Balancing Work and Life: Working from Home, Wages, and Part-time Work in the UK*

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Abstract

We use UK microdata to estimate the effect on wages of the widespread adoption of working from home in the UK since 2020. Leveraging differences in exposure to remote work across occupations, we find that an additional percentage point of remote work caused a 8 basis point increase in the real weekly wage between 2019 and 2022. This translates into a 3 percentage point higher real wage growth over the period for the top quintile of occupations by remote work relative to the bottom quintile, or around half of the 2.7% increase in the UK mean real wage over 2019-2022. We document that more than 50% of the impact of remote work on wages is due to hours worked, and in particular to a decrease in the use of part-time work, with the remaining share due to firm-level factors.

Keywords: working from home, remote work, wages, part-time work.

JEL Codes: J24, J31, J81, L23.

*All errors are our responsibility only. The views expressed in this paper are solely those of the authors and should not be taken to represent those of the Bank of England.

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1 Introduction

The Covid-19 pandemic brought about a remarkable change in the way work is organised. Governments across the world mandated to work from home (WFH) whenever possible to reduce the spread of the virus, hugely accelerating a shift to remote work which had been creeping up over the previous decade.

The increase in remote work appears is a structural break. Figure 1 shows a permanent jump in the share of job vacancy postings allowing remote work in English-speaking nations (Hansen et al., 2023), despite government mandates disappearing by 2021 and a growing number of firms encouraging or requiring employees to return to the office a minimum number of days.

The United Kingdom appears as the ideal setting to investigate the implications of working from home: as Figure 1 shows, the increase in remote-work job ads in the UK dominates that of the other countries. To give an idea of the magnitude of the change for the stock of UK jobs, Figure 2 shows a 5-fold increase in the share of UK working-age employees who mainly work from home by 2022 relative to the pre-2020 level.[1]

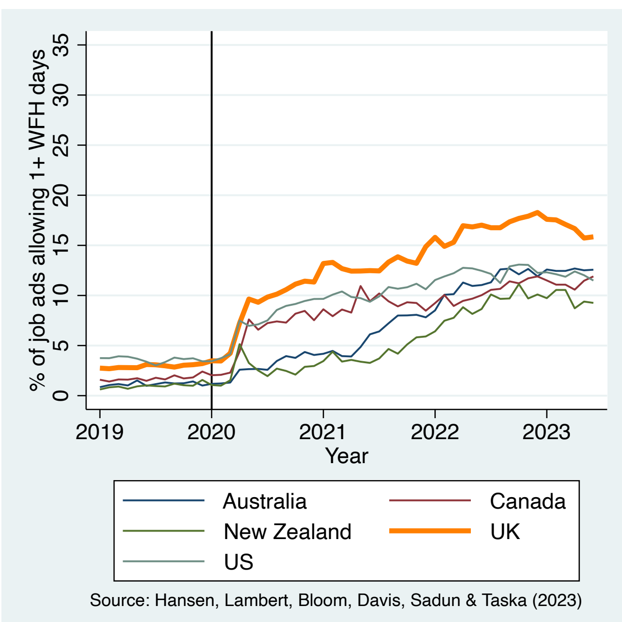


Figure 1: Share of job vacancy postings allowing remote work

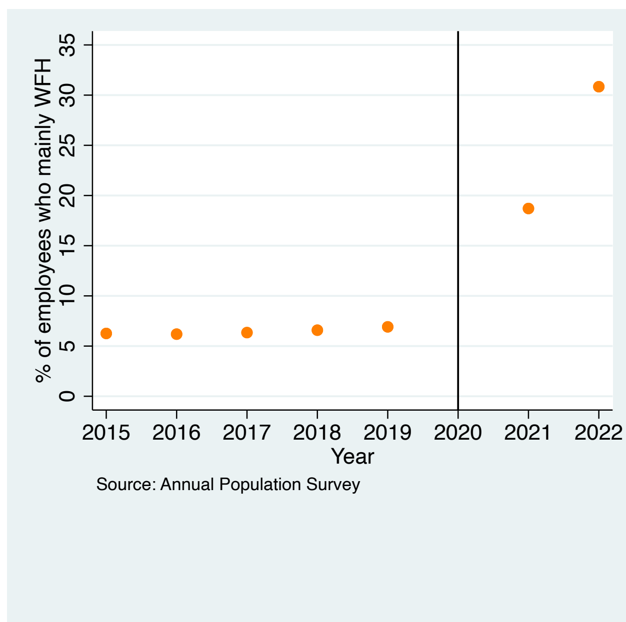


Figure 2: Share of working-from-home employees in the UK

Motivated by this evidence, our paper studies how remote work affects wages using UK microdata. Answering this question is difficult. A burgeoning literature has shed light on opposing channels through which remote work can affect wages. On the one hand, there

[1] More details on the data is provided in Section 2.

is some evidence of a positive effect of remote work on productivity (e.g. Bloom et al. 2015, Behrens et al. 2021), at least in the short run (Emanuel et al., 2023). On the other hand, to the extent that working from home carries an amenity value, a compensating wage differential should lower wage growth in jobs more suitable to be performed remotely (e.g. Barrero et al. 2022, Bagga et al. 2023). In the end, which channel wins out is an empirical question.

