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Worker Productivity During Covid-19 and Adaptation to Working From Home

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Non-Technical summary

The Covid-19 pandemic caused widespread changes to economic life, of which probably the most salient was a large increase in working from home (WFH). As the pandemic has faded, it has become clear that the increase in WFH will continue for the foreseeable future. Given that other parts of the economy have returned to the way they functioned before the pandemic, a key question is why shifts in WFH have been so persistent. Answering this question requires exploring individuals' experiences of WFH over the pandemic period.

This paper performs this analysis using representative data from the UK Household Longitudinal Survey (UKHLS), which provides repeated observations of the same individuals over much of the pandemic in the UK, including both periods of strict lockdown, and of looser restrictions. The survey captures location of work as well as wide-ranging background characteristics. In terms of experiences, we focus on responses to detailed and original survey questions asking individuals about their productivity at work.

We show three main sets of results. We first document systematic inequalities in productivity changes since before the pandemic, with workers in jobs less suitable for WFH reporting lower productivity. Additionally, mothers experienced worse productivity outcomes, and particularly at the start of the pandemic in the first lockdown. In contrast, workers with higher earnings (i.e. those in 'good jobs') reported better productivity outcomes.

Building on this we next examine the factors influencing workers choice of location (home or in the office) as the pandemic unfolded. We show that workers and their employers made these choices based on previous individual-specific productivity outcomes.

Finally, we perform a detailed and rigorous analysis of worker performance *across* working locations. Among other results, we find that the productivity advantage experienced by those in `good jobs' (in large firms, with managerial duties and high earnings) pertained particularly to the *home* environment. These advantages were not present in the usual place of work.

These results have important practical implications: large firms were better at making WFH work effectively, and so smaller employers should look for ways to mirror their structures. This information is also useful for policy makers looking to provide these smaller employers with support. Policy makers could also look for ways to support parents, and mothers in particular, who find it harder to perform their work at home, but may stay at home for other reasons.

Worker Productivity During Covid-19 and Adaptation to Working From Home[*]

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Abstract

We examine reported productivity changes of workers over the course of the Covid-19 pandemic, which we validate against external metrics. On average, workers report being at least as productive as before the pandemic's onset. However, this average masks substantial heterogeneity, which is linked to job quality, gender, the presence of children, and ease of working from home. As the pandemic progressed, those who previously performed well at home were more likely to remain there. Building on these findings, we estimate factors affecting productivity outcomes across locations controlling for endogenous selection. We find that those in 'good' jobs (with managerial duties and working for large firms) were advantaged specifically in the home environment. More generally we find an effect of key personality traits – agreeableness and conscientiousness – on productivity outcomes across locations.

Keywords: Worker Productivity, Working From Home, COVID-19, Inequality, Gender

JEL Codes: D24, I24, I30, J21, J22, J24, L23

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1 Introduction

Across the world, the Covid-19 pandemic caused widespread disruption to working practices, including, most saliently, a vast increase in working from home (WFH). The share of the labour force working from home increased from around 5% to over 40% in the U.S. during the first lockdown of Spring 2020 (Bloom, 2020), with a similar change seen in the UK (Reuschke and Felstead, 2020). As the pandemic progressed, evidence accumulated that increased WFH will likely persist for the foreseeable future (Barrero et al., 2021b).[1] Indeed, in the UK by end-2022, 44% of the labour force worked from home at least partially (Office for National Statistics, 2023), even as the pandemic was largely over.

The shock of Covid-19 raises many questions on which evidence is still needed. For example, how did the change in working practices affect workers of different types, in different jobs and with different household circumstances? Focusing more specifically on WFH, how did job experiences and performance during Covid-19 shift patterns of worker location as the pandemic progressed? And what factors affected this performance across locations?[2] These last two questions are particularly important for assessing the evolution of preferences for WFH (Aksoy et al., 2022). The rise in WFH has important implications for labour markets and economic geography, with evidence accumulating that its rise has already affected, for example, the distribution of house prices as well as wage inequality (Barrero et al., 2022).

In this paper we address these questions using the Covid-19 module from the UK Household Longitudinal Survey (UKHLS), which provides representative panel data for much of the pandemic in the UK, from April 2020 to September 2021. In this survey, all workers were asked about both their current working location as well as about changes in their productivity since a reference period before the pandemic's onset. These data allow us to examine how worker performance varied across job and worker types and was influenced by, for example, the presence of children, as well as housing characteristics. These data also allow us to track the joint evolution of productivity and worker location through various stages of the pandemic, both at times of strong restrictions, and when policies were more relaxed. Compared to other related datasets used in the literature, such as the Survey of Working Arrangements and Attitudes (Barrero et al., 2021b), these data allow us to track the *same* individuals over time.

[1] For a wider discussion and extensive references see also the dedicated discussion of the literature below.

[2] Throughout the paper we use the term 'location' to refer to the worker's physical location, either at home (WFH) or in a workplace away from home, such as an office or building site.

We make three main contributions to the already large literature on inequality during Covid-19 and to the growing literature on working from home (WFH). First we provide the most systematic evidence of working location and productivity outcomes over the course of the pandemic using representative labour market data. Compared to papers using similar data to ours from self-reports (e.g. Deole et al., 2023; Aksoy et al., 2022; Felstead and Reuschke, 2021), we document more extensively inequalities in how productivity varied over time. For example, we find that workers in jobs that are less suitable for WFH reported lower productivity than before the pandemic. Consistent with this, and with the literature, females and low earners also reported worse productivity outcomes on average. The findings for females varied systematically with the presence of children in the house and the severity of restrictions; in fact the gap with males attenuated as the pandemic progressed. The opposite types of workers, e.g., those in the 'right' occupations and with high incomes, reported higher productivity than previously.

A particular strength of our analysis is that we incorporate external measures of both potential and realized productivity. Building on our earlier work (Etheridge et al., 2020) we examine: feasibility of home work (from Adams-Prassl et al., 2022); the need for physical proximity to others (Mongey et al., 2021), as well as realized output statistics at the industry level from the National Accounts. The sector-level correlations between our reported productivity changes and these external measures are always of the expected sign, which acts as a powerful validation of the survey data. The advantages of using individual-level reported productivity over these external measures on their own are that we can go beyond the characteristics of the job to look at the joint contribution of individual and job characteristics, as well as, for example, the role of the housing environment. An additional strength of our analysis over studies that use the same data as us (such as Deole et al., 2023) is that we go beyond using Likert-type responses and exploit the full quantitative implications of the survey: specifically we analyse in detail the answers to additional survey questions that elicit a quantitative assessment of productivity changes.

Our second contribution is to use the longitudinal aspect of our data to provide evidence on factors determining worker location as the pandemic progressed. Evidence on this front is important for understanding how preferences for WFH are continuing to evolve (Aksoy et al., 2022; Chen et al., 2023). We focus on productivity experiences and provide original evidence that workers positively selected into the home environment, based on previous productivity outcomes. In general terms, this evidence indicates that factors of production were better allocated as the pandemic progressed and provides a microfoundation for why the macroeconomy performed much better in the second lockdown than in the first. Interestingly, we also show that the marginal group - those who were most likely to change location in subsequent periods - evolved over the pandemic in intuitively credible ways. For example in the easing of September 2020, the group that were full-time WFH in June 2020 showed the greatest flexibility in whether they subsequently returned to the usual place of work, and depended most on their realized productivity in the earlier period. Alternatively in the return to lockdown in January 2021, it was the group that were part-time WFH in September 2020 that most responded to their earlier productivity outcomes: those who had previously WFH full-time naturally remained at home, however they previously performed.

Building on these results, our third contribution is to examine in detail factors affecting work performance *across* work locations. To do this rigorously we carefully formulate a selection model of location choice, and use it to estimate models separately at home and at the usual place of work. For exclusion restrictions we use pre-pandemic commuting patterns, which we show to be important in determining location during the pandemic. Here we go beyond examining the effect of standard job and individual characteristics only. We also examine the role of the home environment and, perhaps with most novelty, the role of cognitive ability and personality traits, about which the survey contains rich measures. Relating to our earlier results, we find that the productivity advantage experienced by those in 'good jobs' (in large firms, with managerial duties and high earnings) pertained particularly to the *home* environment. Those working for large firms, for example, did not fare better than those working for smaller firms while in the usual place of work. Among other results, we find that those high in agreeableness and conscientiousness performed better generally, while those with higher cognition experienced worse productivity growth while at home. We interpret this latter result as indicating that the advantage of high cognitive skills was blunted somewhat in the home environment. Overall our results provide rich insights on which factors affected productivity differentially across locations during the pandemic. These insights are useful for policy makers and planners within firms considering how to make WFH work in the future.

The paper proceeds as follows: We begin in Section 2 with a brief review of the related literature. Section 3 introduces the data, discussing how we use the questions on productivity and documenting basic trends in WFH and productivity across the pandemic. In Section

4 we investigate in further detail unequal outcomes in how productivity changes related to individual and job characteristics, as well as assessing dynamics in location choice. In Section 5 we use the selection model to examine outcomes within each location specifically. Section 6 concludes. Extensive Appendices provide further details of our analyses.

2 Related Literature

Our paper relates to three broad strands of literature. First it contributes to papers studying working from home as an 'alternative' practice. This literature has focused both narrowly on estimating the treatment effect of WFH on productivity, and more broadly on the long-term viability of WFH as a central component of working life, and its implications for labour markets and economic geography. Second our paper contributes to the literature documenting the complex movements in inequality across gender and socioeconomic groups both during and after Covid-19, as well as other recessions. Finally our estimates of outcomes by occupation and industry relate to the macro literature on sector-specific productivity changes and optimal policies during the Covid-19 pandemic.

First, how WFH impacts productivity has received increasing attention in recent years, especially since the Covid-19 outbreak, with mixed results. One approach to addressing this question has been to focus on a single inherently remotable job within a single firm. Bloom et al. (2015) study workers' productivity and attitude towards WFH using a randomized control trial of call-centre workers in a Chinese travel agency. They find that WFH led to a 13% performance increase and that, after the experiment, over half of the workers chose to switch to home-working. Recent research, however, finds more negative effects. Emanuel and Harrington (2023) examine work performance at a US call centre before and during the pandemic, using Covid-19 office closures to separately identify the impact of WFH and worker selection. Their estimates suggest that WFH has a negative impact on both the quality and quantity of output, and that home workers are negatively selected on baseline productivity. Conducting an experiment in the data-entry sector in India, Atkin et al. (2023) similarly find that randomly assigned home workers are 18% less productive than their office working colleagues. They also find a positive selection into home working, but also importantly a *negative selection on treatment effect*: those who select into the home would in fact gain most from being in the office. They explain this finding by arguing that those who are most constrained in terms of productivity at home, such as mothers, often have the strongest preference for home work. Focusing on the pandemic period, Gibbs et al. (2023) examine IT workers in Asia and also find detrimental effects of WFH. Thinking about the possible longer-term implications, Emanuel and Harrington (2023) and Gibbs et al. (2023) find that WFH is associated with a reduction in on-the-job training and coaching, which may eventually negatively impact worker productivity and worker retention.

While these papers all focus on particular narrow occupations, the Covid-19 outbreak and related lockdowns in many countries dramatically increased the prevalence of WFH in almost *all* occupations. Indeed, the above papers point towards heterogeneous outcomes across job types suggesting that the overall impact of WFH on productivity across industries/occupations/jobs requires closer investigation if we are interested in how a general shift to WFH will impact the economy. Specifically relating to these findings on productivity and selection, while we are not able to provide precise estimates of average treatment effects, our results do indicate that selection on treatment effect is, on average, *positive*. In contrast to Atkin et al. (2023) whose results come from asking workers for their own preferences, our results come from observed transitions, presumably resulting from a bargaining process between worker and employer. Overall, it seems sensible that employers would want the workers who adapt least well to WFH to return to the office.

Our results also relate to work on broader trends across the labour market. Using data similar to ours Felstead and Reuschke (2020) document the increase in WFH after March 2020. They find little effect of workers' productivity at home on average during the first lockdown. 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 the Netherlands; Eurofound, 2020 for Europe as a whole; and Brynjolfsson et al., 2020 for the US). Also using the UKHLS, Deole et al. (2023) report that average reported productivity was slightly higher at home as the pandemic progressed, but take no account of the endogeneity of work location as we do here. Complementing this evidence from individuals, Brinkley et al. (2020) provide evidence from a small survey of firms that also supports broadly non-detrimental effects of WFH during the pandemic. We go beyond these papers in providing richer evidence from across the pandemic: We use full quantitative information on productivity in the UKHLS Covid module and incorporate a wider array of evidence both from within the main UKHLS survey and from external sources.

More broadly still, the literature has begun to explore how persistent the move to home working will be, and effects on economic geography. Prior evidence indicates that most workers value the ability to WFH (Mas and Pallais, 2017). Barrero et al. (2021b) report survey evidence from individuals of their employers' stated intentions post-pandemic and find that 20% of working hours will be conducted from home in the medium term, compared to 5% pre-pandemic and a peak of around 40-50% at the pandemic's start. Their rule of thumb is that 50% of workers will be able to work an average of 2 days a week at home. Bick et al. (2021) and Felstead and Reuschke (2021) similarly provide evidence of workers' beliefs about future WFH. As the Covid-19 pandemic has drawn to a close, more direct evidence about WFH has begun to emerge. Utilizing natural language processing methods on vacancy data, Hansen et al. (2023) find that the percentage of new job postings continues to have a positive trend, with 18% of new jobs in the UK advertised as remote work in January 2023. Alternative evidence of long-term changes comes from house prices, with Gupta et al. (2021) and Brueckner et al. (2023) finding changing patterns of inner-city and sub-urban prices, consistent with anticipated long-term shifts and Mondragon and Wieland (2022) finding an increase of remote work causing housing price increase, consistent with anticipated long-term shifts.[3] Augmenting these studies, our work provides evidence on which types of workers are most likely to persist with home working, and how this relates to, for example, housing conditions and commuting patterns.

Second our work contributes to the large literature on the complex heterogeneous effects of Covid-19, and implications for inequality that are still developing after the pandemic. Early in the Covid-19 pandemic, it was found that the economically disadvantaged groups, such as low-income groups and females, suffered larger declines in economic outcomes: for example, Adams-Prassl et al. (2020) document that female workers reported a lower ability to work from home, and also document that women were more likely to lose their jobs in the UK and in the US early in the pandemic, finding worse outcomes for lower earners. Alon et al. (2022) provide evidence that the Covid-19 recession was a "shecession" in many countries, attributing the heterogeneity to different industrial structure and variation in Covid related policies. However, patterns of inequality following the initial lockdown have been complex, and evidence is emerging that the tight labour market following the end of the pandemic has

[3]See also a survey by Garrote Sanchez et al. (2021) covering many of these issues. Additionally Gottlieb et al. (2021) assess possibilities for WFH across several developing countries.

benefited low-wage workers in the US substantially (Autor et al., 2023). Our paper contributes to this strand of the literature by studying inequality of worker productivity across gender and socioeconomic groups, and across the whole of the pandemic. We find that females and mothers in particular suffered larger productivity declines during the lockdowns, but less so during the rest of the pandemic. Our work also naturally lends itself to future work assessing the role of WFH on the evolution of inequality post-pandemic.

Finally, our results can be used by the literature on sector-specific productivity of working from home, and optimal sectoral policies. 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, such as that developed by Baqaee and Farhi (2022). Bonadio et al. (2021) study the impact of the Covid-19 pandemic on GDP growth and the role of the global supply chains. These papers typically discipline the labor supply shock across sectors using ex-ante measures of exposure, such as those provided by Dingel and Neiman (2020), Adams-Prassl et al. (2022), Mongey et al. (2021) or Alipour et al. (2023). However, there is space for improvement in these macro studies by using measures of realized labor productivity changes.

3 Data

We use data from the UKHLS (also known as 'Understanding Society'), a large-scale national household panel survey that covers a representative sample of UK households administered from 2009. In April 2020, the survey created the Covid-19 Study - an additional web survey fielded to collect information about survey members' experiences and behaviours during the pandemic. The Covid-19 module was initially conducted monthly from April 2020 until July 2020 and then at lower frequencies thereafter - in September and November 2020, and then in January, March and September 2021. The analysis makes specific use of the Covid-19 study waves three, five, seven and nine, conducted in June and September 2020, and January and September 2021, each of which include questions on self-reported productivity. To provide information on the early lockdown, we make use of data from the April and May 2020 waves of the Covid module. We also make extensive use of the '2019 wave' of the UKHLS main survey. This 2019 wave merges data collected in the main survey's waves 10 and 11. Additionally, we use further data from even earlier main survey waves, as discussed below.

