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Work that can be done from home: Evidence on variation within and across occupations and industries

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Abstract

Using large, geographically representative surveys from the US and UK, we document variation in the percentage of tasks workers can do from home. We highlight three dimensions of heterogeneity that have previously been neglected. First, the share of tasks that can be done from home varies considerably both across as well as *within* occupations and industries. The distribution of the share of tasks that can be done from home within occupations, industries, and occupation-industry pairs is systematic and remarkably consistent across countries and survey waves. Second, as the pandemic has progressed, the share of workers who can do all tasks from home has increased most in those occupations in which the pre-existing share was already high. Third, even within occupations and industries, we find that women and workers with less stable work arrangements can do fewer tasks from home. Using machine-learning methods, we extend our working-from-home measure to all disaggregated occupation-industry pairs.

JEL: J21, J24

Keywords: Working from home, occupations, industry, Coronavirus, Covid-19, telework

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1 Introduction

The shift to working from home has been one of the most rapid and widespread changes developed economies have seen in recent times. Catalyzed by the onset of the Covid-19 pandemic, this shift has exposed previously overlooked differences across workers. Most notably, differences in workers' ability to work from home have become extremely salient. With lockdown and social distancing measures in place, telework has often been the only way for non-essential workers to carry out their work (Adams-Prassl et al. 2020*b*; Bick and Blandin 2020).

Given the changing landscapes of work, living and leisure, and that economic hardship of the pandemic will be related to the extent to which workers can perform their jobs from home, it is necessary to know whether workers' ability to work from home varies systematically across *and* within occupations and industries, and whether it differs across workers by different background characteristics such as gender, education, or type of contract. Understanding how the ability to work from home is distributed across the population and jobs can help inform the design of short-time work schemes, policies aimed at re-opening the economy after the pandemic, family policies aimed promoting the ability of working parents to reconcile work and family life, and optimize commuting networks and urban planning.

We fill this gap in the literature by providing the first comprehensive analysis of heterogeneity in the ability to work from home within occupations and industries, and across workers with different characteristics. For the purpose of this study, we use three waves of data collected in March, April, and May 2020 as part of the COVID Inequality Project in two large economies, the United States and the United Kingdom (N=24,924). To capture individual ability to work from home, we ask survey respondents to state what share of job tasks they could theoretically do from home. Responses are recorded on a continuous 0-100% scale, thus allowing us to capture individual differences in the realities workers face.[1]

Several results emerge from our study. First, we document a high degree of heterogeneity in workers' ability to work from home. While on average respondents in the US and UK report being able to do 42% and 39% of their work tasks from home respectively, a non-negligible share of workers reports values of 0 or 100%. At the same

[1]Our measure is similar to one administered in surveys conducted as part of Mas and Pallais (2017) and Mas and Pallais (2019). However, these studies do not provide any analysis of variation in this measure across occupations, industries, or worker characteristics. The authors instead use the measure to condition the sets of vignettes that respondents observe.

time, the vast majority of workers report values that lie strictly between 0 and 100%, highlighting the importance of using a continuous metric.

Second, we document large differences in workers' ability to work from home not just across but also *within* occupations and industries. We find that occupation and industry fixed effects can only account for about one quarter of the variation in the share of tasks workers report being able to do from home. Alternative measures that assume that the ability to work from home is constant within occupations or industries mask a considerable degree of heterogeneity across workers; they cannot capture the complex work realities people face. In Adams-Prassl et al. (2020*b*), we show that the ability to work from home significantly predicts job loss due to the pandemic *over and above* what can be predicted by occupation and industry fixed effects. To fully understand the economic consequences of the pandemic and how policies can help buffer the economic shocks, it is crucial to take differences across workers within occupations and industries into account.

One potential concern is that the limited explanatory power of the occupation and industry fixed effects could be explained by measurement error in our working-from-home measure. While we cannot rule out that some measurement error exists, we provide evidence from six independent surveys conducted in two countries at three different points in time to show that the variation in our metric is reliably systematic. For instance, we examine the mean, median, standard deviation, coefficient of variation and share of respondents reporting being able to do 0 or 100% of their tasks from home across occupations, industries or occupation-industry pairs, and find very high correlations in these statistics across the different countries and independent survey waves.

We further examine the distributions of our working-from-home measure within occupations and industries in more detail. Some striking patterns emerge. For some occupations, for instance 'Architecture and Engineering,' many respondents report being able to do an intermediate share of tasks from home and the distribution can be well approximated by a normal distribution. However, for other occupations, for instance 'Office and Administrative Support,' the distribution is bi-polar, with many workers within that occupation being able to do either very few or almost all tasks from home. These patterns provide important insights for the design of labor market policies aimed at buffering economic shocks of a pandemic. Furloughing schemes, for example, typically allow workers to either keep working at 100% or to stop working altogether. Such policies may not provide enough flexibility for workers in occupations or industries in which most workers can do an intermediate share of their job tasks from home. In Adams-Prassl et al. (2020*a*), we provide evidence that workers in the UK who can do work tasks from home are more likely to work while furloughed, even when forbidden by the scheme. Short-time work schemes, on the other hand, might be more suitable as they allow employers to reduce workers' hours more flexibly.

We document large differences in the ability to work from home across workers with different characteristics. Male workers, workers with a university degree, and workers with permanent contracts report that they can do a significantly higher share of their job tasks from home. Remarkably, these gaps persist even once we control for occupation and industry fixed effects.

Finally, we also consider time trends in the ability to work from home in more detail. We find that the share of tasks that can be done from home increased between March and May. It appears that this increase is mainly driven by occupations in which many workers were already capable of working from home more. Still, it remains an open question whether this increase in the share of doable tasks is fueled by firm-based technology investments, as documented by Barrero, Bloom and Davis (2020), or learning-by-doing of employees is an interesting open question.

The data generated as part of this project can be used as inputs for macroeconomic models that incorporate the possibility of working from home. Depending on the substitutability or complementarity of inputs in production functions, our measures can have implications for models based on a sectoral approach (e.g. Baqaee and Farhi 2020; Brinca, Duarte and Faria-e Castro 2020; Bodenstein, Corsetti and Guerrieri 2020) or on an approach based on industries combined with occupations (e.g. Alon et al. 2020; del Rio-Chanona et al. 2020; Aum, Lee and Shin 2020; Kaplan, Moll and Violante 2020; Papanikolaou and Schmidt 2020). The measures we construct can also be used for the identification of bottlenecks in production networks, as in Carvalho, Elliott and Spray (2020), if output differs when half of suppliers can produce all, and half cannot produce any goods, compared to the case where all suppliers can produce half of their goods.[2]

Finally, because our sample does not cover all industry-occupation pairs, we use a machine-learning algorithm, i.e. a random forest, to train a model that predicts the mean share of tasks that can be done from home using tasks specified by the O*NET

[2]Of course, an individual's production function might not be linear either. Therefore, the share of tasks that can be done from home might not perfectly reflect individual output produced. Occupation-specific production functions in terms of the substitutability between home inputs and inputs outside the home form a deeper and important layer for future research.

data. This allows us to expand our dataset to include almost 1,000 disaggregated occupations and almost 80,000 occupation-industry pairs.[3]

We build on and contribute to several strands of the literature. First, we contribute to the literature which assesses the feasibility of working from home for workers in different occupations using occupation-level data (see, e.g., Baker 2020; Boeri, Caiumi and Paccagnella 2020; del Rio-Chanona et al. 2020; Dingel and Neiman 2020; Gottlieb, Grobovšek and Poschke 2020; Lekfuangfu et al. 2020; Mongey, Pilossoph and Weinberg 2020). The occupation-level indices used in these studies are primarily constructed based on O*NET data and manual classification, and line up closely with the mean shares we measure across occupations. We contribute to this work by measuring the ability to work from home at the individual level and investigating how the ability to work from home varies across and within occupations and industries, as well as across workers with different characteristics. Importantly, we also find that the mean share of tasks that can be done from home within an occupation varies systematically across industries, and the patterns are very similar across both countries. Moreover, we find that individual characteristics relate systematically to the share of tasks that can be done from home even within occupations and industries. Second, our paper relates to the literature documenting the prevalence of alternative work arrangements including telework before and during the pandemic as well as individual preferences for alternative work arrangements (e.g. Oettinger 2011; Mas and Pallais 2017, 2020; Hensvik, Le Barbanchon and Rathelot 2020; Bick, Blandin and Mertens 2020; Brynjolfsson et al. 2020; Barrot, Grassi and Sauvagnat 2021). We contribute to this strand of literature by documenting the fraction of tasks workers report they *could* do from home, i.e. what would be technologically feasible. Whether workers who could work from home do so will depend on a range of different factors such as worker preferences, the cost to firms of offering different work arrangements, and government policies. Finally, our paper also relates to previous work studying the impact of working from home on productivity (e.g. Bloom et al. 2015; Angelici and Profeta 2020).

2 Data

To provide evidence on the share of tasks that can be done from home across workers in different occupations and industries, we exploit three independent waves of survey data

[3]All survey and predicted measures of tasks that can be done from home are available for download at `www.covidinequalityproject.com`.

that we collected between late March and May in the US and the UK.[4] The sample consists of survey respondents who are resident in the US or the UK, aged 18 years or older, and who engaged in paid work at any point during the 12 months prior to data collection. In each country, no individual was surveyed twice, and in each wave, we sampled around $4,000$ individuals, for a total sample size of $24,924$ respondents. We use quota-based sampling to ensure geographical representativeness in terms of area codes in the US and regions in the UK.[5] Appendix Table A.3 reports information on the background characteristics of respondents in our samples, separately for each survey wave, and compares it to the characteristics of representative samples of the working population in the US and the UK. The latter is taken from the February 2020 monthly CPS data for the US and the 2019 Labour Force Survey data for the UK. Compared to the nationally representative data, our geographically representative samples for both the US and the UK include somewhat younger individuals, a larger share of women, and more workers with a college degree.

To capture heterogeneity in the share of tasks that can be done from home, we ask respondents in all survey waves to report what share of tasks they could do from home in their main job or in their last job, if they report being out of work.[6] We record answers to this question on a continuous scale ranging from 0 to 100%. We illustrate the question with the help of examples, e.g. *'Andy is a waiter and cannot do any of his work from home (0%)'* or *'Beth is a website designer and can do all her work from home (100%)'*. This question allows us to capture heterogeneity in the proportion of tasks workers could do from home across respondents. Aggregating individual responses allows us to construct detailed measures on the shares of tasks that can be done from home for different occupations or industries.

In all countries and survey waves, we collect information on the occupation of the respondents' main job if they report having a job or their last job if they report being out of work. Occupations are classified according to the Standard Occupations Classification 2018 major groups (or Job Families). In the early April and late May survey

[4] All survey data were collected by the professional survey company Pureprofile; the three different waves were collected on March 24-26, 2020, April 9-14, 2020, and May 20-21, 2020, respectively.

[5] For a comparison of the distribution of our respondents across the relevant geographic areas to the national distribution of the population aged 18 or above in the two countries of interest, see Appendix Tables A.1 and A.2.

[6] In particular, individuals who report having a job are asked, *'In your main job, what percentage of the tasks could you do from home?'*, while individuals who report being out of work are asked, *'In your last job, what percentage of the tasks could you do from home?'*. A similar question has previously been included in the Understanding America Study (Mas and Pallais 2020).

waves, we additionally ask for the industry the respondents work in or used to work in, following the Standard Industry Classification. In the late May survey wave, we also collect information on the detailed occupation and industry classification of the respondent's main or last job. The detailed breakdown for occupations matches the 8-digit SOC codes, and detailed industry classifications are provided at the Division level. The occupation and industry classifications span 23 different occupations and 22 different industries when we use the coarse measures, while the detailed breakdown spans 1110 and 86 possible occupation and industries, respectively.

The data further contain information on the background characteristics of respondents, including age, gender, and educational attainment. We additionally ask respondents to report their gross individual annual earnings from all sources for 2019. Throughout, we restrict the sample to respondents who are either still in work at the time of data collection or report having been in paid work at any time since February.

3 Working from home

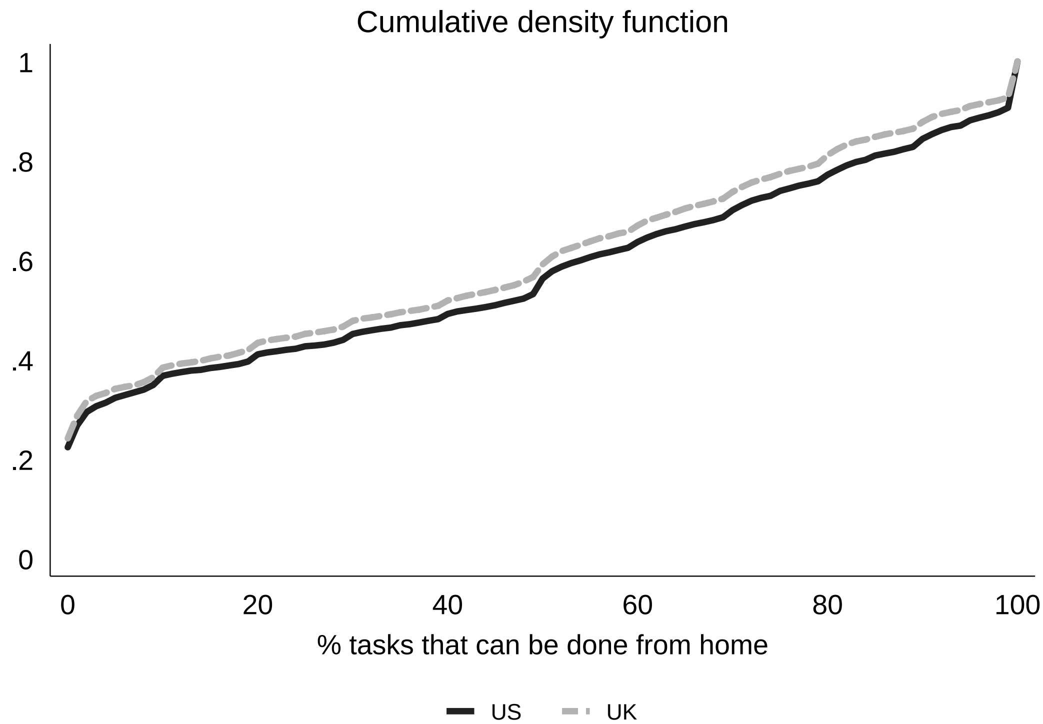
3.1 Mean and median shares

Using our novel survey data, we first document that there is considerable variation in the percentage of tasks workers can do from home. Across all survey waves, respondents in the US (UK) on average report being able to do 43% (41%) of their tasks from home. Figure 1 displays the cumulative distribution function for the share of tasks individuals can do from home in the US (blue solid line) and the UK (red dashed line). The distributions for the US and UK track each other very closely and display the high degree of heterogeneity in the working-from-home measure.[7] While a non-negligible share of workers in both countries report values of zero or 100%, the vast majority of workers report shares that lie strictly between zero and 100%, highlighting the fact that the ability to work from home is best captured by a continuous metric.

Consistent with results from previous studies, we find significant differences across occupations, and we also document significant differences across industries. The mean share of tasks that can be done from home varies significantly across occupations, ranging from 14% for 'Food Preparation and Serving' to 68% for 'Computer and Mathematical' (see column 1 of Table 1). Similarly, there are large differences in mean shares

[7]In Appendix Figure B.4, we further break down the cumulative distribution functions by survey wave and see that they track each other closely as well.

Figure 1: Distribution of Tasks that can be done from home



Notes: The figure shows the cumulative density function (CDF) of the share of tasks that individuals report being able to do from home in their main or last job. The blue solid line and red dashed line represent the CDF for the US and the UK, respectively.

across industries (see column 1 of Appendix Table B.3). The mean ranges from 18% for 'Accommodation and Food Service Activities' to 70% for 'Information and Communication'.[8]

While differences in mean shares across occupations and industries are sizeable, we also find a considerable degree of heterogeneity *within* occupation and industry. Within each occupation and industry, the standard deviation of the working-from-home measure is large (see column 2). Thus, alternative measures that are constant within occupation or industry mask a considerable degree of heterogeneity across workers. This is further reflected by the fact, that for many occupations and industries, the *median* share of tasks that can be done from home is very different from the *mean* share (see column 3). For example, in 'Food Preparation and Serving' where the mean share is

[8]In Appendix Tables B.1 and B.2 we present the measures separately by country.

estimated to be 14%, the median is 0%. Neglecting heterogeneity within occupation or industry would not give a full account of the realities workers face in the workplace. We explore the dispersion in our working-from-home measure within occupations and industries in more detail in Section 3.2, revealing strikingly systematic patterns.