We combine two datasets from the Office for National Statistics between 2015 and 2022. The Annual Population Survey (APS) allows us to compute a measure of remote work in each occupation and year, while the Annual Survey of Hours and Earnings (ASHE) – a matched employer-employee panel dataset – is the source of data on weekly wages and hours worked.

We exploit differences in workers' exposure to remote work across occupations to estimate the impact of working from home on real weekly wage growth. Dingel and Neiman (2020) document systematic differences in the suitability of jobs to be performed from home. Mondragon and Wieland (2022) leverage this feature to instrument variation in remote work across US metropolitan areas after 2020 with its variation before 2020, and estimate the impact of working from home on house price growth.

We confirm that in our UK data the suitability of an occupation to remote work before 2020 is a sufficient statistic for its suitability after 2020. Figure 3 plots the relationship between remote work shares pre- and post-2020 across occupations: the post-2020 shares are approximately an affine function of the pre-2020 shares. This allows us to use the WFH shares pre-2020 as instrument for the WFH shares post-2020 and overcome concerns about the endogeneity of remote work with respect to wages due to its amenity value or other unobservables such as the availability of WFH technologies.

For each year in our data after 2020, we estimate the impact of remote work on the cumulative growth in real weekly wages since 2019 using two-stage least squares. The large, precise and stable estimates of the first stage across various specifications confirm that our instrument is relevant. Inspection of pre-trend graphs and regression event analyses reassure us that the instrument is exogenous: before 2020, real wage growth is not significantly different irrespective of whether workers were in low or high WFH occupations. However, after 2020, workers in occupations that were ex-ante more suitable to remote work experience higher wage growth.

In our baseline specification with time-by-sector, time-by-local authority and time-by-age fixed effects, as well as other demographic and job controls, working in an occupation with a 1 percentage point higher share of remote work led to a 6.2 basis point (bp) higher real weekly wage growth between 2019 and 2021, increasing further to 7.9 bps from 2019 to 2022.

These effects are economically significant. After 2020, the difference in the share of

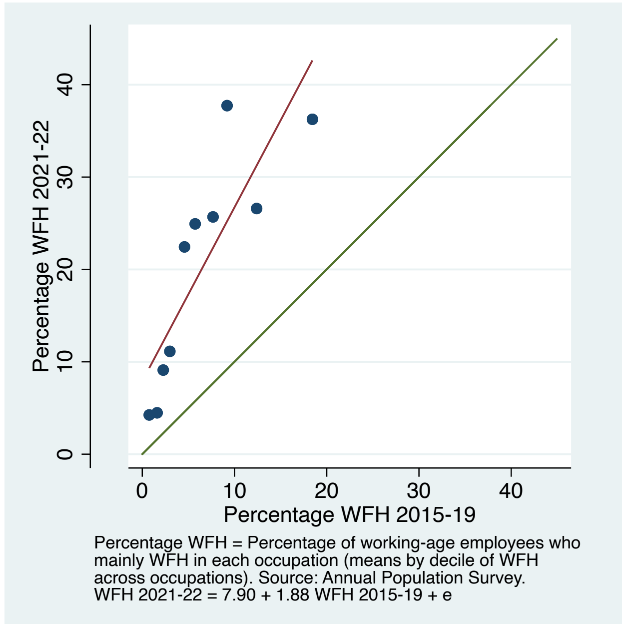


Figure 3: Remote share post-2020 as function of remote share pre-2020 across occupations

workers who mainly work remotely in the top vs. bottom quintile of occupations is 42%. Our estimate then implies a 3.3 percentage point higher real weekly wage growth between 2019 and 2022 at the top relative to the bottom of occupations by remote work. This is a sizeable difference, considering that the mean real wage increased by 2.7% over the same period. As another way to gauge the importance of our results, the share of remote work among all UK employees increased by 18 percentage points from its pre-2020 level. Hence, the increase in working from home since 2020 has accounted for 1.4 percentage points of mean real wage growth between 2019 and 2022 – or slightly more than 50% of the total.

The implications of our analysis for labor income inequality are not as obvious as they may seem. We document that the relationship between working from home and wages has a slanted inverted U-shape: remote work is generally increasing in wages (Dingel and Neiman, 2020), except towards the top where there are high-wage occupations, such as doctors, with low remote work. Therefore, while our results imply an increase in income inequality along most of the distribution, they translate into a decrease in inequality towards the top.

