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Worker Productivity during Lockdown and Working from Home: Evidence from Self-Reports

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Non-Technical Summary

The Covid-19 pandemic has caused widespread disruption to working practices. The most noticeable change has been the vast increase in working from home. While some changes to work are probably temporary, many could well be persistent. Even after the pandemic ends, home working in particular is expected to be much more prevalent than previously. A key policy issue, therefore, both in the near and the far term, is how these changes in working practices impact productivity.

In this paper we use the Covid-19 module from the UK Household Longitudinal Survey, which provides representative data on home workers' self-reported productivity towards the end of the lockdown period in the UK. In this survey, anyone working from home at least some of the time was asked about changes in their productivity since just before the pandemic period. These data allow us to examine how productivity varies across job and worker types and is influenced, for example, by the home environment.

Overall we find that workers at home report being approximately as productive as before the pandemic, on average. However, productivity varies substantially across socioeconomic groups, industries and occupations. Workers in sectors that are less suitable for home working, according to external metrics, report productivity declines. Groups reporting worse productivity are low earners, the self-employed and women, particularly those with children.

Finally, we document that productivity declines are associated with substantially worse mental well-being. Using information on stated reasons for difficulty working, we provide evidence for a causal pathway from productivity to well-being.

This paper contributes to the growing evidence on the efficacy of home work. It indicates that home working can be effective, as long as workers have the right support. The evidence in this paper can also contribute to the design of sector-specific policies that might be used in the short term, such as rationed access to work places.

Worker Productivity during Lockdown and Working from Home: Evidence from Self-Reports*

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Abstract

We examine self-reported productivity of home workers during lockdown using survey data from the UK. On average, workers report being as productive as at the beginning of the year, before the pandemic. However, this average masks substantial differences across sectors, by working-from-home intensities, and by worker characteristics. Workers in industries and occupations characterized as being suitable for home work according to objective measures report higher productivity on average. Workers who have increased their intensity of working from home substantially report productivity increases, while those who previously always worked from home report productivity declines. Notable groups suffering the worst average declines in productivity include women and those in low-paying jobs. Declines in productivity are strongly associated with declines in mental well-being. Using stated reasons for productivity declines, we provide evidence of a causal effect from productivity to well-being.

Keywords: Worker Productivity, Working From Home, COVID-19, Sectors, Inequality, Gender, Mental Well-Being

JEL classifications: D24, I14, I30, J22, J24

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1 Introduction

The Covid-19 pandemic has caused widespread disruption to working practices. The most noticeable change has been the vast increase in working from home. The share of the labour force working from home increased from around 5% to over 40% in the U.S. during the lockdown (Bloom, 2020). While some changes to working practices are probably temporary, many could very likely be persistent. Even after the pandemic ends, home working in particular is expected to be much more prevalent than previously.[1]

A key policy issue, therefore, both in the near and the far term, is how these changes in labour practices impact worker productivity. Despite previous research on the effects of working from home (Bloom et al., 2015), given the size of the changes seen during the pandemic the evidence base is inevitably thin. Most research since the onset of the pandemic has focused on characteristics of jobs through objective measures such as those provided by O*NET.[2] There is little direct evidence on productivity in the new working environment and how it varies not only across job types, but also worker characteristics.

In this paper we use the Covid-19 module from the UK Household Longitudinal Survey (UKHLS), which provides representative data on home workers' self-reported productivity towards the end of the lockdown period in the UK, in June 2020.[3] In this survey, anyone working from home (WFH) at least some of the time was asked about changes in their productivity since before the pandemic period, at the beginning of the year. These data allow us to examine how productivity changes vary across job and worker types and are influenced by, for example, the presence of children. The advantage of using individual-level reported productivity over data obtained from, say, characteristics of jobs, is that we obtain a more direct measure of the key object of interest. The advantage of using individual-level over aggregate data reported in national statistics is that we can examine the rich causes of productivity changes at the micro level, as well as examining effects on other outcomes of interest. Overall we find that workers report being approximately as productive as before the pandemic, on average. However, productivity varies substantially across socioeconomic groups, industries and occupations.

In more detail, we find that workers in industries and occupations that are less suitable for working from home report lower productivities than before the pandemic. Consistently with this, and with the literature, females and low earners also report lower productivity at home on average. The opposite

[1] Again, see Bloom (2020). For a wider discussion see also the dedicated discussion of the literature below.

[2] See, for example, Dingel and Neiman (2020) and Mongey, Pilossoph, and Weinberg (2020).

[3] In the UK, the official 'lockdown' began on March 23 when a widespread stay-at-home order was introduced. The lockdown eased as the incidence of Covid declined, over May and June. On June 1, restrictions were lifted which allowed people to meet with up to six others from separate households in outdoor places. An accepted date for the end of lockdown is July 4, when many businesses, especially in retail and food were allowed to re-open.

types of workers, e.g., those in the "right" occupations and with high incomes, report higher productivities than previously. More specifically, we incorporate external measures of feasibility of home work from Adams-Prassl et al. (2020b), and need for physical proximity to others from Mongey et al. (2020). The sector-level correlations between our reported productivity changes and these job-based measures are always of the expected sign. In fact they are higher when comparing occupations than industries: For example, the correlation with feasibility of home work across occupations is 0.56, and across industries it is 0.23. This difference suggests that while occupational job characteristics provide quite accurate information about the impact of working from home on productivity, the industry characteristics are more noisy; it is at the job-task level that most impacts of the pandemic have been felt. Our direct measure of productivity changes allow us to understand how well those measures — feasibility of home working and physical proximity — capture the realized productivity changes in different contexts.

In addition, workers' productivity changes correlate with other aggregate outcomes: occupational job losses recorded in early lockdown, and aggregate labor productivity changes at the industry level.

We then examine individual characteristics in further detail. Females, low earners and the self-employed report worse productivity outcomes than their counterparts. Their low productivity is not only related to their job characteristics, but is also directly affected by their socioeconomic conditions. For example, while females are more likely to work in occupations less suitable for home work (Adams-Prassl et al., 2020b), productivity of females is also more negatively affected by the presence of children. This finding shows the strength of the measure used here over those based purely on characteristics of the job.

Third, we find that home workers' productivity during the lockdown is related to the *intensity* of working from home and its change since the prior period. Those who previously worked from home at least sometimes and then increased the intensity of home-working experienced a productivity increase. Those who did not increase their home-working frequency or never worked from home before the pandemic report a large productivity decline. This pattern is partly explained by the occupational characteristics of the jobs in each category. However it also suggests two counterveiling forces: a positive productivity effect of increased home working alongside a direct negative effect of the pandemic itself. The productivity decline reported by those who have always worked from home is evidence of this latter phenomenon.

A noteworthy feature of the pandemic period has been a decline in mental well-being, observed particularly in the UK (Banks and Xu, 2020; Etheridge and Spantig, 2020). We therefore assess the association of workers' mental well-being with productivity changes. We find strong correlations between the two: those who state they get much less done at home report declines in well-being comparable to the effect of an unemployment shock. We also find evidence of a causal effect from productivity to well-being: using ineffective equipment as an instrument for productivity declines, we find a 1 standard deviation lower productivity causes a 0.24 standard deviation lower mental well-being, as measured by general health questionnaire scores. This result is consistent with Etheridge and Spantig (2020) who find that females and low income groups have experienced large deteriorations in mental well-being compared to their counterparts. Our paper therefore offers a novel explanation for the recent declines in mental well-being among certain groups. It also suggests that policies that target workers in the vulnerable socioeconomic groups or certain jobs with large productivity drops may not only boost productivity but also mental well-being on aggregate.

Related Literature

Our paper is related to four strands of literature: (1) working from home as an alternative practice; (2) sector-specific productivity changes and optimal policies during the current pandemic; (3) inequality across gender and socioeconomic groups, especially during difficult times such the current pandemic and other recessions; and (4) mental well-being during the current pandemic.

First, working from home and its impact on productivity have been getting increasing attention in recent years, and especially since the Covid-19 outbreak. Bloom et al. (2015) study workers' productivity and attitude towards working from home using a random experiment on call-center workers in a Chinese travel agency. They find that home-working led to a 13% performance increase and that, after the experiment, over half of the workers chose to switch to home-working. While Bloom et al. (2015) focus on one particular narrow occupation, the Covid-19 outbreak and the lockdowns in many countries has dramatically increased the prevalence of working from home in almost all occupations.

Felstead and Reuschke (2020) document that in the UK, while 5% of workers worked from the home before the pandemic, the share increased to 45% in April 2020, remaining high thereafter. They also find little effect of workers' productivity at home on average during the pandemic. The same patterns — increasing home-working and not much change in workers' average productivity at home — are also found in Europe and North America (see Rubin et al. (2020) for Netherlands, Eurofound (2020) for the Europe as a whole, and Brynjolfsson et al. (2020) for the US).