Table 1: Measures of ability to work from home by occupation

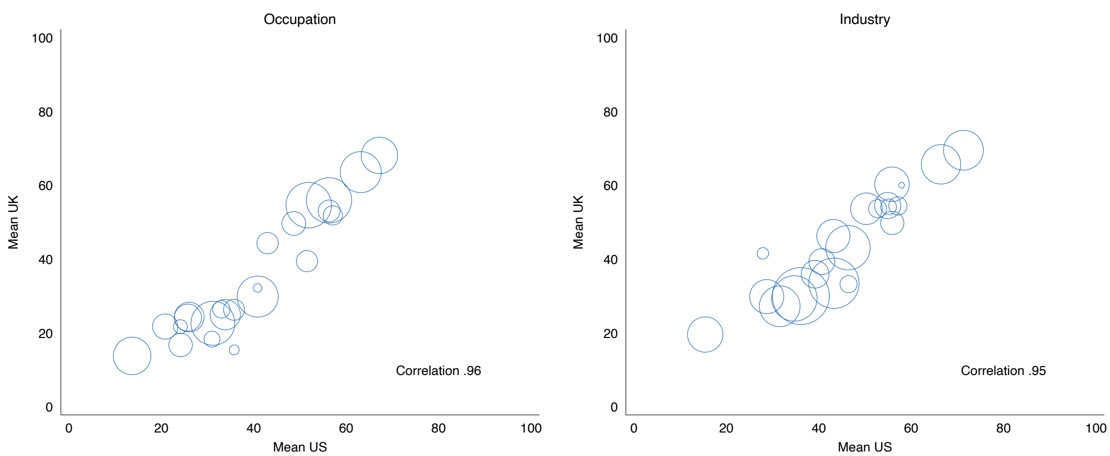
Occupation	Mean	SD	Median	Ones	Zeros
Food Preparation and Serving	13.71	25.83	0	.02	.53
Personal Care and Service	21.13	32.72	1	.05	.47
Transportation and Material Moving	21.39	31.82	1	.03	.45
Protective Service	22.73	31.11	2	.03	.44
Building and Grounds Cleaning and Maintenance	23.92	32.82	1	.04	.42
Production	24.74	33.48	2	.04	.42
Healthcare Practitioners and Technical occ.	25.18	32.38	6	.04	.36
Farming, Fishing, and Forestry	25.22	33.68	6	.07	.27
Sales and Related Occupations	26.57	35	2	.05	.4
Healthcare Support	29.14	35.88	4.5	.07	.33
Installation, Maintenance, and Repair	29.4	33.59	10	.03	.3
Construction and Extraction	30.85	33.92	15	.03	.29
Educational Instruction and Library	35.06	32.78	27	.06	.16
Military Specific Occupations	36.16	30.06	34	.04	.15
Life, Physical, and Social Science	43.65	32.59	46	.06	.13
Community and Social Service	45.25	35.22	50	.07	.19
Arts, Design, Entertainment, Sports, and Media	49.14	36.93	51	.13	.16
Office and Administrative Support	53.68	38.4	60	.16	.16
Legal	54.15	31.08	53	.06	.07
Architecture and Engineering	54.5	27.73	56	.06	.04
Management	56.07	32.63	61	.09	.07
Business and Financial Operations	63.35	29.8	68	.14	.05
Computer and Mathematical	67.61	27.6	72	.16	.02

Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. 'Ones' are the share of respondents reporting 100%, while 'Zeros' are the share of respondents reporting 0%.

Before turning to the dispersion within occupations and industries in more detail, we note that one potential concern with our working-from-home measure is measurement error. Given the self-reported nature of the survey measure we use, it may be that people are not paying sufficient attention to the question while answering the survey, or that they may interpret the question differently, thus contributing to noise in the measure. While we cannot rule out that some measurement error exists, we provide evidence that the relationships are systematic by comparing the results across independent survey waves and countries.

We first investigate whether the *mean* shares of tasks we estimate for each occupation and industry (column 1 in Tables 1 and B.3) are similar in the US and the UK. For this purpose, in Figure 2, we plot the mean tasks that can be done from home within each occupation (left) and industry (right) in the UK (y-axis) against the mean shares we estimate for the US (x-axis). The size of each bubble is proportional to the number of observations for each occupation and industry. As can be seen from these figures, the mean shares we estimate are remarkably similar between the two countries, exhibiting a correlation of 0.96 (occupations) and 0.95 (industries). We further investigate whether the correlations are similarly high between waves and within countries. These relationships are illustrated in Appendix Figures B.5 and B.6, which display a similarly high correlation, ranging from 0.93 to 0.97. Given that no survey respondent was surveyed twice, the systematic patterns we demonstrate strongly validate our mean share metric.

Figure 2: Mean tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

An alternative to using the mean is the *median*. We investigate whether the correlation between the median values we estimate for each occupation and industry is similarly high across countries and survey waves. In Figure B.1, we show that there is a strong correlation between the median values in the UK and the US (0.97 for occupations and 0.94 for industries), and that the relationships are similarly strong across survey waves within countries, with values ranging from 0.92 to 0.98 (see Appendix

Figures B.7 and B.8).

Having established the high correlation between the mean and median measures across countries and waves, we explore the extent to which these measures correlate with the two different measures provided in Dingel and Neiman (2020), which are based on manual classification and O*NET classifications, respectively. In Appendix Figures B.9 and B.10, we show that our mean and median measures correlate highly (0.86 and 0.90), lending additional credibility to the mean measures constructed using different methodologies. There is one notable difference between the mean/median shares we estimate and the measures provided by Dingel and Neiman (2020). As can be seen in the two figures, we have fewer measures close to 0% and 100%, i.e. our spread is smaller.

Similar to Mongey, Pilossoph and Weinberg (2020), we find a strong negative correlation between the share of tasks that can be done from home within an occupation and the physical proximity indicator computed using O*NET. In Appendix Figure B.11, we compare our mean and median measures of the share of tasks that can be done from home to the physical proximity indicator and find negative correlations of -0.60 and -0.59, respectively. Given that the share of workers with sick pay tends to be lower amongst workers in occupations that are done at high physical proximity (Adams-Prassl et al. 2020*c*), this relationship could play a particular role in the transmission of airborne viral diseases, such as Covid-19 or the flu.

3.2 Dispersion

So far, the literature has assumed that workers within an occupation are equally able to work from home. We find considerable heterogeneity in the ability to work from home within occupations and industries, illustrated by the high standard deviation of the working-from-home measure within occupation and industry (column 2 of Tables 1 and B.3). Amongst occupations, the standard deviation ranges from 28% for 'Computer and Mathematical' to 38% for 'Office and Administrative Support,' while for industries it ranges from 23% for 'Mining and Quarrying' to 38% for 'Arts, Entertainment and Recreation'.

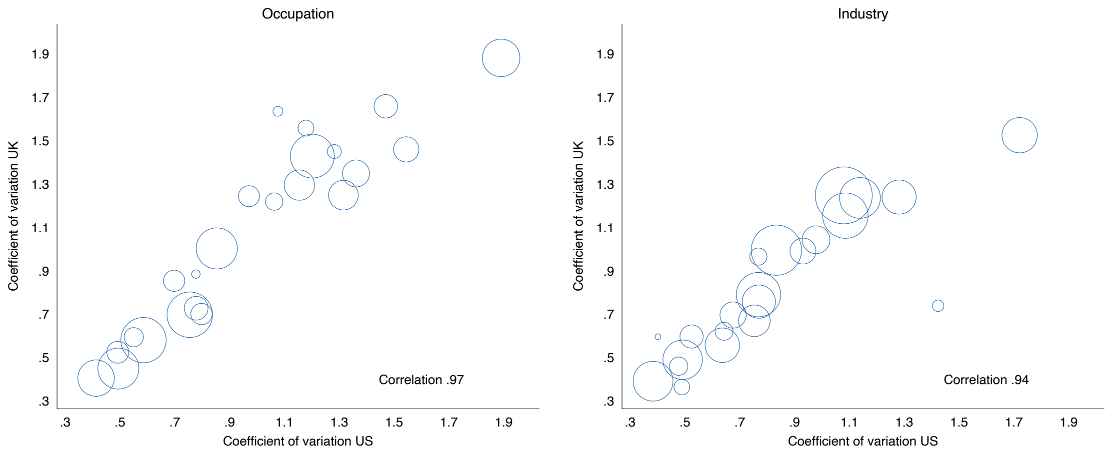
Figure 3 plots the coefficient of variation, i.e. the standard deviation deflated by the mean, for the share of tasks that can be done from home within occupation (left) and industry (right) in the US (x-axis) and UK (y-axis). The correlation between the coefficient of variation within occupations and industries across countries is 0.97 and

0.94, respectively. In Appendix Figure B.12, we perform a similar analysis using the standard deviation and find large positive correlations between the US and UK as well. In Appendix Figures B.13 and B.14, we show that these relationships also hold within countries across survey waves for both the coefficient of variation and the standard deviation, respectively.

We further document that the *shape* of the distribution varies considerably across different occupations and industries, with some distributions being well approximated by bell-shaped curves, while others are left- or right-skewed or bi-modal. Remarkably, we find very similar distributions for the US and the UK. To illustrate the different patterns, in Figure 4, we plot histograms of the share of tasks that can be done from home for four occupations within the US (blue bars) and the UK (transparent black bars). In the top left panel, we see an example of an occupation, 'Food Preparation and Serving,' for which many respondents can do very few tasks from home. The distributions in the US and the UK are virtually identical. The correlation between the shares in the bins between the US and the UK is 0.9989. In the top right panel, we can see that working in 'Computer and Mathematical' occupations, in contrast, allows many respondents to do a large fraction of their tasks from home. However, we also see that a high proportion of workers can do an intermediate share of their tasks from home.

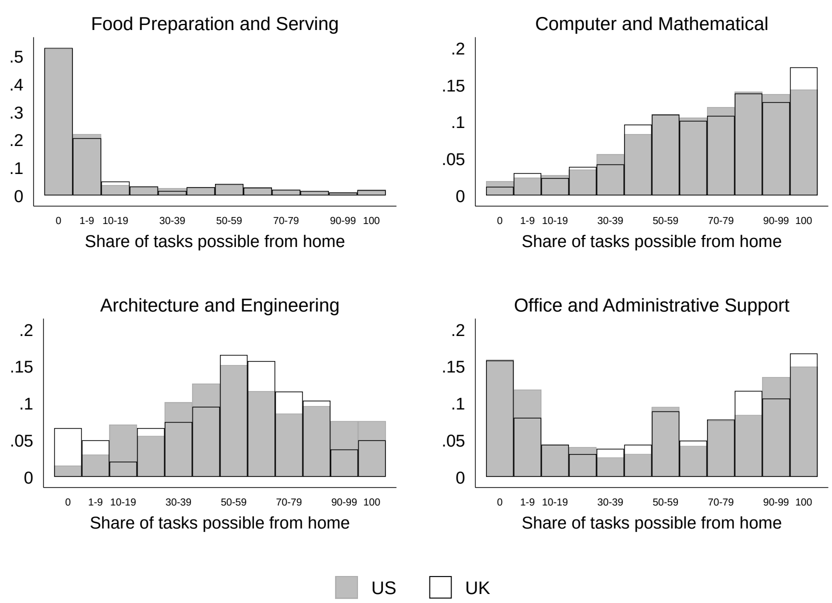
The occupations in the bottom two panels of Figure 4 have very similar mean shares of tasks that can be done from home. Looking at the entire sample, it is 55% for 'Architecture and Engineering' and 54% for 'Office and Administrative Support.' For those working in 'Architecture and Engineering,' displayed on the bottom left, the distribution can be well approximated by a normal distribution. In contrast, the bottom right panel displays a polarized or bi-modal distribution for workers in 'Office and Administrative Support,' with many workers being able to do close to 0 or 100% of their tasks from home. In Appendix Figures B.15 and B.16, we show the distributions of the remaining occupations and industries.

Figure 3: Coefficient of variation of tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

Figure 4: Distribution of the share tasks that can be done from home within occupations



Notes: The light blue bars display the share of responses by bin for the US and the black transparent bars for the UK.

3.3 All or nothing

Within each occupation, some workers can do all (100%) or none (0%) of their tasks from home. We show that there is considerable variation in those shares across occupations and industries (columns 4 and 5 of Tables 1 and B.3), and that those shares are also remarkably similar across countries and independent survey waves.

Amongst occupations, the share of those who can do all tasks from home ranges from 2% for 'Food Preparation and Serving' to 16% for 'Office and Administrative Support' and 'Computer and Mathematical'. Within industries, this share ranges from 5% for 'Activities of Household as Employers' to 17% for 'Information and Communication'. The share of workers who can do zero tasks from home ranges from 2% for 'Computer and Mathematical' to 53% for 'Food Preparation and Serving' amongst occupations, and from 2% for 'Information and Communication' to 49% for 'Accommodation and Food Service Activities' amongst industries.

To investigate whether these differences are systematic, we again turn to a comparison across countries and waves. In Figure B.2, we see that the correlation between countries for those who can do all tasks from home is 0.83 across occupations and 0.84 across industries. Similarly, for those who can do no tasks from home, we see in Figure B.3 that the correlations are 0.97 and 0.93. In Appendix Figures B.17 and B.18, it becomes clear that the corresponding correlations across waves within countries are very high as well.

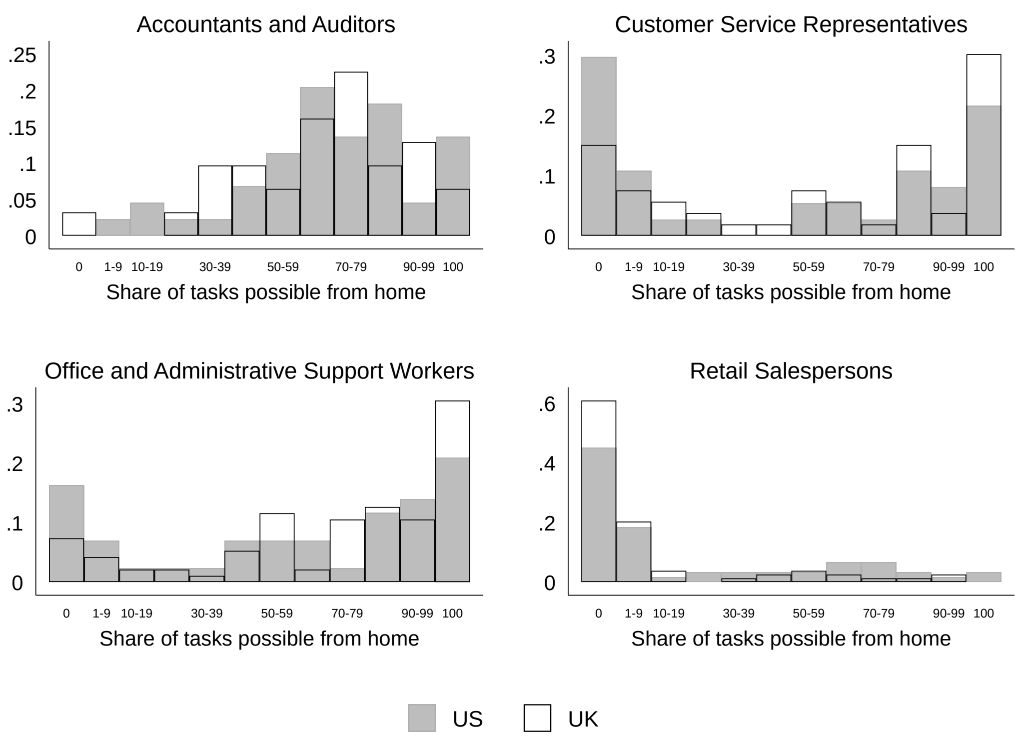
3.4 Occupations and industries at the disaggregated level

The occupation and industry classifications used in the previous analyses span 23 different occupations and 22 industries. The classifications are coarse and subsume different sub-categories. Our third wave of data also contains disaggregated information, spanning 1110 and 86 possible occupations and industries, respectively. We explore the distribution of our working-from-home measure within and across disaggregated occupations and industries to demonstrate that (i) there is also considerable variation within and across those sub-categories, and (ii) the patterns across the US and UK are remarkably similar even when we consider the disaggregated occupation and industry classifications.

In Figure 5 we show the distribution of the share of tasks that can be done from home within four disaggregated occupations by country. Again we, see that occupations exhibit similar patterns as at the aggregate level and that distributions in the US and

UK overlap closely.

Figure 5: Distribution of the share of tasks that can be done from home within disaggregated occupations

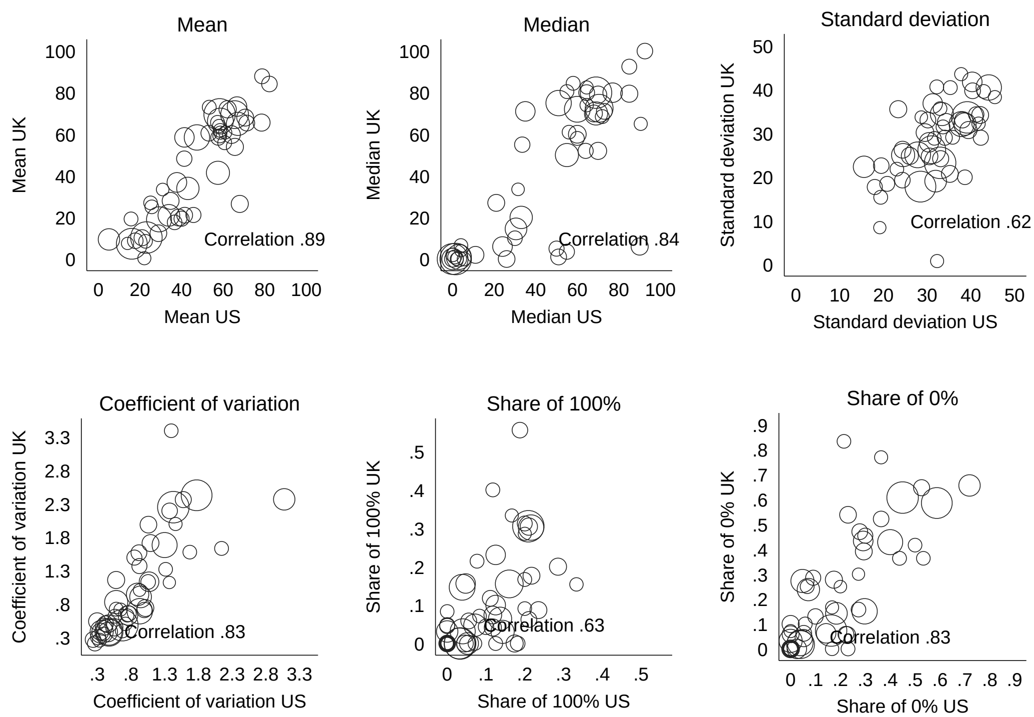


Notes: The light blue bars display the share of responses by bin for the US and the black transparent bars for the UK. We keep all cells with at least ten observations.