Some background details on the UKHLS Covid-19 study are as follows: The underlying sampling frame consists of all those who participated in the UKHLS main survey's waves 8 and 9 (sampled over 2016-2018). To conduct the fieldwork, the sample was initially contacted using a combination of email, telephone, postal and SMS requests.[4] Of those eligible, and who responded to the main survey wave 8 or 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 stratification of the sample by post (zip) code, 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 in the month of the interview and compared to a stated baseline from before the pandemic. To elicit this the survey includes some bespoke questions. Precisely, in the fifth, seventh and ninth waves (September 2020, January 2021, September 2021) all those in work 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"*.

Interviewees who report productivity changes to this qualitative question are asked additional quantitative questions regarding productivity changes:

> *"Would you say that what you can do in an hour now would previously have taken you:"*

If interviewees report a productivity gain, they select one choice from the following:

> *"1 - Up to an hour and a quarter"*;
>
> *"2 - Between an hour and a quarter and an hour and a half"*;
>
> *"3 - More than an hour and a half"*.

[4] The interviews in the fifth and seventh waves, for example, were conducted in the seven days from Thursday June 25 and September 24, with around 75% of interviews completed within the first three days.

If interviewees report a productivity decline, they are given equivalent choices.

In order to generate a continuous measure of productivity change, we fit a Pearson type VII distribution to these responses. We find this fits the data better than a Gaussian distribution, which does not allow for suitably thick tails (see Table A.2 for quantitative results, including goodness of fit measures). Using this fit we impute mean productivity changes for all the seven possibly banded quantitative answers. For example, for those who say that they can now do in an hour what used to take more than an hour and a half we impute a productivity increase of 78%. Full details and results of the estimation are provided in Appendix A.[5]

One important issue arises during this process. The information from June 2020 is more limited: only the qualitative question was asked, and only to those who were working from home at least some of the time. We exploit these responses by first estimating productivity change cutoffs for each of the qualitative questions in September 2020, using the shape parameters estimated from the coincident quantitative data. We then assume that these cut-offs apply equally to the June responses. Using these cut-offs we can impute mean productivity changes in the June wave for each choice category. Our estimated cut-offs imply similar conclusions for the June wave to those in Etheridge et al. (2020) where we 'semi-standardized' the data by cardinalizing the Likert responses as -2, -1 ,0, 1, 2, and scaling by the standard deviation. In that paper, we in turn also showed that similar results were given using ordered probit models. However, our approach here improves on that earlier analysis, as well as related papers (such as Deole et al., 2023), by providing fully quantified results.

Beyond the information on productivity, we make use of much auxiliary information contained in the UKHLS surveys and other sources. Of particular interest, all respondents were asked to report their baseline earnings and place of work just before the pandemic, in January/February 2020. The survey elicits industry of work both in the baseline period and currently.

An objective of our analysis is to validate our findings by making comparisons with job-level metrics obtained elsewhere in the literature, typically using data on occupation. Unfortunately, current occupation was not collected directly in the Covid survey. We therefore use occupational information from the 2019 wave. These data are based on the SOC 2000 classi-

[5]In the Appendix we also assess the internal validity of the data in several ways. Specifically we show that: a) the estimated cut-offs are very similar over time; b) qualitative and quantitative responses are highly correlated within waves (within groups who report positive experiences and negative experiences respectively); c) both qualitative and quantitative responses are highly correlated across waves.

fication. To link these to external metrics founded on the US-based O*NET classification, we use the cross-walk described in Appendix B.1. For additional validation, we also use aggregate production data from the UK Office for National Statistics; see Appendix B.2 for further discussion.

Finally, in Section 5 we make use of two additional bodies of data from the main survey collected before the pandemic. First, to examine selection into work location, we use data on patterns of commuting to work, including reports of travel mode and any travel difficulties. These were collected in main survey waves 10 (collected over 2018−19), 8 (2016−17), 6, 4 and 2. To make as full use of the data as possible, we include individuals for which any of these reports is available, taking the most recent provided. Second, to examine individual characteristics potentially affecting work productivity during the pandemic, we use data on cognitive function and 'big-5' personality traits. These were collected over 2011−12 in main survey wave 3. The cognitive assessment comprises scores from four tests - on completing number series, immediate word recall, delayed word recall, and verbal fluency (see McFall, 2013, for extensive documentation) - from which we take the first principle component. Personality traits were measured using averages of scales for responses to 3 questions for each of the big-5 traits, borrowing the methodology documented in John et al. (1999).[6]

To give an example of sample sizes, our total number of adjusted interviews in the September 2020 wave, which is the first to provide full data on productivity, is 10,607. Of these interviews, 5,794 individuals were in work and reported information about working location; 5,717 additionally answered the productivity question. Overall, we work with three main samples. The full sample, analyzed in Section 4, contains 19,293 total observations across the four Covid waves. The sample containing information on pre-covid commuting patterns, analyzed in Section 5, contains 18,557 person-wave observations. In Section 5 we also analyse the sample containing information on personality traits and cognition, for which 13,552 person-wave observations are available. Full summary statistics are presented in Table C.1 in Appendix C.

[6]For example, to assess agreeableness, interviewees are asked to assess themselves on a scale of 1-7 on the following statements: 'I see myself as someone who is sometimes rude to others' (reverse coded), 'I see myself as someone who has a forgiving nature', and 'I see myself as someone who is considerate and kind to almost everyone'.

3.1 Proportions in Work and at Home

Before moving on to the analysis behind our main contributions, we review patterns of working from home and reported productivity during the pandemic. Our evidence here follows up on Etheridge et al. (2020), who report findings from the first wave of data in June 2020, as well as, among others, Felstead and Reuschke (2020), Felstead and Reuschke (2021) and Deole et al. (2023).

We first show patterns of WFH over time in Table 1. It shows, in simple format, some of the characteristics of our sample and broad trends in both frequencies of WFH and productivity changes. It also shows, in the final column, the stage of the pandemic in terms of national policy on social distancing. In June 2020 and January 2021 strong distancing policies were in place, including the widespread closure of hospitality and restricted rules on even small-scale social interaction. September 2020 and September 2021 were in periods of far more relaxed rules, including, for example, availability of hospitality and restaurants.

The first row of Table 1 shows that 76% of the working-age population were in work just before the pandemic. The second column reports an estimate of the proportion of working hours spent at home. We calculate this simply by imputing 20% for those who say 'sometimes' and 60% for those who say 'often'. We find that home work accounted for only around 12% of working hours prior to the pandemic, but around 38% of working hours in June 2020. The third and fourth columns show simple averages of our variable capturing change in productivity. In June 2020 this is available for the WFH sample only, and the fourth column shows that for this group reported productivity was roughly flat.

The second row of the middle block shows that, by September 2020, the number in employment had increased compared to June, while the proportion of hours WFH had declined. In this month, individuals reported an increase in productivity on average, and those working from home reported an increase that was even larger. The next row shows that the proportion in work decreased slightly going into the lockdown in January 2021, and unsurprisingly the proportion of hours spent working from home increased again by 8 percentage points. Notably, self-reported productivity fell again compared to the previous wave both for the sample as a whole and for those working at home. Finally, by September 2021, the proportion in work increased again, while the proportion of hours at home declined to its lowest since before the

Table 1: WFH and Productivity Change During the Covid-19 Pandemic

		Proportion in work	Proportion WFH	%ΔProd	%ΔProd if WFH	Strong Social Distancing
January-February 2020	Mean	0.76	0.12			
	Sample Size	14,490	11,292			
June 2020	Mean	0.59	0.38	-0.90*	-0.90	Yes
	Sample Size	10,336	7,825	3,498*	3,498	
September 2020	Mean	0.67	0.32	5.40	8.64	
	Sample Size	9,267	6,903	5,533	2,849	
January 2021	Mean	0.64	0.40	0.08	0.69	Yes
	Sample Size	8,443	6,247	4,753	2,887	
September 2021	Mean	0.70	0.30	9.04	13.00	
	Sample Size	9,212	6,944	5,509	2,750	
Total	Mean	0.65	0.35	4.09	4.94	
	Sample Size	37,258	27,919	19,293	11,984	
	# Individuals	12,438	9,828	7,713	4,928	

Note: This table reports employment, WFH and productivity change by Covid module wave. The base sample comprises working-age individuals (17-65). The first column corresponds to the proportion of the sample in work. The second column reports the proportion of time in work spent WFH. Following Felstead and Reuschke (2021), we weight the 4 possible responses in the raw survey question as 0 = *never*, 0.2 = *sometimes*, 0.6 = *often*, 1 = *always*. The third column relates to the percentage change in productivity. In June 2020 this includes those with some WFH only. The final column corresponds to the change in productivity for those that report any WFH in the current period. The top row provides information for the baseline period, elicited using retrospective questions in the Covid module. Those on furlough or working less than one hour per work are treated as if they are out of work. The sample for the last two columns is restricted to include those with a full set of control variables (individual characteristics, employment variables and household characteristics) to be consistent with the sample used in the main analysis.
* Excludes those in the usual place of work full-time.

pandemic. In this month, workers reported the highest levels of productivity, indicating that they had adapted to work during the pandemic, either at home or in the office.

To show some of the wide variation during the first year of the pandemic, Appendix Tables C.2 and C.3 show breakdowns by industry and occupation respectively. Focussing on industry, the first column of Table C.2 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. The exceptions are industries (such as Accommodation and Food Service) for which 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 little change in working patterns by this metric even as the lockdown eased. The fourth column demonstrates the change in proportion of home workers from June to September 2020 after the first lockdown was fully eased. While the remaining industries show marginal increases in the proportion spending at least some of the time WFH, significant decreases are shown in three particular industries: 'Electricity and Gas', 'Financial and Insurance', and 'Education'.

4 The Evolution of Working from Home and Productivity Through the Pandemic

4.1 Change in Productivity by Worker Characteristics

We now document in further detail variation in the self-reported changes in productivity by characteristics of the worker. Our evidence is presented in Table 2. The 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. The observations are pooled across survey waves. It seems the lowest earning group faced relatively worse productivity outcomes on average, while productivity change of top earners was roughly 5.5% more than before lockdown and at least 2 percentage points more than either of the other two groups. It is worth re-emphasizing here that, as discussed in Section 3, the productivity changes reported in this table come from the distributional imputation using quantitative and qualitative survey questions, as explained in Appendix A.

Despite the gradient by earnings, column two of Table 2 shows that on average productivity changes are not substantially dependent on degree holding itself, with both degree holders and non-degree holder showing similar increases in productivity. Although not shown here, productivity is also not noticeably different across age. The third to the sixth columns then illustrate gender gaps that differ across the stages of the pandemic and by demographic characteristics. The last two rows of this block show males and females without children, while the first two rows show those with at least one child aged under 16. In June 2020, females suffered productivity declines while males did not, with mothers suffering the most. This likely reflected the unequal burden of home work, childcare and other distractions (Andrew et al., 2020). Thereafter, in September 2020, as lockdown eased, all groups saw considerable productivity increases including women with children. Consistent with Table 1, self-reported productivity then declined broadly for most groups in the second lockdown in January 2021. Again, mothers experienced the worst reduction, experiencing a reduction in productivity compared

Table 2: Percent Changes in Productivity During Covid-19 by Worker Characteristics

DV = %Δ Productivity	(1)	(2)	(3) June'20	(4) Sept.'20	(5) Jan.'21	(6) Sept.'21	(7)	(8)	(9)	(10)
Monthly net earnings terciles:										
Bottom	2.50***									
	(0.72)									
Middle	3.14***							0.49	0.56	0.59
	(0.60)							(0.93)	(0.94)	(0.93)
Top	5.51***							3.50***	2.57**	2.58**
	(0.50)							(0.98)	(1.09)	(1.04)
Education:										
No degree		3.92***								
		(0.46)								
Degree		4.33***						0.30	0.19	0.14
		(0.51)						(0.75)	(0.80)	(0.80)
Parenthood and gender:										
Parent × Female			-5.01***	6.51***	-3.46***	7.68***				
			(1.26)	(1.18)	(1.30)	(1.15)				
Parent × Male			0.36	5.24***	1.46	8.49***		0.63	0.53	0.41
			(1.34)	(0.91)	(2.09)	(1.31)		(1.18)	(1.12)	(1.12)
No children × Female			-1.48	5.06***	0.87	10.22***		1.76*	1.82*	1.44
			(1.30)	(0.87)	(1.05)	(0.69)		(0.92)	(0.93)	(0.95)
No children × Male			2.05*	5.21***	0.50	8.77***		1.25	1.81*	1.43
			(1.09)	(0.77)	(0.94)	(0.91)		(0.99)	(1.03)	(1.05)
Employment type:										
Self-employed							-0.38			
							(1.35)			
Employee							4.34***	4.39***	3.03**	3.23**
							(0.35)	(1.37)	(1.53)	(1.54)
Constant								-1.64	44.76	47.20
								(1.57)	(41.32)	(41.46)
Observations	19,293	19,293	3,498	5,533	4,753	5,509	19,293	19,293	19,293	19,293
Wave dummies								Yes	Yes	Yes
Individual controls									Yes	Yes
Employment controls									Yes	Yes
Housing controls										Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The dependent variable is imputed productivity change measure. Columns (1) to (7) show group means for displayed characteristics. Columns 8 to 10 show results from multivariate regressions including additional controls. Presence of child is defined as living with a biological child which is under the age of 16. In columns (8) to (10) the omitted wave is September 2020. Additional background controls used in columns (9) and (10) are as follows: Individual controls - quartic in age, marital status, BAME status (binary), region of residence; Employment controls - managerial duties, log of the number of employee in firm of employment, industry of work, occupation; Housing controls - number of rooms in house per occupant, home ownership, whether the house has internet access. Survey weights are used throughout and standard errors are clustered at the primary sampling unit level.

to the baseline. By September 2021, all groups were performing well, although mothers still appeared to lag the rest slightly.

More detail on parental productivity changes is provided in Appendix Table C.4, which shows that for those with the youngest children (under the age of 5), fathers performed better than mothers in June 2020, but as badly as mothers in January 2021, and substantially worse than fathers with older children during the second lockdown. This indicates that outcomes for parents with very young children equalized across the pandemic somewhat.

Moving on, the seventh column shows that employees had significantly better outcomes than the self-employed. The right hand side of Table 2 then shows the effects of these same characteristics when we combine them in a multivariate regression with and without additional controls. The first column of this panel shows the most basic specification, additionally including a constant and wave dummies only. In this column, as with the subsequent two, we have chosen as the omitted category the worst performing group in each domain. The relative sizes of most of the factors (earnings tercile, degree holding and employment status) remain similar to the raw group mean estimates. The results by gender and household composition, which are now averaged over the stages of the pandemic also confirm the impression from the left-hand side: women with children, who are the omitted category, had the worst productivity outcomes and those without the children the best. Notice, however, that the average gaps between the groups compressed considerably since the earliest estimates from June 2020, and the differences between demographic groups, when averaged across all the available waves, are only marginally significantly different.

To further put the heterogeneity in experiences into perspective, the estimate on the constant therefore implies that the worst performing group (low-skilled, low-educated, self-employed mothers) experienced an average productivity decline of around 1.5%, referenced to September 2020. By comparison, adding up the effects on the groups with the best performing outcomes implies that employed, top-earning, female degree holders, without children reported an average increase in productivity of over 8% or 10 percentage points more, on average.

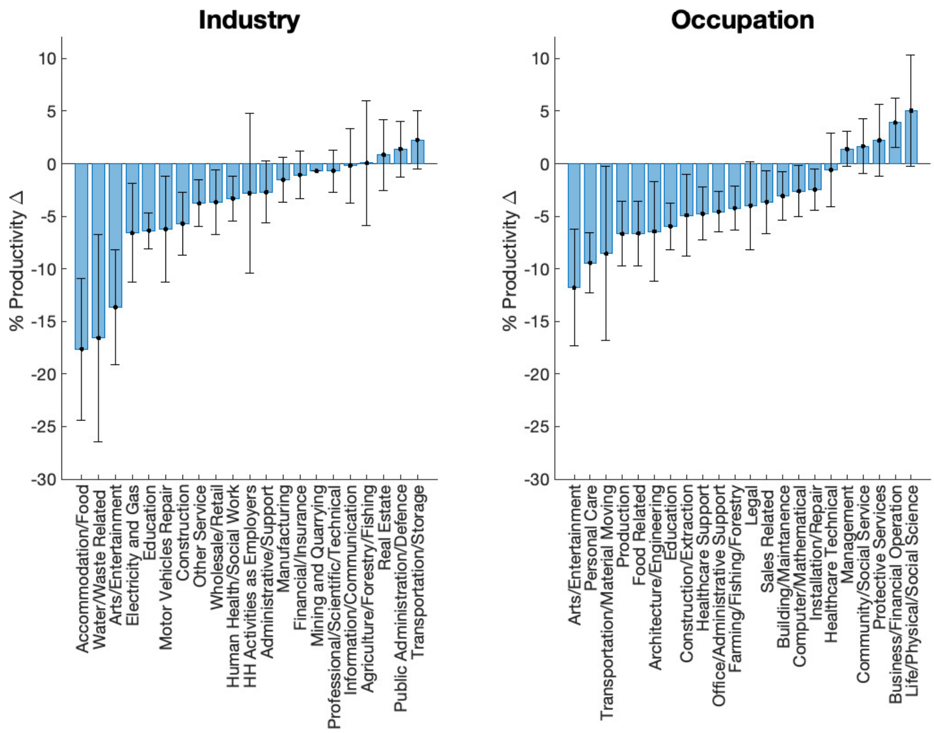
The remaining columns introduce additional controls, specifically dummies for industry, occupation, age and housing conditions. Interestingly, when we control for the housing environment, including the presence of spare rooms, a garden and adequate desk space, we find that these controls do little to explain away effects, apart from the coefficients on gender and parenthood. However it should be noted that these controls are fairly coarse, and we presume that fine occupational detail and a detailed treatment of the housing environment would explain a larger fraction of these productivity differences.