The second strand of the literature is the sector-specific productivity of working from home, and optimal sectoral policies. The existing papers pioneered by Dingel and Neiman (2020) use characteristics of jobs to provide predictions on home-working productivities across occupations and industries. Dingel and Neiman do this by constructing a measure of feasibility to work from home across industries and occupations using data from O*NET. Adams-Prassl et al. (2020b) follow this by eliciting a conceptually similar measure derived using individual self-reports. Again similarly, Mongey et al. (2020) also use O*NET to construct a measure of need for physical proximity to co-workers to carry out one's work effectively. The direct evidence of productivity changes provided in the current paper can be used to understand how well the measures constructed from job characteristics capture the real productivity changes across sectors, and can potentially be used in macro models of the pandemic with sector-specific shocks and optimal policies.

In this way, estimates of productivity changes by sector are important for macroeconomic models that try to capture the sectoral and aggregate labor and output changes during the Covid-19 pandemic, e.g., Baqaee and Farhi (2020). Bonadio et al. (2020) study the impact of the Covid-19 pandemic on GDP growth and the role of the global supply chains. They discipline the labor supply shock across sectors using the fraction of work that can be done from home across generations measured by Dingel and Neiman. While the correlation of this measure with our measure of realized labor productivity is reasonably high, there is space for improvement by obtaining better measures of realized labor productivity changes.

Third, the differential impacts of working from home across sectors and socioeconomic groups implies that inequality is strongly affected by enforced home working in the pandemic. Income inequality has also been increasing since the 1980s both in the U.S. (Heathcote et al., 2010), and in the UK (Blundell and Etheridge, 2010). Inequality has often been found to increase during recessions (see Perri and Steinberg, 2012 for a discussion of the great recession after 2008). In the current pandemic, it is also the economically disadvantaged groups, such as low-income groups and females, that are suffering larger declines in economic outcomes.

In this vein Alon et al. (2020) study the potentially different impacts of Covid-19 pandemic on the employment of men and women given the gender differences in occupation and childcare. They predicted that women's employment would suffer disproportionately. Adams-Prassl et al. (2020a) document that female workers report a lower ability to work from home, and Adams-Prassl et al. (2020a) document that women are more likely to lose their jobs in the UK and in the US (though not in Germany, around early April 2020). They also find worse outcomes for lower earners. Our paper contributes to this strand of the literature by studying inequality of worker productivity across gender and socioeconomic groups. Our findings confirm the prediction of this literature: Females and low income groups have suffered larger productivity declines while working from home during the lockdown, indicating an increase in inequality.

The fourth strand of related literature is that on mental well-being during Covid-19. Early in the pandemic, international organizations and researchers warned about the resulting psychological effects (Holmes et al., 2020; World Health Organization, 2020). The pandemic imposes large risks and potential damages to mental well-being through a variety of channels. Anxiety is caused by the disease's spread: Fetzer et al. (2020) conduct a survey covering 58 countries and show, by exploiting time variation in country-level lockdown announcements, that people's perception of the spread of the disease causes lower mental well-being. Lower mental well-being is also caused by adverse economic shocks (see Chang et al., 2013; Dagher et al., 2015 for the 2008 recession, and Janke et al. (2020) for UK during 2002–2016). Finally, loneliness and social isolation can be induced by quarantine (Brooks et al., 2020) and lockdown (Brodeur et al., 2020; Knipe et al., 2020; Tubadji et al., 2020).

Banks and Xu (2020) and Etheridge and Spantig (2020) document decline in mental well-being during the Covid-19 pandemic in the UK using the same dataset as the current paper. We add to these papers by documenting an association between mental well-being and worker productivity. More widely the literature on the relation between economic conditions and mental well-being is vast; see for example, Janke et al. (2020) who study how macroeconomic conditions affect health condition, especially mental health conditions, using British data over the period 2002–2016.

2 Data

We use the Covid-19 module from the UK Household Longitudinal Survey (UKHLS), administered monthly from April 2020. The analysis makes specific use of the Covid module's third wave, conducted in June, which includes questions on self-reported productivity. These interviews were conducted in the seven days from Thursday June 25, with around 75% of interviews completed within the first three days. We merge these data with the April and May waves of the Covid module as well as with wave 9 of the 'parent' UKHLS (also known as 'Understanding Society'), a large-scale national survey administered yearly from 2009. Wave 9 of the parent survey was itself administered between 2017 and 2019.

The UKHLS Covid module is conducted as a web survey. The underlying sampling frame consists of all those who participated in the UKHLS main survey's last two waves. To conduct the fieldwork, the sample was initially contacted using a combination of email, telephone, postal and SMS requests. Of those eligible, and who responded to the main survey wave 9, the response rate was a little under 50%. To adjust our analysis for non-response, we use the survey weights provided. In addition, to allow for the fact that many respondents are related either through primary residence or through the extended family, we cluster all regressions at the primary sampling unit level. For a further discussion of the Covid module and underlying UKHLS design see (Institute for Social and Economic Research, 2020).

The main variable of interest is self-reported productivity while working from home and compared to a stated baseline. To elicit this the survey includes a bespoke question. Precisely, respondents are asked as follows:

"Please think about how much work you get done per hour these days. How does that compare to how much you would have got done per hour back in January/February 2020?"

If the respondent did not work from home before the pandemic, then the question ends with:

"...when, according to what you have previously told us, you were not working from home?"

Interviewees are then asked to respond on a Likert-type scale of 1 to 5 ranging from "I get much more done" to "I get much less done".

We transform the variable as follows: we invert so that responses are increasing in productivity; we re-centre so that the response "I get about the same done" is valued 0, and we divide the distribution by its standard deviation. In this way the mean response across the population can be interpreted in terms of standard deviations away from a neutral effect. When discussing results we sometimes term the resulting variable as a 'semi-standardized' productivity change.

It is worth discussing the question and resulting data in more detail. Notice first that the question explicitly attempts to ask about productivity per hour, and so corresponds to a concept of labour productivity. We examine the relationship between the variable here and aggregate productivity data from the National Accounts in more detail in section 3. Notice further that the question actually makes no reference to working from home itself, except in the qualifier referencing prior working location. In principle, therefore, this question could be asked of workers in any location. It was in fact only asked of those working from home to save valuable survey time. In future waves it is hoped this question is asked of all respondents. Most importantly, perhaps, it should be remembered that the scale is ordinal. As with all similar Likert-type scales, however, it is anchored with a natural reference point at 3, and responses above or below can be considered as improvements or declines compared to the pre-Covid period. In this paper we typically use simple means, effectively re-interpreting the scale as cardinal. For much of our analyses, however, we provide parallel results using ordered probit models in Appendix B, where we show that marginal effects computed this way are nearly identical.

We make use of much auxiliary information contained in the surveys. Of particular interest, all respondents were asked to report their baseline earnings and place of work just before the pandemic, in 'January/February'. The survey elicits industry of work both in the baseline period and currently. Unfortunately, the Covid survey does not elicit information on occupation. For this we use occupational information from wave 9, which relates to the job performed in either 2017 or 2018, whenever that wave's interview was performed. For occupation we make additional use of metrics obtained elsewhere in the literature which have typically been collected using the classification used in the US-based O*NET. We therefore typically convert our occupational information to this alternative using our own cross-walk. Our procedure is described in Appendix A. Finally, we also use productivity data from the

UK Office for National Statistics; see Appendix B for a further discussion.

For mental well-being we use a Likert well-being index derived from the 12 questions of the General Health Questionnaire (GHQ-12). The GHQ battery asks questions regarding, for example, the ability to concentrate, loss of sleep and enjoyment of day-to-day activities. The GHQ questionnaire has been administered in all waves of UKHLS in exactly the same form, allowing us to examine changes in well-being from a base period. We use a standardized and inverted index so that higher scores indicate higher well-being. Here we exactly follow the procedures in Etheridge and Spantig (2020); see that paper for further details.

Our total number of adjusted interviews in the June module is $11,496$. Of these interviews $6,504$ individuals were in work and reported information about working location. Of these the number who answered the question about productivity changes was $3,411$.

3 Results

3.1 Patterns of Working from Home

The largest change in working conditions during the pandemic has been the increased prevalence of working from home. We accordingly show patterns of home work over time in Table 1. To show some of the wide variation during the pandemic, we show a breakdown by industry. This variation has also been documented by Felstead and Reuschke (2020), among others. The first column reports baseline home work patterns in January/February, before the pandemic, and documents the proportion of workers who worked at home at least some of the time. The second column shows the proportion of workers in this category in April, at the height of the lockdown period. It shows a very large increase in the proportion working from home across almost all industries. There are, however, some exceptions: in 'Accommodation and Food Service', for example, the effect of the lockdown was seen not so much in an increase in home work, but rather widespread job losses. The third column then records the change in proportion of home workers from April to June. It shows there was very little change in working patterns by this metric even as the lockdown eased.