Across these fine-grained occupations, the mean share of tasks that can be done from home varies from 3% for 'Bartenders' in the family of 'Food Preparation and Serving Related' occupations to 89% for 'Software Developers, Applications' in the family of 'Computer and Mathematical' occupations. For industries, it varies from 16% for 'Food and Beverage Service Activities' in the family of 'Accommodation and Food Service Activities' to 89% in 'Publishing Activities' in the family of 'Information and Communication' industries.

In Figure 6, we plot the mean, median, standard deviation, coefficient of variation, share of respondents with 100%, and share of respondents with 0% for the disaggregated occupations in the US (x-axis) and the UK (y-axis). The correlations are close to 0.90 for the mean, median, coefficient of variation, and share of respondents with 0%. This

Figure 6: Measures of tasks from home in the US and the UK by occupation at the two-digit level



Notes: Each bubble is proportional to the number of observations and represents one occupation at the two-digit level.

suggests that the within variation we document at the aggregated level is unlikely to be solely driven by different occupation types within each family but also by varying shares within a specific sub-occupation. The correlations in Appendix Figure B.19 for industries at the disaggregated level support the same argument for industries.

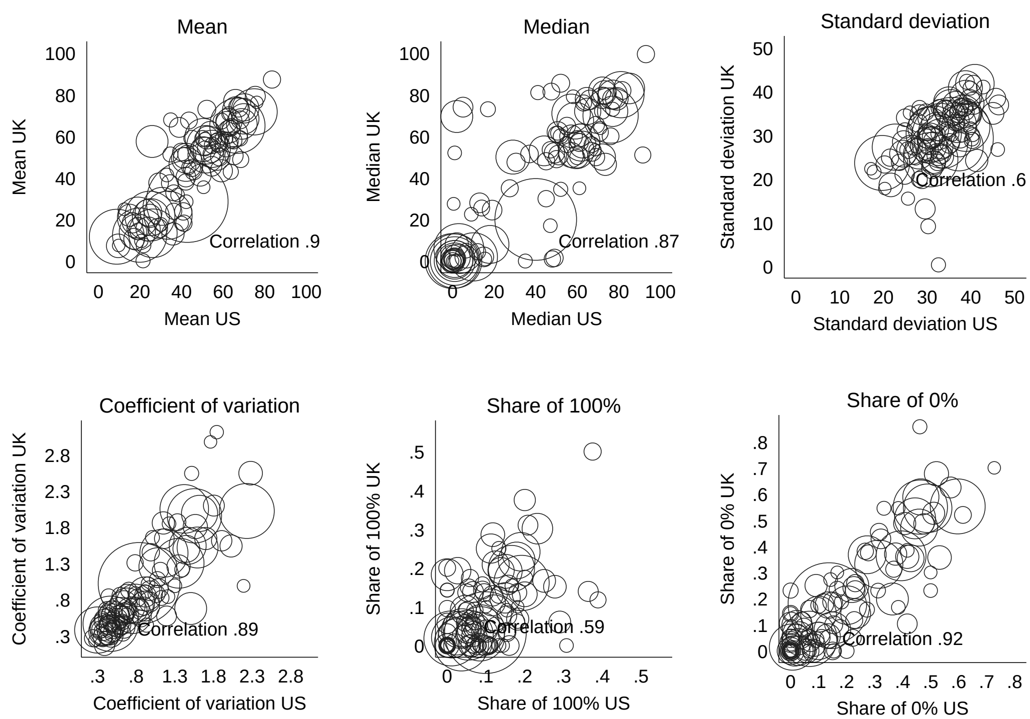
3.5 Occupation-industry pairs

We now explore the extent to which the share of tasks that can be done from home varies within occupations across different industries. For that purpose, we examine the mean share of tasks that can be done from home by occupation within industries, i.e. we cross-tabulate occupation and industry. We keep all cells with at least ten observations, which leaves us with 170 occupation-industry pairs. Across the occupation-industry pairs, the share of tasks that can be done from home varies from 5% for the occupation

'Food Preparation and Serving' in the 'Education' industry to 87% for the occupation 'Computer and Mathematical' in the industry 'Financial and Insurance Activities'.

In Figure 7, we plot the mean, median, standard deviation, coefficient of variation, share of respondents with 100%, and share of respondents with 0% for the occupation-industry pairs in the US (x-axis) and the UK (y-axis). We find correlations that are close to 0.90 for the mean, median, coefficient of variation, and share of respondents with 0%. We conclude that our data cannot only be used to proxy the share of tasks that can be done from home by occupation and industry, but also by occupation-industry pairs. This even seems to be the case for occupation-industry pairs at the disaggregated level as can be seen in Appendix Figure B.20, though here cell sizes become small.

Figure 7: Measures of tasks from home in the US and the UK by occupation-industry pairs



Notes: Each bubble is proportional to the number of observations and represents one occupation-industry pair. A pair has to have at least 10 observations in each country.

3.6 Predicting the working-from-home measure

Using the survey data from the third wave, we have at least 10 observations for 126 out of the 1110 disaggregated occupations. For the remaining occupations, the number of respondents in our sample is below ten, which we consider too few to obtain credible estimates directly from our data. However, we use a machine-learning method to fill this gap and construct the working-from-home measure for all disaggregated occupations. We do the same for occupation and industry pairs.

Most approaches quantify the share of tasks that can be done from home for a given occupation by classifying the task list provided by O*NET. We use this task list combined with industry fixed effects to predict our individual responses of the share of tasks that can be done from home for all disaggregated occupations. To do so, we train a random forest model to predict the mean share of tasks. As predictors, we include the list of 38 binary work tasks presented in Appendix Table compiled by Dingel and Neiman (2020) using the O*NET data. For the second survey wave, where we only have information on respondents' aggregated occupation, we take the mean share for each work task within that occupation group. Despite the resulting measurement error for the data from the second wave, we still profit from the increase in the training sample size.

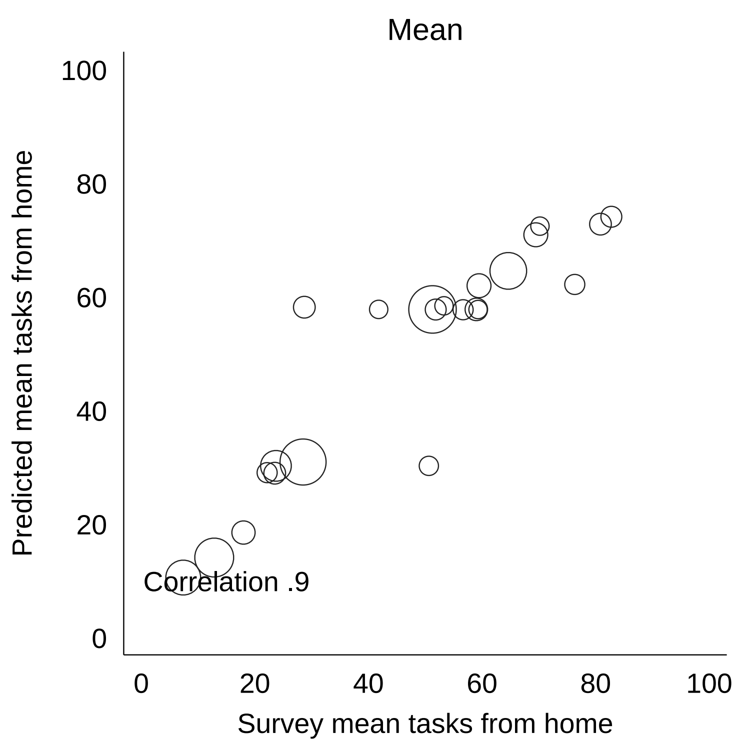
In terms of prediction algorithms, we use a random forest regression tree for the share of tasks due to its continuous nature. A random forest has the great advantage that it can detect the relation of the share of tasks that can be done from home with non-linear combinations of work tasks and their interactions with industries. Moreover, predicted values are bound by observed shares, so that unlike for OLS, we cannot have predictions lying below 0% or above 100%. The fact that predictions are then averaged across many decision trees with bootstrapped samples, i.e. a random forest, safeguards against overfitting. The tree depths and numbers of trees are determined by three-fold cross-validation.[9]

In Figure 8, we compare the mean share of tasks that can be done from home according to our survey (x-axis) and the predicted mean share by the random forest for the disaggregated occupation codes for which we have at least 10 observations. After having chosen the hyperparameters, we test the validity of our prediction model by training the random forest on 70% of the occupations and then predict out-of-sample on the remaining 30%. The model provides a close approximation with a correlation

[9]The algorithm settles on a depth of 6 and 400 trees for the share of tasks.

of 0.9 between the observed and predicted measures and an R^2 of 0.82 when regressing one on the other. As a comparison, training an OLS model on the same training sample achieves a correlation of 0.51 and an R^2 of 0.26 between the true and predicted shares out-of-sample, which is respectable but clearly lower. These results raise our confidence that the extrapolations to other occupations, for which we have no or few observations, using a random forest provide valuable information.[10]

Figure 8: Survey mean versus predicted out-of-sample mean for occupations based on O*NET tasks



Notes: Each bubble is proportional to the number of observations and represents one disaggregated occupation-industry pair.

We then train a model on the full sample to predict the mean share of tasks that can be done from home for each occupation-industry pair. Given that this would be difficult to display at the disaggregated level, in Figure 9 we show a heatmap of the predicted means at the aggregated occupation-industry level. The y-axis displays occupations,

[10]We repeat the same procedure, while excluding the aggregated industry level as a predictor. The predictive performance is, as expected, lower, as the correlation between survey and predicted means is 0.73 out-of-sample, which can be seen in Appendix Figure B.26.

while the x-axis classifies industries. The darker the shade of a cell, the more tasks can be done from home. While some occupations, such as ‘Business and Financial Operations,’ display high shares across all industries, other occupations, such as ‘Office and Administrative Support,’ are characterized by a higher variance. Not surprisingly, this coincides with our findings from the variations across respondents.

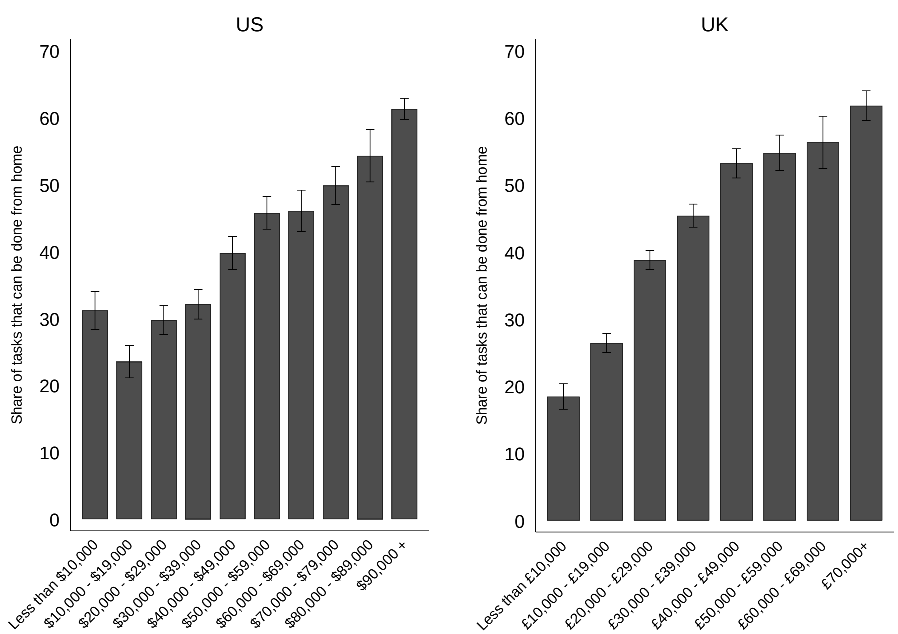
Figure 9: Heatmap of predicted mean for occupation-industry pairs

Notes: The darker the shade of a cell, the more tasks can be done from home. The y-axis displays occupations and the x-axis classifies industries.

4 Who can work from home

Having established differences in the ability to work from home across occupations and industries, we now turn to the question of which individual characteristics predict the share of tasks individuals can do from home. We start by documenting differences across socio-economic background. In Figure 10, we see how the share of tasks that can be done from home is spread across the income distribution. On the x-axis, we show total individual gross labor income, and, on the y-axis the average percentage of tasks that can be done from home. We see that both in the US (left) and the UK (right) those with high incomes can do a substantially larger share of their work tasks from home.

Figure 10: Tasks that can be done from home by gross labor income in 2019



Notes: Earnings are defined as total gross individual labor income in 2019. The black bars represent 95% confidence intervals.

Next, we regress the share of tasks that can be done from home on job and individual characteristics. In column (1) of Table 2, we see that the share is strongly and negatively related to age, and, on average, 5.7 percentage points lower for women and 16.7 percentage points higher for university graduates. Furthermore, workers employed on varying hour contracts determined by the employer can do 14.1 percentage points less, and those with temporary contracts 9 percentage points less. However, in column (3), we see that once we add occupation and industry fixed effects, the coefficient for the female dummy drops to -1.9 percentage points, and the coefficient for university graduates to 10.4 percentage points. Together, these variables explain close to 30% of the variation in the share of tasks that can be done from home. In columns (4) and (5), we look at the relationships separately for the US and the UK, respectively. While the coefficients for university graduates is similar across countries, the gender difference is driven by the US. In Appendix Table B.4, we show that the results hold when controlling for disaggregated occupation and industry fixed effects, which are available for the May wave only, and in Table B.5 when estimating for each survey wave separately.

Given the prominence of a university degree in explaining the possibility to work from home and the significant negative coefficient for women, we further look within each occupation and industry to determine whether these same relationships hold. Specifically, for each occupation (industry), we regress the share of tasks that can be done from home on dummies for gender, contract type, a university degree, survey wave, and country while at the same time controlling for industry (occupation) fixed effects. We see in the top panel of Figure 11 that women working in healthcare and education report being able to do significantly fewer tasks from home, while respondents with a university degree can do significantly more tasks from home across almost all occupations. The patterns for women reporting a lower share of tasks they can do from home in sales and education are consistent with the patterns for industries as well, as can be seen in Appendix Figure B.22. University graduates also report being able to do more tasks from home across almost all industries. Finally, in Appendix Figures B.23 and B.24, we show the coefficients estimated for temporary and varying hour contracts (relative to permanent and fixed hour contracts). Workers with temporary contracts, in particular in occupations related to construction, sales, healthcare, and community and social services, report being able to do fewer tasks from home. In contrast, workers on varying hour contracts report being able to fewer tasks from home within the great majority of occupations and industries.

In Figure 12 we relate the mean (top) and coefficient of variation (bottom) of the share of tasks that can be done from home on the x-axis to the same metrics of hours worked at home last week (first column), at the office last week (second column), at home in a typical week before the pandemic (third column), and at the office in a

Table 2: Tasks from home

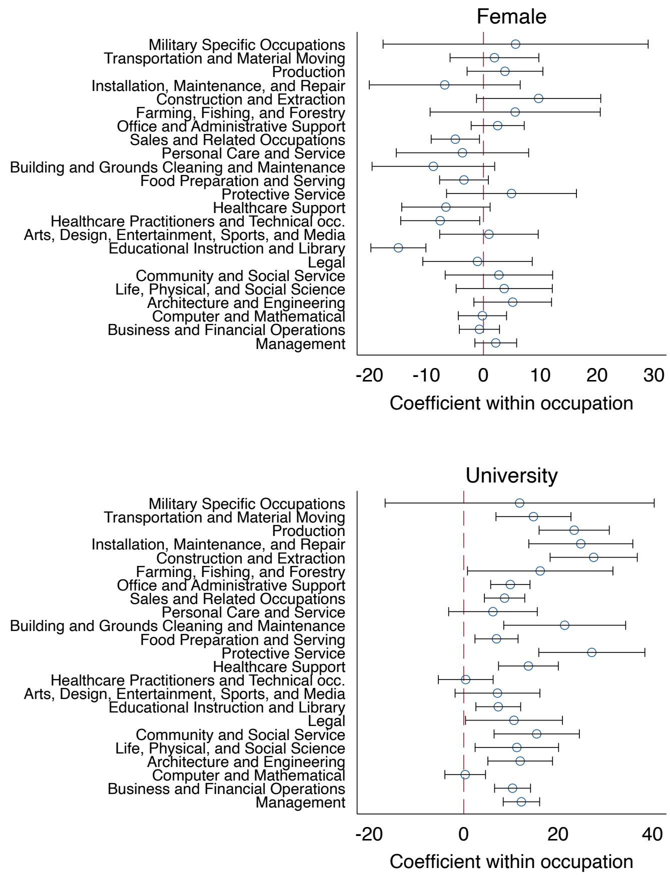
	(1)	(2)	(3)	US (4)	UK (5)
Age	-0.0025***	-0.0022***	-0.0021***	-0.0019***	-0.0020***
	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Female	-0.0569***	-0.0281***	-0.0192***	-0.0326***	-0.0080
	(0.0054)	(0.0054)	(0.0067)	(0.0107)	(0.0087)
University degree	0.1669***	0.1178***	0.1040***	0.0994***	0.1042***
	(0.0055)	(0.0053)	(0.0067)	(0.0107)	(0.0086)
Temporary contract	-0.0923***	-0.0605***	-0.0520***	-0.0664***	-0.0307**
	(0.0066)	(0.0061)	(0.0078)	(0.0100)	(0.0131)
Varying hours	-0.1407***	-0.1026***	-0.0956***	-0.1010***	-0.0937***
	(0.0070)	(0.0066)	(0.0085)	(0.0119)	(0.0122)
April	0.0289***	0.0213***			
	(0.0063)	(0.0059)			
May	0.0812***	0.0679***	0.0456***	0.0514***	0.0408***
	(0.0066)	(0.0061)	(0.0061)	(0.0095)	(0.0080)
Constant	0.4866***	0.5822***	0.5792***	0.5806***	0.5252***
	(0.0376)	(0.0355)	(0.0538)	(0.0615)	(0.0510)
Observations	16551	16551	10556	4662	5894
R^2	0.1481	0.2762	0.2961	0.2791	0.3264
Region F.E.	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	yes	yes
Industry F.E.	no	no	yes	yes	yes

Notes: OLS regressions. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regions are states for the US. The dependent variable is the share of tasks (0-1) respondents report to be able to do from home. In column (4) the sample is restricted to the US and in column (5) to the UK. The baseline category for the type of work arrangement are those with temporary contracts.

typical week before the pandemic (fourth column) on the y-axis in the US.[11] We see that the mean and coefficient of variation of tasks that can be done from home correlate positively with the same metric of hours worked from home and negatively with the hours worked on site. These correlations are much stronger during the pandemic than before. This suggests that outside the pandemic, whether or not a worker works from home depends more on other factors unrelated to the technological feasibility aspect.