4.2 Changes in Productivity by Job Characteristics

A noticeable feature of the pandemic was differential performance and outcomes across different job types. For example, industry-specific policies were exploited during the pandemic, such as the prominent 'Eat Out to Help Out' policy instigated in the UK in August 2020, which successfully stimulated demand in the restaurant sector (Fetzer, 2022). More generally, commentators and researchers have observed the wide differential impacts by sector. Baqaee and Farhi (2022), 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.

We document some of this heterogeneity in Figure 1 by showing average productivity changes across industries and occupations in January 2021 compared to the baseline. Focussing on industries (left panel), the figure shows that during the second lockdown the majority of industries experienced a productivity loss compared to the pre-pandemic level. Indeed, 'Real Estate', 'Public Administration/Defence' and 'Transportation/Storage' were the only industries that exhibited productivity gains. As we show shortly, the degree of change in productivity across industries depends on job characteristics, as measured by external metrics. The ordering of industries is intuitive with the in-person services (such as 'Motor Vehicles Repair', 'Accommodation/Food' and 'Arts/Entertainment') experiencing the sharpest reductions in productivity while industries more suitable for home-work such as IT and finance sectors, performed reasonably well although the lockdown still created some productivity loss.

Figure 1: Mean Productivity Change in January 2021, by Industry and by Occupation



Note: This figure depicts the mean percentage productivity change by industry (left) and by occupation (right) from January/February 2020 to January 2021 using UKHLS Covid-19 module data. The lines correspond to the 95% confidence interval. Occupation information is taken from the 2019 UKHLS main survey responses and is converted into the 2-digit O*NET codes. See Appendix B.1 for additional details.

The right sub-plot of Figure 1 shows average productivity changes by occupation, also in January 2021. Here we take reported occupation stated in the 2019 wave of the UKHLS main survey as baseline and categorize workers using the 22 two-digit O*NET codes.[7] This panel shows that the occupation with the largest productivity increases were 'Life, Physical, and Social Science' and 'Business and Financial Operations'. These occupations require less physical contact than some of the other occupations and are relatively easier to be done at home than some other occupations, such as 'Healthcare Support'. The worst performing O*NET occupations include 'Personal Care', 'Education' and 'Arts/Entertainment'. For completeness, similar plots for June 2020, September 2020 and September 2021 can be found in Appendix C.

We next examine how our self-reported productivity changes relate to important job characteristics examined in the literature, again focusing on variation across occupations and industries. To this end, Figure 2 shows variation for January 2021 for three important metrics.

The top left sub-figure plots our measure of productivity change against average feasibility of WFH by occupation, taken from Adams-Prassl et al. (2022) who 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. Indeed we find a positive, albeit moderate correlation (weighted by occupation size) between this feasibility measure and reported productivity changes, $corr = 0.48$.

The top right sub-figure plots our self-reported productivity change against a measure of need for physical proximity with others, derived by Mongey et al. (2021), again using occupational O*NET descriptors. We expect a negative correlation between change in productivity and the need for physical proximity if our measure is capturing a similar underlying trait of occupations. Indeed, those occupations which are indicated to require close physical interaction between workers, such as 'Personal Care' and 'Arts and Entertainment' show the largest productivity declines during the lockdown. In fact, the correlation here is -0.37, indicating that individual productivity is just as much affected by this factor as pure feasibility of home work.

The bottom sub-figure compares our measure of productivity against aggregate output (value added) data from the ONS, which is provided at a relatively coarse industry division

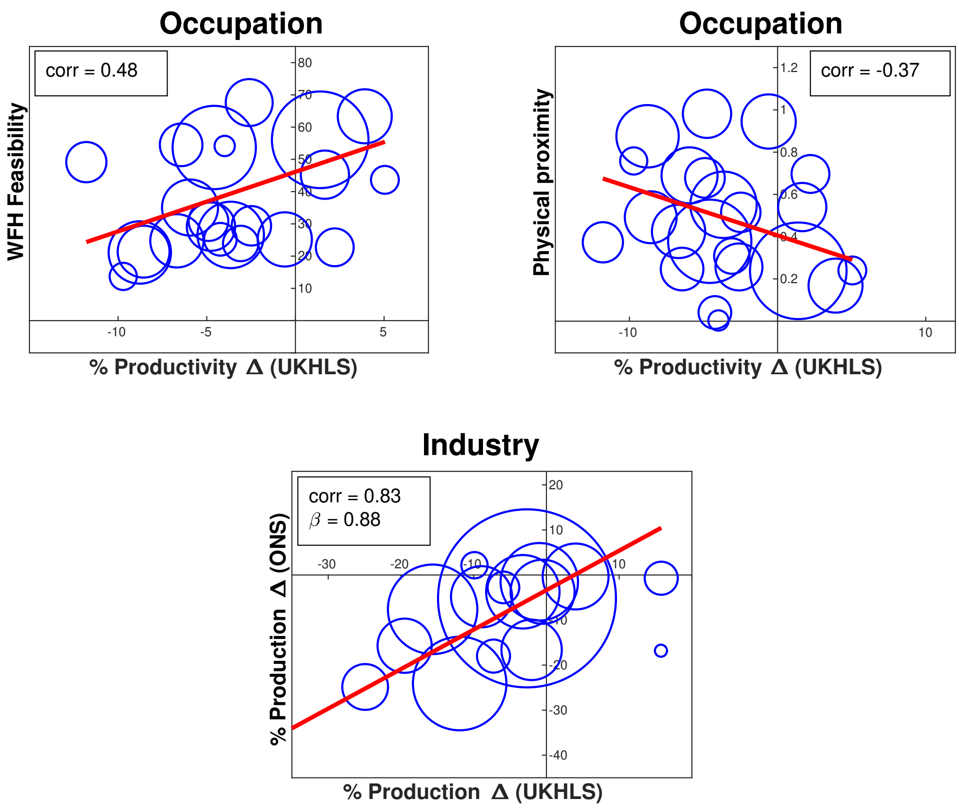
[7] As explained in Appendix B.1 and discussed above, the two-digit O*NET codes are derived by using a crosswalk to convert the 3-digit SOC 2000 codes contained in the UKHLS.

code level. For this plot we aggregate our individual level measure of productivity change into an implied sectoral-level change in total *output*, additionally using data on employment size and individual-level earnings and hours levels. We use output level rather than industry-level change in *productivity*, because a comparison with output change is in fact more straightforward to implement. We discuss this issue in further detail in Appendix B.2, where we show the calculations used to make either comparison.

This subplot shows that, in January 2021, the two measures have a strong correlation of 0.83. We also report that the beta on a weighted regression is 0.88, showing that the measures line up strongly in terms of quantitative magnitudes. We consider this relationship as remarkably strong given that there remain a few conceptual differences between our aggregated measure of output change and the change in sectoral output from the national statistics: in particular the measure on the horizontal axis accounts only for real productivity experienced by employees, while, for example, changes in profits due to shifts in output prices may also be important to changes in output at the sectoral level.

For completeness, we show the full set of comparable plots for each of these three measures additionally for June 2020, September 2020 and September 2021 in Appendix C, figures C.5, C.6 and C.7, with similar implications.

Figure 2: External Validation of Productivity Change Data for January 2021



Note: This figure depicts scatter plots of the UKHLS productivity change measure against alternative measures related to WFH used in the literature. The top two sub-figures compare the measures by occupation and the bottom sub-figure by industry. Bubble sizes are proportional to occupation/industry employment. The straight lines are the (weighted) lines of best fit. All statistics are weighted by employment. The top left sub-figure plots the UKHLS mean productivity change by occupation against the average WFH feasibility measure from Adams-Prassl et al. (2022). The top right sub-figure plots UKHLS mean productivity change by occupation against the measure of physical proximity from Mongey et al. (2021). The bottom sub-figure plots the UKHLS percentage change in output by industry against the ONS percentage change in output measure. For a discussion of the aggregation process see Appendix B.2. UKHLS occupation information is taken from the 2019 UKHLS main survey responses and is converted into the 2-digit O*NET codes. See the main text and Appendix B.1 and Appendix B.2 for a fuller discussion.

4.3 The Dynamics of Location Over the Pandemic

Section 3 showed that the proportion of hours spent WFH waxed and waned during the pandemic as various restrictions were tightened and relaxed. We have also shown that productivity during the pandemic varied systematically by characteristics of the individual and of the job. An interesting and natural question, therefore, is whether productivity experiences influenced location decisions as the pandemic progressed. We explore this question here.

To do this, we run dynamic regressions of the choice of location at time t during the pandemic on current characteristics, as well as past location outcomes. We additionally interact these past location outcomes with reported productivity change. The idea is that this interaction picks up the possibility of positive selection into WFH over time. When individuals were exposed to WFH early in the pandemic, those who reported productivity increases since the baseline should be more likely to continue WFH when restrictions were lifted in the autumn of 2020: Presumably both individuals would be more persuasive in asking for continued WFH, and firms would be more happy to carry on the arrangement. Likewise, those who reported productivity declines early in the pandemic would be more likely to be brought back into the workplace.

Table 3 reports the results of this exercise. Each column shows the estimates of a multinomial logit model of WFH in a separate wave of data, with successive addition of controls. The first column shows results for September 2020 with a full set of demographic controls, but not yet controlling for job or housing characteristics. Here the lagged observations of WFH come from June 2020 when, recall, we observe productivity outcomes only for those at least sometimes at home, and not those who remained full-time in the workplace. Our base omitted category in the lagged period is those who 'sometimes' or 'often' (which we refer to as 'part-time') WFH. Our prior belief is that this group is generally most likely to be the margin of moving between work locations. However, as we shall see, the group most on the margin differs from period to period.

The first column shows while there is a positive estimated coefficient on productivity for those who were part-time WFH in June 2020, it is not statistically significant. Neither is the full-time group significantly different from this part-time group. However, the bottom of the table shows that the marginal effect for those working full-time at home in June 2020 ('Sum: (1) + (3)') is 0.92 and is statistically significant. This implies that for those full-time at home in June there was a strong effect of reported productivity on later work location. This is intuitive: as restrictions were lifted, those who were full-time at home often had varied options of location in September. Their employers may have required them to come into work or kept them at home depending on the most productive outcome. The second column shows that this relationship remains when employment and housing controls are included.

The middle rows of Table 3 also show the pure effects of WFH status in the baseline period, from just before the pandemic, and in the previous period. All of these estimates have the expected sign. As seems intuitive, lagged WFH is much more important in predicting WFH status in September 2020 than the baseline WFH status. The point estimates imply that, conditional on full controls, an individual who was otherwise marginal and who was at home in

June 2020 was 20 percentage points more likely to WFH in September than someone who was previously in the workplace.

The third and fourth columns of Table 3 show results when we examine location choice during the second main lockdown in January 2021. In this set of regressions we can now also examine not only those who WFH part-time or full-time in September 2020, but those who never worked from home in this preceding period. The evidence presented in these columns is overall weaker, but again we see some revealing patterns. The top row of column four shows that, when we include a full battery of controls, there is some evidence that subsequent work location depended on productivity experiences for those who were part-time at home in September 2020: those who performed better were more likely to be at home in January 2021. On the other hand, for the other groups (full-time or never) there is no evidence of any effect of productivity. The contrast with June-September 2020, however, is important. Compared to that previous interval, as the economy transitioned back into lockdown in January 2021 then those who were full-time WFH in September 2020 were no longer marginal candidates for location choice, and their productivity experiences were no longer important. In fact, and although not shown explicitly in the table, among the group who WFH full-time in September 2020 we see very little variation in location outcomes in January 2021, which explains the larger standard errors.

Finally, we examine the interval from January 2021 to September 2021. Again the difference in results compared to the earlier intervals is instructive. Now the stand-out estimate is for those who were in the workplace in January 2021 (WFH_{t-1}=No). For these individuals, those who were more productive in the office were more likely to stay there and *less* likely to return home. In terms of quantities, for an otherwise marginal worker, being 10 percentage points more productive in the office translates to a 3 percentage points higher chance of staying away from home.

We view this 'negative' result for those not at home at all as a good test of our framework. To add to this, we hypothesize that for those not at home at all in June 2020, the effect of productivity experiences on subsequent WFH status would also be strongly negative. Unfortunately, however, the data are not available to test this.

The marginal effects from Table 3 (given by rows '(1)', 'Sum: (1) + (2)' and 'Sum: (1) + (3)') are also shown in Figure 3. We see clearly, and as just described, that the strongest effects on subsequent WFH status are for those who were full-time at home in June 2020 (positive effect)

Table 3: Dynamics of WFH: Effect of Past Productivity Outcomes

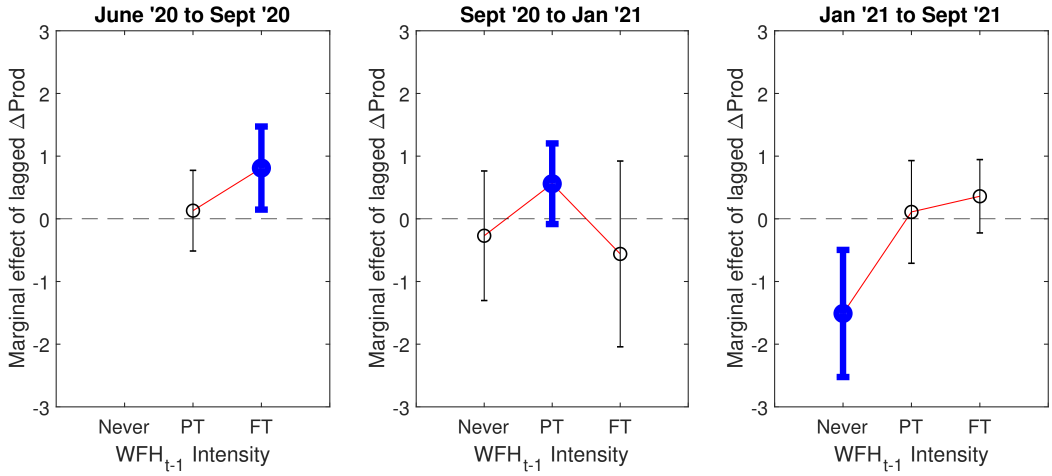
DV= WFH_t	Sept. 2020	Sept. 2020	Jan. 2021	Jan. 2021	Sept. 2021	Sept. 2021
(1) $\Delta Prod_{t-1}$	0.43	0.17	0.39	0.54*	0.10	0.07
	(0.30)	(0.32)	(0.32)	(0.32)	(0.41)	(0.42)
(2) $\Delta Prod_{t-1} \times WFH_{t-1} = \text{No}$			-0.58	-0.71	-1.46**	-1.57**
			(0.67)	(0.59)	(0.63)	(0.67)
(3) $\Delta Prod_{t-1} \times WFH_{t-1} = \text{Full-time}$	0.49	0.56	-1.10	-1.13	0.25	0.29
	(0.44)	(0.47)	(0.92)	(0.82)	(0.49)	(0.51)
WFH_{base} = No	-0.87***	-0.84***	-0.54***	-0.49***	-0.51***	-0.44***
	(0.10)	(0.12)	(0.15)	(0.16)	(0.13)	(0.14)
WFH_{base} = Full-time	0.58*	1.11***	-0.50	-0.48	0.45	0.54
	(0.34)	(0.36)	(0.54)	(0.59)	(0.32)	(0.34)
WFH_{t-1} = No			-1.61***	-1.68***	-2.08***	-2.17***
			(0.16)	(0.17)	(0.25)	(0.25)
WFH_{t-1} = Full-time	2.66***	2.38***	2.89***	2.77***	0.75***	0.74***
	(0.12)	(0.14)	(0.28)	(0.28)	(0.18)	(0.18)
Sum: (1) + (2)			-0.19	-0.16	-1.36***	-1.50***
			(0.59)	(0.51)	(0.48)	(0.53)
Sum: (1) + (3)	0.92***	0.73**	-0.71	-0.59	0.35	0.36
	(0.33)	(0.35)	(0.87)	(0.77)	(0.30)	(0.30)
Observations	2,789	2,789	3,845	3,845	3,435	3,435
Lagged WFH status (full set)	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Employment controls		Yes		Yes		Yes
Housing controls		Yes		Yes		Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: This table reports the estimates of an ordered logit model. The dependent variable is a trichotomous WFH variable valued 0 if never WFH, valued 1 if WFH part-time (sometimes or often) WFH, valued 2 if WFH full-time (always). The omitted category for lagged dependent variables on the right hand side is part-time WFH. The background control variables used are the same as those in the final column of Table 2, together with a full set of indicators for lagged WFH status. Survey weights are used throughout. Standard errors are clustered at the primary sampling unit level.

and never at home in January 2021 (negative effect), with some evidence of positive effects for those part-time at home in September 2020 and going into the subsequent lock-down.

