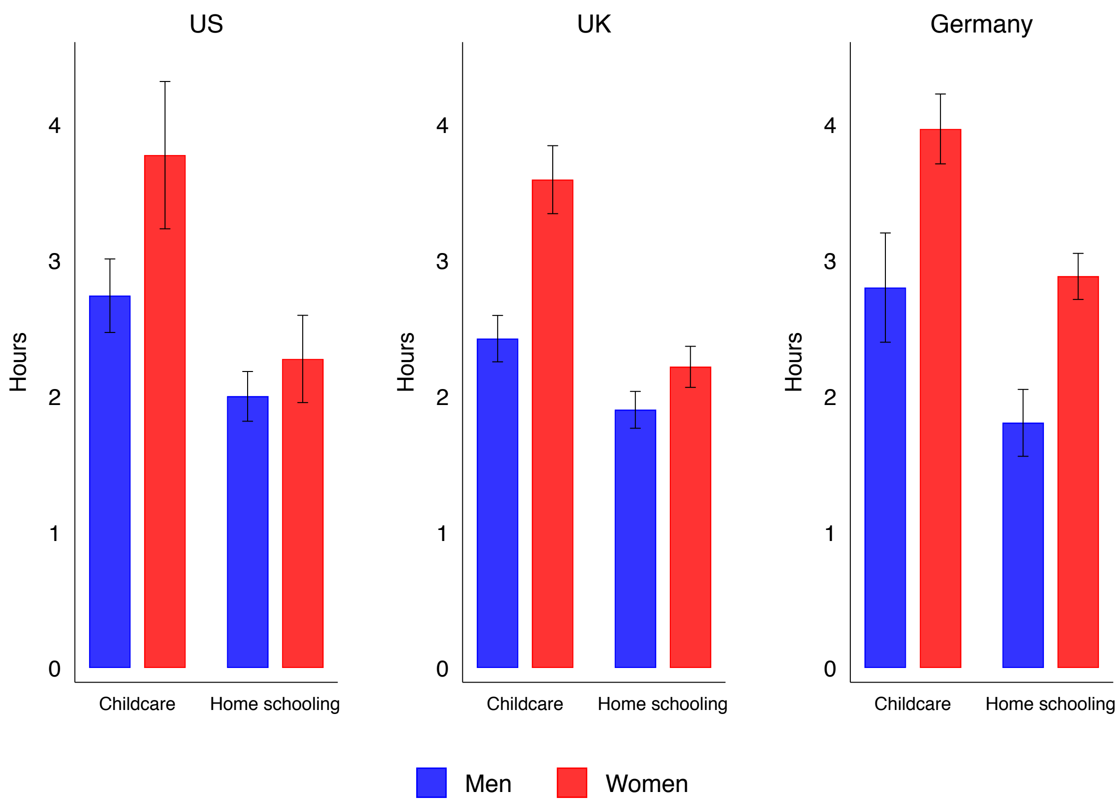
Notes: The thin black bars represent the 95% confidence intervals. The bars represent coefficients for occupation fixed effects from the regressions in Table 2 columns (2), (4), and (6) for the US, UK and Germany, respectively. Agriculture, forestry and fishing is the baseline industry.

Figure D.13: Occupation fixed effect for job loss



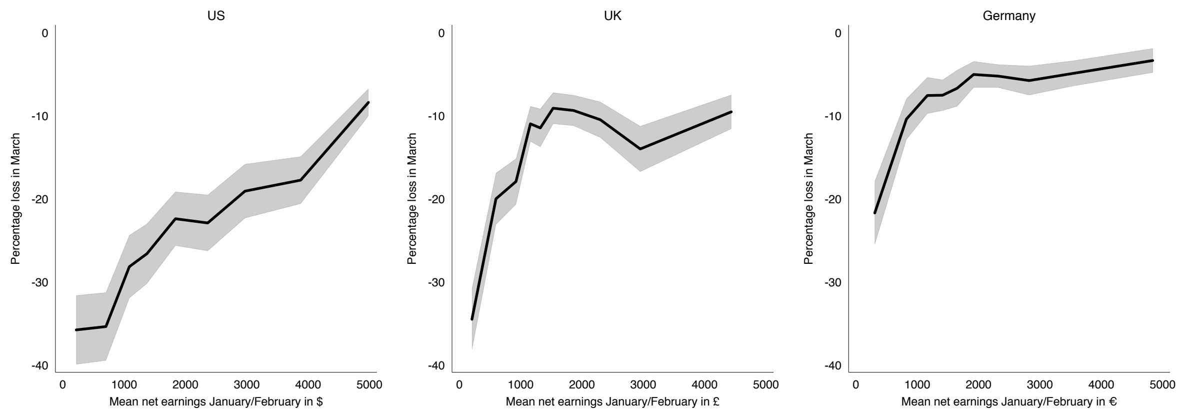
Notes: The thin black bars represent the 95% confidence intervals. The bars represent coefficients for occupation fixed effects from the regressions in Table 2 columns (2), (4), and (6) for the US, UK and Germany, respectively. Management is the baseline occupation.

Figure D.14: Hours spent on a "typical" work day during the past week on active childcare and home schooling



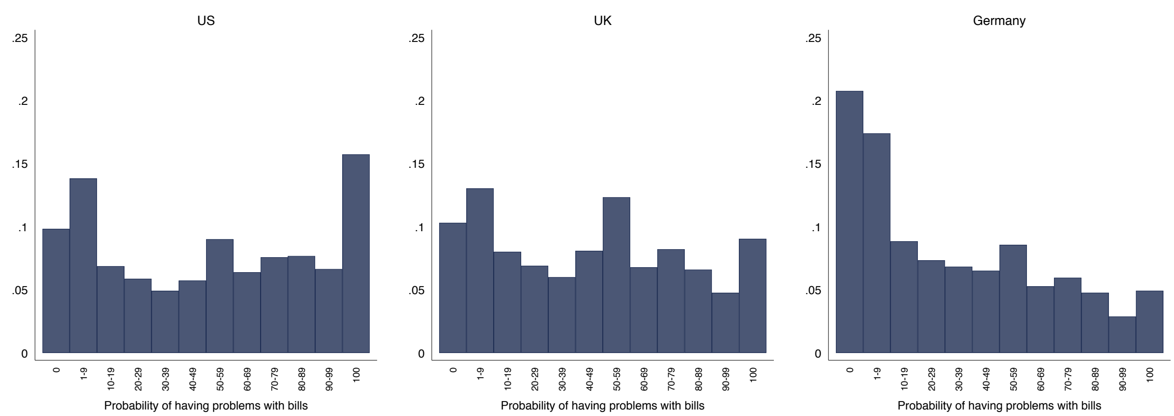
Notes: Data from the April wave of the surveys. The thin black bars represent the 95% confidence intervals. The figure shows average number of hours that men and women reported spending on childcare and homeschooling. We restrict the sample to individuals with children who report working from home, and whose answers to the time use questions combined do not exceed 24 hours.