The final two columns of Table 1 show the proportion of respondents *always* working from home. Here we don't show results for the baseline because, in most industries, the numbers were small. The fourth column shows that in some sectors, such as 'Information and Communication', a large proportion of workers relocated to home permanently in April. By June, the proportion of workers always at home had declined slightly (Felstead and Reuschke, 2020). This is only slightly evident in the industry breakdown shown in column 5. However, one example stands out: a noticeably higher fraction of

Table 1: Proportions of Working from Home: By Industry

	At least some of the time			Always	
	Jan/Feb	April	April to June	April	April to June
Agriculture, Forestry and Fishing	0.23	0.29	-0.03	0.15	-0.05
Mining and Quarrying	0.21	0.54	-0.06	0.47	0.00
Manufacturing	0.16	0.36	-0.05	0.23	-0.05***
Electricity and Gas	0.36	0.54	0.05*	0.48	-0.03
Water Supply and Sewerage	0.30	0.70	-0.02	0.45	0.01
Construction	0.24	0.37	-0.03	0.24	-0.03
Wholesale and Retail Trade	0.13	0.19	-0.02	0.10	-0.01
Repair of Motor Vehicles and Motorcycles	0.25	0.21	0.01	0.16	-0.08
Transportation and Storage	0.11	0.17	0.01	0.11	-0.00
Accommodation and Food Service	0.11	0.10	0.02	0.06	-0.00
Information and Communication	0.62	0.86	-0.01	0.75	-0.01
Financial and Insurance	0.48	0.86	-0.00	0.73	0.04
Real Estate Activities	0.45	0.71	0.04	0.40	-0.02
Professional and Technical	0.56	0.82	-0.02	0.67	-0.04
Administrative and Support Service	0.31	0.62	-0.04	0.47	0.00
Public Administration and Defence	0.38	0.67	0.01	0.49	0.02
Education	0.31	0.72	-0.01	0.44	-0.10***
Human Health and Social Work	0.25	0.39	-0.01	0.18	-0.02
Arts, Entertainment and Recreation	0.55	0.65	-0.04	0.51	-0.05
Other Service Activities	0.32	0.46	-0.03*	0.32	-0.02
Activities of HHs as Employers	0.18	0.22	0.04	0.12	-0.02
Observations	5601	5486	5475	5486	5475
Adjusted R^2	0.369	0.605	0.002	0.461	0.014

Source: UKHLS Covid module

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$, used in third and fifth columns only.

Note: This table reports proportions of respondents who WFH for at least some time and always, respectively for each industry in the United Kingdom in 2020. The first two columns illustrate the proportions who spent at least some of the time WFH in January/February, and in April, respectively. The third column reports changes in proportions of WFH at least for some time from April to June. The last two columns demonstrate the proportion of always WFH in April and change in the proportion of always WFH from April to June, respectively. Standard errors omitted.

teachers worked away from home at least some of the time as schools partially reopened before the summer vacation. Table B.1 shows proportions of working from home by occupation, using reported occupation from wave 9 of the main survey. Similar patterns are seen as with industry, with the major change from spring to summer in occupations relating to teaching.

3.2 Changes in Productivity by Basic Characteristics

We now document the changes in productivity reported in the June survey module, and for those working at home at least some of the time. We first document average changes according to characteristics of the worker. Our evidence is presented in Table 2. The table's first column examines the relationship between productivity changes and earnings, with workers split into terciles according to take home pay across the whole labour force in the baseline period. It seems the lowest earning group faced the worse decline in productivity on average, while productivity of top earners has been boosted significantly. As discussed in Section 2, the data here come from an ordinal Likert scale. In Table 2, as in the rest of the analysis, we construe responses as cardinal and interpret marginal effects in terms of standard deviations away from no productivity change. We provide robustness to these results in Appendix B where we perform the same analysis using ordered probits, with near identical results.

Despite the gradient by earnings, column two of Table 2 shows that on average productivity changes are not significantly dependent on degree holding itself. Although not shown here, productivity is also not noticeably different across age. The third column then illustrates a gender gap: on average females experienced a significant productivity fall, whereas males were not noticeably impacted. A possible cause for this is the unequal burden of home work, childcare and other distractions (Andrew et al., 2020). However, in terms of preliminary evidence here, the fourth column shows that productivity is not noticeably affected by the presence of children, at least not across the population as a whole. The final column shows that the self-employed group experiences a significantly worse productivity loss than employees. One important reason is that many self-employed were already in their ideal working environment before the pandemic, so they endured the negative effect of Covid, but did not feel the positive effect of relocating to a more productive space. For example, in January 2020, already 24.2% of self-employed worked at home. Though the fraction increased to 36.4% in April 2020, the increase is much smaller than that of the employed — from 3.8% to 34.5%.

To explore the gender divide in reported productivity in further detail, we present results broken down by gender together with other characteristics in Table 3. Now columns 1 and 2 do indeed show an effect of the presence of children: females with childcare duty suffer a significant loss in productivity, while males are not so affected. This analysis demonstrates one of the strengths of our metric over and

Table 2: Productivity Changes During Covid19: By Characteristics

Earnings: Bottom	-0.29***				
	(0.06)				
Middle	-0.03				
	(0.05)				
Top	0.07**				
	(0.04)				
Education: No Degree		-0.04			
		(0.04)			
Degree		-0.01			
		(0.03)			
Gender: Male			0.05		
			(0.04)		
Female			-0.09**		
			(0.03)		
Children: None				-0.01	
				(0.03)	
At least one				-0.09	
				(0.07)	
Employment: Employed					0.02
					(0.03)
Self-employed					-0.31***
					(0.07)
Observations	2912	3254	3034	3254	3067
Adjusted R^2	0.019	0.000	0.004	0.000	0.011

Source: Covid module of UKHLS

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses. Table displays group means of variable of interest, which is semi-standardized productivity change in June 2020 compared to Jan/Feb 2020. The first column reports the changes in productivity for respondents grouped into tertiles of earnings reported for Jan/Feb. The fourth column is an indicator for the presence of children in the house. See text for more details.

above those used elsewhere in the literature, which typically focus on properties of the job specifically: our results indicate an important role for the circumstances of the individual over and above the pure effect of the job they are matched to. Turning to skill level, columns 3 and 4 again show differential effects across gender: on average, the productivity of females in the bottom earnings tercile fell significantly, whereas the productivity of males with the high (top) level of earnings increased noticeably. Although this analysis is very broad brush, it indicates, over and above the results for the presence of children, an important role for the different types of jobs that males and females are matched to across the earnings distribution. As the literature has emphasized, therefore, it is important to examine the characteristics of jobs themselves.