Figure 3: Marginal Effect of Lagged $\Delta Prod$ Across Lagged WFH Status



Note: The above figures plot point estimates, together with 95% confidence intervals, of the marginal effects of lagged change in productivity, by lagged WFH status, on current WFH status. The raw estimates can be found in the second, fourth and final columns of Table 3. Solid and bolded points show effects that are significant at the 10% significance level. See text for more details.

We finish this section by examining again the middle rows of Table 3. The table shows that lagged and baseline WFH status continued to have a strong effect on current WFH status throughout the pandemic, even conditional on labour market controls such as industry and occupation and housing controls. In line with our main point, the coefficient on lagged WFH status also reflects the accumulation of previous experiences in specific work locations. As a nuance, it is worth noting that during the second lockdown of January 2021, baseline WFH status was less important in determining the location of work. For example, the coefficient on $WFH_{base} = Full{-}time$ is negative, and almost identical to $WFH_{base} = No$. This is not only compared to within-pandemic lagged WFH status, but also compared to the effect of baseline WFH status on locations in September 2020 and September 2021.[8] Clearly, in these periods of eased restrictions baseline WFH status was more indicative of workers' propensity to be at home.

5 Factors Affecting Productivity Across Locations

5.1 Empirical Framework

Section 4 showed that productivity changes since before the pandemic have varied systematically by individual characteristics, household circumstance and, importantly, characteristics

[8] Although not shown here, the coefficient on $WFH_{base} = Full{-}time$ is significantly different from that on $WFH_{base}{=}No$ at the 1% level in September 2021.

of the job. While this evidence provides important insights into unequal outcomes during the pandemic, and the evolution of WFH, it doesn't answer perhaps the key questions for individuals, businesses and policy makers. These include: what is the effect on productivity of WFH, and how does this depend on these characteristics? These are the raw questions addressed by Bloom et al. (2015), Atkin et al. (2023), Emanuel and Harrington (2023), and Gibbs et al. (2023). We now discuss our approach to answering these questions using a simple model of self-selection as in Heckman (1979) and French and Taber (2011). Intuitively to obtain selection-free estimates of key parameters we exploit instruments that affect preferences for work location during the pandemic but do not affect productivity. As we shall see in our application, unfortunately our empirical setting does not provide precise estimates of average treatment effects, but we can provide empirical rigour in identifying and estimating the marginal effect of characteristics across locations. In this way we contribute new evidence that is missing from studies that focus on narrower subsets of the population.

We lay out a full empirical framework in reasonable detail in Appendix D. Here we provide an intuitive discussion of the approach and discuss in further detail the elements that are non-standard. In particular, when considering selection into home/workplace, it is the difference in contemporaneous productivity across work locations that matters, but, in our data, we only observe productivity *changes*. Here we show that the model can be re-stated in terms of productivity changes naturally.

Our basic setup is as follows. Let productivity in each setting be given by:

$$\begin{aligned} prod^h_{it} &= g^h\left(X_{it}\right) + \epsilon^h_{it} \\ prod^f_{it} &= g^f\left(X_{it}\right) + \epsilon^f_{it} \end{aligned} \tag{1}$$

such that $prod^j_{it}$ is productivity in some suitable units (e.g. the logarithm of monetary units per hour), for individual i at time t, during the pandemic, in location j, with $j \in \{h, f\}$ denoting WFH or working from the office, respectively. X_{it} captures the bulk of characteristics that are relevant in either or both work locations, and which could be time-varying, such as work sector or infection status, or fixed, such as education, baseline WFH status, or the presence of children. ϵ^j_{it} is an unobserved mean-zero disturbance capturing idiosyncratic factors in each location.

Now define the extra utility effect of WFH compared to being located in the usual workplace as:

$$V_{it}^h = k\left(z_i, X_{it}\right) + \nu_{it} \tag{2}$$

where, importantly, z_i captures individual characteristics that affect utility but *not productivity* and v_{it} captures unobserved disturbances. The existence of z_i is key for identification. It is worth emphasizing that this model allows for decision making about location equally by the firm as much as by the individual. We use the term 'utility' broadly to capture all these factors, which might include strong employer preferences (even requirements) to be at home or in the office.

Given this set-up the decision rule is simple, individuals choose to work from home if there is an overall net gain in terms of productivity and utility. This is specified as:

$$j_{it}^* = \begin{cases} h & \text{if } prod_{it}^h - prod_{it}^f + V_{it}^h > 0 \\ f & \text{otherwise} \end{cases} \tag{3}$$

where j_{it}^* denotes the optimal work location choice for individual i at pandemic time t.

As mentioned above, in our data we only have access to productivity change information relative to a common baseline period. Therefore, to fit the data we have available, we next define *quasi*-differences in productivity as follows:

$$\tilde{\Delta} prod_{it}^j \equiv prod_{it}^j - prod_{i0}^{j^*}$$

This, importantly, captures the change in productivity at time t in each location j compared to the *observed* location j_0^* at time zero. Pre-pandemic work location is treated as given. The model could be enriched in this regard, but this would require additional instruments and is thus not pursued here. See Appendix D for further discussion.

Building on (3), it's the case that:

$$\begin{aligned} & prod_{it}^h - prod_{it}^f + V_{it}^h > 0 \\ \iff & \left(prod_{it}^h - prod_{i0}^{j^*}\right) - \left(prod_{it}^f - prod_{i0}^{j^*}\right) + V_{it}^h > 0 \\ \iff & \tilde{\Delta} prod_{it}^h - \tilde{\Delta} prod_{it}^f + V_{it}^h > 0. \end{aligned}$$

Therefore,

$$j^*_{it} = \begin{cases} h & \text{if } \tilde{\Delta} prod^h_{it} - \tilde{\Delta} prod^f_{it} + V^h_{it} > 0. \\ f & \text{otherwise.} \end{cases} \tag{4}$$

Thus we can rewrite the decision rule for location during the pandemic in terms of the quasi-differences, lending itself naturally to the data on productivity changes that are available.

In terms of identification, we observe j^*_{it}, $\Delta prod_{it} \equiv \tilde{\Delta} prod^{j^*}_{it}$ and the full array of covariates, including instruments z_i that affect the selection rule, but do not affect productivity. With these we can identify factors that affect productivity changes across locations. Again see the Appendix D for a more formal discussion.

Our candidates for instruments are variables affecting travelling to work in the pre-covid period: mode of travel, distance from work and reported travel difficulty. Our arguments for using these are twofold. First, we rely on a temporal argument: these variables are determined prior to the pandemic, and so they are not endogenous to work choices and outcomes during the Covid-19 outbreak. Second commuting difficulty should *prima facie* not affect productivity in any working location. As we will see, however, these variables clearly affected location choices.[9] One obvious reason for this is that how an individual travels to work impacts their exposure to infection and so their willingness to work away from home. As a final point, note that these variables are clearly not available for those who WFH full-time prior to the pandemic. We therefore exclude this 5% of the population, and base our conclusions on the sub-population of the workforce who previously worked away from home at least part time.

5.2 How Did Productivity Vary Across Work Location?

We now implement the selection framework presented above using a standard two-stage Heckman procedure. We start by presenting the first-stage probit regression of location choice on individual, employment and housing characteristics, and our excluded variables, the results for which are shown in Table 4. Here, and for the remainder of this section, we use a

[9] As discussed, we treat baseline WFH status as given, or exogenous in the model. In effect we argue that outcomes in the pre-pandemic period do not depend on commuting mode. As discussed in Appendix D our formal argument for this is that idiosyncratic productivity disturbances do not vary across work locations in the baseline period. Intuitively, the argument is that factors affecting productivity across locations before the pandemic were not nearly so heterogeneous, so selection issues are not such a concern.

binary outcome for location choice, combining as the WFH group those who are at home 'always' or 'often', and as the non-WFH group those who report 'sometimes' or 'never'. Across the dataset this splits the sample roughly in half.

The first column of Table 4 shows results for a model which includes pre-covid mode of transport interacted with distance to work. Most saliently, and as suspected, it shows that pre-pandemic commuting distance is strongly related to within-pandemic WFH for those who previously used public transport. It is likely that, for these workers, alternative routes to work were less available, and the danger of infection in transit was higher. On the other hand, distance does not seem so important for car users or users of other modes (mainly walking or cycling).

In the second column, we omit distance from work but include a binary indicator for reporting pre-covid travel difficulties. This indicator is only applicable to those who travelled by car or public transport. Overall the results show that, of all the groups, those who previously commuted by car, and without difficulties (the omitted category), were the most likely to continue visiting the workplace, and significantly more so than those who walked or cycled (see the 2nd row). Those who previously travelled to work by car and *did* have travel difficulties were also significantly more likely to WFH during the pandemic than the base group. This result suggests that commuting by car didn't become much easier during the pandemic, and that those whose commute was difficult took the opportunity to WFH when it was presented to them.

Finally, in the rightmost column, we include all of our instruments. Most of the insights remain, except that the role of travel difficulties is less significant when controlling for distance to work. Looking at the bottom of the table, we also notice that the chi-squared statistic on the excluded instruments is high across specifications indicating that these instruments have good explanatory power.

We now use these exclusion restrictions to explore factors that affect productivity, both at home and in the office. Of particular interest are the range of characteristics, such as features of the home environment, that are provided in the UKHLS survey, but difficult to find evidence on elsewhere. Results are shown in Table 5, where, as discussed above, we combine those who are 'always' or 'often' at home into the WFH group. It shows a range of factors across both locations, for two main specifications. The first two columns correspond to the broadest sample available. In all the regressions shown we use extensive controls, including for age,

Table 4: First Stage Estimates, WFH During Covid-19 and Pre-Pandemic Commuting Patterns

DV = WFH$_t$	(1)	(2)	(3)
Commuting mode (Base = Car)			
Public	-0.05	0.06	-0.04
	(0.08)	(0.09)	(0.09)
Other	0.23*	0.27***	0.27**
	(0.12)	(0.10)	(0.12)
Distance to work (Car)	0.02		0.01
	(0.02)		(0.02)
Distance to work × Public	0.23***		0.22***
	(0.05)		(0.06)
Distance to work × Other	-0.01		0.00
	(0.05)		(0.05)
Travel difficulties (Car)		0.09**	0.09*
		(0.05)	(0.05)
Travel difficulties × Public		0.11	0.01
		(0.12)	(0.13)
Observations	18,557	18,557	18557
χ^2 on displayed variables	29.09***	14.80***	34.23***
Wave dummy	Yes	Yes	Yes
Lagged WFH status	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes
Employment controls	Yes	Yes	Yes
Housing controls	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: This table presents estimates of a probit model of a WFH binary (= 1 if WFH full-time or WFH often) on the instruments displayed, and the same controls as those listed in Table 5. Distance to work is measured in the 10s of miles. Individual controls include region of residence, degree status, quartic age variable, earnings tercile, whether have a child under the age of 16, BAME status (binary), marital status and sex. Employment controls include occupation, industry, log of the number of employees in the firm the individual works for, whether the individual has managerial responsibilities, and whether the individual is self-employed. Housing controls include the number of rooms per person, home ownership binary variable, internet access, and whether everyone who works from home has sufficient desk space. Survey weights are used throughout. Standard errors are clustered at the primary sampling unit level.

education, together with occupation and industry dummies. In Table 5 we report results for those factors which have previously been shown to be generally important to productivity during the pandemic, or which we think *a priori* might affect productivity differentially across locations.

The first three rows of Table 5 show the role of key and relevant individual characteristics. Columns 1 and 2 show that, as might be expected, parenthood had a negative effect on productivity while WFH, but not on productivity in the workplace. The third column, which shows p-values on the differences between the first two columns, confirms this conclusion. The second row then shows the coefficient on a gender dummy. Here males reported relatively better productivity outcomes than females when in the office. Given that we control extensively for job and demographic characteristics we find this result somewhat surprising. Nevertheless, it may reflect the fact that the workplace environment changed substantially during the pandemic, and this affected different types differentially. We return to this point later in the discussion. Finally, among individual characteristics, we examine the effect of BAME status, for which unequal outcomes have been documented elsewhere during the pandemic (e.g. Crossley et al., 2021). Here, however, we find no evidence of differential productivity outcomes.

The next block of rows of Table 5 show the roles of job characteristics. Concentrating still on the results presented in columns 1 and 2, we find that those with managerial duties performed better than those without while in the home environment. Column 2, however, shows that this difference was not apparent in the workplace. These results suggest that managerial duties were positively impacted by the enforced introduction of remote working technology. The second row in the block echoes the findings from Table 2, and shows that the self-employed performed particularly badly away from the home, although the difference compared to the home environment is not significant. Moving on, the third row shows that those working for larger firms performed better at home than those working for smaller firms, and that this gap was significantly smaller in the workplace. This result confirms the natural suspicion that large firms were better able to adapt to a home working environment. Finally, we re-examine the association of productivity with position in the earnings distribution, shown previously in Table 2, where we documented that those in the top tercile of the earnings distribution performed significantly better than those on the lowest wages. The point estimates suggest that those with top earnings performed better than those in the bottom tercile when WFH, but overall, we lack the power to say anything more conclusive here. Nevertheless, in combination, the overall impression from the second block is that those in good jobs, with managerial duties, high earnings and working for large firms, enjoyed an advantage while WFH, and that, among employees, fewer differences arose in the workplace.

Rows 9-12 show three characteristics of the housing environment. Aside from providing substantive insights, these characteristics provide a validation of the data and framework, because they should not affect outcomes in the workplace. Indeed, column 2 shows that none of these characteristics are significant at the 10% level away from the home. In terms of the home environment, we find that the size of the house, as measured by rooms per person, actually had no noticeable effect on productivity. We next examine the presence or not of broadband connection. The prior here is of course that a good internet connection was crucial for home working (Barrero et al., 2021a). The point estimate on broadband is indeed large, but the proportion of people who report *not* having broadband is in fact tiny, and so the precision on this estimate is very low. Finally, we examine the effect of having deskspace for all members of the household who need it, which seems to have a substantial association with productivity changes when WFH. Of course, we should not overstate this result given that it is measured during the pandemic. Nevertheless, it does show that this is the type of characteristic blamed by those with adverse productivity experiences.[10]

We also report outcomes for those who previously had experience of WFH. Interestingly, we find no strong evidence that they performed better at home than those who were never at home just before the pandemic. Finally, at the bottom of the table we also report the coefficient on the inverse mills ratio, capturing the strength of selection. Although results here are not strong, the coefficients are of the anticipated signs and the point estimate in column one has a p-value of 0.11 (not shown). This is consistent with the message from Section 5 that selection into work location is important.

The right-hand side of Table 5 then shows effects when we include extra information on individual characteristics. Specifically we include measures of personality traits that have been found to relate strongly to outcomes during the pandemic, mainly in terms of mental health (See, for example, Proto and Zhang, 2021). It seems plausible that workplace performance has a role in this relationship. These measures of traits were collected in wave 3 of the main UKHLS survey, around a decade before the pandemic. We also include a derived cognitive test score from the same wave, that may also impact outcomes. We make additional use of the cognitive test score by trimming the bottom 5% of the score distribution in our base sample, in line with recent evidence that those with low scores are not able to formulate precise answers to the type of question we assess very well (D'Acunto et al., 2022). Accordingly, the sample size when using these data is somewhat smaller than in the results shown previously. In particular, the sample now includes very few individuals under age 30, for whom the cognitive tests and personality questionnaire was not administered.

The upper rows of the right-hand side of Table 5 repeat results for those characteristics shown on the left-hand side. Reassuringly, results are highly similar and only in a couple of instances do the reported levels of significance change.

[10] Respondents were asked: 'Thinking about everyone in your household who is currently working from home or home schooling. Does everyone have their own quiet space at a desk or table to work at?'

Turning to the cognitive score, we see that cognitive function, as measured by the first principle component from a battery of cognitive tests, did not impact outcomes in the workplace. However, the fourth column shows that those with higher cognitive function had *worse* outcomes while at home. Given that we control extensively for occupational and industrial characteristics, we interpret this not in terms of the type of work that more intelligent individuals perform, but rather that, for a given work task, the advantage that higher cognitive function confers was dampened while WFH.