We show that our results are robust in various specifications, such as constructing the remote-work variable post 2020 in differences instead of levels, and controlling for job switches, multiple jobs and the differential impact of remote work based on gender.

We then dig deeper to study the extent to which the effect of remote work on wage growth is driven by productivity or hours worked. To this end, we introduce time-by-firm fixed effects, and look at hourly wage growth and the effect of part-time work after 2020.

Our analyses show that more than half of the total impact of remote work on real weekly wage growth in both 2021 and 2022 is due to relatively more hours worked by employees in higher WFH occupations – in particular due to a decrease in the probability of working part time. The remaining effect is driven by common factors at the firm level. In other words, as remote work allows for better work-life balance, workers need to rely less on part-time work, resulting in higher wage growth since 2019.

Literature

The literature that looks at the effect of working from home on productivity, wage and employment dynamics is closely related to our paper. Bloom et al. (2015) look at a Chinese experiment and find that WFH leads to a performance increase due to working more hours and higher productivity. Deole et al. (2023) use UK data and find that WFH leads to higher self-perceived hourly productivity. Emanuel et al. (2023) look at the benefits of proximity for software engineers, and find that less proximity harms especially young and female workers in the long-run in terms of human capital formation. However, proximity reduces short-run output due to time spent on mentoring. In a related paper, Harrington and Kahn (2023) find that increased WFH leads to higher employment of mothers, especially in family-unfriendly occupations. Barrero et al. (2022) find a reduction in wage-growth pressures since the Covid-19 pandemic, because workers accept a lower wage if they are allowed to WFH. Bagga et al. (2023) look at the impact of remote work on the compensating wage differential in the US using a theoretical model. The increase in WFH in their model is due to a shift in preferences and thus WFH lowers wage growth for jobs more suitable to remote work. In our paper, we look directly at the effect of increased remote work on wages. Liu and Su (2023) also look at the effect of an increase in WFH on wages. They find a decrease in the urban wage premium in their model, and they verify this model prediction empirically. While Liu and Su (2023) focus on the spatial distribution of wages, we look at the effect of WFH on wages across the entire UK.

Another strand of the literature uses theoretical models to investigate the effect of WFH on house prices and wages jointly, which then allows to make a statement about the effects on inequality. Davis et al. (2024) find an increase in the productivity of WFH, which benefits high-skilled workers, because they can work remotely to a greater extent. Thus, more WFH leads to higher income inequality. Behrens et al. (2021) also assume in their model that high-skilled workers can WFH to a greater extent, and WFH increases productivity as long as it is not too large. Thus, the authors find that WFH raises income inequality. In the paper by Richard (2023), working from home is less productive than working in the office, but a tele-premium arises, which increases consumption inequality. Our paper complements the theoretical literature on remote work and inequality by providing empirical evidence on the effect of WFH on wages, which is crucial for statements about inequality in response to higher remote work.

Outline

The rest of the paper is organized as follows. Section 2 presents the data and Section 3 the methodology, discussing the validity of our instrument. Section 4 contains the results and robustness exercises, while Section 5 extends the analysis to assess the contribution of productivity and hours worked. Section 6 concludes.

2 Data

To capture the effect of working from home on wages, we combine two different data sources from the Office for National Statistics (ONS) between 2015 to 2022.[2]

We use the Annual Population Survey (APS) for our working-from-home (WFH) measure, while data on wages and hours worked comes from the Annual Survey of Hours and Earnings (ASHE).

For both data sources, we restrict our sample to working age individuals between the ages of 25 and 60 years old. We necessarily exclude the self-employed, given our analysis examines wages.

2.1 Annual Population Survey (APS)

To compute our proxy measure of working-from-home, we use data from the APS. The APS is a sample-based survey that started in 2004 to provide estimates between censuses of main social and labor market variables at a local area level. It is annually representative and has the largest coverage of any UK household survey. It combines data from two waves of the Labor Force Survey (LFS) with data collected on a local sample boost, achieving a sample size of approximately 320,000 respondents on each annual dataset.

Specifically, we rely on the following question asking about remote work habits:

"(In your main job) do you work mainly . . . 1) in your own home, 2) in the same grounds or buildings as your home, 3) in different places using home as a base, 4) or somewhere quite separate from home?"

Following ONS (2022), our WFH measure is defined as a discrete variable where if the respondent selects any of the first three answers we classify them as working remotely, but

[2] Due to data reliability, we exclude 2020 from our analysis.

if they select the fourth answer they are not.