Table 3: Productivity Changes by Gender and Other Characteristics

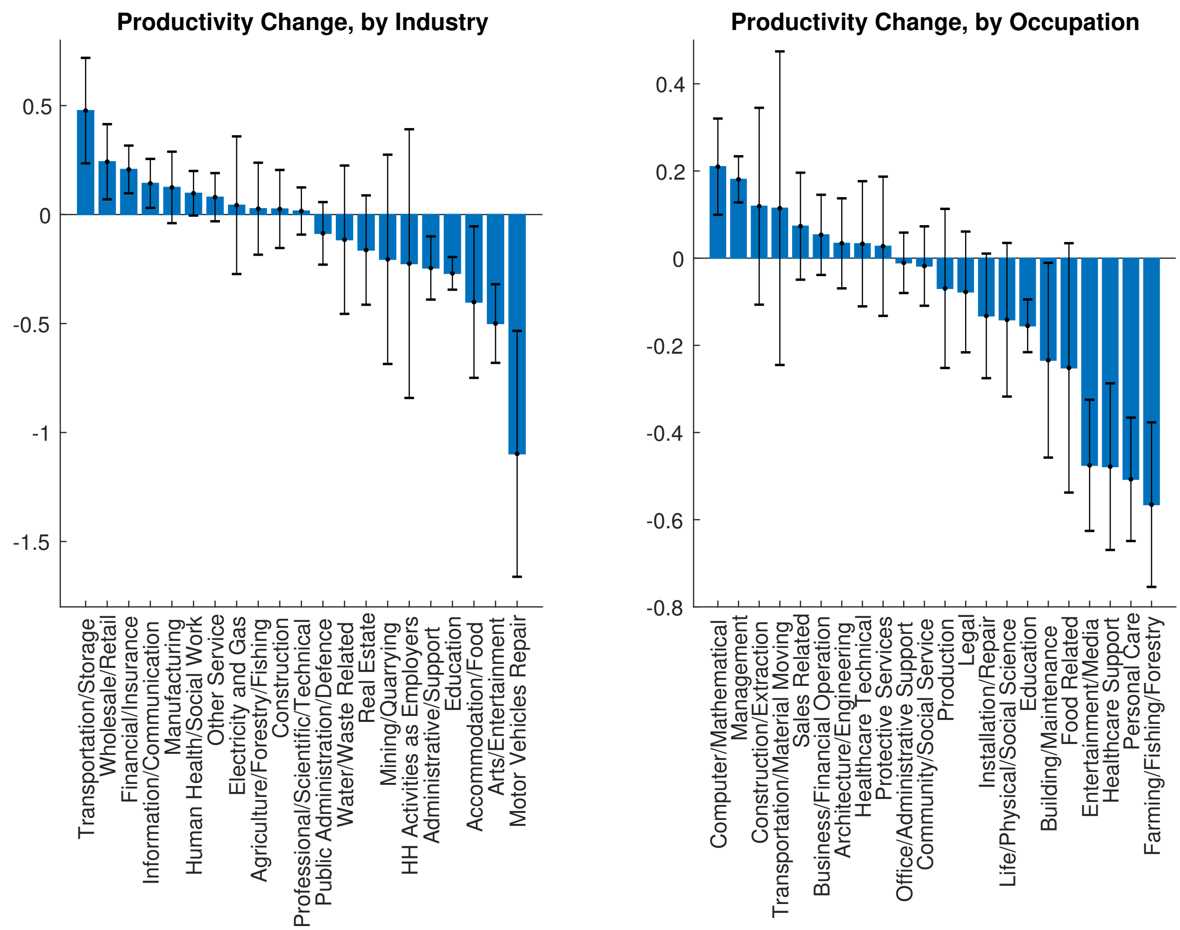
	Children: Male	Children: Female	Earnings: Male	Earnings: Female
Children: None	0.05	-0.07*		
	(0.04)	(0.04)		
At least one	0.09	-0.22**		
	(0.10)	(0.09)		
Earnings: Bottom			-0.07	-0.37***
			(0.15)	(0.07)
Middle			-0.06	-0.01
			(0.08)	(0.06)
Top			0.10**	0.04
			(0.05)	(0.06)
Observations	1244	1790	1102	1619
Adjusted R^2	-0.001	0.001	0.005	0.025

Source: Wave 9 and Covid module of UKHLS.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Note: Standard errors in parentheses. This table reports grouped mean of variable of interest, which is semi-standardized productivity change over Jan/Feb to June 2020. See text for more details. Children is an indicator for the presence of children in the house. Last two columns report changes for individuals grouped into tertiles according to earnings reported in Jan/Feb.

3.3 Productivity Changes by Job Characteristics

We now examine reported productivity changes, focusing on characteristics of the job. As above, we first examine differential performance across industries. Industry-specific policy has been exploited already in the pandemic, such as with the 'Eat Out to Help Out' policy instigated in the UK in August, targeted at the restaurant sector. More generally, commentators and researchers have observed the wide differential impacts by sector. Baqaee and Farhi (2020), for example, examine changes in hours by industry and show that such sector-specific supply shocks, together with demand shocks, are necessary for capturing the disaggregated data on GDP, inflation and unemployment. They further show how a multi-sector Keynesian framework can be used to design optimal monetary policies.

Figure 1: Mean Productivity Change, by Industry and by Occupation



Source: Wave 9 and Covid module of UKHLS
Note: Bars represent the average semi-standardized productivity change. See text for more details. Lines illustrate 95% confidence intervals. Industry computed using current industry code. Occupation taken from occupation worked in wave 9. For consistency with other tables and the US-based literature, occupation is converted to a 2-digit O*NET classification.

Average productivity changes by industry are shown in the left sub-plot of Figure 1, which plots the 21 industries recorded in the survey ranked by average performance. The figure shows that productivity declines are largest for those working in 'Repair of Motor Vehicles', at least for those individuals doing some work from home. The magnitude of the decline is large, averaging one standard deviation of the entire distribution of reported changes. Other industries which show a decline that is statistically significant include 'Education', which was transformed by the pandemic, and arts-related activities. This latter industry is an interesting case: While the realized productivity change in this industry is negative (as reported both in our household data and official aggregate productivity statistics), job characteristics themselves predict a large fraction of jobs in this industry can be done at home.

The left sub-plot of Figure 1 also shows industries for which workers report productivity increases. As one might expect, these include jobs in both the IT and finance sectors, which external metrics indicate require less face-to-face interaction. The other two sectors which report significant productivity increases are trade, and transport and storage. Although jobs in these sectors are less able to be performed at home than those in, say, IT, they do not require physical proximity to other individuals. These observations indicate that there are multiple reasons why productivity may change after work is re-arranged. Again we explore these points in further detail below.

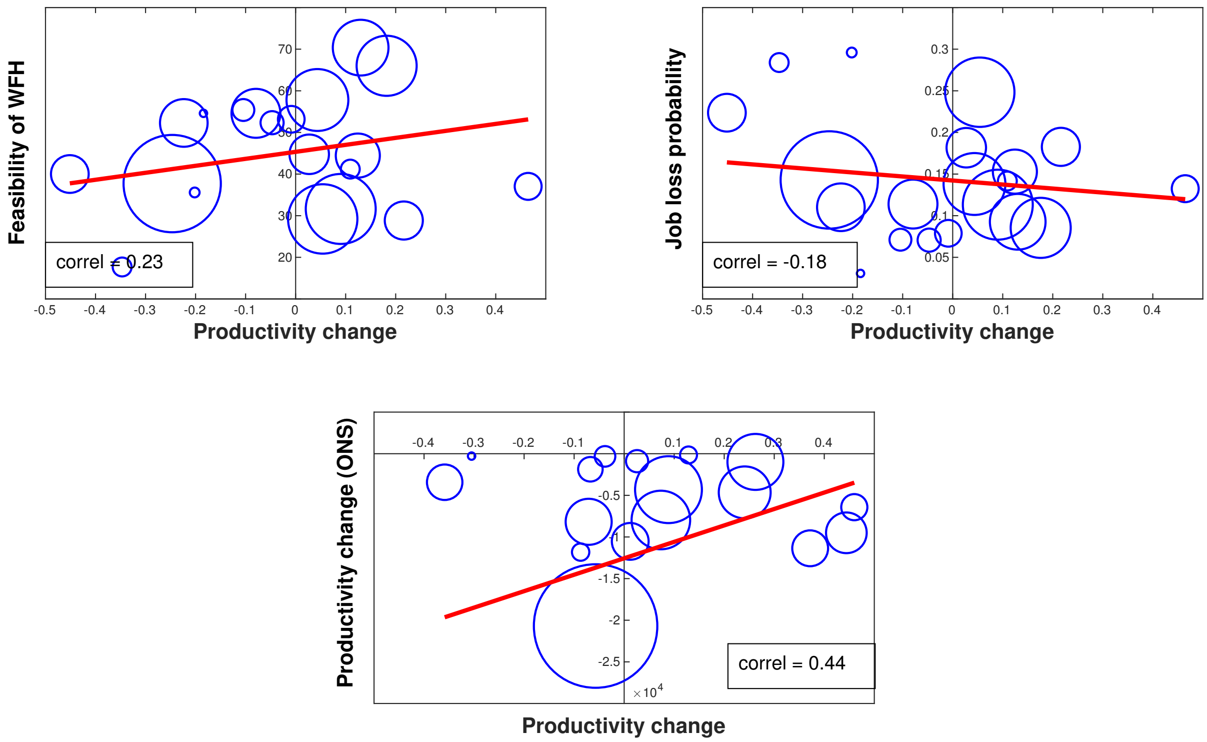
The right sub-plot of Figure 1 shows average productivity changes by occupation. Here we take reported occupation stated in wave 9 as baseline and categorize workers using the 22 two-digit O*NET codes. As explained in Appendix A, the two-digit O*NET codes are derived by using a cross-walk to convert the 3-digit SOC 2000 codes contained in the UKHLS.[4] Looking at the top of the sub-plot, the occupation that shows the largest productivity increase, 'Computer/Mathematical', is similar to the IT industrial sector in requiring little face-to-face interaction. The next occupation, 'Management', is an interesting case, given that it is one of the job types requiring the most interaction on most measures. That managers report productivity increases is possibly very dependent on the current state of information technology. Very likely, if the pandemic had occurred 10 or 20 years previously, the ranking of occupations would look different. Looking at the bottom of the sub-plot, again some expected occupations, such as 'Personal Care', and 'Education' show productivity declines.