Focusing next on the effect of traits, we see that the most noteworthy results are for agreeableness and for conscientiousness. As background to the discussion it is worth noting first that conscientiousness is reliably shown to be strongly positively associated with earnings *level* (Almlund et al., 2011; Prevoo and ter Weel, 2015): It captures facets such as industriousness and orderliness that promote high productivity and the accumulation of human capital (Gensowski, 2018). Here, we find positive point estimates on productivity changes in both working environments, even if the estimate is significant only in the workplace itself. Overall, this result indicates that those high in conscientiousness were better able to adapt to a working landscape that was rapidly changing. Indeed, and although not shown here, an average of the two coefficients from the fourth and fifth columns is significant at the 5% level.

Among the other traits, agreeableness is also typically shown to be associated with earnings, but *negatively* (Mueller and Plug, 2006): The polar opposite of agreeableness is disagreeableness, which is aligned with competitiveness (Almlund et al., 2011), and which has been shown to be predictive of labour market success (Reuben et al., 2015). Interestingly, however, we find that agreeableness is associated with significantly better outcomes during the pandemic in both home and workplace environments. One interpretation of this result therefore, is that the conditions which enable better outcomes for those who are more competitive, such as proximity to colleagues, were absent, and those with softer interpersonal styles were better able to adapt to new ways of interacting.

To conclude this section, we provide an estimate of the treatment effect of WFH on productivity. As discussed above, this is a key parameter that has been the subject of recent work, such as in Bloom et al. (2015). However, as also discussed previously, the breadth of our empirical setting and data do not suit a precise analysis. Nevertheless, we present results in Table 6. Recall first that Table 1 showed a naive comparison of means indicating that WFH correlated with better productivity growth during the pandemic on average. Pushing this further, the first column of Table 6 shows OLS results when adding background controls. It shows that the estimate on WFH remains positive and highly significant. The second column presents the estimates of a model with individual fixed effects, and therefore examines effects for those who move in and out of the home. For this group, the positive effect of WFH disappears. The final column shows the IV estimate, for which precision is noticeably reduced. In the context of our instruments, it indicates little evidence for a positive treatment effect. To say anything more conclusive, however, would require larger sample sizes or a research design which provides more power, such as examining a narrower set of occupations.

Table 5: Productivity Changes by Location: Controlling for Selection

DV = % Δ Productivity	WFH	Not WFH	p-value on difference	WFH	Not WFH	p-value on difference
Demographics						
Parent	-3.07**	0.07	0.02	-2.51*	-0.63	0.03
	(1.22)	(0.96)		(1.42)	(0.98)	
Male	-1.59	1.97**	0.01	-2.12*	1.75	0.00
	(1.16)	(0.86)		(1.34)	(1.03)	
BAME	-0.39	1.46	0.22	0.37	-0.79	0.12
	(1.96)	(1.42)		(2.24)	(1.60)	
Job Characteristics						
Managerial duties	2.99**	-0.24	0.02	4.15***	-0.40	0.00
	(1.22)	(0.84)		(1.33)	(0.98)	
Self-employed	-3.94	-5.14***	0.36	-0.92	-3.94**	0.00
	(2.89)	(1.73)		(3.01)	(1.97)	
Log size of firm	0.91**	-0.04	0.01	2.59***	0.34	0.01
	(0.36)	(0.24)		(0.81)	(0.58)	
Monthly net earnings: Middle tercile	0.69	0.58	0.48	0.19	-0.51	0.24
	(2.20)	(1.02)		(2.37)	(1.09)	
Monthly net earnings: Top tercile	3.22	0.71	0.01	2.63	-0.71	0.00
	(2.15)	(1.34)		(2.34)	(1.47)	
Housing characteristics						
Number of rooms in home, per person	0.85	0.54	0.38	0.69	0.86*	0.43
	(0.72)	(0.40)		(0.75)	(0.45)	
Home has internet access	8.82	4.45	0.00	6.23	6.11	0.45
	(7.61)	(4.37)		(8.54)	(4.51)	
All who WFH have desk space	4.82***	0.40	0.00	4.84***	-0.54	0.00
	(1.57)	(0.94)		(1.75)	(1.11)	
Baseline WFH						
Often/Sometimes	3.33	1.85	0.07	3.17	2.76	0.34
	(2.27)	(1.98)		(2.18)	(2.28)	
Cognition & Pers. Traits						
Cognition				-1.78**	0.01	0.04
				(0.70)	(0.48)	
Agreeableness				1.28**	0.86**	0.34
				(0.65)	(0.43)	
Conscientiousness				0.65	0.87**	0.41
				(0.60)	(0.44)	
Extraversion				0.54	-0.67	0.11
				(0.64)	(0.43)	
Openness				0.40	0.54	0.44
				(0.72)	(0.44)	
Neuroticism				-0.71	-0.46	0.40
				(0.65)	(0.41)	
$\widehat{\text{Inverse Mills}}$	-4.52	2.55	0.00	-3.50	1.28	0.00
	(2.86)	(2.98)		(2.64)	(3.48)	
Observations	8,873	9,684		6,649	6,903	
Wave dummy	Yes	Yes		Yes	Yes	
Region of residence control	Yes	Yes		Yes	Yes	
Occupation and industry controls	Yes	Yes		Yes	Yes	
Additional individual controls	Yes	Yes		Yes	Yes	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: This table presents estimates of OLS regressions of percentage change in productivity controlling for selection effects. The columns headed by ”WFH” contains estimates when using the sub-sample of individuals who reported WFH as ”always” or ”often”. The columns headed by ”Not WFH” contain estimates when using the sub-sample of individuals who reported WFH as ”sometimes” or ”never”. Additional individual controls include: age up to and including the fourth power, marriage dummy, degree dummy, whether home is owned. when estimating the model controlling personality traits, the sample is trimmed at the bottom 5% of cognitive scores, corresponding to a threshold standardized score of -1.5. Survey weights are used throughout. Standard errors are clustered at the primary sampling unit level.

Table 6: Effect of WFH on Productivity Change

DV = % Δ Productivity	OLS	FE	IV
WFH_t	4.11***	-0.27	4.65
	(0.92)	(1.14)	(13.29)
Observations	18,557	18,557	18,557
Background controls	Yes	Yes	Yes
Individual fixed effects		Yes	
Commuting instruments			Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The table presents estimates of various models specified by the column titles. The dependent variable is productivity change (percent) since the baseline period. Background controls are those reported in Table 4. Survey weights are used throughout. Standard errors are clustered at the primary sampling unit level.

6 Conclusion

Across the world, the Covid-19 pandemic caused widespread disruption to working practices, including, most saliently, a vast increase in working from home (WFH). This increase in WFH seems certain to persist beyond the end of the pandemic. This change has important implications for labour markets and economic geography and raises many questions on which answers are still needed. Most pertinently, it is important to understand which types of workers perform well at home, and why, and what factors determine workers' choice of location.

In this paper we investigate these issues using representative panel survey data from the UK, spanning the pandemic. These data contain both information on workers' current working location as well as detailed reports on changes in their productivity since before the pandemic's onset. The survey also contains a host of additional information on individuals, their jobs and their background environment.

We present three broad findings: First, we show that productivity changes were heterogeneous across the workforce, and systematically related to factors associated with ease of WFH: overall job quality as measured by wage level; gender and the presence of children, and feasibility of WFH in terms of job tasks. Second, we show that, as the pandemic progressed, workers sorted into locations - WFH or working in the office - depending on their previous productivity experiences. Third, and building on these insights, we control for endogenous sorting and estimate factors affecting productivity *across* locations: We find direct evidence that those with better jobs and working for larger firms had better productivity outcomes *at home* in particular; outcomes were more equal in the office.

Our findings show that workers and firms are able to sort into locations to suit individual-specific productivity outcomes. Our findings also have important practical implications: large firms were better at making WFH work effectively, and so smaller employers should look for ways to mirror their structures. This information is also useful for policy makers looking to provide these smaller employers with support. Our findings also prompt further research: the survey we use here will in future enable an analysis of post-pandemic outcomes. These data are also highly suited for examining the potentially important interplay between WFH with health outcomes, which we do not address here.

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Appendix A Imputing Productivity Changes from Qualitative and Banded Quantitative Survey Responses

As discussed in Section 3, and compared to wave 3 of the UKHLS Covid module survey (June 2020), waves 5, 7 and 9 ask two additional quantitative questions regarding productivity changes, for all interviewees who have reported productivity changes in the qualitative question. Specifically, for those who have reported gains in productivity the survey asks:

> *"Thinking about how much more you get done these days, would you say that what you can do in an hour now would previously have taken you:"*

Then interviewees are supposed to select one choice from following:

> *1 - Up to an hour and a quarter;*
>
> *2 - Between an hour and a quarter and an hour and a half;*
>
> *3 - More than an hour and a half*

Similarly, respondents who have reported declines in productivity are asked:

> *"Thinking about how much less you get done these days, would you say that what you can do in an hour now would previously have taken you:"*

Then they can select one choice from below:

> *4 - Between 45 minutes and an hour;*
>
> *5 - Between 30 and 45 minutes;*
>
> *6 - Less than 30 minutes.*

These choices directly imply percentage changes in productivity. For example, choosing "*1. Up to an hour and a quarter*" translates into what can be done in 60 minutes now would have previously taken up to 75 minutes. Thus, the upper threshold of percentage productivity change $\Delta prod$ during lockdown can be computed as:

$$\Delta prod = \frac{\frac{1}{60} - \frac{1}{75}}{\frac{1}{75}} = \frac{1}{4} = 25\%.$$

Therefore, choices 1 to 6, together with respondents answering their productivity stays the same as before the lockdown, imply the frequencies shown in the left hand labels column of Table A.1.

Table A.1: Response Frequencies of Productivity Change Variables

	June 2020	Sept. 2020	Jan. 2021	Sept. 2021
Quantitative question				
$>$ +50%		4.18	3.42	4.61
+25% to +50%		8.93	8.29	10.42
below +25%		9.71	9.74	10.45
no change		61.92	55.66	64.28
above -25%		6.47	8.62	4.55
-25% to -50%		5.65	8.06	3.69
-50 % to -100%		3.14	6.21	2.00
Qualitative question				
Much more	12.43	11.51	10.66	13.6
Little more	14.79	11.51	10.94	12.36
Same	43.05	61.32	54.73	63.62
Little less	19.72	9.92	13.75	7.45
Much less	10.00	5.74	9.92	2.87

Note: This table presents the response frequencies of the productivity questions in the UKHLS Covid waves. In each of the waves presented individuals are asked to qualitatively compare their current productivity per hour to their productivity in Jan/Feb 2020 (bottom half of table). From Sept 2020 onwards individuals that indicated their productivity changed in the qualitative question are also asked to quantify that change. Specifically they are asked how much time it would have taken them to get done what they previously achieved in an hour. Response options are specified in the row labels. See the text for more details. Sample weights are used throughout.

We fit a flexible Pearson type VII distribution to these quantitative responses. The survey questions provide 2 pairs of symmetric cutoffs for productivity change at -50%, -25%, +25% and +50%, respectively. In addition, we assume there exists a response interval $[a_1, a_2]$ such that any productivity change that falls within this interval is recorded as "same". Figure A.1 plots the Pearson distribution of (quantitative) productivity change, which is divided into 7 areas (A to G) by these thresholds. Let q^A, q^B, q^C, ..., q^G denote the size of area A, B, C, ..., G, respectively in the figure and $\Omega(\frac{(x-\mu)}{S}, \nu)$ denote the Pearson distribution with three distribution parameters: μ represents a shift in the distribution, S is the scaling parameter and ν is the parameter controlling kurtosis. This implies a system consisting of 7 equations corresponding to the size of each area in Figure A.1, with 5 unknown parameters (the distribution parameters plus a_1 and a_2). Then we solve the system of equations by selecting a combination of the parameters that minimize the sum of errors, weighted by the inverse of the actual size (fraction) of each area.

Figure A.1: Distribution of Productivity Change Quantitative Measure

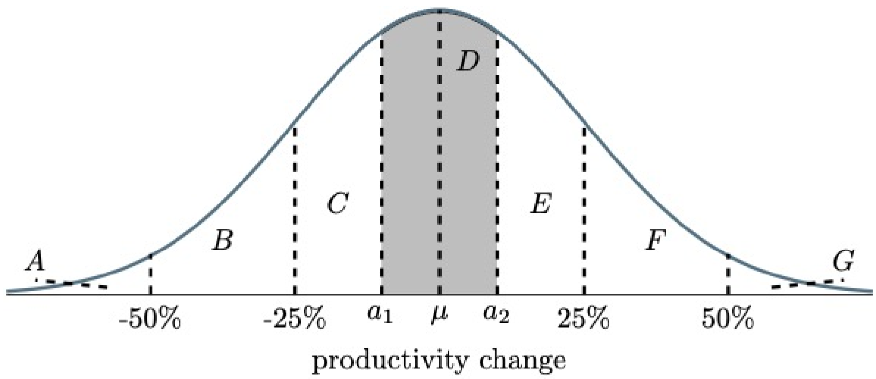


Table A.2 shows results for the three relevant waves. The computed response interval for reporting "same" is $[-0.15, 0.16]$ in September 2020, where a_1 and a_2 are sufficiently close in absolute values. For comparison, we also fit the data with Gaussian distributions, as displayed on the right hand side of Table A.2. The goodness of fit measure on the bottom row shows that the Pearson distribution fits the data much better in all waves.

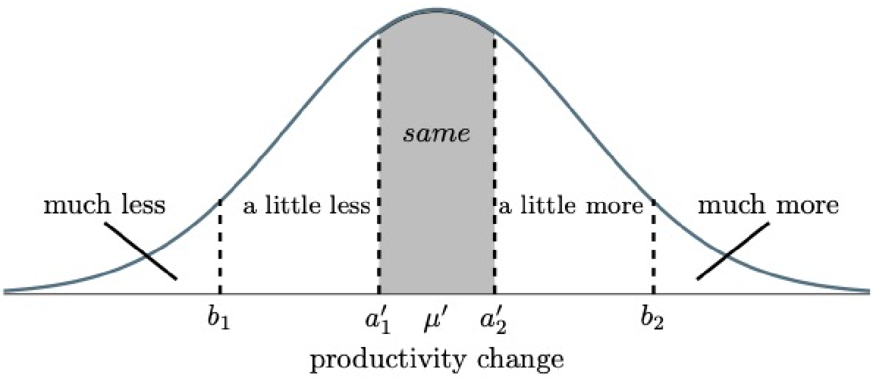
Table A.2: Imputing Productivity Changes from Banded Questions

	Pearson VII			**Gaussian**		
	Sept. 2020	Jan. 2021	Sept. 2021	Sept. 2020	Jan. 2021	Sept. 2021
Parameters						
Location (μ)	3.56	-0.61	7.99	2.04	-0.01	4.22
Scale (σ)	13.52	15.33	11.39	18.94	20.82	18.16
Shape (ν)	1.87	1.77	1.70			
Cut-off 1 (a_1)	-15.21	-15.69	-14.21	-17.49	-16.73	-18.21
Cut-off 2 (a_2)	16.14	14.20	17.55	16.69	15.89	17.06
Cell means						
$>$ +50%	76.19	78.08	76.16	56.06	56.90	55.83
+25% to +50%	34.17	34.6	33.78	33.04	33.48	32.98
below +25%	20.07	18.95	20.86	20.55	20.12	20.76
no change	1.70	-0.70	4.67	0.19	-0.36	0.75
above -25%	-19.51	-19.86	-18.86	-20.94	-20.6	-21.31
-25% to -50%	-34.5	-34.55	-34.71	-32.61	-33.49	-32.07
-50 % to -100%	-77.69	-77.84	-79.66	-55.72	-56.91	-55.16
Goodness of fit	4.24E-04	0.0073	0.0025	0.0208	0.0271	0.0197

Note: To impute the percentage change values for each band of the productivity change responses we assume a continuous underlying distribution and minimize the squared distance between the simulated density and observed density for each of the Pearson VII distribution and the Gaussian distribution. Figure A.1 and Figure A.2 illustrate how the bands make up the continuous distribution. The top half of the table presents the parameters from the resulting distributions. The bottom half of the distribution provides the estimates of the mean percentage change in productivity within each band. The goodness of fit displays the sum of squared distances. See text above for more details.

Our analysis also makes use of the qualitative information from June 2020. To illustrate the data structure for these, Figure A.2 plots the distribution for qualitative answers to productivity change, with two thresholds that distinguish answers of "a little less productive" from "much less productive", and "a little more productive" from "much more productive", respectively and the response interval $[a'_1, a'_2]$ for reporting "same". We use these data by first comparing the qualitative and quantitative responses from *September* 2020 as follows: From the fitted distribution above, we impute the two pairs of threshold, b_1, b_2 and a'_1, a'_2, to match the distribution of responses to the September wave qualitative question. b_1 and b_2 are found to be -34.17% and 27.29%, respectively, and $[a'_1, a'_2]$ is near identical to $[a_1, a_2]$.