While we exclude self-employed respondents, employment can be in either the private or public sector. For each 3-digit SOC occupation[3], we compute the share of employees who work from home using the population weights. Given the stability in remote work adoption before 2020 and the jump thereafter, we collapse the WFH shares for each occupation to two numbers by taking simple averages pre-2020 and post-2020.[4]

2.2 Annual Survey of Hours and Earnings (ASHE)

Data on wages and hours is obtained from the ASHE. The ASHE is the most comprehensive source of information on labor earnings in the UK. It is an employer-based survey carried out each April at the start of the fiscal year and is based on a 1% sample of employees who participate in HM Revenue and Customs' (HMRC's) Pay As You Earn (PAYE) system.[5]

For wages, we use real weekly earnings. For hours, we use basic paid weekly hours. Both our wage and hours measures exclude overtime.[6]

We follow Bell et al. (2022) and limit the sample to those who are working at least 7 hours/week at the prevailing minimum wage to ensure enough labor force attachment. We also winsorize the top 0.5% of hours worked[7] as well as the top and bottom 2.5% of wage and hours growth.

This gives us as our baseline sample a balanced panel from 2015 to 2022 (excluding 2020) with approximately 18,000 observations per year.

We merge both data sources at the 3-digit SOC level, such that for each employee in the ASHE and each year (2021 or 2022) there is an associated working-from-home share pre-2020 and post-2020 based on their occupation.

2.3 Descriptive Statistics

Table 1 presents a range of descriptive statistics from our baseline sample.

[3] The 3-digit SOC, or Standard-Occupational-Classification, captures occupations at a detailed level, e.g. road transport drivers, hairdressers, or accountants.

[4] Out of 116 occupations from the APS, we end up with 115 occupations (losing 1 due to a small sample size).

[5] Once employees are selected, they will typically remain in the sample irrespective of their employer, so long as they are in employment.

[6] For employees who work in multiple jobs (only 3% each year in our baseline sample, see Table 1), we assign their occupational classification as that which pertains to their main job, but we sum their total wages and hours across all the jobs they hold.

[7] Due to some unrealistically high observations for hours worked, in excess of 70 hours/week.

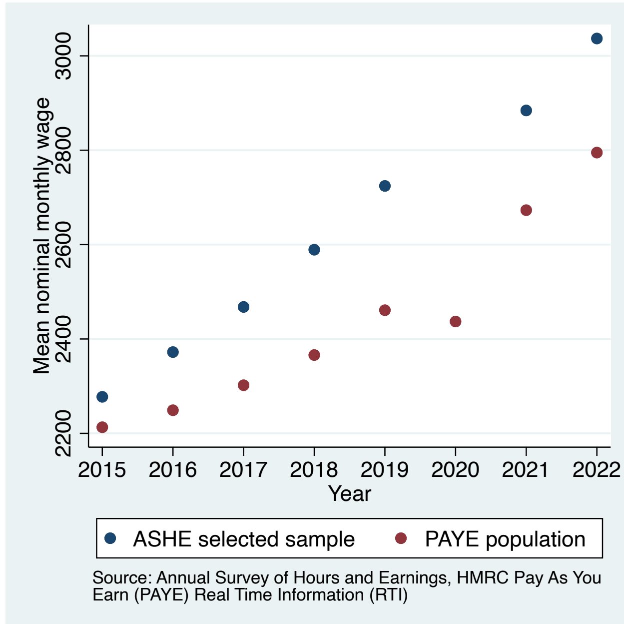


Figure 4: Comparison of mean nominal monthly wage in our sample and in HMRC data

The mean nominal weekly wage in 2019 is £629, increasing to £701 in 2022. Over the period, the dispersion of nominal wages also increases, by nearly 13%. Figure 4 compares the mean nominal wage (at monthly frequency) in our selected sample against the mean wage in the population of PAYE employees. Unsurprisingly given that our sample construction criteria tend to exclude low earners, the mean wage is higher than in the PAYE population (by around £230 per month in 2018), but the evolution over time is similar.

The mean age of workers in our sample is 48 as of 2022, and they are evenly split between male and female. As concerns job characteristics, 19% of our workers work part time in a given year and only 3% have multiple jobs. The rate at which workers changed jobs in 2021 and 2022 is 4%. As expected, by 2021 most of the employees in our data (92%) were not furloughed. Finally, the geographical distribution of our workers is close to the 2021 distribution in the ONS official statistics[8], except for London which is underrepresented in our data (9% vs 17%) and Scotland which is overrepresented (13% vs 8%).

3 Methodology

We are interested in measuring the impact of working from home on wage growth. Let i denote an employee in our dataset and t denote the year (2021 or 2022). Let $\Delta^{t-2019} \log w_{t,i}$

[8]Where however employees are defined as "anyone aged 16 years or over that an organisation directly pays from its payroll(s), in return for carrying out a full-time or part-time job or being on a training scheme".