We next examine how our self-reports of productivity changes relate to other measures of job performance examined in the literature, focusing on variation across occupations and industries. To this end, Figure 2 shows variation across the 21 industry codes, and according to three external measures. The top left subfigure plots our measure of productivity change against a measure of feasibility of working from home, taken from Adams-Prassl et al. (2020b). As discussed in the introduction, they obtain their measure by asking workers to report the fraction of job tasks that can be performed from home. As such, we would expect this feasibility measure to be a key input into observed productivity during the lockdown period. Here we take Adams-Prassl et al.'s industry averages. Indeed we find a positive, albeit weak correlation between this feasibility measure and reported productivity changes,

[4]For practical survey reasons, occupational data were not collected in the Covid module.

with an estimated coefficient, weighted by industry size, of 0.23.

Figure 2: Productivity Changes by Industry, and Industry Characteristics



Source: Adams-Prassl et al. (2020b), Office of National Statistics (ONS) and wave 9 and Covid module of UKHLS
Note: Figure shows scatter plot of productivity changes against external measures, by industry. Bubble sizes are proportional to industry employment. Solid line is a line of (weighted) best fit. Top left plot uses the feasibility of home work measure of Adams-Prassl et al. (2020a). Top right plot uses industry-specific job loss in April 2020, again from Adams-Prassl et al. (2020a). Bottom plot uses aggregate productivity change by industry from 2019Q4 to 2020Q2 from the UK ONS. See text for more details.

The top right sub-plot then shows a comparison of our productivity change measure with job loss by industry, also taken from Adams-Prassl et al. (2020b). The definition of job loss used includes anyone detached from their previous job, not including those on furlough. Here, the relationship between our measure and the external indicator is not so clear cut. We would expect those industries where working is more difficult to show more job losses. On the other hand, and theoretically at least, heterogeneity might be important. Adams-Prassl et al. (2020b) report wide dispersion in feasibility of home work within industries, and varying degrees of this dispersion across industries. In some industries we might therefore expect job losses among those who cannot work productively in the new environment, but high productivity among those who stay. Moreover, industries with less labour hoarding should exhibit higher productivity. These latter two effects would induce a relationship between productivity and job loss that is positive. Overall, however, we do see a negative correlation between job losses and reported productivity, albeit a weak one.

Finally, the bottom sub-plot of Figure 2 compares our self-reported productivity changes with official aggregate productivity by industry reported by the ONS.[5] For better comparison with the external measure, here we compute a measure of industry-level aggregate productivity change. We do this by weighting the reported changes by earnings reported in January. This weighted correlation coefficient is higher than those in the top two panels, at 0.44. Of course, the discrepancy between our measure and official productivity may be caused by any number of factors. These include biases in self-reporting, and the fact that our data omits those still always working outside the home.

We show variation by occupation in Figure 3.[6] Whereas our industry measure captures current work status, our measure of occupation is taken from wave 9, just before the pandemic. Nevertheless, this measure should capture baseline occupation well; the available evidence suggests there was little noticeable rise in occupational mobility during the Covid-19 period (Office for National Statistics, 2020). As discussed above and in Section 2, the occupational information in UKHLS is provided at the 3-digit SOC 2000 level. In order to compare to measures in the literature we convert to 2-digit O*NET occupations using the cross-walk described in Appendix A.

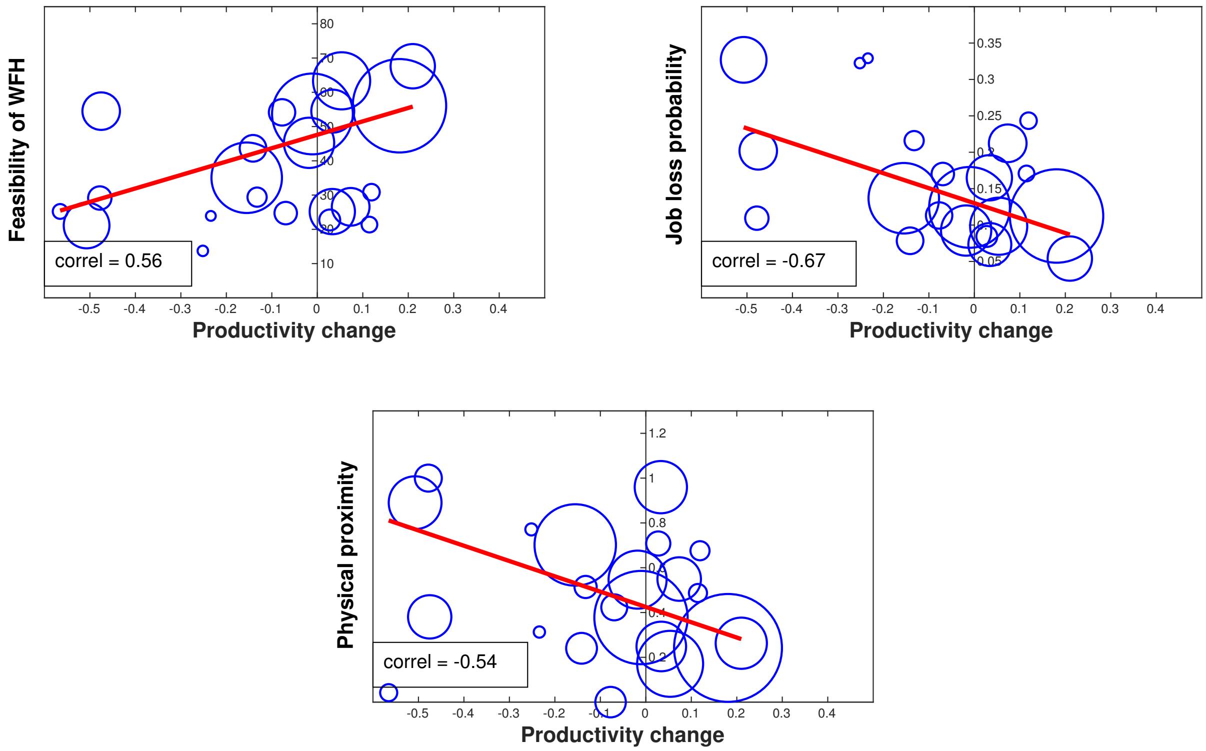
The top left panel again shows a comparison with feasibility of working from home, taken from Adams-Prassl et al. (2020b). Compared to the equivalent subpanel in Figure 2, the correlation between our measure and the external measure is now stronger, at 0.56. This is perhaps to be expected: feasibility of working from home presumably depends more on occupational rather than on industrial characteristics. The top right sub-plot of Figure 3 also shows the equivalent panel to that shown previously, plotting productivity change against job losses. Now the negative correlation with productivity changes is particularly strong, at -0.67. This indicates that it is at the occupation level that productivity changes determine job losses, rather than at the industry sector level.

The bottom sub-plot of Figure 3 now introduces another metric discussed in the literature that should be related to productivity. It compares our reported changes to a measure of need for physical proximity with others, derived by Mongey et al. (2020) using O*NET descriptors. Again these measures are reported by the authors at the 2-digit O*NET occupation level. Those occupations which are indicated to require close physical interaction between workers, such as 'Personal Care' and 'Health-

[5]The ONS combines three industries, 'Public Administration and Defense', 'Education', and 'Human Health and Social Work Activities' into one category and also combines 'Other Service Activities' and 'Activities of Households as Employers' into another category. Therefore, for consistency, we combine our industry data similarly.

[6]In this figure, the category 'Farming, Fishing, and Forestry Occupations' is dropped, for comparability with Adams-Prassl et al. (2020b).

Figure 3: Productivity Changes by Occupation, and Occupation Characteristics



Source: Adams-Prassl et al. (2020a, b), Mongey et al. (2020) and wave 9 and Covid module of UKHLS
Note: Figure shows scatter plot of productivity changes against external measures, by occupation. See text and notes to Figure 2 for details on overall structure of top two plots. Occupation is from wave 9, converted to 2-digit O*NET code. See appendix for full discussion. Bottom plot uses measure of physical proximity in job, from Mongey et al. (2020).

care Support' show the largest productivity declines. In fact the correlation here is also strong, at -0.54, indicating that individual productivity is just as much affected by this factor as pure feasibility of home work.

We finish this subsection by exploring productivity changes by intensity of home working, with results reported in Table 4. In this table, the rows record the intensity of working from home in January/February, and the columns record status in June. Respondents are put into groups by homeworking intensity change.[7] The left panel of the table illustrates average productivity change for each group. The general pattern is the following: If there are large increases in homeworking intensity (from 'Never' or 'Often/Sometimes' to 'Always'), then workers typically report productivity increases; otherwise, i.e. there are little or no increases in the intensity, workers report productivity declines. This pattern

[7]Note that, those never work from home in June are not asked about their productivity changes and thus 'Never' is omitted in the column dimension.

suggests that productivity changes are the net outcome of two off-setting effects. The implementation of nation-wide lockdown was a negative shock to productivity, but increasing homeworking intensity yields positive impacts.