[11]For hours worked before the pandemic, we ask respondents in the third wave "Think about a typical week in February for you at work (in all of your jobs). How many hours did you work from home in a typical week in February?".

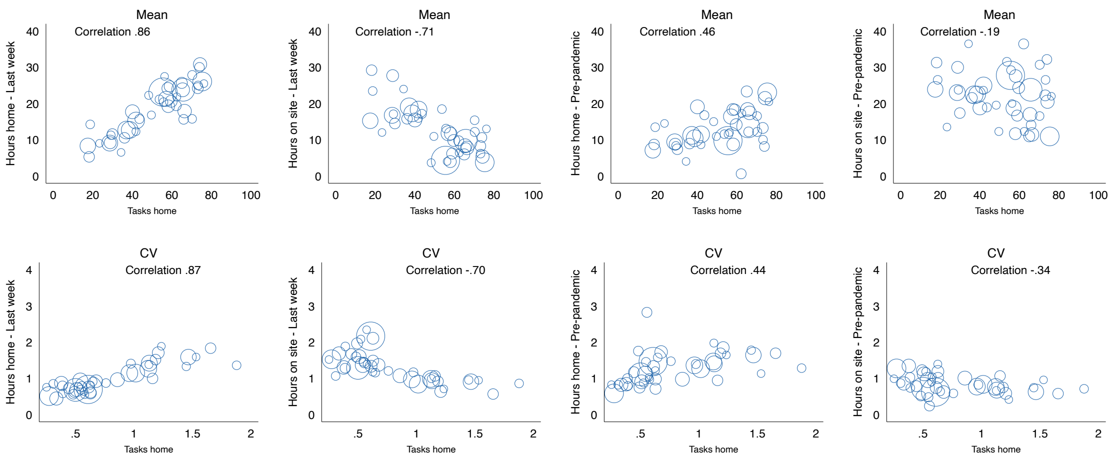
Figure 11: Coefficients on gender and education from separate regressions of each occupation explaining share of tasks from home



Notes: Additional controls are country and wave dummies, industry fixed effects, and contract type. The black bars represent 95% confidence intervals.

During the pandemic, however, how much is worked from home or on site depends strongly on the capability to work from home. In Appendix Figure B.25 we show that the same patterns hold true for the UK.

Figure 12: Relationship between share of tasks from home and hours worked from and on site before and during the pandemic across occupation-industry pairs in the US

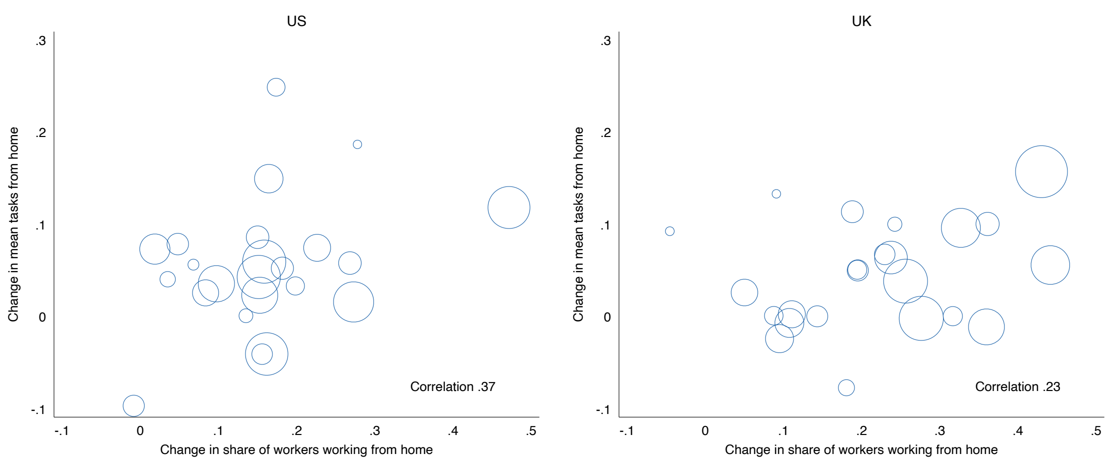


Notes: Each bubble represents an occupation-industry pair with at least 10 observations and the size is proportional to the number of observations. The x-axis shows the mean (top) and coefficient of variation (bottom) of the share of tasks that can be done from home, and the y-axis the same metrics of hours worked at home last week (first column), at the office last week (second column), at home in a typical week before the pandemic (third column), and at the office in a typical week before the pandemic (fourth column) for the US. The sample is restricted to wave 3 as for the other waves we do not have all the corresponding information on hours worked.

4.1 Changes over time

With the onset of the pandemic, many workers who had not previously worked from home were suddenly expected to do so. Firms had to change processes and the way decisions were made in order to facilitate working from home. While the cross-wave correlations of measures of work that can be done from home are extremely stable across survey waves, the regressions in Table 2 indicate that some changes in the share of tasks that can be done from home have taken place. In Figure 13 we show that the increase in the reported share of tasks that can be done from home from wave 1 to wave 3 seems to be greater in occupations in which more workers have switched from not working from home before the pandemic to working from home in wave 3 in the US (left) and the UK (right).

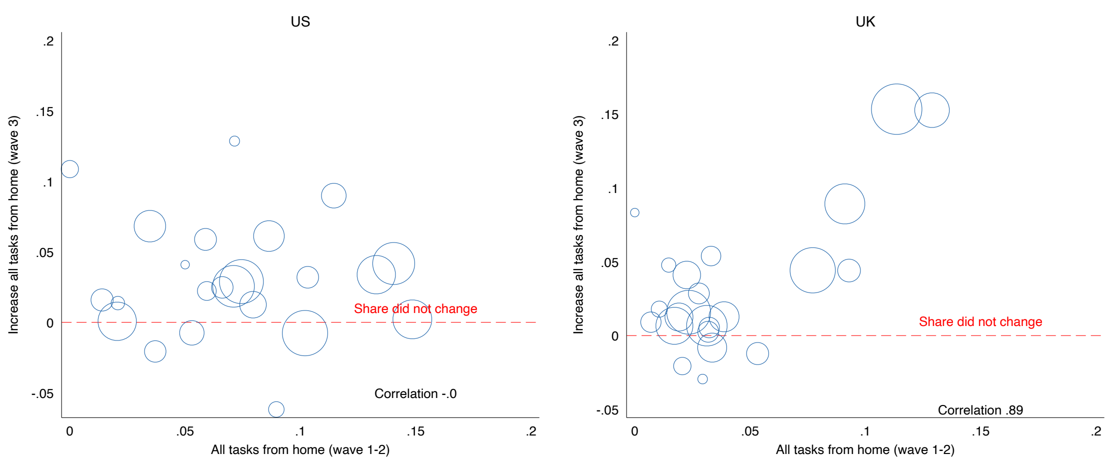
Figure 13: Change in share of workers working from home compared to before pandemic and change in mean share of tasks possible from home by occupation



Notes: Each bubble is proportional to the number of observations in wave 3 and represents one occupation. The x-axis features the change in the average share of tasks that can be done from home in wave 1 to wave 3, while the y-axis shows the change in the share of people working from home in wave 3 who were not working from home before the pandemic. The left panel shows data from the US and the right panel from the UK.

Moreover, it appears that there is an increase in the share of respondents who can do all tasks from home. In Figure 14 we look into which occupations saw this increase in the US (left) and the UK (right). On the x-axis we display the average share of respondents reporting the ability to do all tasks from home across the first two survey waves, while on the y-axis we see the increase in the third wave. In the US we see no systematic evidence in the changes. However, for the UK we see that those occupations which already had the largest share of workers who could do all tasks from home also saw the largest increases. In Appendix Figure B.21, we verify that this change has taken place amongst respondents who still have a job. This increase at the top hints towards further job polarization in terms of being able to work from home. Whether this increase has been driven by changes in employees' approaches to their work, or whether employers made investments to increase the capacity to work from home, cannot be determined with the data at hand.[12]

Figure 14: Increase of share that can do all tasks from home



Notes: Each bubble is proportional to the number of observations and represents one occupation.

5 Conclusion

In this paper, we exploit new survey data from the US and the UK to document differences in the extent to which workers can perform their tasks from home across occupations and industries. We show that workers' ability to work from home varies considerably both across and within, occupations and industries. Relatedly, we find large differences across occupations and industries in the share of workers that can perform all or none of their tasks from home. The differences that we find in the share

[12] A further open question is whether these changes will be permanent. Part of the ability to do certain tasks from home might depend on colleagues and clients working from home as well. For instance, if a meeting is not streamed because it is taking place in person, then participation in the meeting cannot be done from home.

of tasks that can be performed from home are systematic, as they correlate highly both across countries and survey waves. Even within occupation-industry pairs, our measure of ability to work from home strongly correlates across countries.

The mean shares of tasks respondents to our survey report being able to perform from home, across occupations and industries, correlate highly with existing measures of ability to shift to the home office. However, the evidence presented in this paper highlights the importance of taking variation within industries and occupations into account. We provide the first and second moments, the median, and the shares of respondents that can do all or zero tasks from home by occupation and industry (and occupation-industry pairs where sample sizes allow). Moreover, we find that individual characteristics, such as age, gender, and education, and employment characteristics, such as contract type, are systematically related to differences in the share of tasks that can be done from home within industries and occupations. The importance of being able to work from home as a protection from job loss during the Covid-19 pandemic, above and beyond occupation and industry, has been highlighted by Adams-Prassl et al. (2020*b*). Therefore, we argue that our measures can serve as informative inputs into macroeconomic models accounting for the ability to work from home, a feature that has become particularly important when studying the impact of the Covid-19 pandemic.

Finally, we train a prediction model using the task information from the O*NET to extrapolate to disaggregated occupations for which we don't have information about the share of tasks that can be done from home. We find that the trained model has a high predictive performance.

For our most recent survey wave in May, we document an increase in the share of tasks that can be done from home at the top end of the distribution. This increase is driven by occupations in the UK that already permitted a large share of tasks to be done from home, suggesting further expansion of job polarization along a new dimension. Whether this increase is driven by the adaptation of employers or employees is an exciting question left for future research.

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A Data Description

Table A.1: Distribution of respondents across area codes - US

Region	National	Late March	Early April	Late May
Area code 0	7.40	7.39	7.40	7.41
Area code 1	10.33	10.32	10.33	10.36
Area code 2	10.04	10.04	10.05	10.03
Area code 3	14.41	14.41	14.40	14.45
Area code 4	10.02	10.02	10.03	10.01
Area code 5	5.25	5.25	5.25	5.24
Area code 6	7.17	7.17	7.18	7.16
Area code 7	11.94	11.94	11.95	11.93
Area code 8	7.13	7.12	7.13	7.11
Area code 9	16.30	16.34	16.30	16.30
Observations		4003	4000	4007

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

Table A.2: Distribution of respondents across regions - UK

Region	National	Late March	Early April	Late May
Scotland	8.42	8.48	8.54	8.48
Northern Ireland	2.76	2.57	2.80	2.74
Wales	4.79	4.83	4.87	4.79
North East	4.06	4.08	4.12	4.04
North West	11.00	11.02	11.11	10.95
Yorkshire and the Humber	8.24	8.28	8.34	8.21
West Midlands	8.80	8.86	8.92	8.78
East Midlands	7.27	7.32	7.38	7.26
South West	8.59	8.63	8.70	8.61
South East	13.70	13.79	13.87	13.69
East of England	9.29	8.91	8.03	9.30
Greater London	13.15	13.24	13.32	13.15
Observations		3974	4931	4009

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

Table A.3: Demographic Variables in the Population & Surveys

	US				UK			
	CPS	March	April	May	LFS	March	April	May
Female	0.472	0.621	0.581	0. 616	0.47	0.532	0.552	0.550
University	0.395	0.440	0.494	0.488	0.357	0.422	0.488	0.464
<30	0.231	0.322	0.255	0.340	0.232	0.295	0.281	0.283
30-39	0.224	0.262	0.264	0.243	0.230	0.272	0.333	0.264
40-49	0.203	0.179	0.215	0. 176	0.217	0.203	0.238	0.196
50-59	0.198	0.130	0.136	0. 121	0.217	0.151	0.114	0.163
60+	0.144	0.107	0.130	0.120	0.104	0.079	0.033	0.095

Notes: The table shows the mean demographic characteristics of economically active individuals in each respective country. These were calculated using the frequency weights provides in the CPS for the US and the LFS for the UK. The unweighted averages of these demographic variables in our survey waves are also reported.

B Additional Tables and Figures

Table B.1: Summary statistics of working from home by occupation

	US					UK				
Occupation	Mean	SD	Median	Ones	Zeros	Mean	SD	Median	Ones	Zeros
Food Preparation and Serving	13.64	25.79	0	.02	.53	13.76	25.88	0	.02	.53
Transportation and Material Moving	20.8	32.12	1	.02	.45	21.72	31.68	1	.03	.45
Protective Service	24.09	30.88	2	.03	.42	21.68	31.41	1.5	.03	.46
Personal Care and Service	24.13	35.47	2	.08	.44	16.72	27.7	0	.01	.52
Production	25.72	35	2	.05	.41	24.15	32.54	2	.03	.44
Healthcare Practitioners and Technical occ.	26	34.2	4	.06	.38	24.28	30.29	9	.02	.34
Building and Grounds Cleaning and Maintenance	30.94	36.46	7	.07	.38	18.32	28.51	1	.02	.46
Sales and Related Occupations	31.13	37.4	7	.08	.36	22.61	32.28	1	.03	.44
Installation, Maintenance, and Repair	32.97	35.02	15	.04	.28	26.39	32.14	8.5	.01	.32
Healthcare Support	33.81	39.02	7.5	.1	.33	24.95	32.27	3	.04	.34
Construction and Extraction	35.71	34.65	25.5	.03	.24	26.27	32.64	4	.03	.35
Farming, Fishing, and Forestry	35.74	38.47	10	.12	.21	15.39	25.15	3.5	.02	.33
Military Specific Occupations	40.81	31.69	48	.06	.1	32.17	28.42	29	.03	.19
Educational Instruction and Library	40.82	34.81	36.5	.08	.14	29.84	29.9	20	.03	.19
Life, Physical, and Social Science	42.96	34.25	44.5	.08	.17	44.31	31	47	.04	.09
Arts, Design, Entertainment, Sports, and Media	48.64	37.83	50	.15	.16	49.65	36.05	52	.11	.16
Community and Social Service	51.49	35.9	56	.12	.15	39.44	33.63	43	.03	.22
Office and Administrative Support	51.86	39.12	56	.15	.16	54.6	38.01	61	.17	.16
Management	56.26	32.95	61	.1	.07	55.9	32.38	61	.09	.07
Architecture and Engineering	56.28	27.67	56	.08	.02	53.03	27.74	56	.05	.07
Legal	57.08	31.39	58	.07	.07	51.84	30.71	51	.05	.07
Business and Financial Operations	63.12	31.17	68	.16	.06	63.57	28.47	68	.12	.04
Computer and Mathematical	67.17	27.7	71	.14	.02	68.08	27.5	73	.17	.01

Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. ‘Ones’ are the share of respondents reporting 100%, while ‘Zeros’ are the share of respondents reporting 0%.