Figure D.15: Average percentage drop in earnings from January/February to March



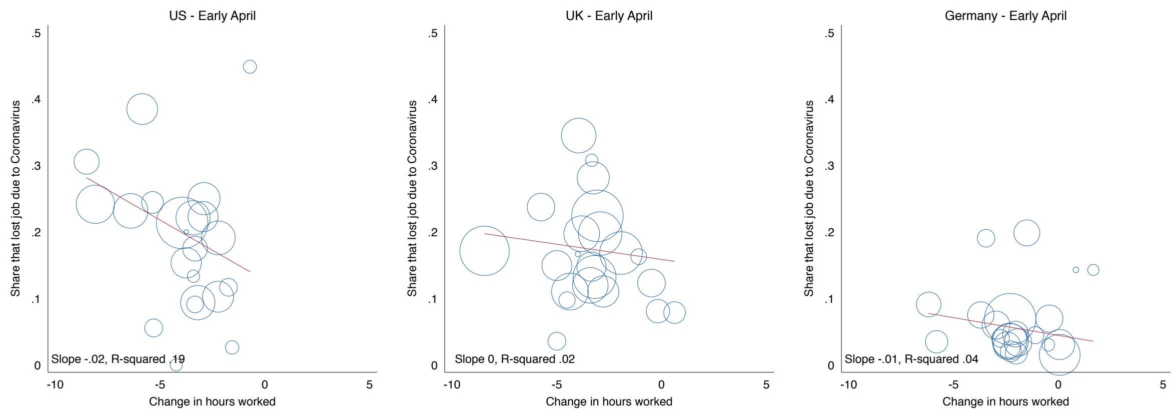
Notes: The line is computed by splitting respondents with average earnings between 10 and 5000 in the respective currency into earnings deciles and the gray area is the 95% confidence interval.

Figure D.16: Distribution of perceived likelihood of struggling with bills/expenses



Notes: Data from the April wave of the surveys. This figure displays the distribution of the perceived likelihood of struggling to pay usual bills/expenses in the near future (before August 1st) in the US (left), UK (center) and Germany (right). Responses to this question are recorded on a 0-100% scale.

Figure D.17: Change in hours worked (conditional on working) vs jobs lost due to Coronavirus by industry

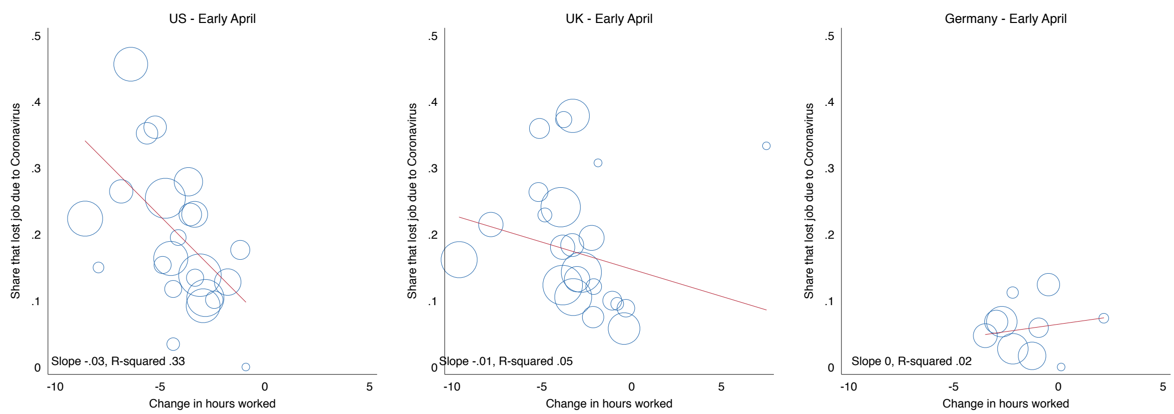


Notes: Each bubble represents an industry and the size is proportional to the number of observations we have for that industry. The figure shows the average change in hours between a usual and the last work week by industry on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure D.18: Change in hours worked by occupation