Figure A.2: Distribution of Productivity Change Qualitative Measure



Finally, to operationalize the June 2020 data, we assume that the thresholds b_1, b_2, a'_1 and a'_2 are identical across June and September. All that remains is to fit another Pearson distribution (i.e. mean, variance and kurtosis parameters) to match the distribution of responses in *June* 2020. Therefore, we solve a system of 5 equations in terms of the size of each areas in Figure A.2, with three unknown distribution parameters. Based on this fitted distribution the imputed average productivity changes to answers of "*much less productive*", "*a little less productive*", "*a little more productive*" and "*much more productive*", for June 2020, are -44.9%, -22.4%, 22.3% and 40.8%, respectively.

To validate the data and our imputation we carry out basic analyses to test internal consistency. These are shown in Table A.3. The first two columns show logit regressions of the responses to the qualitative questions in waves 5, 7, and 9, on the responses to the banded quantitative questions. They show, for example, that when someone responds "much more" to the qualitative question, they are far more likely to also provide the strongest response to the quantitative question than the less strong response. The third column uses ordered logit regressions to show correlations over time. It shows that those who responded "much more" in the previous wave respond with far stronger responses in the current wave. While there could be many reasons for this pattern, including individual fixed effects in the nature of responses, this column does show convincingly that the survey responses are not just random noise. Finally the last column shows a similar pattern using the imputed quantitative questions as a continuous measure. The R^2 indicates that the correlation of the responses across waves is around 0.35.

Table A.3: Internal Consistency of Productivity Questions

	Logit	Logit	Ordered Logit	OLS
	"Much more"	*"Much less"*	Qual. cat.	$\Delta Prod$
	(1)	(2)	(3)	(4)
Quantitative category				
(base α_2 to -25%)				
+25% to +50%	0.62			
	(0.07)			
>+50%	1.56			
	(0.10)			
Quantitative category				
(base α_1 to -25%)				
-25% to -50%		0.80		
		(0.11)		
-50% to -100%		2.46		
		(0.12)		
Lagged qualitative category				
(base *"Much less"*)				
"Little less"			0.42	
			(0.09)	
"Same"			1.22	
			(0.08)	
"Little more"			2.29	
			(0.09)	
"Much more"			3.13	
			(0.095)	
$\Delta Prod_{t-1}$				0.31
				(0.01)
Constant	-0.55	-1.51		0.07
	(0.07)	(0.10)	(0.01)	
N	4,046	2,605	10,818	10,631
(pseudo) R^2	0.05	0.15	0.07	0.13
Wave dummies	Yes	Yes	Yes	Yes

Note: Table shows results of four exercises to examine the properties of the productivity change data. Columns 1 and 2 show correlations of the qualitative question and quantitative question within period. Columns 3 and 4 show correlations within the question type over time. Specifically, Column 1 shows results of a logit regression comparing responses *"Much more"* and *"Little more"* with the three possible associated quantitative responses, treated as categorical outcomes. Column 2 shows a parallel logit regression for responses "Much less" and "Little less" with binaries for the associated quantitative responses. Column 3 shows an ordered logit of the response to the qualitative question in wave t on the lagged qualitative question. Column 4 shows a parallel OLS regression the qualitative question, here treated as a continuous variable. See text for more details.

Appendix B Additional Information on Supplementary Data Sources

B.1 Cross-walk between SOC2000 and O*NET Occupation

Table B.1 shows the cross-walk this paper adopts to convert the Standard Occupational Classification (SOC) 2000 to the Occupational Information Network (O*NET) codes, taken from 2020. Specifically, we assign each 3-digit SOC (sub-major occupation groups) into 2-digit O*NET codes (major occupation groups) by first matching 4-digit SOC (sub-sub-major occupation groups) codes 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.

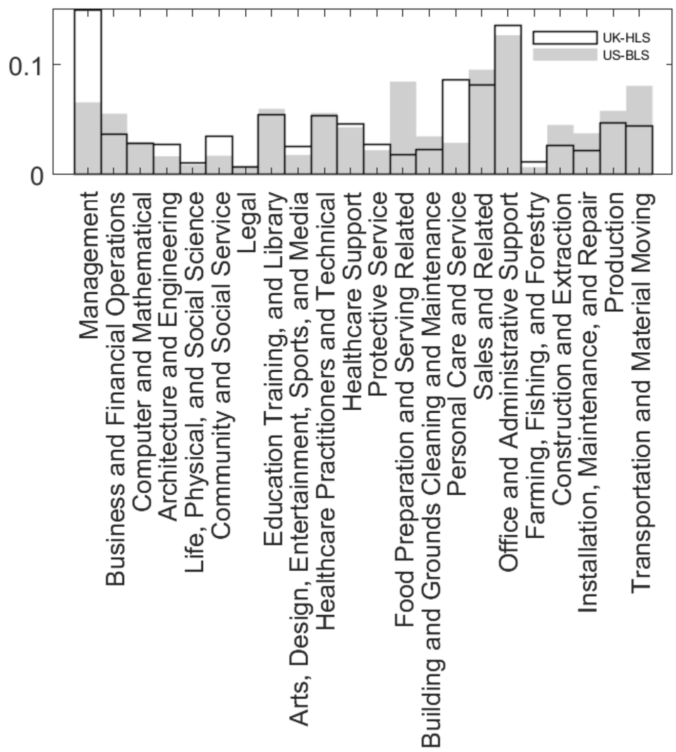
Although in most cases the overwhelming majority of 4-digit SOC codes are assigned to the same 2-digit O*NET code, this is not always the case. As a result, some matches between SOC 2000 and O*NET codes are necessarily imprecise. For instance, SOC 231 'Teaching Professionals' is classified into O*NET 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 in the UKHLS, we are unable to specifically subtract sub-sub-major occupation group SOC 2317 from sub-major occupation group SOC 231. [11] In one case, we use industry information to split SOC 922 'Elementary Personal Services Occupations', which is mainly lined up with O*NET code 39. In this case, however, 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 these respondents into O*NET 35 'Food Preparation and Serving Related Occupations'. Table B.1 shows the full assignment.

To show the quality of the match, Figure B.1 plots occupation distributions of respondents from wave 9 and the Covid module of UK Household Longitudinal Study (UKHLS), based on the imputed O*NET employment shares, together with national employment statistics from 2019 US Bureau of Labor Statistics (BLS). In the figure, white columns represent occupation

[11] As an additional example, we would ideally move SOC 5241 'Electricians' out of O*NET 49 'Installation, Maintenance, and Repair Occupations' and into O*NET 47 'Construction and Extraction Occupations' if we had the 4-digit measures.

percentages in UKHLS and grey columns represent 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. (2022). Similarly, the US is more intensive in Food Serving (waiting). If we exclude these occupations, the correlation coefficient between UK and US occupation percentage rises to around 0.8.

Figure B.1: Occupation Percentage Distributions, UKHLS and US-Bureau of Labor Statistics (BLS)



B.2 Aggregate Production Data from the ONS

Figure 2 in Section 4 shows a comparison of the UKHLS-Covid productivity data with aggregate information from the UK Office for National Statistics ONS. As discussed in the main text, the ONS data are presented at a much coarser industry division level of aggregation. For example the Covid survey has 13 sub-industries within the single ONS category of 'manufacturing'. The ONS categories are (with rough shortened titles): Agriculture; Mining and Quarrying; Manufacturing; Energy; Water supply and Sewage; Construction; Wholesale and

Retail Trade; Transportation and Storage; Accommodation and Food; Information and Communication; Finance; Real Estate; Professional Services; Administrative Services; Government Services; Arts; and Other Services. We use data from the quarter which contains the month of the UKHLS wave. However, for baseline data we use those from 2019 Q4. We consider this as providing a better fit with the January/February 2020 baseline in the Covid survey, because 2020 Q1 data are affected by the start of the pandemic.

The more complicated aspect of the comparison is that comparing individual productivity changes to aggregate data is non-trivial. We show the relevant calculation below. To simplify the computation somewhat we align our data to a measure of aggregate production change from labour inputs at the industry level as follows:

$$
\begin{aligned}
\Delta \ln Y_t \approx & \quad \frac{\sum_i y_{it} - \sum_i y_{it-1}}{\sum_i y_{it-1}} \\
= & \quad \frac{1}{\bar{Y}^{S+L}_{t-1}} \left[p^S \bar{Y}^S_{t-1} \sum_{i \in S} w^S_{it-1} \left(\Delta \ln prod_{it} + 1 \right) \frac{h_{it}}{h_{it-1}} + p^E \bar{Y}^E_t - p^L \bar{Y}^L_{t-1} \right]
\end{aligned} \tag{5}
$$

where we decompose the industry-level workforce into three groups: stayers, S; industry leavers, L, and industry entrants E. Then $\bar{Y}^X_t$ is average output at time t for group X (e.g. stayers), n^X is population size of group X and $p^X \equiv \frac{n^X}{n^{S+L}}$. h_{it}, h_{it-1} are hours of individual i at times t and $t-1$, and y_{it-1} is output/earnings of individual i at time $t-1$. Finally, and importantly, we calculate weights, $w^S_{it-1} \equiv \frac{1}{n^S} \sum_{i \in S} \frac{y_{it-1}}{\bar{Y}^S_{t-1}}$ that sum to 1 and capture relative position in the earnings/output distribution.

Almost all of the elements in (5) are observable. In particular, individual-level industry codes are observed in each of waves 3, 7 and 9. The only component we do not directly observe is earnings y_{it} in the Covid period. Here we assume that average earnings for this group $\bar{Y}^E_t$ are equal to baseline earnings for the stayers. The calculation is robust to altering this assumption because for most industries the proportion of entrants p^E is small, and so the contribution to the overall calculation is also small.

On the side of the aggregate data we use the percentage change in gross value added. In terms of national accounting concepts, this quantity includes not only change in contribution of workers, but change in profits. In effect therefore, we assume that these components move in parallel.

Figure C.7 shows this computation in each wave of data: June and September 2020, and January and September 2021.

To complete the discussion we return to the comparison of aggregate productivity. Aggregate productivity can be expressed in terms of individual level variables as follows:

$$\Delta \frac{\ln Y_t}{\ln H_t} \approx \frac{\frac{\sum_i y_{it}}{\sum_i h_{it}} - \frac{\sum_i y_{it-1}}{\sum_i h_{it-1}}}{\frac{\sum_i y_{it-1}}{\sum_i h_{it-1}}}$$
$$= p^S \frac{\bar{Y}^S_{t-1}}{\bar{Y}^{S+L}_{t-1}} \left(\frac{\dot{Y}^S_t}{\dot{H}_t} \sum_{i \in S} w^S_{it} \Delta \ln relhours_{it} + \sum_{i \in S} w^S_{it-1} \Delta \ln prod_{it} \right) + p^E \frac{\bar{Y}^E_t}{\bar{Y}^{S+L}_{t-1} \dot{H}_t} - p^L \frac{\bar{Y}^L_{t-1}}{\bar{Y}^{S+L}_{t-1}}$$

where we use the same notation as that used in (5), and additionally $\dot{X}_t \equiv \bar{X}^{E+S}_t / \bar{X}^{S+L}_{t-1}$ is the growth in the average of variable X, $\dot{X}^S_t \equiv \bar{X}^S_t / \bar{X}^S_{t-1}$ is the growth for stayers only, and $\Delta \ln relhours_{it} \equiv \frac{h_{it} - h_{it-1} \dot{H}_t}{h_{it}}$ is a measure in change of hours share: Intuitively, if relative hours go down for low-wage workers, then aggregate productivity goes up.

Table B.1: Cross-walk from 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

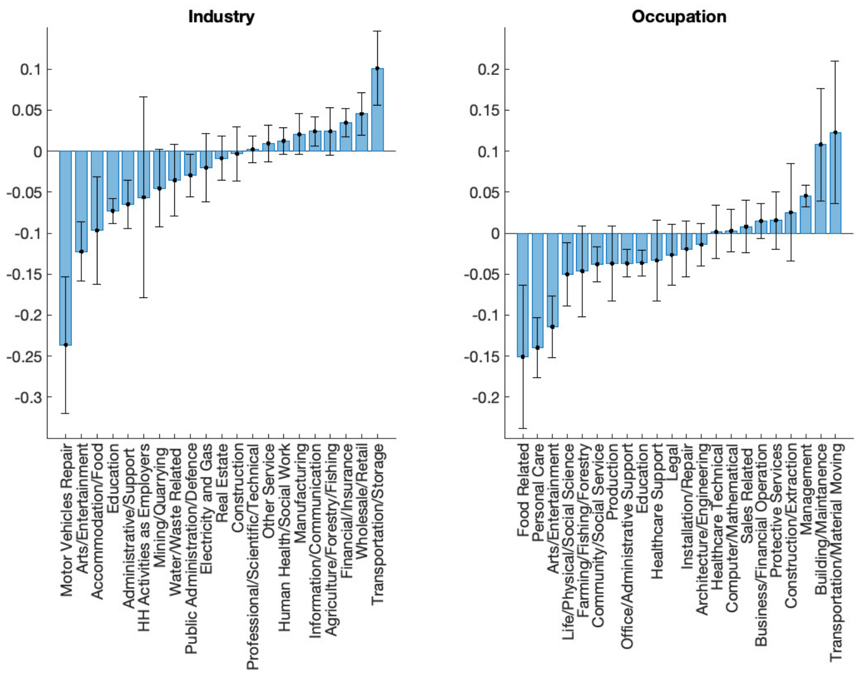
Cross-walk from 3-digit SOC 2000 to 2-digit O*NET Classification (continued)

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.

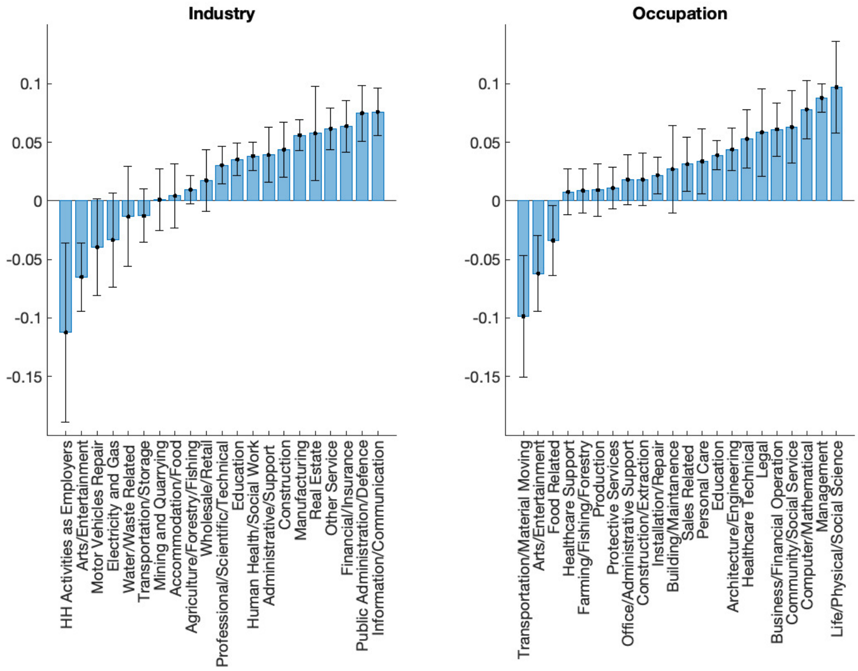
Appendix C Additional Figures and Tables

Figure C.1: Mean Productivity Change in June 2020, by Industry and by Occupation



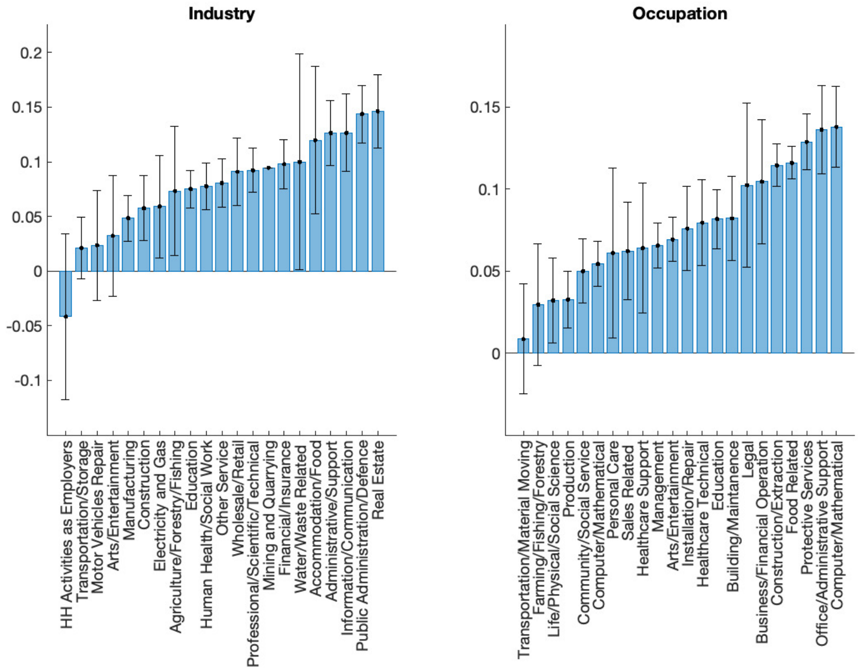
Note: This figure depicts the mean semi-standardized productivity change by industry (left) and occupation (right) from January/February 2020 to June 2020 using UKHLS Covid-19 module data. The lines correspond to the 95% confidence interval. Occupation information is taken from the 2019 UKHLS main survey responses and is converted into the 2-digit O*NET codes. See Appendix B.2 for additional details.