	Mean	SD	Min	Max	Share
Nominal weekly wage 2019 (£)	628.69	383.11			
Nominal weekly wage 2021 (£)	665.61	407.80			
Nominal weekly wage 2022 (£)	700.80	433.27			
Real weekly wage growth 2019-21	0.03	0.17	−0.47	0.47	
Real weekly wage growth 2019-22	0.01	0.20	−0.56	0.53	
Real hourly wage growth 2019-21	0.03	0.12	−0.28	0.36	
Real hourly wage growth 2019-22	0.01	0.14	−0.32	0.38	
WFH share pre-2020 (given 2022 occup.)	0.06	0.04	0.00	0.32	
WFH share post-2020 (given 2022 occup.)	0.21	0.15	0.01	0.56	
Age 2022	48.00	7.90	32.00	60.00	
Male					50%
Part-time 2019					19%
Part-time 2021					19%
Part-time 2022					19%
Multiple jobs 2019					3%
Multiple jobs 2021					3%
Multiple jobs 2022					3%
New job 2021					4%
New job 2022					4%
Not furloughed 2020					72%
Furloughed 2020					13%
Missing furlough info 2020					15%
Not furloughed 2021					92%
Furloughed 2021					7%
Missing furlough info 2021					1%
Work region 2022:					
North East					4%
North West					11%
Yorkshire					9%
East Midlands					8%
West Midlands					9%
South West					9%
East					9%
London					9%
South East					12%
Wales					6%
Scotland					13%
Observations	18,300				

Table 1: Descriptive statistics

be real wage growth for employee i between 2019 and year t. Let $wfh^{post}_{t,o(i)}$ be the WFH share post-2020 for employee i given their occupation $o(i)$ in year t – our proxy for the extent to which i works from home in t. Given the imputation at the occupation level, this variable is constant across employees within each occupation. Then the equation we would like to estimate is

$$\Delta^{t-2019} \log w_{t,i} = \alpha^{sector}_{t,s(i)} + \alpha^{LA}_{t,l(i)} + \alpha^{sector}_{2019,s(i)} + \alpha^{LA}_{2019,l(i)} + \beta_t wfh^{post}_{t,o(i)} + X'_{t,i}\delta_t + \epsilon_{t,i} \quad (1)$$

where α's are time-by-sector and time-by-local-authority fixed effects[9] – flexibly capturing changes in demand and prices across localities and sectors during the period[10] – and $X_{t,i}$ are employee-specific controls: 1-year real wage growth for each year from 2016 to 2019, a full set of age dummies, sex, whether the employee was furloughed in 2020 or 2021, whether they were working part-time in 2019 and whether they had more than one job in 2019.

The coefficients of interest are $\{\beta_t\}_{t\in\{2021,2022\}}$, capturing the extent to which a different degree of remote work across employees – due to different occupations – translates into different real wage growth.

Wage growth and working from home tend to be determined together. In particular, to the extent that remote work carries an amenity value, workers will tend to accept lower wages to work from home more (Barrero et al., 2022, Bagga et al., 2023). There are also other reasons, such as the increasing availability of WFH technologies during the pandemic, that mean that working from home post-2020 could be correlated with other unobservables.

We adopt an instrumental variable approach to overcome these endogeneity issues. We use the WFH share pre-2020 $wfh^{pre}_{t,o(i)}$, for employee i, given their occupation in time t, as an instrument for $wfh^{post}_{t,o(i)}$. The two-stage least squares (2SLS) equations we estimate are

$$\text{1st stage: } wfh^{post}_{t,o(i)} = \kappa^{sector}_{t,s(i)} + \kappa^{LA}_{t,l(i)} + \kappa^{sector}_{2019,s(i)} + \kappa^{LA}_{2019,l(i)} + \gamma_t wfh^{pre}_{t,o(i)} + X'_{t,i}\theta_t + u_{t,i} \quad (2)$$

$$\text{2nd stage: } \Delta^{t-2019} \log w_{t,i} = \alpha^{sector}_{t,s(i)} + \alpha^{LA}_{t,l(i)} + \alpha^{sector}_{2019,s(i)} + \alpha^{LA}_{2019,l(i)} + \beta_t \widehat{wfh^{post}_{t,o(i)}} + X'_{t,i}\delta_t + \epsilon_{t,i} \quad (3)$$

where X_i's are the same controls as in Equation 1. We cluster standard errors at the occupation level, given WFH shares are imputed by occupation.

Next, we verify that the two assumptions of relevance and exogeneity of the instrument are satisfied.

[9] In 2023, there were 317 local authorities in England, 32 local authorities in Scotland, 22 principal councils in Wales and 11 local councils in Northern Ireland.

[10] We include fixed effects for 2019 and year t since employees may have changed firm (and thus sector) and/or place of work. We consider the local authority where an employee works, as opposed to where she lives, since it is more relevant in capturing demand and price dynamics that in turn can have an impact on wages.