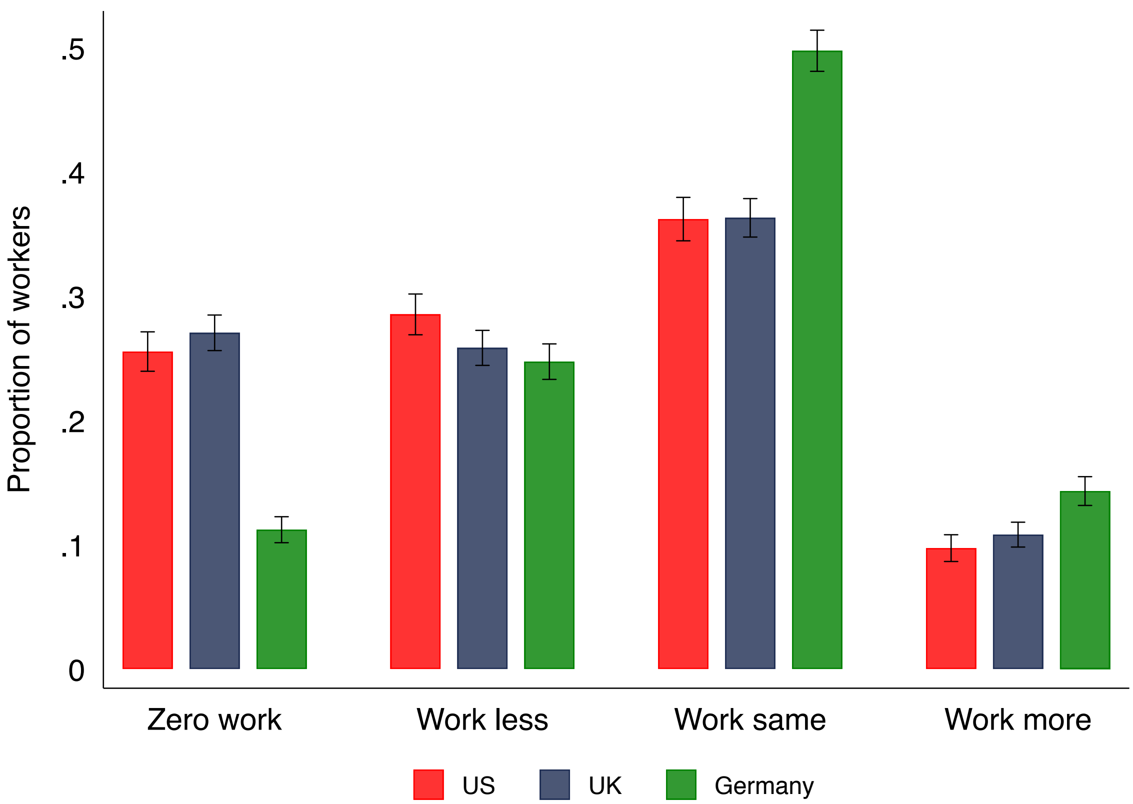
Notes: The thin black bars represent the 95% confidence intervals. The figure shows the change in hours worked between a usual work week in February and the last work week amongst those still working for the US (top), the UK (center) and Germany (bottom).

Figure D.19: Change in hours worked (conditional on working) vs jobs lost due to Coronavirus by occupation



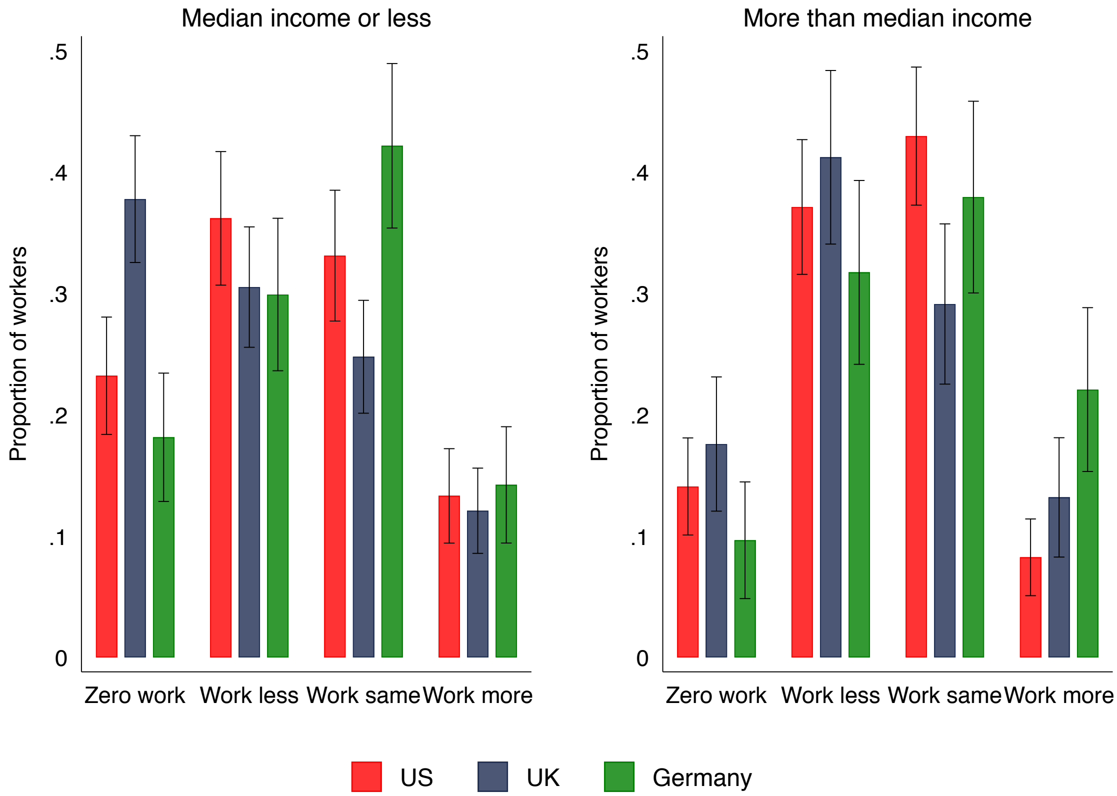
Notes: Each bubble represents an occupation and the size is proportional to the number of observations we have for that occupation. The figure shows the average change in hours between a usual and the last work week by occupation on the x-axis and the share of workers that their jobs due to Coronavirus on the y-axis.

Figure D.20: Hours worked compared to a typical week by country



Notes: Data from the April wave of the surveys. The thin black bars represent the 95% confidence intervals. Whether a worker works less or the same as usual is judged compared to a typical week in February before the pandemic. Those working zero hours include those that have lost their job.