Of course this simple interpretation glosses over other possible explanations, such as that workers in each cell vary systematically by their own or their job characteristics. In this light, the right part of Table 4 reports average feasibility to work from home using the occupation-level measure from Adams-Prassl et al. (2020b). The table shows, as expected, that those working always at home in June are systematically in jobs that are better suited to home work. However, the combination of left and right panels yields an interesting finding: those who always worked from home both before and during the pandemic have experienced productivity declines despite a high score on home-working feasibility. Again this finding suggests a negative direct impact of the pandemic on worker productivities.

Table 4: Productivity Changes and Feasibility of Working from Home, by WFH Intensity

		Working from home in June			
		Often/Sometimes	Always	Often/Sometimes	Always
		Average productivity change		Average feasibility	
WFH in Jan/Feb	Never	-0.24***	0.08**	40.21	47.48
		(0.05)	(0.04)	(0.35)	(0.27)
	Often/Sometimes	-0.10**	0.11***	42.69	50.97
		(0.05)	(0.04)	(0.38)	(0.22)
	Always	-0.15	-0.26***	42.36	47.24
		(0.16)	(0.06)	(1.52)	(0.50)

Source: Wave 9 and Covid module of UKHLS and Adams-Prassl et al. (2020b)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses. The left panel reports average productivity change by intensity of WFH in Jan/Feb and June 2020. Right panel reports average feasibility of WFH, using data from Adams-Prassl et al. (2020a). This feasibility measure is computed using occupational data from wave 9, converted to 2-digit O*NET occupational categories. See text for more details. Stars for statistical significance are omitted in the right panel.

3.4 Productivity Changes and Well-Being

A well-documented feature of the lockdown period has been a noticeable decline in well-being (Banks and Xu, 2020; Etheridge and Spantig, 2020). An association of well-being with changing work patterns, and particularly home work, has been documented by Felstead and Reuschke (2020). Here we examine the association of well-being with productivity changes. Mental health problems are known to adversely affect productivity on the job (Greenberg et al., 2003). It is reasonable to hypothesize that difficulty in performing one's job is a stressor and cause of mental health problems likewise.

Table 5: Reasons for Declines in Productivity: By Gender

	Gender		
Fall in productivity, working at home	male	female	Total
I have had less work to do	30.98	28.99	29.79
I have had to provide childcare/home schooling and/or care for others	22.59	33.37	29.03
The equipment, software and/or internet connection limits what I can do	11.56	12.30	12.00
Lack of motivation/focus/concentration	6.85	6.88	6.92
I have been interrupted by noise made by others	8.51	5.23	6.55
Lack of contact/interaction with colleagues	5.58	1.38	2.99
I have had to share space and equipment	2.92	2.37	2.59
Distractions at home	3.76	1.47	2.35
Need to be at workplace for full role	0.58	3.05	2.13
Changes in how work organised because of Covid-19 restrictions	3.91	1.00	2.11
Tired, ill, other health issues	0.85	1.53	1.28
More work, longer hours	0.89	0.56	0.69
Furloughed	0.76	0.52	0.61
Different/new job	0.27	0.60	0.48
Maternity/paternity leave	0.00	0.76	0.48
Sample size N =	390	686	1076

Source: UKHLS Covid module, June wave
Note: Table shows proportions of stated reasons for productivity declines. Reasons only elicited for those who reported a decline compared to pre-Covid. Survey weights used. See text for more details.

Before examining these associations in detail, we document responses to a question asking for the main reason for productivity declines. This question was asked of anyone responding 'I get much less done' or '...a little less done'. The responses are tabulated in Table 5, and split by gender. A multitude of responses are given, indicating the varied reasons why productivity has declined. The most common reasons relate to childcare and to a lack of available work. Lack of work is evidence of labour hoarding, or perhaps inefficient allocation of work across co-workers. While lack of work is reported with similar frequency across gender, the presence of children is cited as a reason by far more females than males. This latter result is consistent with widespread evidence discussed above finding that the bulk of childcare and homeschooling during lockdown was performed by females (see for example, Andrew et al., 2020). Beyond these causes the next most frequent response relates to lack of adequate equipment or software at home. Further down the list, the only reasons quoted by a non-negligible fraction of respondents are a lack of motivation, and noise distractions by others, presumably other than children. The former reason most directly indicates a causal effect from mental health declines. Reports of noise distractions further indicate the stressful situations under which some workers were required to perform their jobs.

In Table 6 we show the relationship between changes in productivity, working from home and mental well-being. Our measure of mental well-being is the individual change since wave 9 in standardized inverted Likert score. Accordingly, we are associating individual-level changes in well-being with reported changes in various factors. In the first column we regress the change in well-being on dummies for each of the productivity change indicators. Here, a report of 'I get about the same done' is the base category, with its effect on well-being captured by the coefficient on the constant. Relative to this base, those who report getting much less done also report substantially lower well-being. The coefficient of -0.54 standard deviations is large, and roughly in line with what is typically observed during a spell of unemployment. At the other end of the scale, those who report getting much more done report substantially higher well-being. In the second column we perform the same regression, but including controls for gender, age, degree-holding status and industry, with almost identical results.

In the third column we look at the relationship between changes in well-being and working-from-home status during lockdown. These regressions include all workers; those who never work from home are now the omitted category. The relationship between these variables has been explored in a similar way, and using these data, by Felstead and Reuschke (2020), who find that during the early part of the lockdown, workers, who worked at home sometimes, often, or always, all experienced a significant and similar level of decline in mental well-being. The evidence here indicates that by June, well-being has little noticeable relationship with location of work itself. This result pertains with or without basic controls.

As discussed, the strong association between change in productivity and mental well-being likely reflects causal relationships in both directions. In the final column we provide some preliminary evidence for an effect from productivity to mental well-being by instrumenting productivity changes using information available elsewhere in the survey. Here a variety of instruments could be considered. Given the proceeding discussion in this section, obvious candidates are industry or occupation of work. However, it could be argued that industry or occupation affect well-being not only through job efficacy but also through other channels, such as differential social interaction, and differential exposure to Covid-related anxieties. For these reasons we favour an alternative approach. Here we use the reasons for productivity declines stated in Table 5. Specifically we instrument productivity changes with an indicator for whether the individual reports having inadequate equipment or software at home. Our

Table 6: Productivity Changes, Working from Home, and Mental Well-Being

	Change in well-being				
	OLS	OLS	OLS	OLS	IV
Prod. change (index)					0.24^{***}
					(0.07)
Prod: much less done	-0.54^{***}	-0.58^{***}			
	(0.12)	(0.10)			
Get little less done	-0.25^{***}	-0.24^{***}			
	(0.07)	(0.07)			
Get little more done	0.02	0.05			
	(0.07)	(0.07)			
Get much more done	0.30^{***}	0.30^{***}			
	(0.08)	(0.08)			
Working from Home: Always			-0.03	0.01	
			(0.04)	(0.05)	
Often			-0.04	-0.01	
			(0.07)	(0.07)	
Sometimes			-0.06	-0.06	
			(0.09)	(0.09)	
Constant	-0.20^{***}	-0.16	-0.23^{***}	1.64^{***}	-0.08
	(0.04)	(0.19)	(0.03)	(0.11)	(0.22)
Observations	3190	2957	6024	5513	2957
Controls		✓		✓	✓
Adjusted R^2	0.043	0.084	-0.000	0.024	0.081

Source: Wave 9 and Covid module of UKHLS

* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses. In column 5, productivity change is instrumented with report of having ineffective equipment. In columns 2, 4 and 5, regressions include following controls: respondent's gender, age, education level (degree holding) and job industry. In column 3 and 4, we report relationship between mental wellbeing and WFH intensity using June wave of UKHLS Covid module.

maintained hypothesis is that lack of equipment only affects change in well-being through its effect on productivity. A possible criticism of this approach is that, given that the reasons for productivity changes are never elicited from those who report productivity increases, then the 'first-stage' regression is ensured by construction. Nevertheless we feel it is realistic to assume that those who experience equipment problems do find it detrimental on average. Turning to results, we find (but do not show) that those reporting inadequate equipment indeed suffer declines in well-being. Accordingly, and in terms of an IV regression, the fifth column of Table 6 shows that the effect of productivity changes on well-being is strong.

4 Conclusion

The Covid-19 pandemic has caused widespread disruption to working practices. The most noticeable change has been the vast increase in working from home. While some changes to working practices are probably temporary, many could very likely be persistent. Even after the pandemic ends, home working in particular is expected to be much more prevalent than previously.

In this paper we use the Covid-19 module from a household panel in the UK, which provides representative data on home workers' self-reported productivity towards the end of the lock-down period, in June 2020. In this survey, anyone working from home (WFH) at least some of the time was asked about changes in their productivity since before the pandemic period, at the beginning of the year. These data allow us to examine how productivity changes vary across both job and worker types.