Relevance assumption

Working-from-home pre-2020 should be a sufficient statistic for the likelihood of an occupation to remote work (Dingel and Neiman, 2020). We showed in Figure 3 that the share of remote work in an occupation post-2020 is close to an affine function of the share of remote work in that occupation pre-2020. In other words, there are some occupations that cannot be performed from home, such as a waiter job. Hence, the 0 intercept of the affine relationship. Other occupations experienced a boost in the share of workers working remotely after 2020, proportionately to the pre-2020 share.

To formally assess the instrument's relevance, in Tables 2 and 3 we show the first stage of the 2SLS for 2021 and 2022, respectively. Since the estimate of the coefficient $\{\gamma_t\}_{t\in\{2021,2022\}}$ is large, precise, and stable across specifications, we conclude our instrument is a relevant variable, uncorrelated with other shocks.

Exogeneity assumption

Our exogeneity assumption relies on showing that exposure to WFH ($wfh^{pre}_{t,o(i)}$) affects wage growth post-2020 ($\Delta^{t-2019}\log w_{t,i}$) only through its effect on $wfh^{post}_{t,o(i)}$. We use two pieces of evidence in support of this exclusion restriction.

First, we examine pre-trends to rule out other underlying fundamentals that may instead be driving the effect. Figure 5a plots log real wages relative to 2019 – i.e. the cumulative growth in real wages relative to 2019 – for each tercile of pre-2020 WFH shares (based on employees' occupation in 2022).[11] One can see that, before 2020, real wage growth was very similar irrespective of whether workers were in occupations with high or low remote work between 2015-2019. The fact that we cannot observe differences in wage growth trends for different WFH shares is reassuring. However, after 2020, individuals in occupations which had a high ex-ante WFH share saw larger wage growth, relative to individuals in occupations with a low ex-ante WFH share.

Second, we run a standard test of pre-trends regressing $\Delta^{t-2019}\log w_{t,i}$ on $wfh^{pre}_{t,o(i)}$ interacted with year dummies. Figure 5b plots the coefficients and 95% confidence intervals of these interaction terms. Before 2020, the relationship between remote work shares and wage growth is not statistically different from 0 for all years, whereas after 2020, the relationship is positive and significant.[12]

[11] As workers change occupations, we also check pre-trends using workers' occupations in 2021. We get similar results as shown in Figure A.1 in Appendix A.

[12] The values for 2019 are 0 by construction in both panels of Figure 5, since 2019 is the reference year for all real wage growth rates, consistently with the specification in Equation 3.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	WFH share post-2020				
WFH share pre-2020	2.634***	2.631***	2.652***	2.649***	2.413***
	(7.82)	(7.80)	(8.06)	(8.26)	(8.16)
Real wage growth 2015-16		0.000	−0.009	−0.005	−0.002
		(0.01)	(−0.67)	(−0.37)	(−0.22)
Real wage growth 2016-17		0.021*	0.013	0.013	0.007
		(1.87)	(1.23)	(1.31)	(0.81)
Real wage growth 2017-18		−0.008	−0.017	−0.012	−0.010
		(−0.69)	(−1.52)	(−1.22)	(−1.18)
Real wage growth 2018-19		0.002	−0.008	−0.011	−0.000
		(0.18)	(−0.74)	(−1.11)	(−0.02)
Male			−0.019	−0.024**	−0.026***
			(−1.41)	(−1.97)	(−2.61)
2020: Furloughed				−0.032***	−0.024***
				(−3.41)	(−4.77)
2020: Missing furlough info				−0.009**	−0.004
				(−2.23)	(−1.31)
2021: Furloughed				−0.012*	−0.008*
				(−1.67)	(−1.68)
2021: Missing furlough info				−0.037**	−0.031***
				(−2.30)	(−2.85)
2019: Part-time				−0.022***	−0.015**
				(−2.63)	(−2.40)
2019: Multiple jobs				−0.016**	−0.016***
				(−2.55)	(−2.73)
Constant	0.048**	0.048**			
	(2.24)	(2.25)			
Age FEs	*No*	*No*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*No*	*No*	*No*	*No*	*Yes*
Occupation clusters	99	99	99	99	99
F-statistic	61.1	60.9	64.9	68.2	66.7
Observations	18,300	18,300	18,300	18,300	18,297