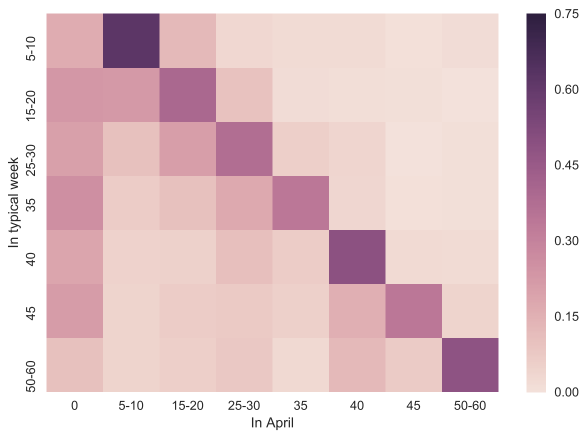
Figure D.21: Hours worked of the self-employed compared to a typical week by country



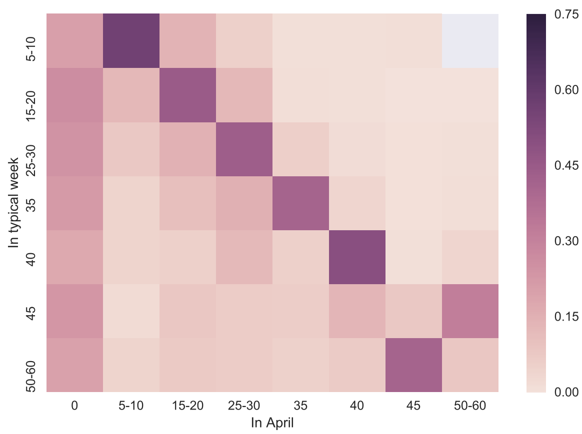
Notes: Data from the April wave of the surveys. the self-employed are split by median total labor income in 2019. The thin black bars represent the 95% confidence intervals. Whether a worker works less or the same a usual is judged compared to a typical week in February before the pandemic. Those working zero hours include those that have lost their job.

Figure D.22: Hours worked in a typical week compared to in April

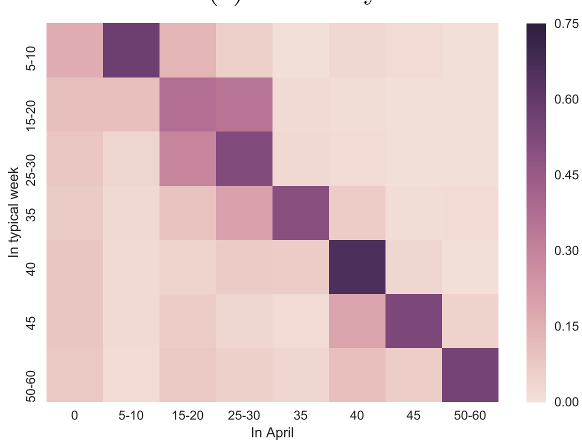
(a) US



(b) UK



(c) Germany



Notes: The figure shows the conditional probabilities of working a certain amount of hours in the April survey given the amount of hours normally worked in a typical week in February for (a) the US, (b) the UK, and (c) Germany. The darker the color of a cell, the higher the probability. The legend on the right indicates the levels of the transition probabilities. Each row sums to one.

Table D.1: Job loss probability - Waves 1 and 2

	United States			United Kingdom		
	(1)	(2)	(3)	(4)	(5)	(6)
Tasks from home	-0.2685***	-0.2436***	-0.2395***	-0.1858***	-0.1503***	-0.1581***
	(0.0117)	(0.0129)	(0.0129)	(0.0112)	(0.0126)	(0.0126)
Wave 2 (April)	0.0905***	0.0940***	0.0929***	0.0882***	0.0889***	0.0879***
	(0.0088)	(0.0087)	(0.0087)	(0.0080)	(0.0080)	(0.0079)
Female		0.0423***	0.0394***		0.0214**	0.0213**
		(0.0097)	(0.0097)		(0.0086)	(0.0085)
University degree		0.0028	0.0101		-0.0064	-0.0039
		(0.0097)	(0.0100)		(0.0086)	(0.0086)
30-39		-0.0049	-0.0034		0.0050	0.0148
		(0.0118)	(0.0118)		(0.0104)	(0.0103)
40-49		0.0044	0.0037		-0.0061	0.0009
		(0.0129)	(0.0130)		(0.0114)	(0.0114)
50-59		0.0015	-0.0016		-0.0242*	-0.0206
		(0.0148)	(0.0148)		(0.0135)	(0.0134)
60+		0.0241	0.0211		0.0039	-0.0021
		(0.0160)	(0.0160)		(0.0195)	(0.0193)
Permanent			-0.0301***			-0.1162***
			(0.0097)			(0.0110)
Salaried			-0.0335***			0.0048
			(0.0113)			(0.0101)
Fixed hours			0.0337***			-0.0035
			(0.0097)			(0.0098)
Constant	0.2557***	0.2178***	0.2330***	0.1363***	0.1003***	0.1996***
	(0.0401)	(0.0431)	(0.0434)	(0.0148)	(0.0219)	(0.0232)
Observations	6289	6282	6280	7024	7010	7009
R^2	0.1007	0.1257	0.1296	0.0553	0.0801	0.0994
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	no	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The sample includes respondents to the March and April survey waves for the US and the UK. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak, and zero if they did not. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.2: Job and earnings loss probability (weighted)

	Job loss			Earnings loss		
	US	UK	DE	US	UK	DE
Tasks from home	-0.2395***	-0.1928***	-0.0761***	-0.1180***	-0.0774**	-0.0035
	(0.0283)	(0.0258)	(0.0237)	(0.0367)	(0.0332)	(0.0371)
Self-employed	-0.0942***	-0.0290	0.0514	0.0018	0.0552	0.0563
	(0.0305)	(0.0386)	(0.0450)	(0.0422)	(0.0523)	(0.0669)
Permanent	-0.0648***	-0.1726***	-0.1036***	0.0142	-0.0515	-0.0281
	(0.0225)	(0.0302)	(0.0325)	(0.0281)	(0.0410)	(0.0369)
Salaried	-0.0596**	0.0193	0.0009	-0.1410***	-0.0107	-0.1040***
	(0.0233)	(0.0198)	(0.0179)	(0.0299)	(0.0259)	(0.0353)
Fixed hours	0.0155	0.0017	0.0056	-0.0949***	-0.1628***	-0.0729***
	(0.0224)	(0.0187)	(0.0146)	(0.0296)	(0.0265)	(0.0274)
Constant	0.3856***	0.3571***	0.1108**	0.5211***	0.3535***	0.3021***
	(0.1138)	(0.1282)	(0.0519)	(0.1504)	(0.1056)	(0.0995)
Observations	2995	3760	3354	2396	3111	3165
R^2	0.1607	0.1131	0.1471	0.1350	0.1160	0.1106
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable in Columns 1 - 3 is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. The dependent variable in Columns 4 - 6 is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. In Columns 4 - 6 the sample is restricted to those who were in work at the time of data collection. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.3: Job loss probability - Individual characteristics (weighted)