We find that workers in industries and occupations that are less suitable for working from home report lower productivities than before the pandemic. Consistently with this, and with the literature, females and low earners also report lower productivity at home on average. For females, this lower productivity is not only due to the average characteristics of their jobs, but also because they are disproportionately effected by the presence of children. When examining workers based on changes in their WFH intensity, the evidence suggests that working from home itself has largely been beneficial, and has offset the other negative effects of the pandemic on productivity. Finally we produce evidence suggesting that difficulty in performing one's job causes lower mental well-being.

The evidence provided in this paper is relevant for policy in several ways. Most importantly it contributes to our understanding of the sector-specific impacts of the pandemic. This in turn helps inform policy-makers of the likely efficacy of targeted policies. It also informs quantitative analyses involving models of sector-specific supply shocks.

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Appendix

A Cross-walk between SOC 2000 and O*NET Occupation

Table A.1 shows the cross-walk this paper adopts to convert the Standard Occupational Classification (SOC) 2000 to the Occupational Information Network (O*NET) codes. Specifically, we assign each 3-digit SOC (sub-major occupation groups) into 2-digit O*NET codes (major occupation groups) by looking into the 4-digit SOC (sub-sub-major occupation groups) under each 3-digit SOC classification and matching them (4-digit SOC) with the most appropriate 2-digit O*NET category. Then, we assign each 3-digit SOC, based on the matching outcomes of 4-digit SOC to 2-digit O*NET code using an employment-weighted majority rule. Further, we also utilize industry information to split occupations under 3-digit SOC. Specifically, under SOC 922 '*Elementary Personal Services Occupations',* several food preparation related occupations are listed, such as '*Kitchen and catering assistants',* '*Waiters and Waitresses'*. These occupations belong to the industry related to food. Therefore, we move those respondents whose 3-digit SOC is 922 and industry related to Food into O*NET 35 '*Food Preparation and Serving Related Occupations'*.

Although in most cases the overwhelming majority of 4-digit SOC codes are assigned to the same 2-digit O*NET code, this is not always the case. As a result, some matches between SOC 2000 and O*NET codes are necessarily imprecise. For instance, SOC 231 '*Teaching Professionals'* is classified into O*NET 25 '*Education, Training, and Library Occupations',* yet under it, SOC 2317 '*Registrars and senior administrators of educational establishments'* is more appropriate to be put into 2-digit O*NET 11 '*Management Occupations*', according to O*NET description. Due to the unavailability of 4-digit SOC information, we are unable to specifically subtract sub-sub-major occupation group SOC 2317 from sub-major occupation group SOC 231. Similarly, we cannot move SOC 5241 '*Electricians'* out of O*NET 49 '*Installation, Maintenance, and Repair Occupations'* and into O*NET 47 '*Construction and Extraction Occupations*'.

Figure A.1 plots occupation distributions of respondents from wave 9 and the Covid module of UK Household Longitudinal Study (UKHLS) and national employment statistics from 2019 US Bureau of Labor Statistics (BLS).

In the figure, white columns represent occupation percentages in UK-HLS and grey columns rep-

Table A.1: Cross-walk between 3-digit SOC 2000 to 2-digit O*NET Classification

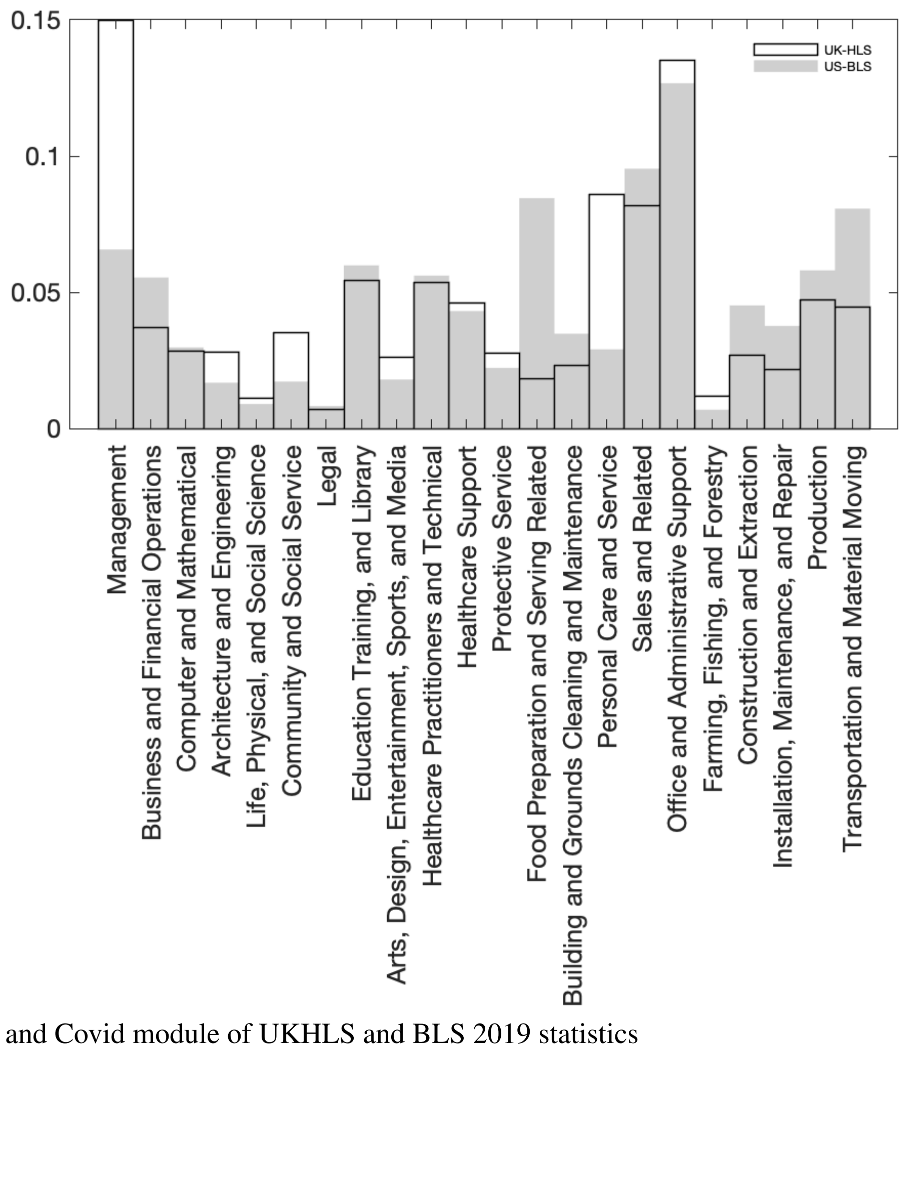
3-digit SOC	SOC title	2-digit O*NET	O*NET title
111	Corporate managers and senior officials	11	Management
112	Production managers	11	Management
113	Functional managers	11	Management
114	Quality and customer care managers	11	Management
115	Financial institution and office managers	11	Management
116	Managers in distribution, storage and retailing	11	Management
117	Protective service officers	11	Management
118	Health and social services managers	11	Management
121	Managers in farming, horticulture, forestry and fishing	11	Management
122	Managers and proprietors in hospitality and leisure services	11	Management
123	Managers and proprietors in other service industries	11	Management
211	Science professionals	19	Life, Physical, and Social Science
212	Engineering professionals	17	Architecture and Engineering
213	Information and communication technology professionals	15	Computer and Mathematical
221	Health professionals	29	Healthcare Practitioners and Technical
231	Teaching professionals	25	Education, Training, and Library
232	Research professionals	19	Life, Physical, and Social Science
241	Legal professionals	23	Legal
242	Business and statistical professionals	13	Business and Financial Operations
243	Architects, town planners, surveyors	17	Architecture and Engineering
244	Public service professionals	21	Community and Social Service
245	Librarians and related professionals	25	Education, Training, and Library
311	Science and engineering technicians	17	Architecture and Engineering
312	Draughtspersons and building inspectors	17	Architecture and Engineering
313	IT service delivery occupations	15	Computer and Mathematical
321	Health associate professionals	29	Healthcare Practitioners and Technical
322	Therapists	29	Healthcare Practitioners and Technical
323	Social welfare associate professionals	21	Community and Social Service
331	Protective service occupations	33	Protective Service
341	Artistic and literary occupations	27	Arts, Design, Entertainment, Sports, and Media
342	Design associate professionals	27	Arts, Design, Entertainment, Sports, and Media
343	Media associate professionals	27	Arts, Design, Entertainment, Sports, and Media
344	Sports and fitness occupations	27	Arts, Design, Entertainment, Sports, and Media
351	Transport associate professionals	53	Transportation and Material Moving
352	Legal associate professionals	23	Legal
353	Business and finance associate professionals	13	Business and Financial Operations
354	Sales and related associate professionals	41	Sales and Related
355	Conservation associate professionals	45	Farming, Fishing, and Forestry
356	Public service and other associate professionals	21	Community and Social Service
411	Administrative occupations: Government and related	43	Office and Administrative Support
412	Administrative occupations: Finance	43	Office and Administrative Support
413	Administrative occupations: Records	43	Office and Administrative Support
414	Administrative occupations: Communications	43	Office and Administrative Support
415	Administrative occupations: General	43	Office and Administrative Support
421	Secretarial and related occupations	43	Office and Administrative Support
511	Agricultural trades	45	Farming, Fishing, and Forestry
521	Metal forming, welding and related trades	47	Construction and Extraction
522	Metal machining, fitting and instrument making trades	51	Production
523	Vehicle trades	49	Installation, Maintenance, and Repair
524	Electrical trades	49	Installation, Maintenance, and Repair
531	Construction trades	47	Construction and Extraction
532	Building trades	47	Construction and Extraction
541	Textiles and garments trades	51	Production
542	Printing trades	51	Production