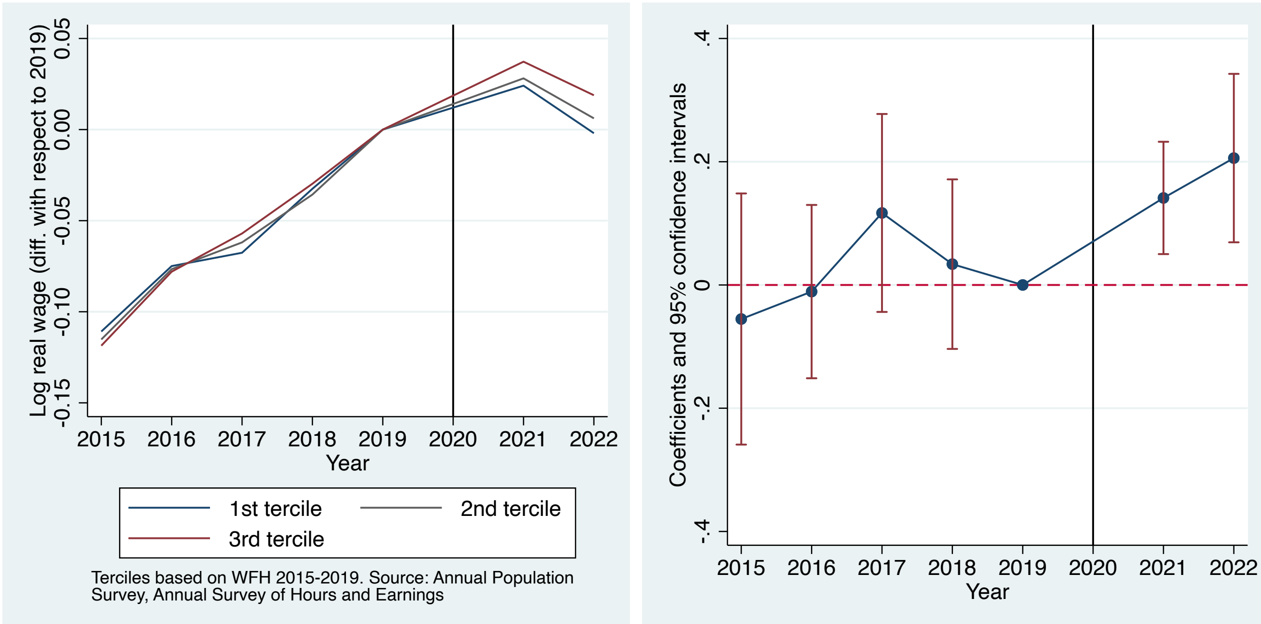
t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 2: 1st stage, based on 2021 occupations

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			WFH share post-2020		
WFH share pre-2020	2.631***	2.628***	2.651***	2.649***	2.425***
	(7.65)	(7.64)	(7.90)	(8.10)	(8.08)
Real wage growth 2015-16		−0.001	−0.010	−0.006	−0.006
		(−0.07)	(−0.79)	(−0.48)	(−0.65)
Real wage growth 2016-17		0.019*	0.011	0.012	0.003
		(1.81)	(1.12)	(1.18)	(0.37)
Real wage growth 2017-18		−0.008	−0.017	−0.013	−0.012
		(−0.70)	(−1.50)	(−1.27)	(−1.41)
Real wage growth 2018-19		0.002	−0.007	−0.011	0.001
		(0.21)	(−0.75)	(−1.17)	(0.07)
Male			−0.019	−0.025**	−0.026***
			(−1.46)	(−2.05)	(−2.60)
2020: Furloughed				−0.032***	−0.024***
				(−3.51)	(−5.13)
2020: Missing furlough info				−0.008**	−0.004
				(−2.19)	(−1.15)
2021: Furloughed				−0.012*	−0.009*
				(−1.84)	(−1.96)
2021: Missing furlough info				−0.039**	−0.034***
				(−2.38)	(−3.27)
2019: Part-time				−0.022***	−0.016**
				(−2.64)	(−2.43)
2019: Multiple jobs				−0.015**	−0.013**
				(−2.32)	(−2.15)
Constant	0.048**	0.049**			
	(2.27)	(2.28)			
Age FEs	*No*	*No*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*No*	*No*	*No*	*No*	*Yes*
Occupation clusters	103	103	103	103	103
F-statistic	58.5	58.4	62.4	65.6	65.3
Observations	18,300	18,300	18,300	18,300	18,295

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 3: 1st stage, based on 2022 occupations



(a) Trends in real wages by WFH pre-2020 (b) Event analysis of wages on WFH pre-2020

Figure 5: Assessment of pre-trends (based on 2022 occupations)

Together, panel a and b of Figure 5 show that the impact of remote work on real wage growth turns positive and significant only after 2020.

Furthermore, as specified in Equation 3, we include additional controls in our main results to capture post-pandemic shocks and other unobservables that may be correlated with $wfh^{post}_{t,o(i)}$.

4 Results

Tables 4 and 5 show our headline results for 2021 and 2022 real wage growth, respectively.

Column 1 displays the OLS regression with yearly real wage growth controls only. Column 2 shows the 2SLS estimate. The 2SLS estimates being higher than the OLS estimates (by nearly 10% in 2021 and 40% in 2022) suggest that there is evidence of a downward bias caused by the endogeneity of remote work – due to its amenity value, for instance. Adding the demographic controls, job controls and fixed effects increases the 2SLS estimates further.