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0484**	0.0383*	0.0325**	0.0330**	-0.0208	-0.0164
	(0.0198)	(0.0202)	(0.0162)	(0.0163)	(0.0138)	(0.0145)
University degree	-0.0852***	-0.0010	-0.0632***	-0.0025	-0.0225	-0.0116
	(0.0196)	(0.0202)	(0.0154)	(0.0160)	(0.0140)	(0.0200)
30-39	-0.0160	-0.0016	0.0034	0.0133	-0.0290*	-0.0001
	(0.0261)	(0.0255)	(0.0197)	(0.0203)	(0.0159)	(0.0157)
40-49	-0.0133	-0.0036	-0.0011	0.0006	-0.0139	0.0089
	(0.0274)	(0.0280)	(0.0208)	(0.0218)	(0.0181)	(0.0182)
50-59	0.0364	0.0467	-0.0010	-0.0024	-0.0305*	-0.0109
	(0.0341)	(0.0322)	(0.0264)	(0.0271)	(0.0160)	(0.0155)
60+	0.0064	0.0009	-0.0231	-0.0265	0.0653*	0.0647*
	(0.0318)	(0.0313)	(0.0361)	(0.0340)	(0.0368)	(0.0360)
Tasks from home		-0.2365***		-0.1939***		-0.0694***
		(0.0285)		(0.0260)		(0.0221)
Self-employed		-0.0988***		-0.0257		0.0363
		(0.0304)		(0.0390)		(0.0452)
Permanent		-0.0630***		-0.1700***		-0.1078***
		(0.0227)		(0.0303)		(0.0326)
Salaried		-0.0551**		0.0187		-0.0007
		(0.0240)		(0.0202)		(0.0178)
Fixed hours		0.0133		-0.0001		0.0100
		(0.0225)		(0.0186)		(0.0144)
Constant	0.2206**	0.3628***	0.1537***	0.3451***	0.0973***	0.1296**
	(0.0952)	(0.1147)	(0.0334)	(0.1289)	(0.0229)	(0.0539)
Observations	3016	2995	3804	3760	3541	3354
R^2	0.0550	0.1644	0.0153	0.1156	0.0703	0.1572
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.4: Job loss probability - Individual characteristics

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Tasks from home	-0.3313***		-0.2308***		-0.0524***	
	(0.0182)		(0.0168)		(0.0111)	
Female		0.0372**		0.0306**		-0.0012
		(0.0161)		(0.0130)		(0.0081)
University degree		-0.0240		-0.0210		0.0003
		(0.0164)		(0.0130)		(0.0092)
30-39		-0.0116		0.0306*		-0.0214**
		(0.0199)		(0.0157)		(0.0099)
40-49		-0.0152		0.0291*		-0.0129
		(0.0213)		(0.0174)		(0.0119)
50-59		0.0217		0.0020		-0.0173
		(0.0246)		(0.0218)		(0.0123)
60+		0.0272		0.0186		0.0323
		(0.0257)		(0.0361)		(0.0202)
Self-employed		-0.1720***		-0.0795***		-0.0052
		(0.0226)		(0.0260)		(0.0169)
Permanent		-0.0789***		-0.1784***		-0.0556***
		(0.0169)		(0.0207)		(0.0113)
Salaried		-0.0853***		-0.0111		-0.0169
		(0.0187)		(0.0156)		(0.0105)
Fixed hours		-0.0032		-0.0074		0.0066
		(0.0168)		(0.0153)		(0.0094)
Constant	0.3564***	0.3200***	0.2721***	0.1718**	0.0775***	0.1352***
	(0.0111)	(0.0904)	(0.0094)	(0.0681)	(0.0059)	(0.0309)
Observations	3006	3014	3772	3804	3393	3536
R^2	0.0990	0.1228	0.0475	0.0947	0.0065	0.0674
Region F.E.	no	yes	no	yes	no	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.5: Probability of job loss II

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0261	0.0269	-0.0047	-0.0042	0.0099	0.0110
	(0.0193)	(0.0193)	(0.0208)	(0.0208)	(0.0101)	(0.0101)
Number of kids	-0.0103	-0.0120	0.0027	0.0028	0.0033	0.0022
	(0.0105)	(0.0105)	(0.0090)	(0.0091)	(0.0056)	(0.0057)
Number of kids x female	0.0072	0.0074	0.0215*	0.0210*	-0.0164*	-0.0177*
	(0.0134)	(0.0134)	(0.0122)	(0.0123)	(0.0091)	(0.0092)
Changed work patterns for care		0.0257*		0.0113		0.0221**
		(0.0151)		(0.0127)		(0.0086)
University degree	-0.0036	-0.0049	-0.0067	-0.0071	0.0051	0.0036
	(0.0163)	(0.0163)	(0.0131)	(0.0131)	(0.0102)	(0.0103)
30-39	-0.0022	0.0007	0.0242	0.0241	-0.0163	-0.0158
	(0.0198)	(0.0198)	(0.0158)	(0.0158)	(0.0104)	(0.0104)
40-49	-0.0055	-0.0013	0.0169	0.0186	-0.0132	-0.0110
	(0.0212)	(0.0212)	(0.0174)	(0.0176)	(0.0124)	(0.0125)
50-59	0.0159	0.0230	-0.0043	-0.0020	-0.0212*	-0.0169
	(0.0242)	(0.0244)	(0.0216)	(0.0218)	(0.0127)	(0.0128)
60+	0.0078	0.0165	0.0138	0.0172	0.0280	0.0336
	(0.0255)	(0.0259)	(0.0362)	(0.0365)	(0.0207)	(0.0208)
Tasks from home	-0.2573***	-0.2587***	-0.1929***	-0.1945***	-0.0390***	-0.0414***
	(0.0219)	(0.0219)	(0.0197)	(0.0199)	(0.0132)	(0.0132)
Self-employed	-0.1001***	-0.1010***	-0.0485*	-0.0496*	0.0051	0.0059
	(0.0230)	(0.0230)	(0.0260)	(0.0261)	(0.0176)	(0.0176)
Permanent	-0.0626***	-0.0642***	-0.1732***	-0.1740***	-0.0511***	-0.0515***
	(0.0166)	(0.0167)	(0.0206)	(0.0207)	(0.0116)	(0.0116)
Salaried	-0.0588***	-0.0586***	0.0129	0.0127	-0.0198*	-0.0189*
	(0.0185)	(0.0185)	(0.0156)	(0.0157)	(0.0109)	(0.0109)
Fixed hours	0.0009	0.0023	-0.0114	-0.0104	0.0052	0.0071
	(0.0165)	(0.0165)	(0.0152)	(0.0153)	(0.0097)	(0.0098)
Constant	0.4376***	0.4236***	0.2450***	0.2423***	0.1299***	0.1133***
	(0.0891)	(0.0894)	(0.0685)	(0.0710)	(0.0359)	(0.0368)
Observations	2995	2993	3759	3746	3354	3348
R^2	0.1621	0.1631	0.1180	0.1183	0.0689	0.0708
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable in Columns 1 - 6 is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.6: Hours spent on a "typical" work day during the past week on active childcare or home schooling