Figure C.2: Mean Productivity Change in September 2020, by Industry and by Occupation



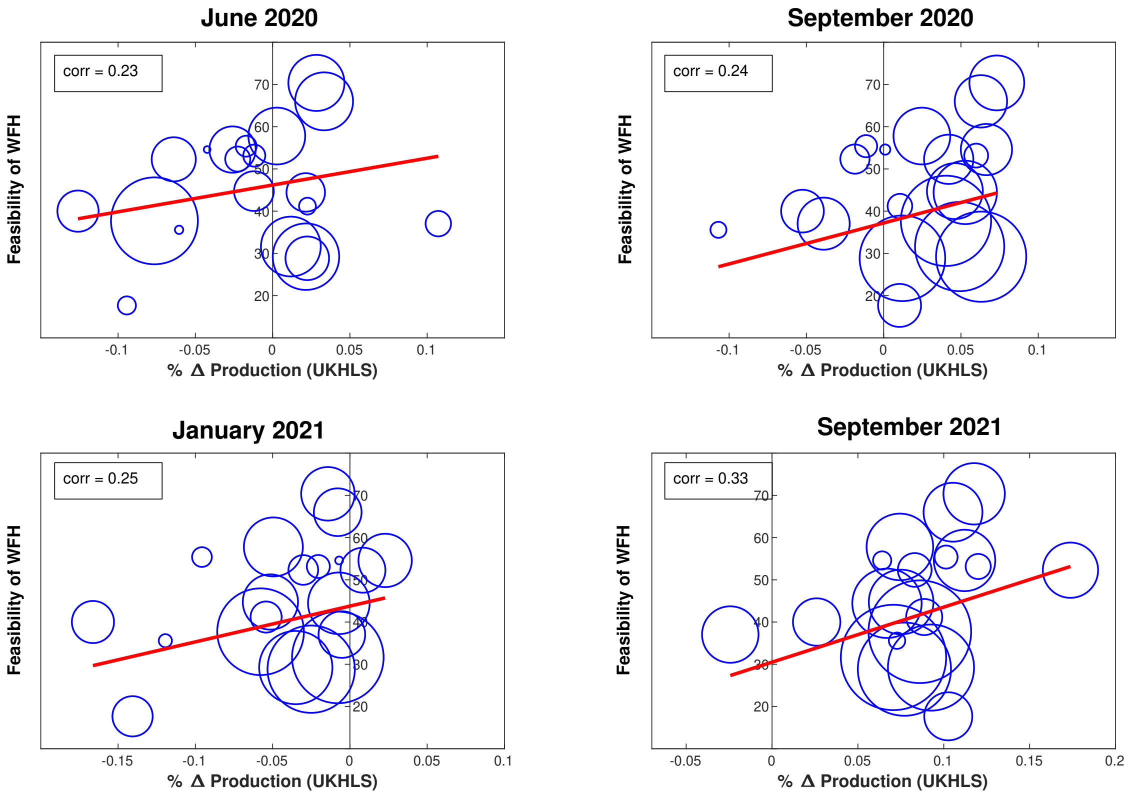
Note: This figure depicts the mean semi-standardized productivity change by industry (left) and occupation (right) from January/February 2020 to September 2020 using UKHLS Covid-19 module data. The lines correspond to the 95% confidence interval. Occupation information is taken from the 2019 UKHLS main survey responses and is converted into the 2-digit O*NET codes. See Appendix B.2 for additional details.

Figure C.3: Mean Productivity Change in September 2021, by Industry and by Occupation



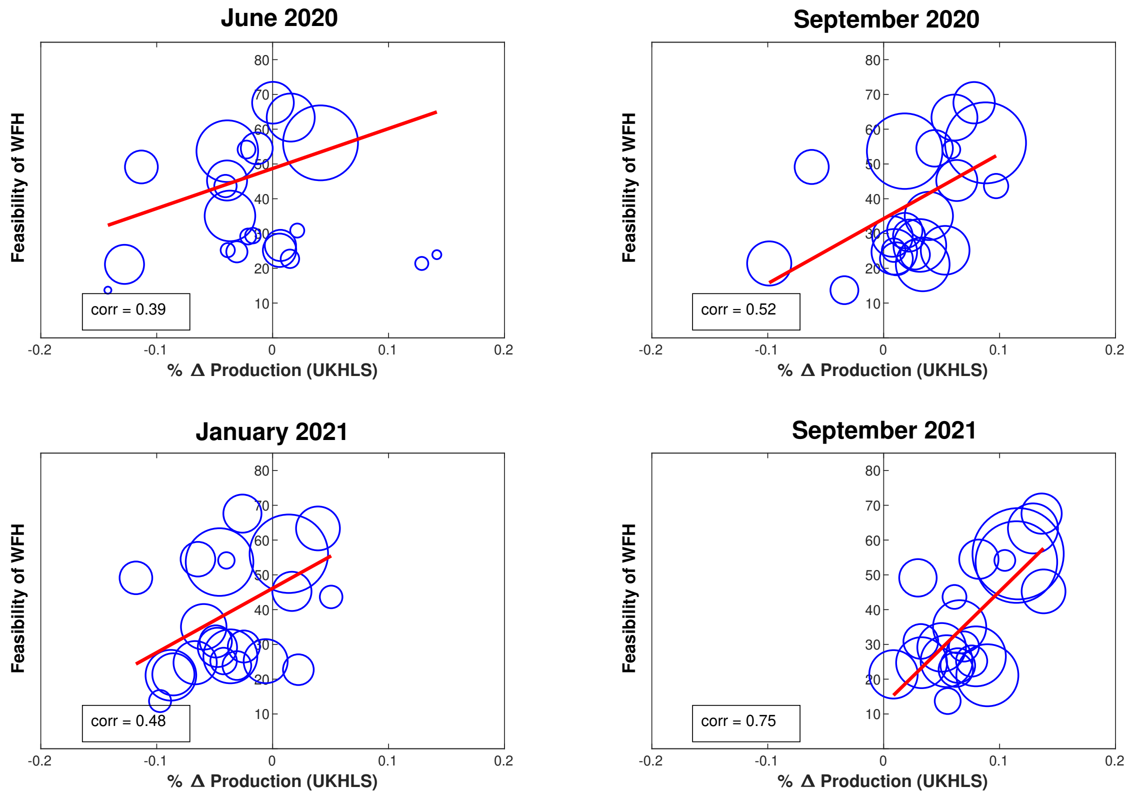
Note: This figure depicts the mean semi-standardized productivity change by industry (left) and occupation (right) from January/February 2020 to September 2021 using UKHLS Covid-19 module data. The lines correspond to the 95% confidence interval. Occupation information is taken from the 2019 UKHLS main survey responses and is converted into the 2-digit O*NET codes. See Appendix B.2 for additional details.

Figure C.4: Productivity Changes and WFH Feasibility by Industry



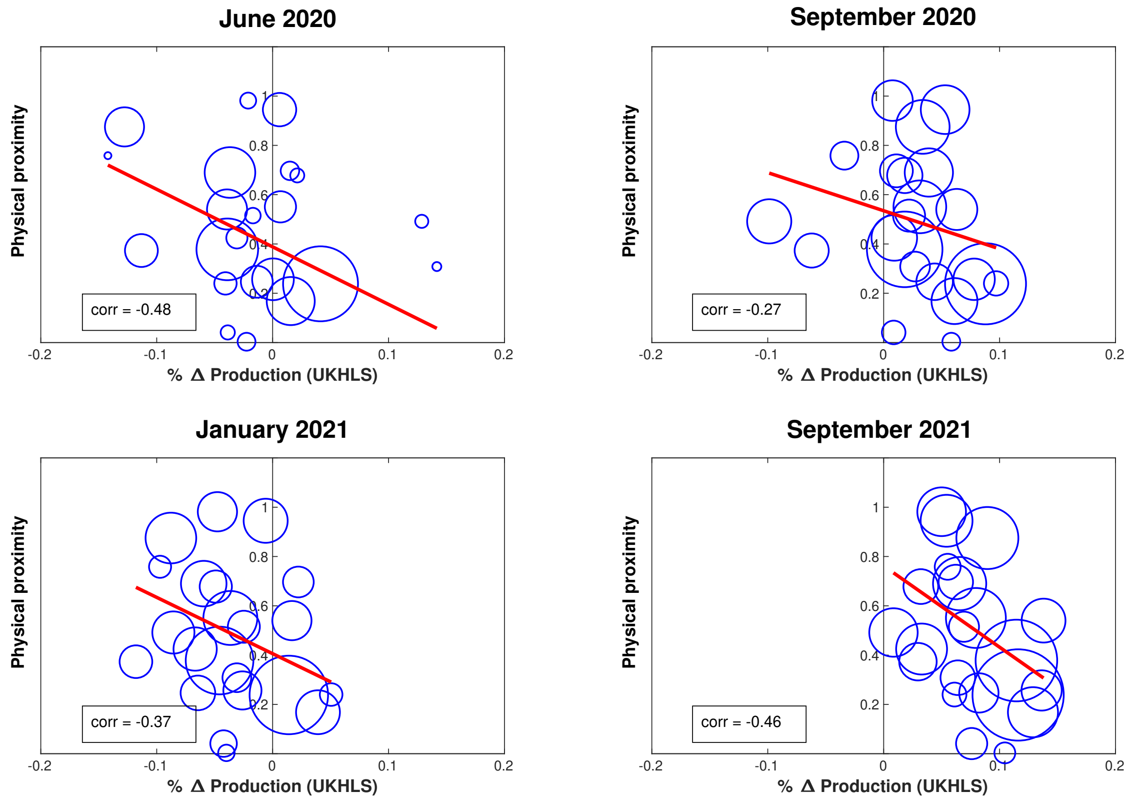
Note: Figure shows scatter plots of productivity changes against the measure of feasibility of WFH from Adams-Prassl et al. (2022), by baseline industry measured in the Covid survey, and by survey wave. Bubble sizes are proportional to industry employment. The solid line is the line of (weighted) best fit. See text for more details.

Figure C.5: Productivity Changes and WFH Feasibility by Occupation



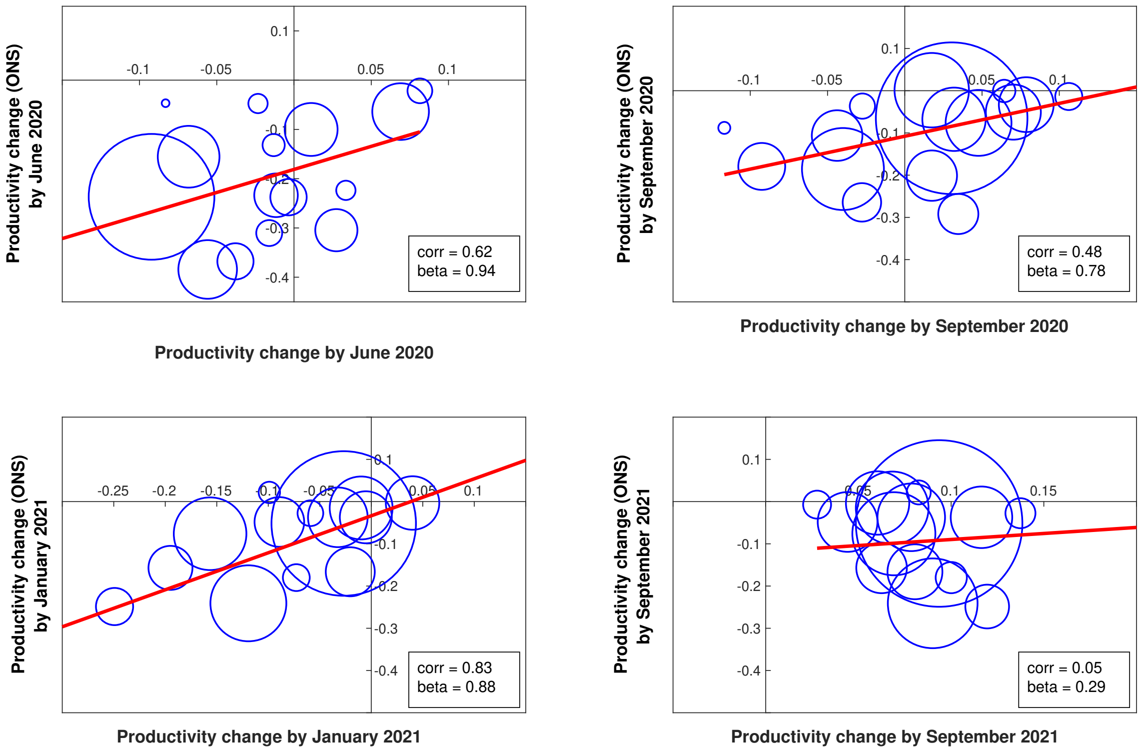
Note: Figure shows scatter plots of productivity changes against the measure of feasibility of WFH from Adams-Prassl et al. (2022), by baseline occupation measured in the Covid survey, and by survey wave. Bubble sizes are proportional to occupation employment. The solid line is the line of (weighted) best fit. See text for more details.

Figure C.6: Productivity Changes and Physical Proximity Needed for Job by Occupation



Note: Figure shows scatter plots of productivity changes against measure of physical proximity in job from Mongey et al. (2021), by occupation and by survey wave. Bubble sizes are proportional to occupation employment. Solid line is a line of (weighted) best fit. Occupation is from 2019 Covid Survey, converted to 2-digit O*NET code. See Appendix B.1 for fuller discussion and main text for further details.

Figure C.7: Production Changes: Self Reported vs ONS aggregate



Note: Data from Office for National Statistics and Covid module of UKHLS. Figure shows scatter plots of aggregate production changes estimated using the UKHLS Covid data against external ONS aggregate data by industry. See Appendix B.2 for detailed details of the computation.

Table C.1: Summary Statistics

	N	Min	Max	Mean	Standard deviation
Demographic					
Male$^{\aleph}$	19,293	0	1	0.47	0.50
Age$^{\aleph}$	19,293	17	65	43.24	12.14
Degree*	19,293	0	1	0.42	0.49
Children in hh$^{\aleph}$	19,293	0	1	0.35	0.48
Region of residence*	19,293	1	12	6.27	3.00
London	19,293	0	1	0.11	0.31
South East	19,293	0	1	0.14	0.35
Married*	19,293	0	1	0.65	0.48
Race$^{\aleph}$	19,293	1	4	1.14	0.51
White	19,293	0	1	0.92	0.27
Covid Work					
Working from home$^{\aleph}$	19,293	1	4	2.68	1.32
Always	19,293	0	1	0.32	0.47
Never	19,293	0	1	0.44	0.50
Baseline period wfh$^{\clubsuit}$	19,293	1	4	3.53	0.80
Always	19,293	0	1	0.04	0.20
Never	19,293	0	1	0.68	0.47
Productivity change (qualitative)$^{\aleph}$	19,293	1	5	3.17	0.94
Imputed productivity change (quantitative)$^{\aleph}$	19,293	-0.80	0.78	0.04	0.25
Other Employment					
Baseline monthly net earnings$^{\clubsuit}$	19,293	125	17,200	1,901	1,225
Self-employed*	19,293	0	1	0.05	0.22
Managerial duties*	19,293	0	1	0.48	0.50
Size of firm*	19,293	1	12	5.80	2.84
1000 + employees	19,293	0	1	0.17	0.37
Industry$^{\aleph}$	19,293	1	22	13.23	5.53
Occupation*	19,293	11	55	30.02	13.90
Commuting to work					
Distance to work*	18,557	1	100	11.26	14.80
Commuting mode*	18,557	1	3	1.31	0.58
Car	18,557	0	1	0.75	0.43
Difficulties travelling to work*	18,557	0	1	0.48	0.50
Housing					
People in household*	19,293	1	11	3.03	1.30
Number of rooms in home*	19,293	2	10	5.03	1.69
Own home*	19,293	0	1	0.74	0.44
Home has internet access*	19,293	0	1	0.98	0.12
All who wfh have desk space$^{\aleph}$	19,293	0	1	0.79	0.41
Individual Traits					
Agreeableness*	13,552	1	7	5.51	1.01
Conscientiousness*	13,552	2	7	5.50	0.99
Extraversion*	13,552	1	7	4.53	1.27
Neuroticism*	13,552	1	7	4.57	1.18
Openness*	13,552	1	7	3.67	1.36

Note: * - Underlying data comes from UKHLS main survey waves. ℵ - Underlying data comes from Covid survey waves. ♣ - Underlying data comes from Covid survey and refers to Jan/Feb 2020. The sample contains working age individuals (17-65) who report being employed or self-employed and are not on furlough. If the individual reports being in work but works 0 hours (less than 5 hours), they are presumed to be on furlough (from wave 4 on wards). Individuals are considered to be married is they are legally married, in a civil union or are cohabiting with a partner. Productivity change variables ask individuals to compare their current productivity to the baseline period Jan-Feb 2020. Difficulties travelling to work are recorded for those who travel by private transport or by public transport. The latter is only asked in UKHLS main survey wave 10. Individual skills information was collected in the third wave of the UKHLS main survey and corresponds to the question about agreeableness. Earnings, the total number of rooms in the house and distance to work have been winsorized at the 99th percentile. Missing variables are imputed for the desk space variable by estimating a probit regression of desk space on individual controls, employment controls and housing controls and obtaining predicted values. If the predicted value was above 0 the individual was assumed to have enough desk space in their household. Survey weights are used throughout.