Table B.2: Summary statistics of working from home by industry

	US					UK				
Industry	Mean	SD	Median	Ones	Zeros	Mean	SD	Median	Ones	Zeros
Accommodation and Food Service Activities	15.4	26.51	0	.02	.52	19.56	29.81	1	.02	.46
Activities of Households as Employers	27.89	39.71	2	.11	.46	41.56	30.65	48	0	.11
Other Service Activities	28.71	36.79	5	.1	.38	29.83	36.96	9	.08	.3
Wholesale and Retail Trade	31.53	35.89	10	.05	.34	27.22	33.6	5	.03	.39
Human Health and Social Work	34.7	37.66	15	.09	.29	29.33	33.82	10	.04	.3
Other	36.11	38.96	17	.11	.33	29.98	37.38	3	.08	.39
Transportation and Storage	39.19	38.33	38	.07	.28	35.91	37.41	19	.06	.3
Arts, Entertainment and Recreation	40.66	37.82	32.5	.11	.26	39.32	38.92	26.5	.11	.27
Construction	43.15	33.19	47	.05	.15	46.23	34.98	50	.06	.18
Education	43.26	36.05	42	.09	.15	33.46	33.25	21	.05	.2
Manufacturing	46.3	35.56	51	.08	.19	43.08	33.99	46.5	.04	.2
Agriculture Forestry and Fishing	46.43	35.63	50	.06	.18	33.21	32.03	25	.05	.18
Administrative and Support Services	50.28	37.86	53	.17	.13	53.64	35.85	56	.16	.11
Real Estate Activities	52.71	33.86	51.5	.11	.06	53.66	33.26	56	.08	.15
Public Administration and Defence	54.9	37.07	65	.07	.16	54.52	37.88	61	.14	.19
Mining and Quarrying	55.09	26.9	65	.05	.04	54.14	19.63	53	.02	0
Professional Activities	55.83	35.52	61	.11	.12	60.27	33.48	66	.15	.07
Electricity, Gas, Steam etc.	55.89	29.27	52.5	.11	.06	49.78	29.65	52	.08	.12
Water Supply etc.	57.1	27.23	56.5	.07	.03	54.4	24.96	58	.03	.04
Extraterritorial Organisations	57.9	23.22	63	0	.1	60	35.7	59	.33	0
Financial and Insurance Activities	66.44	32.64	77.5	.2	.06	65.67	32.08	71.5	.2	.06
Information and Communication	71.29	27.33	77	.17	.02	69.51	27.09	75	.17	.02

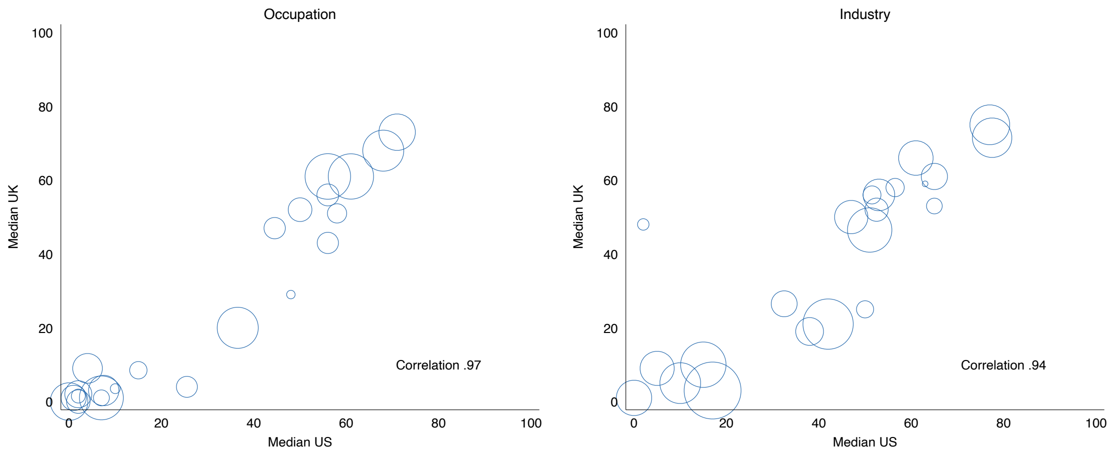
Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. ‘Ones’ are the share of respondents reporting 100%, while ‘Zeros’ are the share of respondents reporting 0%.

Table B.3: Measures of the ability to work from home by industry

Industry	Mean	SD	Median	Ones	Zeros
Accommodation and Food Service Activities	17.68	28.42	1	.02	.49
Wholesale and Retail Trade	28.84	34.52	8	.04	.37
Other Service Activities	29.22	36.84	5	.09	.35
Human Health and Social Work	31.62	35.59	10	.06	.29
Other	33.04	38.29	8	.09	.36
Activities of Households as Employers	35.58	35.28	35.5	.05	.27
Transportation and Storage	37.04	37.71	21.5	.07	.3
Education	37.71	34.82	30	.07	.18
Arts, Entertainment and Recreation	40.01	38.3	30	.11	.27
Agriculture Forestry and Fishing	41.19	34.75	42	.06	.18
Manufacturing	44.44	34.68	49	.06	.19
Construction	44.75	34.14	49	.06	.17
Administrative and Support Services	52.28	36.67	55	.16	.12
Electricity, Gas, Steam etc.	52.34	29.59	52	.09	.1
Real Estate Activities	53.16	33.48	53	.09	.1
Mining and Quarrying	54.59	23.27	56	.03	.02
Public Administration and Defence	54.59	37.68	62	.12	.18
Water Supply etc.	55.39	25.77	57	.04	.04
Professional Activities	57.79	34.67	64	.13	.1
Extraterritorial Organisations	58.69	27.38	59	.13	.06
Financial and Insurance Activities	66.01	32.31	74	.2	.06
Information and Communication	70.37	27.2	77	.17	.02

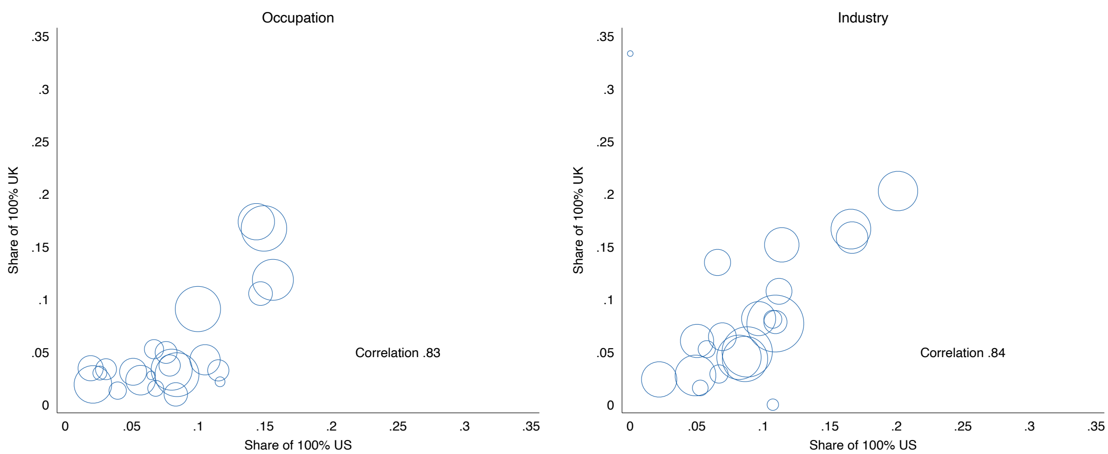
Notes: Mean, standard deviation, and median are computed using a scale from 0-100, i.e. percentages. 'Ones' are the share of respondents reporting 100%, while 'Zeros' are the share of respondents reporting 0%.

Figure B.1: Median tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



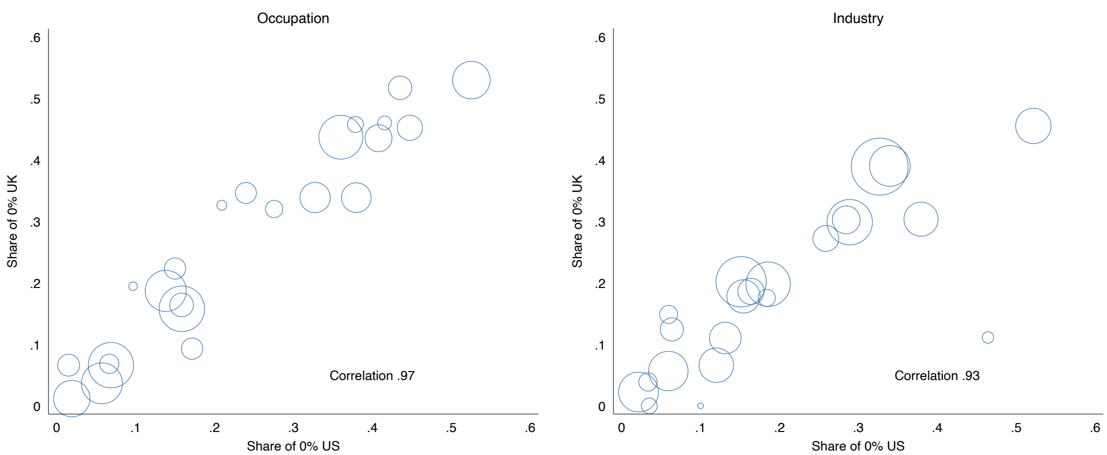
Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right).

Figure B.2: Share of people that can do all tasks from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

Figure B.3: Share of people that cannot do any tasks from home in the US and the UK by occupation (left) and industry (right)



Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

Table B.4: Tasks from home (with disaggregated occupation and industry controls)

	(1)	(2)	(3)	US (4)	UK (5)
Age	-0.0022***	-0.0025***	-0.0015***	-0.0013*	-0.0017***
	(0.0004)	(0.0004)	(0.0004)	(0.0006)	(0.0006)
Female	-0.0376***	-0.0355***	-0.0084	-0.0332*	0.0147
	(0.0104)	(0.0104)	(0.0117)	(0.0182)	(0.0160)
University degree	0.1512***	0.1409***	0.1053***	0.1004***	0.1033***
	(0.0104)	(0.0104)	(0.0115)	(0.0182)	(0.0158)
Temporary contract	-0.0754***	-0.0717***	-0.0614***	-0.0669***	-0.0423
	(0.0129)	(0.0127)	(0.0140)	(0.0175)	(0.0261)
Varying hours	-0.1703***	-0.1448***	-0.1114***	-0.1174***	-0.1078***
	(0.0138)	(0.0137)	(0.0153)	(0.0210)	(0.0235)
Constant	0.5325***	0.5609***	0.3680***	0.3716***	0.4209***
	(0.0728)	(0.0752)	(0.1003)	(0.1161)	(0.1170)
Observations	4920	4917	3833	1737	2096
R^2	0.1252	0.1908	0.2884	0.3049	0.3302
Region F.E.	yes	yes	yes	yes	yes
Occupation F.E.	no	yes	yes	yes	yes
Industry F.E.	no	no	yes	yes	yes

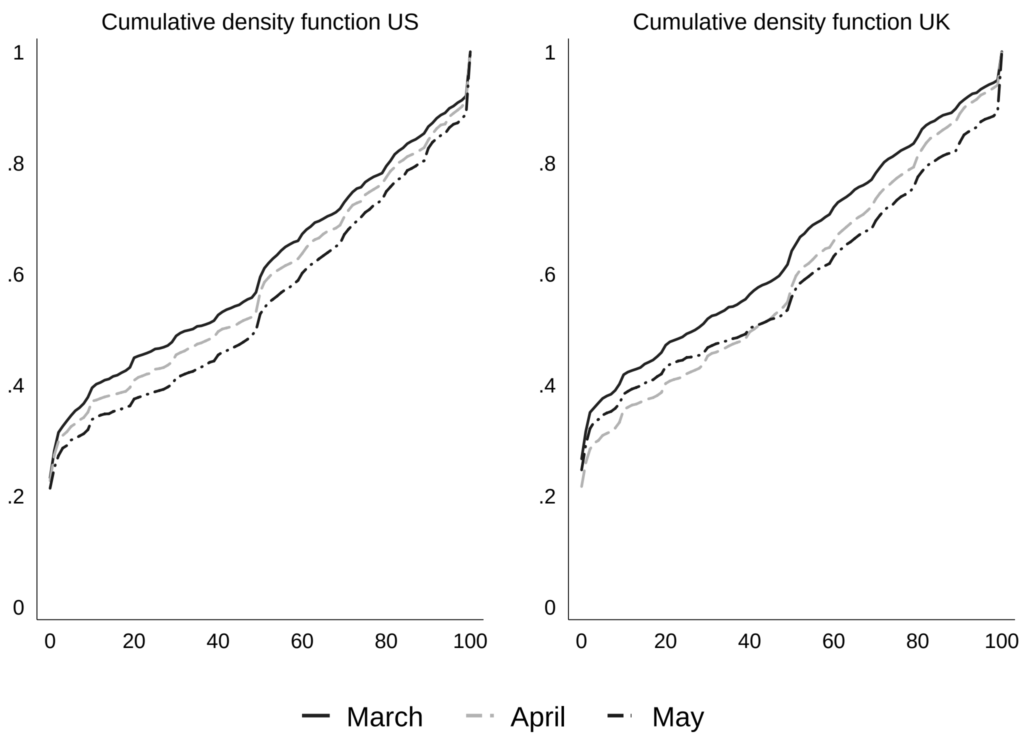
Notes: OLS regressions. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regions are states for the US. The dependent variable is the share of tasks (0-1) respondents report to be able to do from home. In column (4) the sample is restricted to the US and in column (5) to the UK. The baseline category for the type of work arrangement are those with temporary contracts.

Table B.5: Tasks from home (separately by survey wave)

				US			UK		
Wave	March (1)	April (2)	May (3)	March (4)	April (5)	May (6)	March (7)	April (8)	May (9)
Age	-0.0023***	-0.0020***	-0.0023***	-0.0023***	-0.0019***	-0.0019***	-0.0022***	-0.0021***	-0.0024***
	(0.0003)	(0.0003)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Female	-0.0243***	-0.0376***	-0.0206**	-0.0303**	-0.0570***	-0.0307**	-0.0157	-0.0260**	-0.0086
	(0.0089)	(0.0090)	(0.0102)	(0.0134)	(0.0150)	(0.0153)	(0.0119)	(0.0112)	(0.0138)
Uni degree	0.1251***	0.1234***	0.1029***	0.1298***	0.1254***	0.0969***	0.1180***	0.1184***	0.1026***
	(0.0088)	(0.0089)	(0.0101)	(0.0133)	(0.0150)	(0.0151)	(0.0118)	(0.0110)	(0.0136)
Temp.	-0.0625***	-0.0630***	-0.0522***	-0.0764***	-0.0764***	-0.0745***	-0.0422***	-0.0457***	-0.0206
	(0.0099)	(0.0104)	(0.0120)	(0.0127)	(0.0140)	(0.0147)	(0.0163)	(0.0166)	(0.0220)
Varying h.	-0.1056***	-0.0872***	-0.1191***	-0.1122***	-0.0965***	-0.1252***	-0.0981***	-0.0779***	-0.1171***
	(0.0104)	(0.0114)	(0.0130)	(0.0142)	(0.0167)	(0.0173)	(0.0155)	(0.0158)	(0.0196)
Constant	0.5682***	0.6481***	0.6064***	0.5853***	0.6311***	0.5822***	0.5118***	0.5926***	0.6198***
	(0.0549)	(0.0622)	(0.0691)	(0.0589)	(0.0678)	(0.0729)	(0.0334)	(0.0325)	(0.0387)
Obs.	5982	5649	4920	2853	2351	2319	3129	3298	2601
R^2	0.2714	0.2964	0.2557	0.2896	0.2937	0.2400	0.2567	0.3132	0.2942
Reg. FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Occ. FE	yes	yes	yes	yes	yes	yes	yes	yes	yes

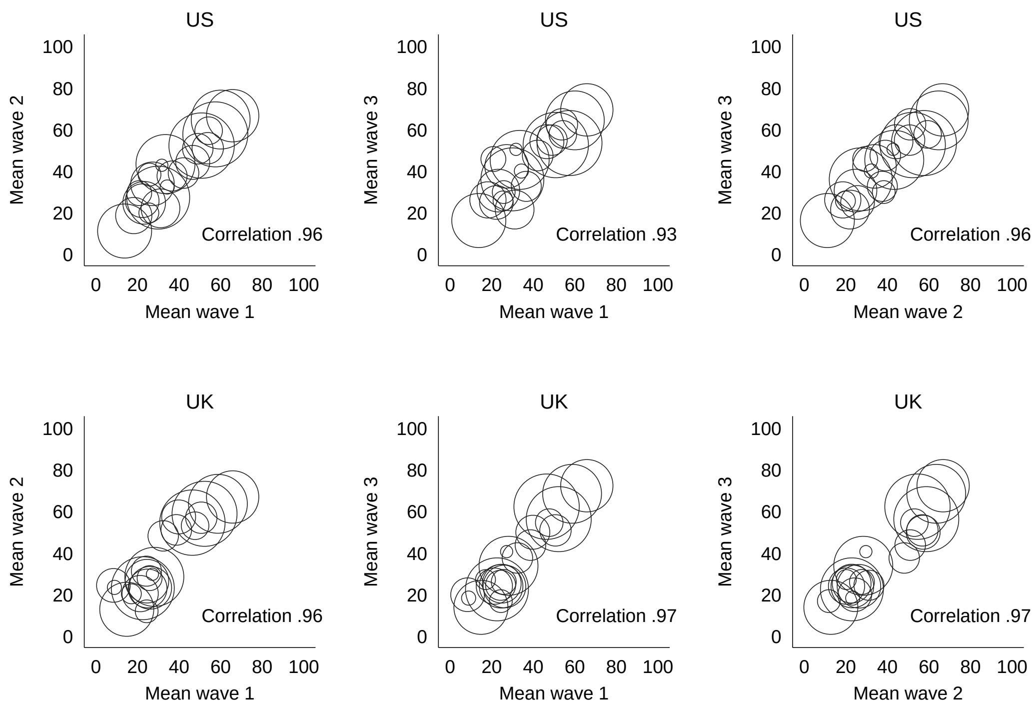
Notes: OLS regressions. Standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.01. Regions are states for the US. The dependent variable is the share of tasks (0-1) respondents report to be able to do from home. In columns (4)-(6) the sample is restricted to the US and in column (7)-(9) to the UK. In each column the sample is restricted to one survey wave.