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	1.0663**	0.9021*	1.2538***	1.2373***	1.8465***	1.8568***
	(0.4758)	(0.4818)	(0.2238)	(0.2236)	(0.4508)	(0.4480)
University degree	0.1077	0.1043	0.1961	0.2005	-0.1497	-0.3216
	(0.4910)	(0.4902)	(0.2302)	(0.2301)	(0.5032)	(0.5049)
Number of kids	0.0790	0.0786	0.6184***	0.6249***	-0.3323	-0.3005
	(0.2359)	(0.2356)	(0.1288)	(0.1286)	(0.2595)	(0.2589)
Married	0.4534	0.4647	0.3673	0.3758	1.4849***	1.6198***
	(0.5525)	(0.5524)	(0.2602)	(0.2603)	(0.4655)	(0.4669)
30-39	-0.4830	-0.4904	0.6391**	0.6397**	1.3540**	1.1695**
	(0.5743)	(0.5759)	(0.2699)	(0.2702)	(0.5226)	(0.5272)
40-49	-0.0719	-0.0982	-0.0413	-0.0413	-0.0911	-0.0024
	(0.6219)	(0.6290)	(0.3043)	(0.3069)	(0.6182)	(0.6157)
50-59	-1.6476*	-1.8368*	-2.2041***	-2.1552***	-2.4099**	-2.4477**
	(0.9919)	(1.0013)	(0.4440)	(0.4457)	(1.2040)	(1.1962)
60+	-1.6823	-1.7829	-2.9806***	-3.0226***	1.5229	1.3897
	(1.1566)	(1.1550)	(0.9515)	(0.9509)	(3.5818)	(3.5957)
Tasks from home	-0.7789	-0.8137	-1.0187***	-1.0978***	-0.7983	-0.7194
	(0.7520)	(0.7647)	(0.3928)	(0.4018)	(0.7514)	(0.7820)
Hours worked outside home		-0.0631		-0.1137**		-0.2074**
		(0.0814)		(0.0472)		(0.0879)
Hours worked from home		0.1067		-0.0520		-0.1076
		(0.0678)		(0.0367)		(0.0841)
Constant	1.1854	1.2252	2.7605**	3.0701***	3.3157**	3.8524**
	(2.3639)	(2.3616)	(1.1043)	(1.1092)	(1.6472)	(1.6568)
Observations	429	429	1273	1273	343	343
R^2	0.2726	0.2810	0.1530	0.1575	0.4044	0.4166
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	yes	yes	yes	yes	yes	yes
Industry F.E.	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is the number of hours spent on child care or home schooling on a typical day during the last week. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.7: Perceived probability of job loss

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.0998***	-0.0590***	-0.0533***	-0.0100	0.0220**	0.0449***
	(0.0138)	(0.0141)	(0.0106)	(0.0107)	(0.0102)	(0.0095)
University degree	0.0198	0.0167	0.0136	0.0092	0.0589***	0.0237**
	(0.0140)	(0.0146)	(0.0106)	(0.0108)	(0.0117)	(0.0118)
30-39	0.0129	0.0075	-0.0491***	-0.0243*	0.0009	0.0161
	(0.0185)	(0.0176)	(0.0135)	(0.0129)	(0.0129)	(0.0117)
40-49	0.0084	0.0022	-0.1407***	-0.0873***	-0.0897***	-0.0208
	(0.0195)	(0.0189)	(0.0147)	(0.0144)	(0.0153)	(0.0140)
50-59	-0.1269***	-0.0849***	-0.2361***	-0.1571***	-0.1444***	-0.0596***
	(0.0229)	(0.0220)	(0.0183)	(0.0177)	(0.0156)	(0.0143)
60+	-0.2102***	-0.1505***	-0.2514***	-0.2087***	-0.1854***	-0.1116***
	(0.0239)	(0.0232)	(0.0317)	(0.0299)	(0.0271)	(0.0241)
Tasks from home		0.1105***		0.1180***		0.1409***
		(0.0200)		(0.0166)		(0.0152)
Self-employed		0.0059		-0.1077***		-0.0932***
		(0.0206)		(0.0231)		(0.0205)
Permanent		0.0443***		-0.0778***		0.0026
		(0.0152)		(0.0186)		(0.0135)
Salaried		-0.0244		-0.0297**		-0.1080***
		(0.0163)		(0.0129)		(0.0125)
Fixed hours		-0.0368**		-0.0587***		-0.0299***
		(0.0150)		(0.0125)		(0.0111)
Measures still in August		0.3562***		0.2170***		0.2154***
		(0.0238)		(0.0203)		(0.0164)
Constant	0.3804***	0.1608**	0.4165***	0.3478***	0.3407***	0.3378***
	(0.0639)	(0.0801)	(0.0214)	(0.0563)	(0.0182)	(0.0420)
Observations	2402	2382	3115	3094	3179	3116
R^2	0.1320	0.2713	0.0831	0.2333	0.0766	0.3075
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. 'Measures still in August' refers to the perceived probability of some social distancing measures being in place in August. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.8: Earnings loss probability - In-work respondents