Table C.2: Proportions WFH By Industry

	Jan/Feb'20	April '20	Change April to June '20	Change June to Sept '20	Change Sept'20 to Jan'21	Change Jan 20 Sept '21
Agriculture/Forestry/Fishing	0.25***	0.30***	-0.07**	0.06	0.02	-0.04
	(0.07)	(0.08)	(0.04)	(0.04)	(0.04)	(0.04)
Mining and Quarrying	0.15	0.50***	-0.07	-0.03	0.06	0.00
	(0.09)	(0.15)	(0.07)	(0.03)	(0.06)	(.)
Manufacturing	0.19***	0.36***	-0.03	-0.00	0.05***	-0.05***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Electricity and Gas	0.31***	0.57***	-0.01	-0.09*	0.06*	-0.03
	(0.06)	(0.08)	(0.05)	(0.05)	(0.04)	(0.11)
Water/Waste Related	0.24***	0.47***	0.06	-0.04	-0.00	-0.01
	(0.06)	(0.09)	(0.04)	(0.06)	(0.05)	(0.04)
Construction	0.22***	0.35***	-0.05**	0.03	0.02	-0.08
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.06)
Wholesale/Retail	0.14***	0.21***	-0.01	0.00	0.03*	-0.03
	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
Motor Vehicles Repair	0.20***	0.23***	-0.14	-0.04	0.24*	-0.08
	(0.07)	(0.07)	(0.13)	(0.07)	(0.13)	(0.07)
Transportation/Storage	0.12***	0.20***	-0.02	0.04	-0.02	-0.02
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Accommodation/Food	0.14***	0.15***	0.04*	0.05	0.00	-0.05
	(0.03)	(0.03)	(0.02)	(0.04)	(0.03)	(0.08)
Information/Communication	0.63***	0.84***	-0.05*	0.03	0.03	-0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Financial/Insurance	0.47***	0.84***	0.01	-0.05**	0.04*	-0.04**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Real Estate	0.44***	0.70***	-0.02	0.10	-0.03	-0.09
	(0.06)	(0.06)	(0.04)	(0.07)	(0.05)	(0.06)
Professional/Scientific/Technical	0.53***	0.80***	-0.04	0.01	0.04	-0.07**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Administrative/Support	0.32***	0.65***	0.00	-0.04	0.12***	-0.06**
	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)
Public Administration/Defence	0.37***	0.69***	-0.00	-0.02	0.03	-0.04**
	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Education	0.31***	0.71***	-0.02	-0.26***	0.25***	-0.29***
	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.03)
Human Health/Social Work	0.25***	0.39***	0.00	0.00	0.05***	-0.03
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Arts/Entertainment	0.50***	0.61***	-0.05	0.07	0.15**	-0.10**
	(0.05)	(0.05)	(0.05)	(0.04)	(0.07)	(0.05)
Other Service	0.29***	0.42***	-0.04**	0.02	-0.01	-0.03
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
HH Activities as Employers	0.15**	0.21**	-0.06	0.05	-0.04	0.16
	(0.06)	(0.08)	(0.08)	(0.04)	(0.04)	(0.12)
Missing	0.25***	0.40***	0.02	0.09	-0.05	-0.01
	(0.01)	(0.02)	(0.02)	(0.08)	(0.05)	(0.05)
Observations	10,408	9,839	7,023	6,086	5,327	5,016
Adjusted R^2	0.333	0.560	0.007	0.066	0.074	0.086

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Current estimates from a regression with a dummy variable which is set equal to 1 if any WFH is reported. All possible observations of working age individuals are used; no restrictions are currently placed on the sample.

Table C.3: Proportions WFH By Occupation

	Jan/Feb'20	April '20	Change April to June '20	Change June to Sept '20	Change Sept'20 to Jan'21	Change Jan 20 Sept '21
Management	0.48***	0.66***	-0.01	0.03**	0.01	-0.04*
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Business/Financial Operation	0.55***	0.90***	-0.04**	-0.02	0.02	-0.06**
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
Computer/Mathematical	0.61***	0.87***	0.03	-0.00	0.01	0.03
	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)
Architecture/Engineering	0.35***	0.71***	-0.04*	-0.05	0.05	-0.10***
	(0.03)	(0.04)	(0.02)	(0.04)	(0.03)	(0.03)
Life/Physical/Social Science	0.34***	0.73***	-0.03	0.01	-0.00	0.01
	(0.05)	(0.05)	(0.07)	(0.04)	(0.03)	(0.03)
Community/Social Service	0.50***	0.80***	-0.03	0.02	0.06**	-0.07**
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)
Legal	0.47***	0.82***	0.01	0.04	0.05	-0.10**
	(0.06)	(0.04)	(0.02)	(0.04)	(0.05)	(0.05)
Education	0.51***	0.88***	-0.01	-0.30***	0.32***	-0.33***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
Arts/Entertainment	0.60***	0.75***	-0.07	0.05	0.09**	-0.08*
	(0.04)	(0.03)	(0.06)	(0.05)	(0.04)	(0.04)
Healthcare Technical	0.25***	0.38***	-0.01	-0.01	0.02	-0.01
	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)
Healthcare Support	0.11***	0.16***	0.00	-0.00	0.04*	0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Protective Services	0.12***	0.24***	-0.05*	-0.08*	0.08**	-0.03
	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.02)
Food Related	0.09***	0.08***	-0.00	0.08**	-0.00	-0.02
	(0.03)	(0.03)	(0.03)	(0.04)	(0.02)	(0.04)
Building/Maintenance	0.12***	0.10***	-0.02	0.04	-0.03*	0.08
	(0.03)	(0.03)	(0.04)	(0.03)	(0.02)	(0.06)
Personal Care	0.14***	0.33***	0.01	-0.17***	0.18***	-0.23***
	(0.02)	(0.03)	(0.02)	(0.03)	(0.05)	(0.04)
Sales Related	0.15***	0.27***	-0.04**	0.03	0.04**	-0.07**
	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Office/Administrative Support	0.21***	0.51***	0.00	-0.05***	0.08***	-0.11***
	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)	(0.03)
Farming/Fishing/Forestry	0.21***	0.30***	-0.04	0.00	0.07	-0.04
	(0.05)	(0.07)	(0.03)	(0.02)	(0.04)	(0.03)
Construction/Extraction	0.11***	0.17***	-0.11**	0.05	-0.04	0.03
	(0.02)	(0.03)	(0.05)	(0.03)	(0.03)	(0.04)
Installation/Repair	0.19***	0.34***	-0.10	0.02	0.10**	-0.12
	(0.05)	(0.06)	(0.07)	(0.06)	(0.04)	(0.10)
Production	0.16***	0.21***	-0.03	-0.02	0.04*	-0.01
	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)	(0.01)
Transportation/Material Moving	0.08***	0.08***	-0.01	0.01	0.00	-0.00
	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
Missing	0.15***	0.31***	-0.04	-0.02	0.11**	-0.09
	(0.03)	(0.05)	(0.04)	(0.05)	(0.06)	(0.07)
Observations	10,408	9,839	7,023	6,086	5,327	5,016
Adjusted R^2	0.391	0.613	0.007	0.053	0.068	0.086

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Current estimates from a regression with a dummy variable which is set equal to 1 if any WFH is reported. All possible observations of working age individuals are used; no restrictions are currently placed on the sample.

Table C.4: Changes in Productivity During Covid-19 by Characteristics - Age of Children

	(1) June'20	(2) Sept.'20	(3) Jan.'21	(4) Sept.'21	(5) June'20	(6) Sept.'20	(7) Jan.'21	(8) Sept.'21	(9) June'20	(10) Sept.'20	(11) Jan.'21	(12) Sept.'21
Children 0-15												
Parent × female	-5.01***	6.51***	-3.46***	7.68***								
	(1.26)	(1.18)	(1.30)	(1.15)								
Parent × male	0.36	5.24***	1.46	8.49***								
	(1.34)	(0.91)	(2.09)	(1.31)								
No children × female	-1.48	5.06***	0.87	10.22***								
	(1.30)	(0.87)	(1.05)	(0.69)								
No children × male	2.05*	5.21***	0.50	8.77***								
	(1.09)	(0.77)	(0.94)	(0.91)								
Children 0-4												
Mother					-6.46***	6.00**	-2.49	9.05***				
					(2.33)	(2.68)	(2.27)	(2.30)				
Father					2.83	4.08***	-4.77**	12.09***				
					(2.27)	(1.12)	(1.99)	(1.60)				
Children 5-15												
Mother									-5.89***	6.71***	-3.87***	7.90***
									(1.35)	(1.20)	(1.42)	(1.14)
Father									-0.03	5.26***	2.18	8.15***
									(1.43)	(0.98)	(2.37)	(1.47)
N	3,498	5,533	4,753	5,509	3,498	5,533	4,753	5,509	3,498	5,533	4,753	5,509

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: Same specification as Table 2. See Table 2 notes and text for further details.

Appendix D Further Details on the Selection Model Presented in Section 5

Section 5 presented our selection model concisely. We now lay out the empirical framework in further detail. In what follows, in the spirit of French and Taber (2011) we discuss identification non-parametrically. It should be borne in mind that, equally in the spirit of French and Taber (2011), we estimate the model in our empirical application in a simple linear setting.

We first recap the basic ingredients of the model presented in the main text. Productivity is as follows:

$$\begin{aligned} prod_{it}^{h} &= g^{h}\left(X_{it}\right) + \epsilon_{it}^{h} \\ prod_{it}^{f} &= g^{f}\left(X_{it}\right) + \epsilon_{it}^{f} \end{aligned} \tag{6}$$

We allow for utility, V_{it}^{h}, of costs or benefits of WFH compared to being located in the standard workplace. This is specified as follows:

$$V_{it}^{h} = k\left(z_i, X_{it}\right) + \nu_{it} \tag{7}$$

Given this set-up the decision rule is simple, and specified as follows:

$$j_{it}^{*} = \begin{cases} h & \text{if } prod_{it}^{h} - prod_{it}^{f} + V_{it}^{h} > 0 \\ f & \text{otherwise} \end{cases} \tag{8}$$

The fundamental identification problem that we need to address is that $\mathbb{E}\left[\epsilon_t^j | X_t, j^*\right]$ is likely not equal to zero for $j^* \in \{f, h\}$. i.e. individuals are selected by idiosyncratic productivity in their observed location. As such, properties of $g^j\left(\right)$ cannot be identified immediately. However, we maintain the standard argument of 'identification at infinity', and suppose that at extreme values of z, utility-based preferences for each location are so strong that productivity no longer plays a role. Suppose that, as $z \to \infty$, then individuals prefer home, and as $z \to -\infty$ individuals prefer the workplace, then formally, and dropping some subscripts, we use:

$$\lim_{z\to\infty} \mathbb{E}\left[\epsilon_t^h | X, j^*, z\right] = \lim_{z\to-\infty} \mathbb{E}\left[\epsilon_t^f | X, j^*, z\right] = 0 \tag{9}$$

Next consider the baseline period 0, before the pandemic. We use a simpler production function and location choice:

$$\begin{aligned}
prod_{i0}^{j} &= l^{j}\left(X_{i0}\right) + \epsilon_{i0}\ ,\ j = h, f \\
V_{i0}^{h} &= m\left(X_{i0}\right) + \nu_{i0} \\
j_{it}^{*} &= \begin{cases} h & \text{if } prod_{i0}^{h} - prod_{i0}^{f} + V_{i0}^{h} > 0 \\ f & \text{otherwise} \end{cases}
\end{aligned}$$

where $l^{j}()$ may differ from $g^{j}()$ because production may differ during the pandemic from before. Further note two simplifications of this pre-pandemic model compared to (6), (7) and (8): the idiosyncratic component ϵ_{i0} does not depend on location, and we do not require any variable to affect $m()$ that is excludable from the production function. In practice, the first assumption ensures that idiosyncratic productivity is exogenous of observed location, and so that location at time 0 can be treated as 'given'. This ensures that an additional instrument is not required. Formally:

$$\mathbb{E}\left[\epsilon_0 | X_0, j_0^{*}\right] = 0 \tag{10}$$

As discussed in the main text quasi-differences in productivity are defined as follows:

$$\begin{aligned}
\tilde{\Delta} prod_{it}^{j} &\equiv prod_{it}^{j} - prod_{i0}^{j^{*}} \\
&= g^{j}\left(X_{it}\right) + \epsilon_{it}^{j} - \left(l^{j_0^{*}}\left(X_{i0}\right) + \epsilon_{i0}\right)
\end{aligned} \tag{11}$$

which, importantly, captures the change in productivity at time t in each location j compared to the *observed* location j_0^{*} at time zero.

Building on (8) since

$$\begin{aligned}
& prod_{it}^{h} - prod_{it}^{f} + V_{it}^{h} > 0 \\
\iff & \left(prod_{it}^{h} - prod_{i0}^{j^{*}}\right) - \left(prod_{it}^{f} - prod_{i0}^{j^{*}}\right) + V_{it}^{h} > 0 \\
\iff & \tilde{\Delta} prod_{it}^{h} - \tilde{\Delta} prod_{it}^{f} + V_{it}^{h} > 0.
\end{aligned}$$

It's the case that,

$$j_{it}^{*}=\begin{cases}h & \text{if } \tilde{\Delta}prod_{it}^{h}-\tilde{\Delta}prod_{it}^{f}+V_{it}^{h}>0.\\ f & \text{otherwise.}\end{cases} \tag{12}$$

Finally we come to identification. We observe j_{it}^{*} , $\Delta prod_{it} \equiv \tilde{\Delta}prod_{it}^{j_{it}^{*}}$ and the full array of covariates. Exploiting orthogonality conditions (9), (10) and the definition of quasi-differences in (11) then we observe the following regression functions:

$$\lim_{z\to\infty}\mathbb{E}\left[\Delta prod_{it}|X,j_{i0}^{*}=\bar{j},z\right]=g^{h}\left(X_{t}\right)-l^{\bar{j}}\left(X_{0}\right)$$
$$\lim_{z\to-\infty}\mathbb{E}\left[\Delta prod_{it}|X,j_{i0}^{*}=\bar{j},z\right]=g^{f}\left(X_{t}\right)-l^{\bar{j}}\left(X_{0}\right)$$

Intuitively, we can both condition on baseline location as given, and condition on pandemic location using the exclusion restrictions.

The model therefore permits identification of key parameters. First, and using economical notation, average treatment effects are identified as follows:

$$\lim_{z\to\infty}\mathbb{E}\left[\Delta prod_{it}|...\right]-\lim_{z\to-\infty}\mathbb{E}\left[\Delta prod_{it}|...\right]=g^{h}\left(X_{t}\right)-g^{f}\left(X_{t}\right)$$

In our empirical application we focus on marginal effects on the production function for different characteristics. To use a concrete example, we want to examine the effect of having adequate home desk space (say $D=1$) compared to inadequate desk space ($D=0$) on the pandemic productivity change for those WFH. We identify this as follows:

$$\begin{aligned}\lim_{z\to\infty}\mathbb{E}\left[\Delta prod_{it}|D=1,...\right]-\lim_{z\to\infty}\mathbb{E}\left[\Delta prod_{it}|D=0,...\right]=&\left(g^{h}\left(D=1\right)-l^{j_{0}^{*}}\left(D=1\right)\right)\\ &-\left(g^{h}\left(D=0\right)-l^{j_{0}^{*}}\left(D=0\right)\right)\end{aligned}$$

If we are willing to push this further, and maintain the assumption that desk space at home should not affect productivity at work, then we can impose that $l^{f}\left(D=1\right)=l^{f}\left(D=0\right)$, and then identify $g^{h}\left(D=1\right)-g^{h}\left(D=0\right)$.