Table A.1 (Continue): Cross-walk between 3-digit SOC 2000 to 2-digit O*NET Classification

3-digit SOC	SOC title	2-digit O*NET	O*NET title
543*	Food preparation trades	35	Food Preparation and Serving Related
549	Skilled trades	51	Production
611	Healthcare and related personal services	31	Healthcare Support
612	Childcare and related personal services	39	Personal Care and Service
613	Animal care services	39	Personal Care and Service
621	Leisure and travel service occupations	39	Personal Care and Service
622	Hairdressers and related occupations	39	Personal Care and Service
623	Housekeeping occupations	37	Building and Grounds Cleaning and Maintenance
629	Personal services occupations N.E.C.	39	Personal Care and Service
711	Sales assistants and retail cashiers	41	Sales and Related
712	Sales related occupations	41	Sales and Related
721	Customer service occupations	43	Office and Administrative Support
811	Process operatives	51	Production
812	Plant and machine operatives	51	Production
813	Assemblers and routine operatives	51	Production
814	Construction operatives	47	Construction and Extraction
821	Transport drivers and operatives	53	Transportation and Material Moving
822	Mobile Machine Drivers And Operatives	53	Transportation and Material Moving
911	Elementary Agricultural Occupations	45	Farming, Fishing, and Forestry
912	Elementary construction occupations	47	Construction and Extraction
913	Elementary process plant occupations	51	Production
914	Elementary goods storage occupations	53	Transportation and Material Moving
921	Elementary administration occupations	43	Office and Administrative Support
922	Elementary personal services occupations	39	Personal Care and Service
923	Elementary cleaning occupations	37	Building and Grounds Cleaning and Maintenance
924	Elementary security occupations	33	Protective Service
925	Elementary sales occupations	41	Sales and Related

Note: Part of occupation 922 is allocated to O*NET occupation 35 Food Preparation and Serving Related. See text for more details.

Figure A.1: Occupation Percentage Distributions, UK-Household Longitudinal Study (HLS) and US-Bureau of Labor Statistics (BLS)



Source: Wave 9 and Covid module of UKHLS and BLS 2019 statistics resent occupation percentages in US-BLS. The correlation coefficient between both is around 0.7. The occupation categories showing largest differences are Management and Food Preparation and Serving Related. The sign of these differences is, at least, very likely genuine. The UK is reported to be particularly intensive in managers (Blundell et al., 2016). Similarly, the US is more intensive in Food Serving (waitering). If we exclude these occupations, the correlation coefficient between UK and US occupation percentage rises to around 0.8.

B Additional Information and Results

B.1 Productivity Data from the ONS

We also utilize the productivity statistics reported by Office for National Statistics (ONS) in each industry in UK. The productivity measures cover from 1997 Q2 to 2020 Q2 for UK main industries. Three seasonally adjusted statistics related to industry-level productivity are reported: gross value added (GVA), hours worked and output per hour. Both GVA and output per hour are measured by 2016 GBP. The relationship between these three statistics is: GVA equals the product of hours worked and output per hour. Further, we derive the industry-level productivity changes by calculating the difference of GVA between 2020 Q2 and 2019 Q4 for each industry. Note that, since for Manufacture industry, 13 sub-industry statistics are reported separately, e.g. Manufacture of food products, beverages and tobacco and Manufacture of textiles, wearing apparel and leather products, we obtain Manufacture-level GVA by aggregating sub-industries through calculating the product of hours worked and output per hour for all 13 individual sub-industries and then summing the 13 products up. The industry-level productivity change for Manufacture is derived by calculating the difference between the derived 2020 Q2 GVA and the 2019 Q4 GVA.

Moreover, in reporting, ONS combines three industries, Public Administration and Defense, Education and Human Health and Social Work Activities into one category and also combines the other three industries, Other Service Activities, Activities of Households as Employers and Activities of Extraterritorial Organizations and Bodies, into one category. For consistency, when plotting ONS measures of productivity change against our productivity change measures, we combine our statistics in the same way as ONS.

B.2 Additional Tables Mentioned in the Text

Table B.1: Proportions of Working from Home, by Occupation

	At least some of the time			Always	
	Jan/Feb	April	April to June	April	April to June
Management	0.49	0.66	-0.00	0.46	-0.03
Business and Financial Operations	0.57	0.92	-0.02	0.79	-0.03
Computer and Mathematical	0.60	0.89	0.01	0.76	-0.07*
Architecture and Engineering	0.34	0.68	-0.03*	0.50	-0.05*
Life, Physical, and Social Science	0.33	0.71	-0.09	0.54	-0.08
Community and Social Service	0.52	0.79	-0.07***	0.56	-0.07*
Legal	0.47	0.84	0.02	0.79	-0.01
Education, Training, and Library	0.49	0.89	-0.02	0.55	-0.15***
Arts, Design, Entertainment	0.64	0.78	-0.07	0.57	-0.05
Healthcare Practitioners and Technical	0.24	0.38	-0.01	0.11	0.01
Healthcare Support	0.11	0.16	0.02	0.07	0.01
Protective Service	0.12	0.22	-0.01	0.08	-0.01
Food Preparation and Serving Related	0.05	0.05	0.04*	0.01	0.01
Building Cleaning and Maintenance	0.11	0.09	-0.04	0.01	-0.01
Personal Care and Service	0.18	0.33	0.04	0.16	-0.01
Sales and Related	0.17	0.25	-0.02	0.18	-0.02
Office and Administrative Support	0.24	0.55	-0.01	0.40	0.00
Farming, Fishing, and Forestry	0.16	0.23	-0.08	0.16	-0.05
Construction and Extraction	0.11	0.18	-0.07	0.06	-0.04
Installation, Maintenance, and Repair	0.13	0.34	-0.14	0.19	-0.09
Production	0.14	0.21	-0.00	0.12	-0.01
Transportation and Material Moving	0.07	0.10	-0.01	0.04	0.01
Observations	6010	6743	5070	6743	5070
Adjusted R^2	0.402	0.622	0.008	0.475	0.016

Source: Wave 9 and Covid module of UKHLS

* $p < 0.10$,** $p < 0.05$, *** $p < 0.01$

Note: This table reports proportions of respondents who WFH for at least some time and always, respectively for each occupation in the United Kingdom in 2020. The classification of occupations is converted from the UK Standard Occupational Classification (SOC) system to US O*NET system. The first two columns illustrate the proportions who spent at least some of the time WFH in January/February, and in April, respectively. The third column reports changes in proportions of WFH at least for some time from April to June. The last two columns demonstrate the proportion of always WFH in April and change in the proportion of always WFH from April to June, respectively.

Table B.2: Productivity Changes during Working from Home: By Characteristics, Ordered Probit vs OLS

	Probit	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit	OLS	Probit	OLS
Earnings: Bottom	-0.27***	-0.29***										
	(0.08)	(0.09)										
Top	0.11*	0.12*										
	(0.06)	(0.07)										
Age: 16 to 29			0.01	0.01								
			(0.09)	(0.10)								
over 50			0.09	0.09								
			(0.05)	(0.06)								
Education: No Degree					-0.03	-0.03						
					(0.05)	(0.06)						
Gender: Female							-0.15***	-0.16***				
							(0.05)	(0.06)				
Children: None									0.08	0.08		
									(0.08)	(0.08)		
Employment: Self-employed											-0.34***	-0.36***
											(0.09)	(0.09)
Constant		2.96***		2.94***		2.99***		3.06***		2.90***		3.38***
		(0.05)		(0.04)		(0.04)		(0.04)		(0.08)		(0.10)
Observations	2912	2912	3254	3254	3254	3254	3034	3034	3254	3254	3067	3067

Source: Wave 9 and Covid module of UKHLS

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Standard errors in parentheses. This table reports estimation results for productivity change during WFH by respondent's characteristics, i.e. earnings, age, education, gender, children and employment type, using ordered probit and OLS, respectively. Omitted groups are base groups.