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0126	0.0143	0.0082	0.0273	0.0104	0.0130
	(0.0202)	(0.0217)	(0.0166)	(0.0174)	(0.0145)	(0.0151)
University degree	-0.1501***	-0.0758***	-0.0206	0.0287	-0.0022	0.0325*
	(0.0209)	(0.0226)	(0.0169)	(0.0176)	(0.0165)	(0.0177)
30-39	-0.0129	-0.0044	-0.0777***	-0.0447**	-0.0567***	-0.0288
	(0.0271)	(0.0272)	(0.0209)	(0.0211)	(0.0182)	(0.0185)
40-49	-0.0484*	-0.0676**	-0.0686***	-0.0219	-0.0302	0.0019
	(0.0286)	(0.0291)	(0.0229)	(0.0235)	(0.0218)	(0.0223)
50-59	-0.0973***	-0.1084***	-0.0994***	-0.0612**	-0.0465**	-0.0121
	(0.0335)	(0.0339)	(0.0285)	(0.0290)	(0.0222)	(0.0228)
60+	-0.1044***	-0.1290***	-0.1045**	-0.0861*	-0.1176***	-0.1072***
	(0.0349)	(0.0356)	(0.0491)	(0.0485)	(0.0382)	(0.0382)
Tasks from home	-0.1224***	-0.1258***	-0.0990***	-0.0785***	-0.0280	-0.0281
	(0.0274)	(0.0304)	(0.0236)	(0.0269)	(0.0213)	(0.0239)
Self-employed		0.0293		0.1045***		0.0678**
		(0.0319)		(0.0377)		(0.0326)
Permanent		-0.0230		-0.0147		0.0078
		(0.0234)		(0.0303)		(0.0214)
Salaried		-0.0683***		-0.0472**		-0.0641***
		(0.0252)		(0.0210)		(0.0198)
Fixed hours		-0.0699***		-0.1087***		-0.0901***
		(0.0231)		(0.0204)		(0.0176)
Constant	0.4013***	0.4164***	0.3640***	0.3751***	0.1789***	0.2812***
	(0.0939)	(0.1225)	(0.0347)	(0.0901)	(0.0272)	(0.0650)
Observations	2405	2396	3123	3111	3201	3165
R^2	0.0661	0.1207	0.0214	0.0932	0.0139	0.0712
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. Sample is restricted to those who were in work at the time of the survey. The dependent variable is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.9: Earnings loss probability - In-work respondents (weighted)

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.0199	0.0286	0.0082	0.0359*	0.0015	0.0056
	(0.0253)	(0.0266)	(0.0209)	(0.0206)	(0.0219)	(0.0226)
University degree	-0.1550***	-0.0837***	-0.0162	0.0357*	-0.0442*	0.0020
	(0.0260)	(0.0284)	(0.0211)	(0.0212)	(0.0268)	(0.0283)
30-39	-0.0327	-0.0179	-0.0924***	-0.0511*	-0.0193	0.0151
	(0.0358)	(0.0359)	(0.0265)	(0.0264)	(0.0293)	(0.0311)
40-49	-0.0963***	-0.1036***	-0.0830***	-0.0342	0.0138	0.0591
	(0.0366)	(0.0377)	(0.0286)	(0.0288)	(0.0349)	(0.0374)
50-59	-0.1604***	-0.1629***	-0.1110***	-0.0680**	-0.0008	0.0446
	(0.0414)	(0.0417)	(0.0341)	(0.0327)	(0.0319)	(0.0339)
60+	-0.1474***	-0.1560***	-0.1400***	-0.1224**	-0.0598	-0.0479
	(0.0449)	(0.0452)	(0.0498)	(0.0499)	(0.0393)	(0.0393)
Tasks from home	-0.1136***	-0.1150***	-0.0965***	-0.0899***	-0.0037	-0.0039
	(0.0333)	(0.0366)	(0.0296)	(0.0331)	(0.0322)	(0.0385)
Self-employed		0.0241		0.0723		0.0608
		(0.0411)		(0.0529)		(0.0682)
Permanent		-0.0026		-0.0383		-0.0284
		(0.0279)		(0.0417)		(0.0376)
Salaried		-0.1099***		-0.0150		-0.1087***
		(0.0301)		(0.0266)		(0.0357)
Fixed hours		-0.0894***		-0.1614***		-0.0780***
		(0.0290)		(0.0263)		(0.0271)
Constant	0.4849***	0.5682***	0.3458***	0.3615***	0.1251***	0.2591**
	(0.1251)	(0.1482)	(0.0398)	(0.1056)	(0.0377)	(0.1042)
Observations	2398	2396	3111	3111	3169	3165
R^2	0.1025	0.1587	0.0251	0.1244	0.0371	0.1178
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. Sample is restricted to those who were in work at the time of the survey. The dependent variable is a binary variable for whether a respondent earned less in March 2020 than the average earnings over January and February 2020. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Self-employed is a binary variable for being self-employed in the main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.10: Probability of being furloughed