Figure B.4: Distribution of tasks that can be done from home by survey waves for the US and UK



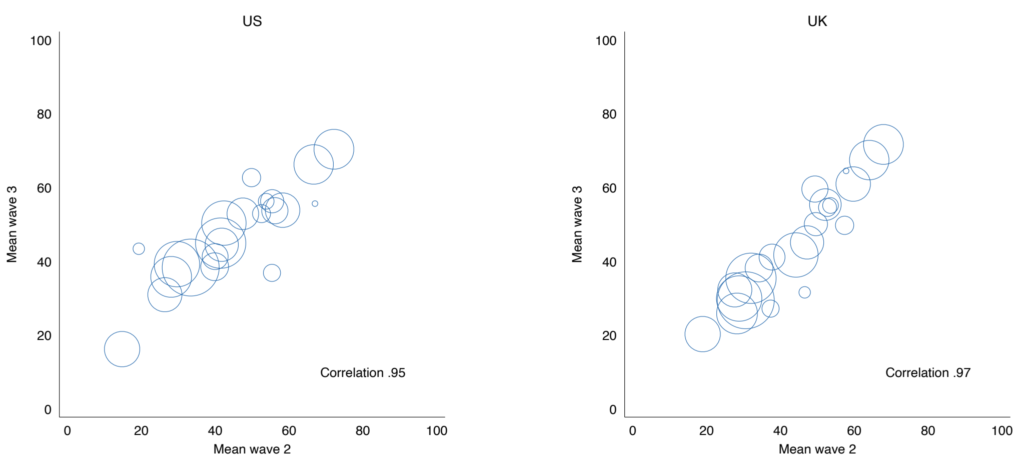
Notes: The figure shows the cumulative density functions (CDF) of the share of tasks that individuals report being able to from home in their main or last job, separately for each country and survey wave.

Figure B.5: Mean of tasks that can be done from home by occupation, within countries, and across survey waves



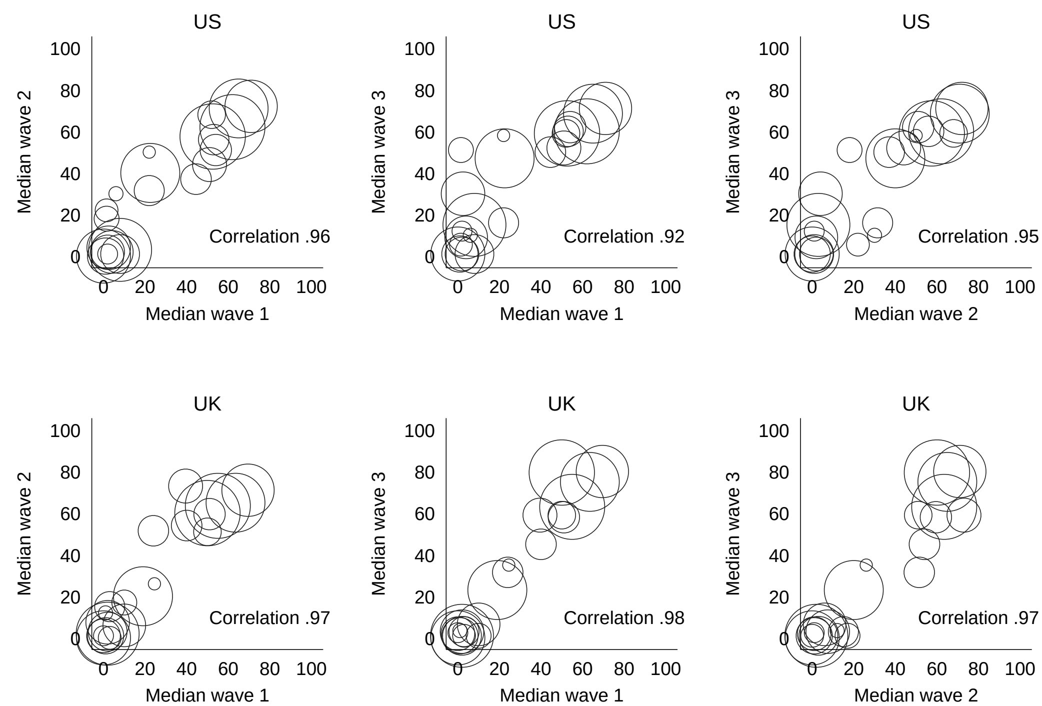
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis and y-axis display the mean in the first, second, and third survey wave end of March, beginning of April, and mid May.

Figure B.6: Mean of tasks that can be done from home by industry, within countries, and across survey waves



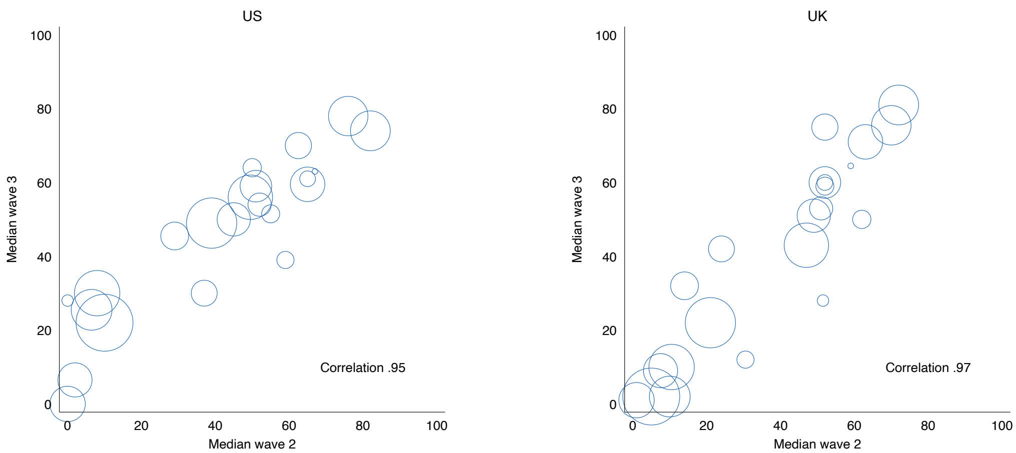
Notes: Each bubble is proportional to the number of observations and represents one industry in the US (left) and the (UK). The x-axis displays the mean in the second survey wave beginning of April and the y-axis in the third survey wave mid May.

Figure B.7: Median of tasks that can be done from home by occupation, within countries, and across survey waves



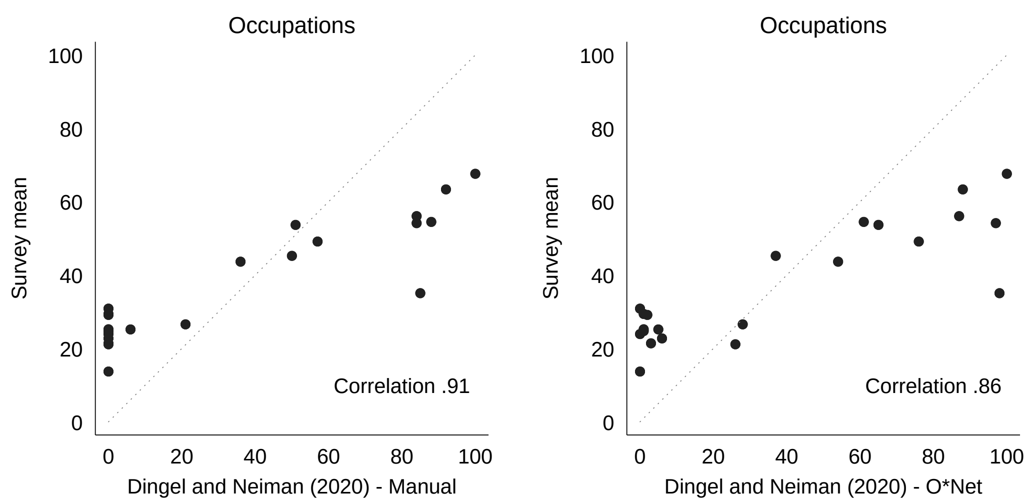
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis and y-axis display the mean in the first, second, and third survey wave end of March, beginning of April, and mid May.

Figure B.8: Median of tasks that can be done from home by occupation, within countries, and across survey waves



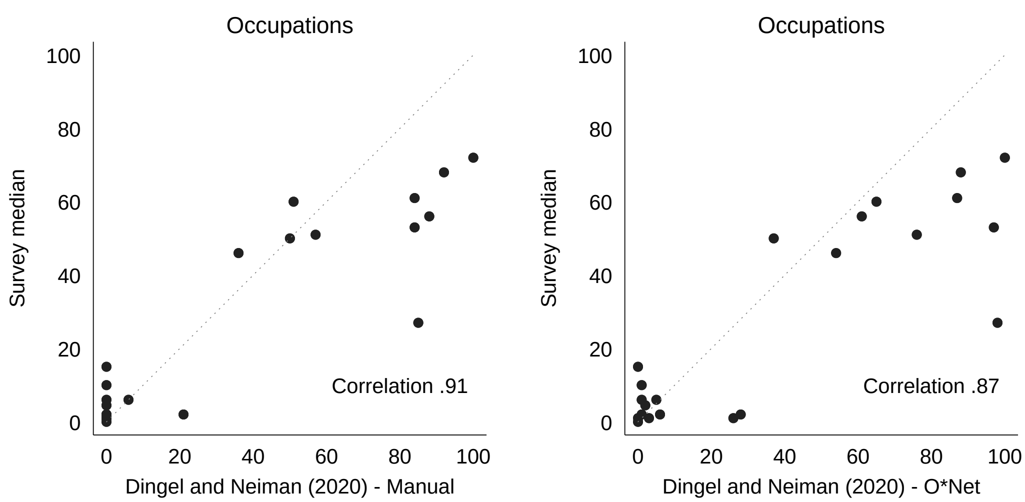
Notes: Each bubble is proportional to the number of observations and represents one industry in the US (left) and the (UK). The x-axis displays the mean in the second survey wave beginning of April and the y-axis in the third survey wave mid May.

Figure B.9: Comparison between our survey mean and the measures by Dingel and Neiman (2020)



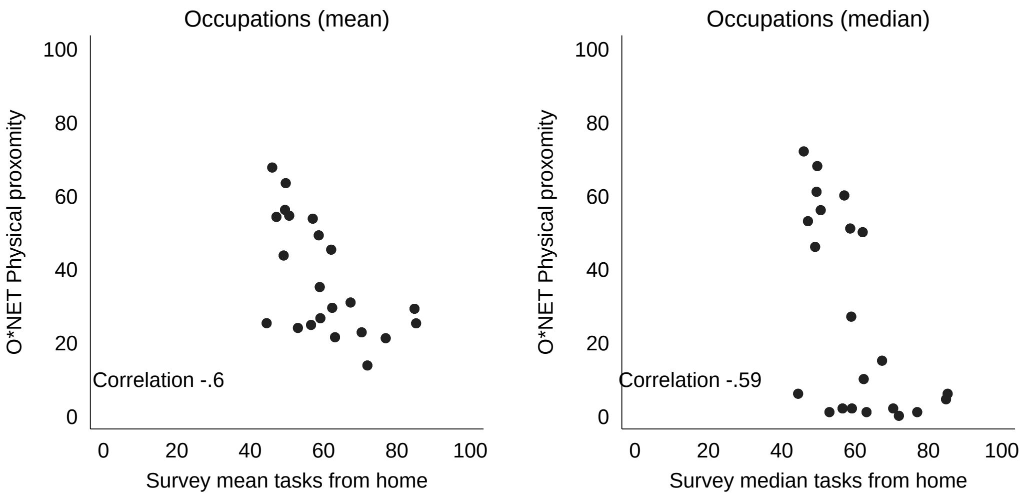
Notes: Each dot represents one occupation. The dotted line represents the 45 degree line.

Figure B.10: Comparison between our survey median and the measures by Dingel and Neiman (2020)



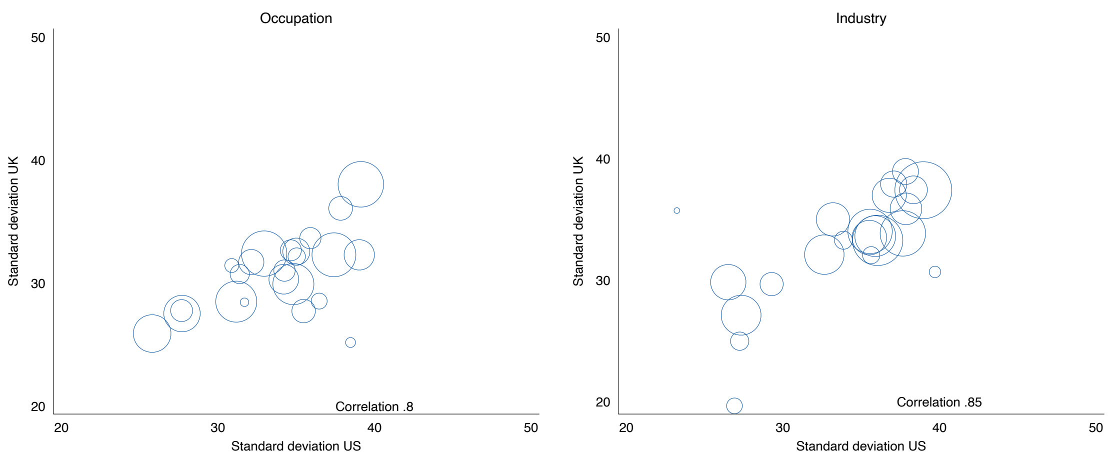
Notes: Each dot represents one occupation. The dotted line represents the 45 degree line.

Figure B.11: Share of tasks that can be done from home compared to physical proximity indicator by occupation



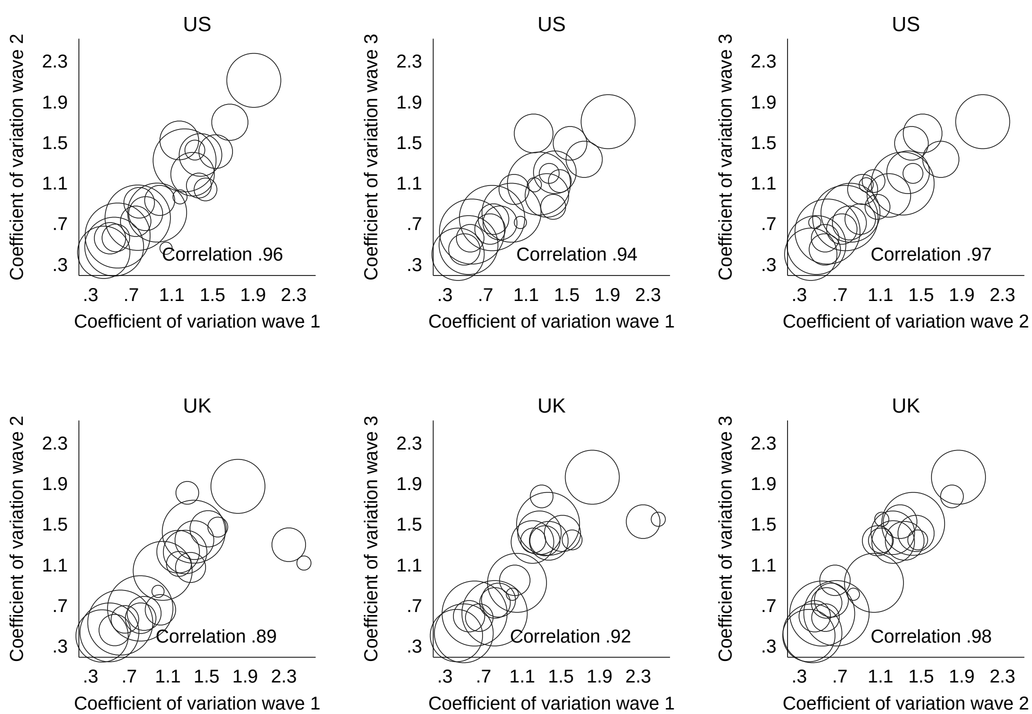
Notes: Each circle represents one occupation. The mean and median are computed using the joint US and UK sample. The physical proximity indicator is computed using the O*NET.

Figure B.12: Standard deviation of tasks that can be done from home in the US and the UK by occupation (left) and industry (right)



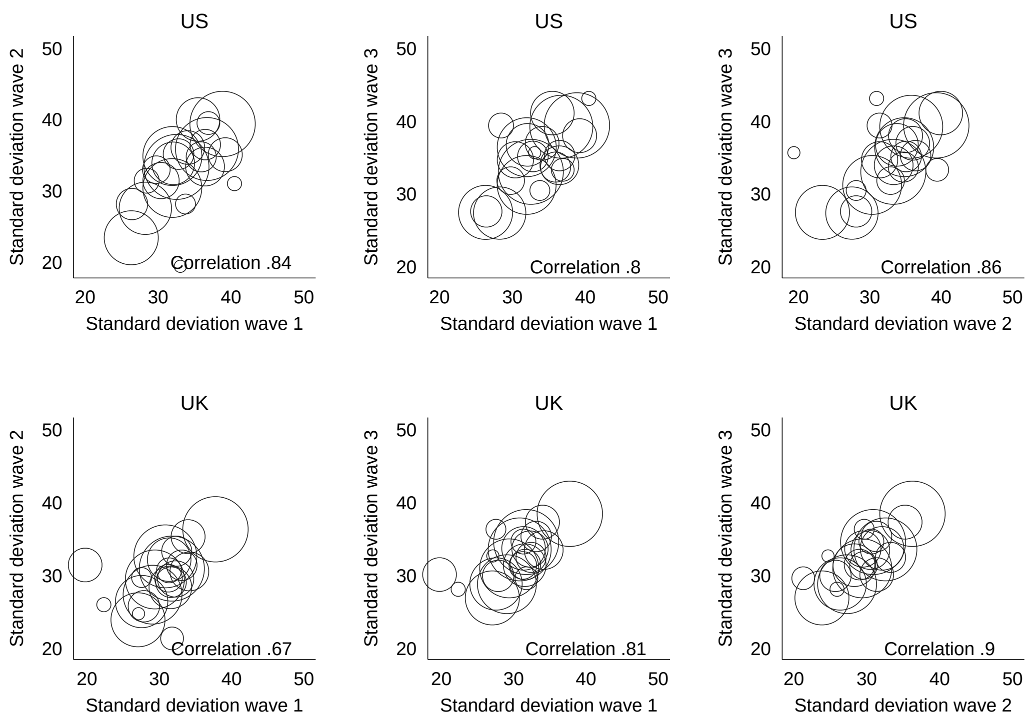
Notes: Each bubble is proportional to the number of observations and represents one occupation (left) or industry (right). The sample includes both the US and UK data.