	United States		United Kingdom		Germany	
	(1)	(2)	(3)	(4)	(5)	(6)
Female	-0.1497***	-0.1131***	-0.0367**	0.0252	0.0210	0.0276*
	(0.0179)	(0.0193)	(0.0166)	(0.0175)	(0.0161)	(0.0166)
University degree	0.0096	-0.0057	-0.0215	-0.0066	0.0875***	0.0092
	(0.0179)	(0.0198)	(0.0167)	(0.0178)	(0.0182)	(0.0208)
30-39	-0.0217	-0.0157	-0.1693***	-0.1276***	0.0655***	0.0519**
	(0.0234)	(0.0234)	(0.0209)	(0.0209)	(0.0204)	(0.0202)
40-49	-0.0111	0.0173	-0.2183***	-0.1454***	-0.0467*	-0.0500**
	(0.0250)	(0.0251)	(0.0231)	(0.0235)	(0.0242)	(0.0246)
50-59	-0.1108***	-0.0578*	-0.2912***	-0.1884***	-0.1830***	-0.1166***
	(0.0299)	(0.0297)	(0.0296)	(0.0299)	(0.0252)	(0.0251)
60+	-0.1512***	-0.0914***	-0.2830***	-0.2237***	-0.2239***	-0.1651***
	(0.0308)	(0.0312)	(0.0516)	(0.0508)	(0.0438)	(0.0423)
Tasks from home		0.0940***		0.0246		0.0871***
		(0.0274)		(0.0276)		(0.0265)
Permanent		0.1486***		0.1698***		0.0509**
		(0.0181)		(0.0259)		(0.0218)
Salaried		-0.0549***		-0.1091***		-0.1311***
		(0.0206)		(0.0198)		(0.0206)
Fixed hours		-0.0426**		-0.0649***		-0.0509***
		(0.0180)		(0.0192)		(0.0183)
Constant	0.3706***	0.3041***	0.5939***	0.5541***	0.5267***	0.6088***
	(0.0822)	(0.1078)	(0.0337)	(0.0905)	(0.0278)	(0.0753)
Observations	2415	2391	3289	3238	3221	3000
Region F.E.	yes	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	no	yes	no	yes
Industry F.E.	no	yes	no	yes	no	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variable is a binary variable for whether a respondent reported being on furlough / STW at the time of our April survey wave. The sample is restricted to current or former employees only. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.11: Multinomial logit - Employment status

	United States		United Kingdom		Germany	
	No job	Furloughed	No job	Furloughed	No job	Furloughed
Female	1.0835	0.5151***	1.1968	1.1888*	1.0901	1.1584
	(0.1470)	(0.0652)	(0.1479)	(0.1113)	(0.2108)	(0.1121)
University degree	0.9127	0.9559	0.9048	0.9510	0.9869	1.0202
	(0.1230)	(0.1278)	(0.1125)	(0.0909)	(0.2538)	(0.1216)
30-39	0.9971	0.8912	0.7829*	0.5142***	0.6866	1.2604**
	(0.1612)	(0.1352)	(0.1142)	(0.0570)	(0.1668)	(0.1407)
40-49	0.8808	1.0553	0.6641**	0.4601***	0.5115**	0.7225**
	(0.1540)	(0.1715)	(0.1083)	(0.0576)	(0.1619)	(0.1040)
50-59	0.9096	0.6051**	0.3937***	0.3177***	0.4724**	0.4262***
	(0.1780)	(0.1330)	(0.0860)	(0.0527)	(0.1468)	(0.0702)
60+	0.8013	0.4567***	0.4076**	0.2696***	1.0231	0.2959***
	(0.1626)	(0.1094)	(0.1469)	(0.0766)	(0.4104)	(0.0953)
Tasks from home	0.1730***	1.1496	0.2065***	0.7861	0.6297	1.5582***
	(0.0357)	(0.2114)	(0.0420)	(0.1163)	(0.2082)	(0.2398)
Permanent	0.8158	2.4630***	0.4268***	1.6128***	0.4681***	1.1912
	(0.1014)	(0.3089)	(0.0673)	(0.2420)	(0.0951)	(0.1517)
Salaried	0.5902***	0.6502***	0.8305	0.5647***	0.5782**	0.5063***
	(0.0882)	(0.0872)	(0.1119)	(0.0590)	(0.1265)	(0.0570)
Fixed hours	0.9409	0.7536**	0.8009*	0.6893***	1.0752	0.7623***
	(0.1161)	(0.0893)	(0.1061)	(0.0696)	(0.2201)	(0.0791)
Constant	1.5753	0.6466	1.3592	2.7972**	0.2172	2.0793*
	(1.2493)	(0.4330)	(0.8594)	(1.3312)	(0.2481)	(0.8286)
Observations	2391		3238		3000	
Region F.E.	yes		yes		yes	
Occupation F.E.	yes		yes		yes	
Industry F.E.	yes		yes		yes	

Notes: Multinomial logit regressions. The coefficients represent relative risk ratios. The base category is working and not being furloughed / on STW. The sample is restricted to former or current employees only. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. Tasks from home is the fraction of tasks respondents could do from home in their main or last job. Permanent, salaried and fixed hours take value 1 for employees with permanent contracts, who are salaried and whose work hours are fixed, respectively. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.

Table D.12: Probability of job loss & furlough

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
United States								
Job loss R^2	0.0946	0.0706	0.1088	0.0565	0.0734	0.1173	0.1290	0.1331
Furlough R^2	0.0784	0.0937	0.1116	0.0904	0.0899	0.1342	0.1414	0.1614
Observations	2406	2406	2406	2406	2406	2406	2406	2406
United Kingdom								
Job loss R^2	0.0581	0.0360	0.0652	0.0160	0.0408	0.0688	0.0911	0.0937
Furlough R^2	0.0527	0.0868	0.1018	0.0528	0.0567	0.1244	0.1268	0.1463
Observations	3280	3280	3280	3280	3280	3280	3280	3280
Germany								
Job loss R^2	0.0283	0.0369	0.0491	0.0199	0.0273	0.0543	0.0607	0.0636
Furlough R^2	0.1305	0.1795	0.2044	0.1122	0.1196	0.2309	0.2301	0.2529
Observations	3181	3181	3181	3181	3181	3181	3181	3181
Occupation F.E.	yes	no	yes	no	no	yes	yes	yes
Industry F.E.	no	yes	yes	no	no	yes	yes	yes
Demographics	no	no	no	yes	no	yes	no	yes
Contract type	no	no	no	no	yes	no	yes	yes
Region F.E.	yes	yes	yes	yes	yes	yes	yes	yes

Notes: OLS regressions. Standard errors in parentheses. * p< 0.1, ** p< 0.05, *** p< 0.01. The dependent variables are a binary variable for whether a respondent lost their job within the past month and attributed the job loss to the coronavirus outbreak, and a binary variable for whether the respondent is currently on furlough / STW. The sample is limited to respondents without missing answers on all control variables in (8). Demographic characteristics are age, and binary variables for whether a respondent is female and has at least university level education. Job contract characteristics are binary variables for whether a job is permanent, salaried or had fixed hours. Region fixed effects refer to state fixed effects for the US and Germany, and fixed effects for regions as reported in Table C.1 for the UK.