Figure B.13: Coefficient of variation of tasks that can be done from home by occupation, within countries, and across survey waves



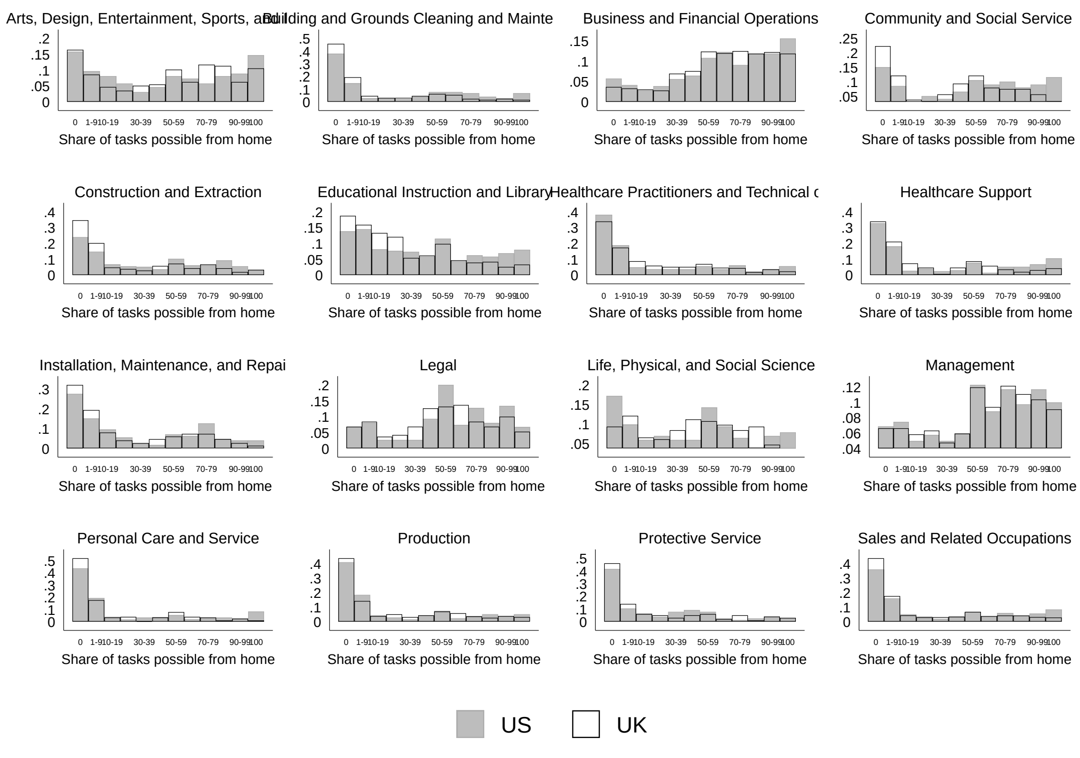
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.14: Standard deviation of tasks that can be done from home by occupation, within countries, and across survey waves



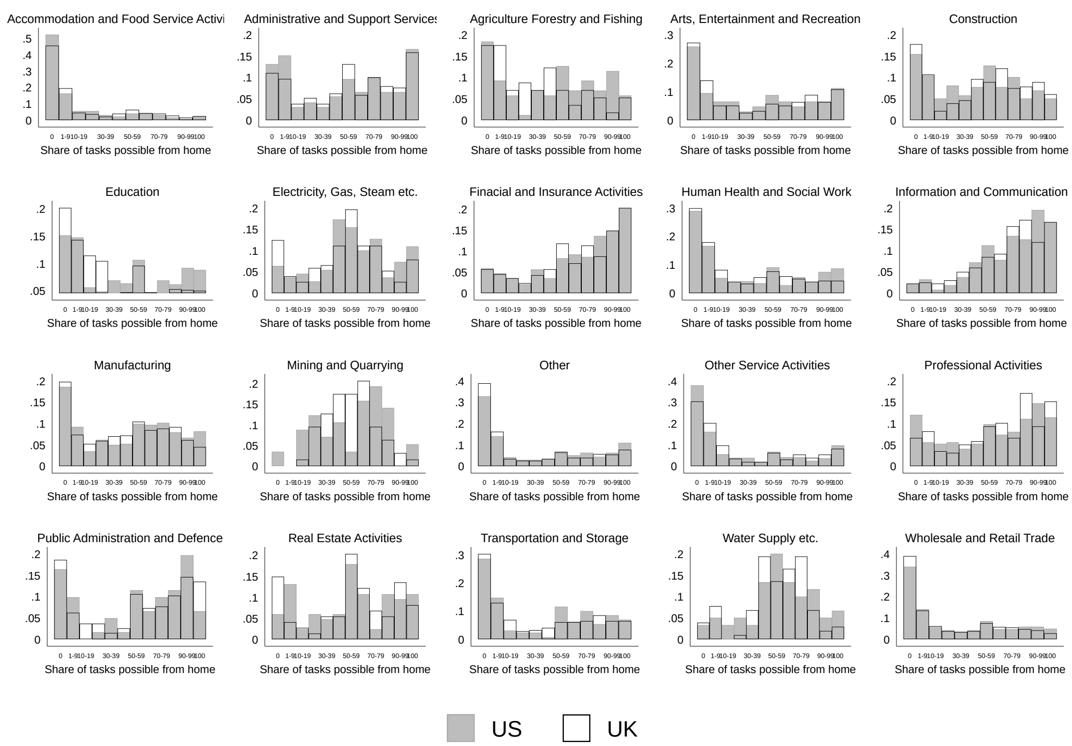
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.15: Distribution of the share tasks that can be done from home within occupations



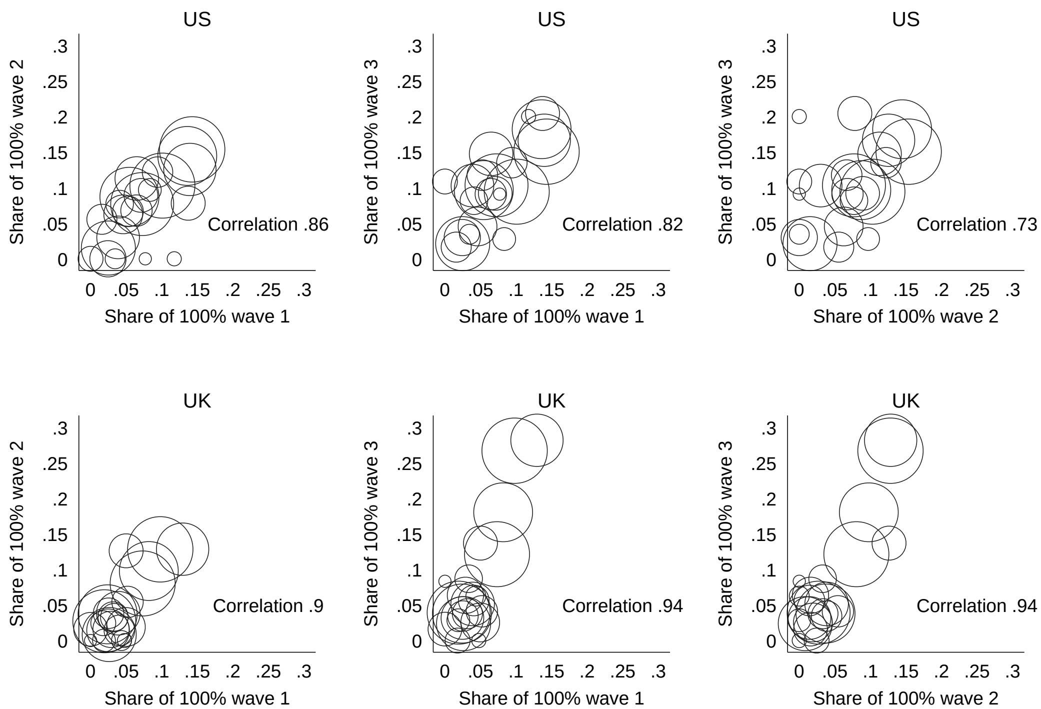
Notes: The light blue bars display the histogram for the US and the black transparent bars the histogram for the UK. We restrict the sample to occupations for which we have at least 50 observations in each country.

Figure B.16: Distribution of the share tasks that can be done from home within industries



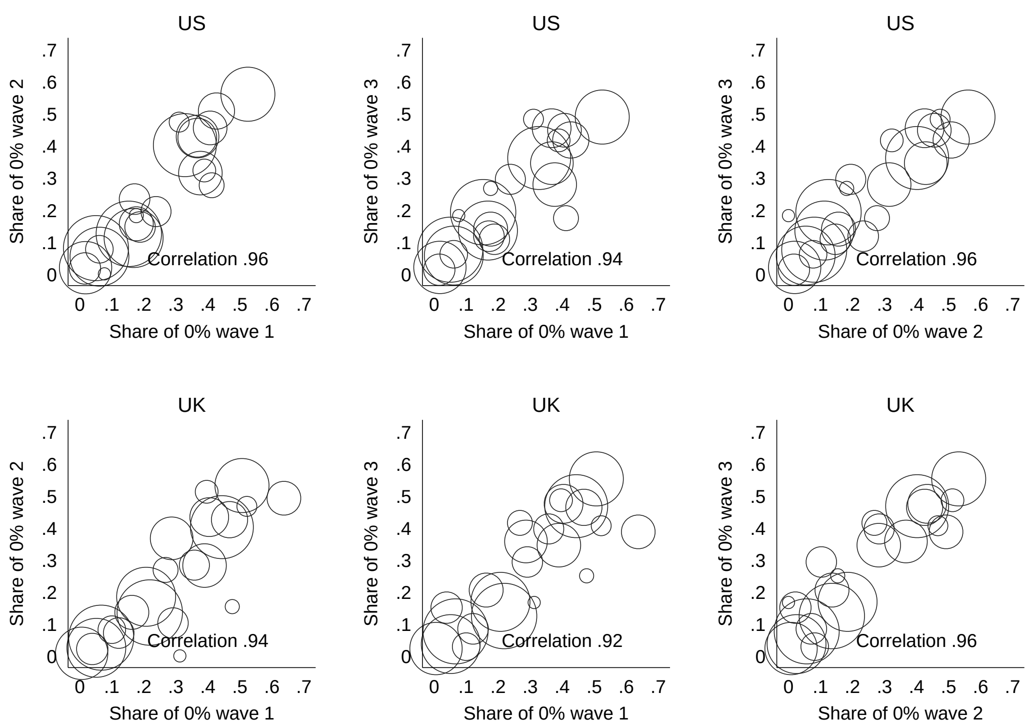
Notes: The light blue bars display the histogram for the US and the black transparent bars the histogram for the UK. We restrict the sample to occupations for which we have at least 50 observations in each country.

Figure B.17: Share of workers that can do all tasks from home by occupation, within countries, and across survey waves



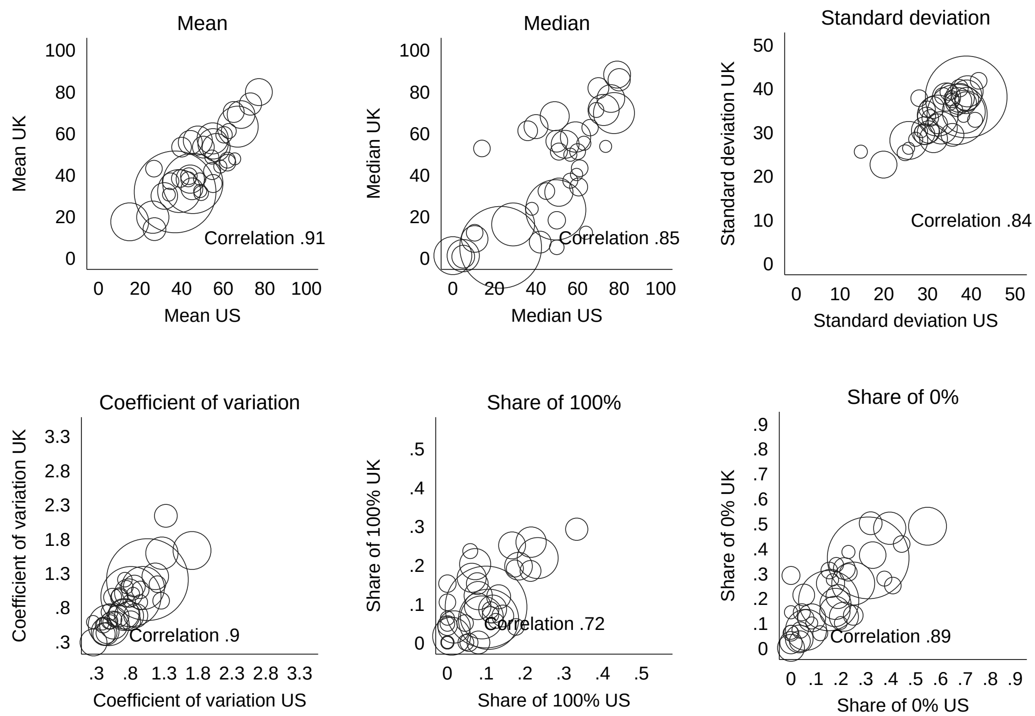
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.18: Share of workers that can do no tasks from home by occupation, within countries, and across survey waves



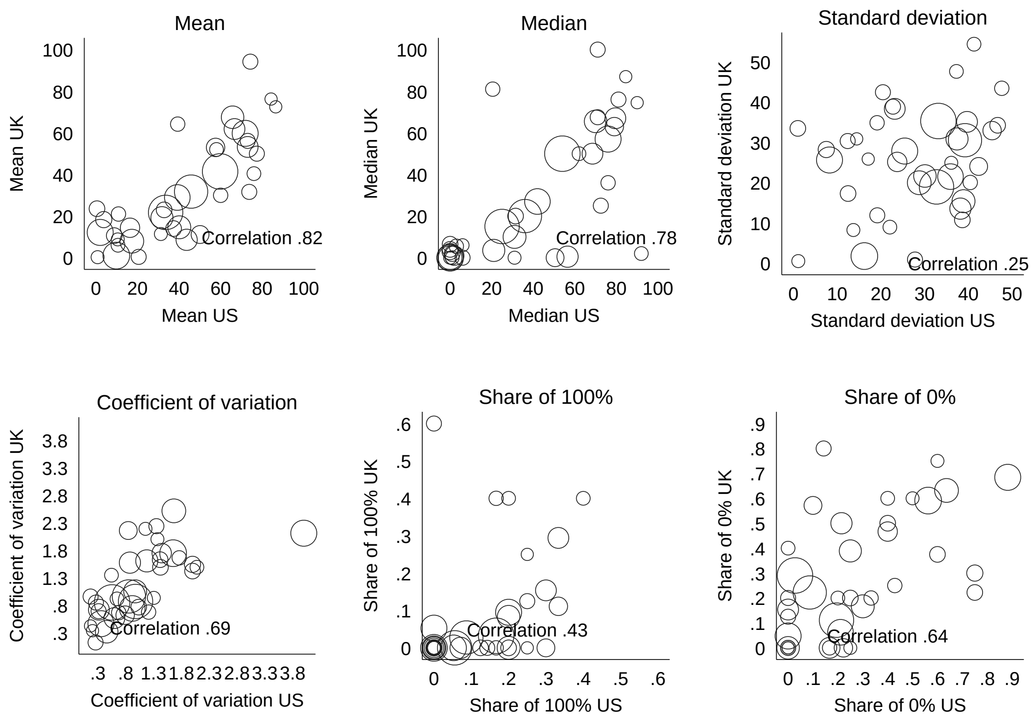
Notes: Each bubble is proportional to the number of observations and represents one occupation in the US (left) and the (UK). The x-axis displays the mean in the first survey wave end of March and the y-axis in the second survey wave beginning of April.

Figure B.19: Measures of tasks from home in the US and the UK by industry at disaggregated level



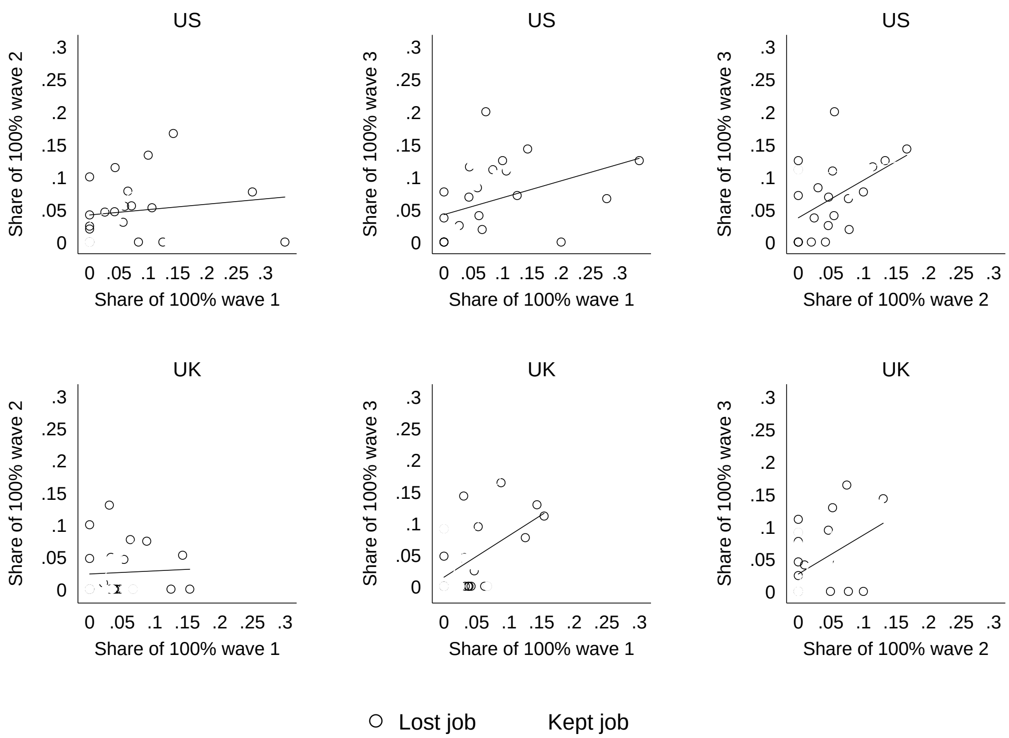
Notes: Each bubble is proportional to the number of observations and represents one industry at the disaggregated level.

Figure B.20: Measures of tasks from home in the US and the UK by occupation-industry pairs at disaggregated level



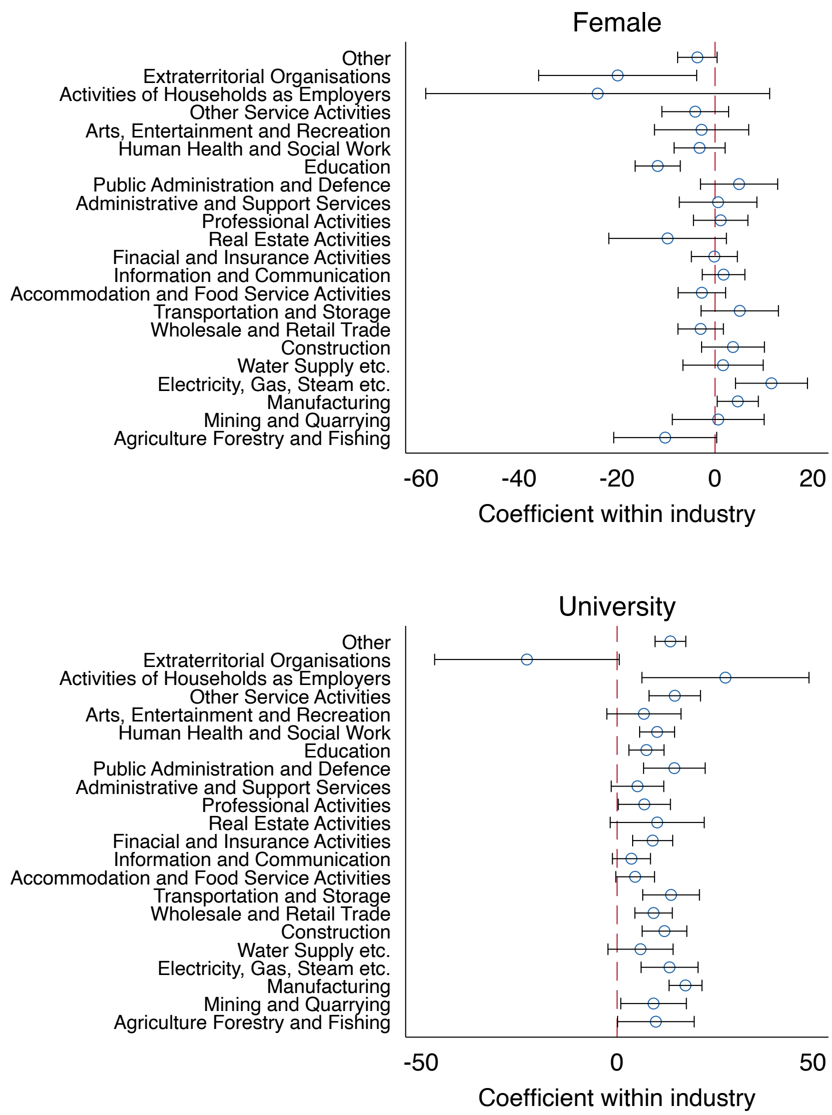
Notes: Each bubble is proportional to the number of observations and represents one occupation-industry pair at the disaggregated level. A pair has to have at least 4 observations in each country.

Figure B.21: Share of workers that can do all tasks from home by occupation, within countries, and across survey waves depending on employment status



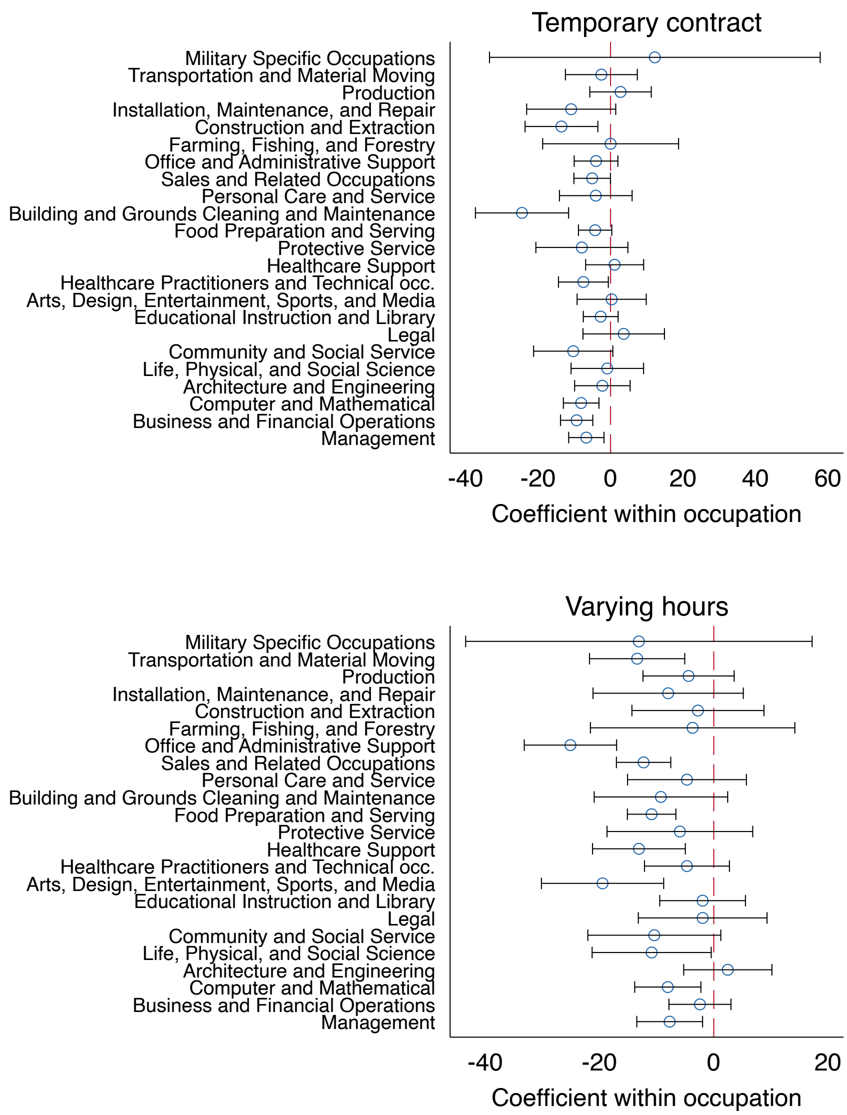
Notes: Each bubble is proportional to the number of observations and represents one occupation at the aggregated level.

Figure B.22: Coefficients on gender and education from separate regressions of each industry explaining share of tasks from home



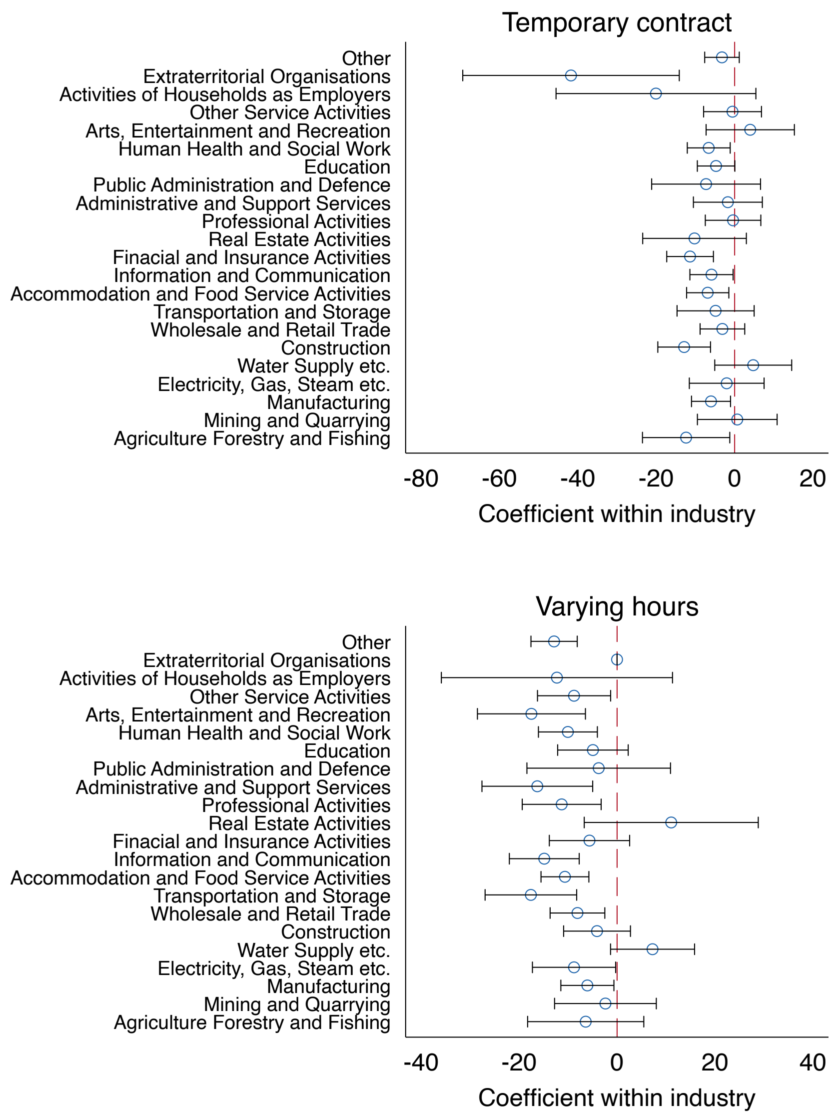
Notes: Additional controls are country and wave dummies, and occupation fixed effects. The black bars represent 95% confidence intervals.

Figure B.23: Coefficients on two different contract types from separate regressions of each occupation explaining share of tasks from home



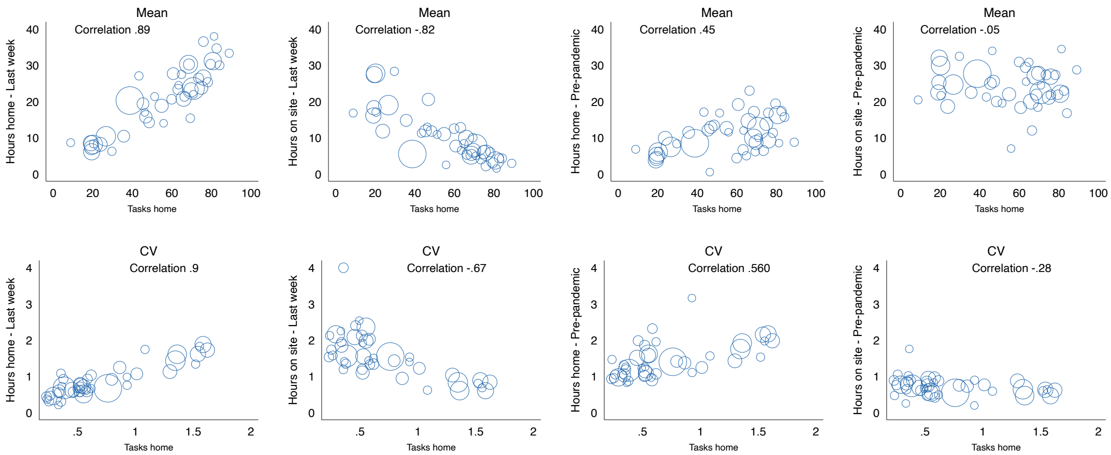
Notes: Additional controls are country and wave dummies, industry fixed effects, gender, and education. The black bars represent 95% confidence intervals.

Figure B.24: Coefficients on two different contract types from separate regressions of each industry explaining share of tasks from home



Notes: Additional controls are country and wave dummies, occupation fixed effects, gender, and education. The black bars represent 95% confidence intervals.

Figure B.25: Relationship between share of tasks from home and hours worked from and on site before and during the pandemic across occupation-industry pairs in the UK



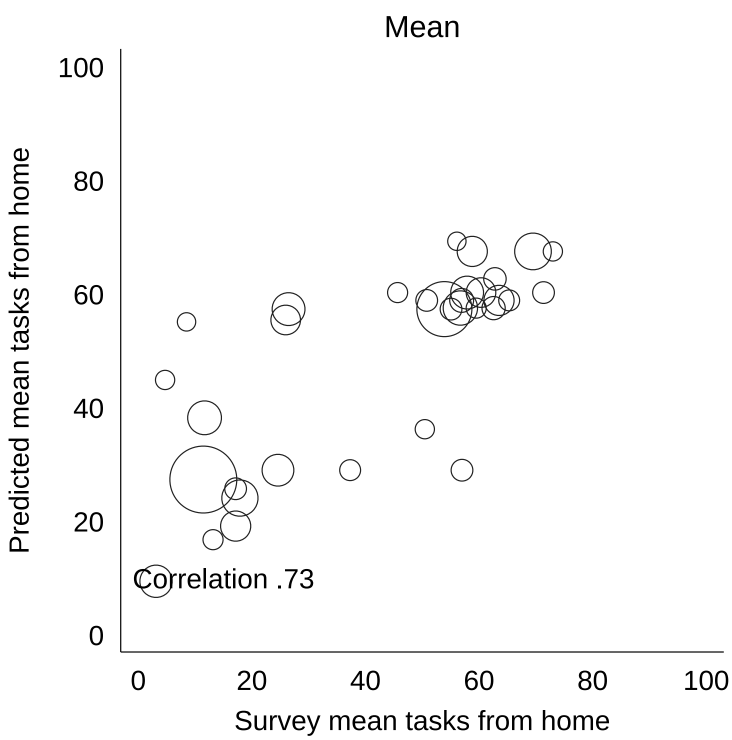
Notes: Each bubble represents an occupation-industry pair with at least 10 observations and the size is proportional to the number of observations. The x-axis shows the mean (top) and coefficient of variation (bottom) of the share of tasks that can be done from home, and the y-axis the same metrics of hours worked at home last week (first column), at the office last week (second column), at home in a typical week before the pandemic (third column), and at the office in a typical week before the pandemic (fourth column) for the UK. The sample is restricted to wave 3 as for the other waves we do not have all the corresponding information on hours worked.

Table B.6: List of tasks from O*NET

Task
Sitting continually
Standing continually
Using your hands to handle, control, or feel objects, tools, or controls
Outdoors everyday
Email less than monthly
Telephone less than monthly
Climbing ladders, scaffolds, poles majority of time
Walking or running majority of time
Kneeling, crouching, stooping, or crawling majority of time
Keeping or regaining balance majority of time
Bending or twisting body majority of time
Making repetitive motions majority of time
Wear specialized protective or safety equipment majority of time
Contact with others majority of time
Dealing with external customers very important
Coordinate or lead others in accomplishing work activities very important
Responsible for other's health very important
Dealing with violent or physically aggressive people at least weekly
In an environment that is not environmentally controlled every day
Physically close to other people at least moderate
Exposed to very hot or very cold temperatures every day
Exposed to contaminants at least weekly
Cramped work space that requires getting into awkward positions everyday
Exposed to whole body vibration at least weekly
Exposed to radiation at least weekly
Exposed to diseases or infection at least weekly
Exposed to high places at least weekly
Exposed to hazardous conditions at least weekly
Exposed to hazardous equipment at least weekly
Exposed to minor burns, cuts, bites, or stings at least weekly
Continuous, repetitious physical activities or mental activities
Handling and moving objects
Controlling machines and processes
Operating vehicles, mechanized devices, or equipment
Performing for or dealing directly with the public
Repairing and maintaining mechanical equipment
Repairing and maintaining electronic equipment
Inspecting equipment, structures, or materials

Notes: The list of tasks is adopted from Dingel and Neiman (2020) who compiled it using the Work Context Questionnaire and Generalized Work Activities Questionnaire from the O*NET.

Figure B.26: Survey mean versus predicted mean based on O*NET tasks (out-of-sample)



Notes: Each bubble is proportional to the number of observations and represents one occupation.