Column 5 contains our baseline specification and results. Working in an occupation with a 1 percentage point higher share of remote work led to a 6.2 bps higher real wage growth between 2019 and 2021, increasing further to 7.9 bps from 2019 to 2022.

To put our results into perspective, consider the following. After 2020, the difference in

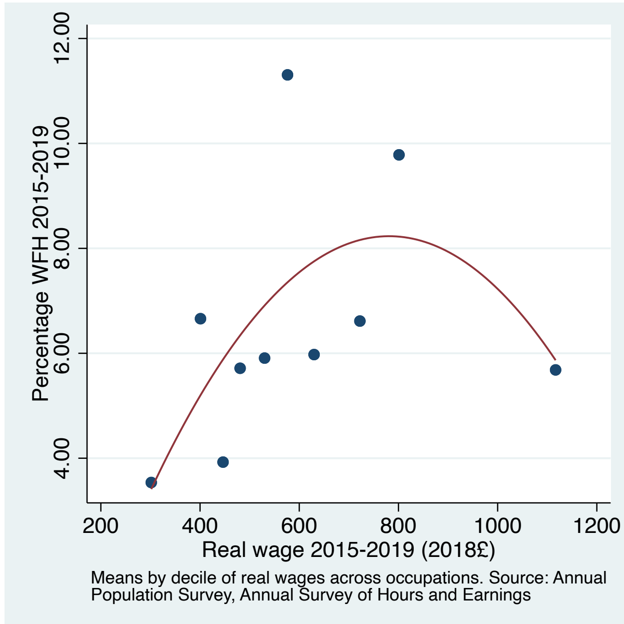


Figure 6: Remote work share pre-2020 by real wage pre-2020

the WFH share between the top quintile (45%) and bottom quintile (3%) of occupations is 42%. Combining this with our estimate means that employees in the top quintile of occupations for remote work experienced a 0.079 x 42 = 3.3 percentage point higher real wage growth between 2019 and 2022. Because the increase in remote work since the pandemic has been skewed towards occupations more suitable to be performed from home, the divergence in wage growth along the remote-work spectrum has been exacerbated. Before 2020, the difference in remote-work shares between the top and bottom quintile of occupations was just around one third as today (13%), implying only a 1 percentage point higher real wage growth at the top.

However, assessing the implications of our estimates for overall labor income inequality is not straightforward. As Figure 6 shows, while low-remote-work occupations generally pay lower wages, there are some high-wage low-WFH occupations (e.g. doctors, professionals and directors in transport) that make the relationship between the level of remote work and the level of real wages non-monotonic. Accordingly, while our results imply an increase in income inequality along most of the income distribution, they may actually imply a decrease in inequality towards the top – as employees in high-wage high-WFH occupations experienced higher wage growth than high-wage low-WFH employees.

Finally, we can extrapolate from our estimates and assess the contribution to UK real wage growth of the increase in remote work since the pandemic. The share of remote work among UK employees increased by 18 percentage points from its pre-2020 level. At the same time, based on HMRC PAYE data, the mean real wage increased by 2.7% between

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Real wage growth 2019-2021		
	OLS	IV	IV	IV	IV
WFH share post-2020	0.047***	0.051***	0.052***	0.062***	0.062***
	(4.61)	(3.75)	(3.74)	(4.57)	(4.00)
Real wage growth 2015-16	0.047***	0.046***	0.017	0.027**	0.028**
	(3.32)	(3.33)	(1.28)	(2.08)	(2.52)
Real wage growth 2016-17	0.003	0.003	−0.028*	−0.009	−0.004
	(0.18)	(0.17)	(−1.90)	(−0.70)	(−0.37)
Real wage growth 2017-18	−0.129***	−0.129***	−0.155***	−0.117***	−0.117***
	(−6.22)	(−6.26)	(−7.76)	(−6.44)	(−6.64)
Real wage growth 2018-19	−0.363***	−0.363***	−0.386***	−0.348***	−0.339***
	(−14.02)	(−14.12)	(−15.30)	(−15.36)	(−16.58)
Male			−0.015***	−0.002	−0.001
			(−6.15)	(−0.73)	(−0.51)
2020: Furloughed				−0.019***	−0.017***
				(−4.78)	(−4.00)
2020: Missing furlough info				−0.006*	−0.005
				(−1.79)	(−1.38)
2021: Furloughed				−0.067***	−0.062***
				(−10.16)	(−10.97)
2021: Missing furlough info				0.012	0.011
				(1.23)	(0.75)
2019: Part-time				0.049***	0.049***
				(11.05)	(11.07)
2019: Multiple jobs				−0.091***	−0.087***
				(−8.70)	(−9.17)
Constant	0.034***	0.033***			
	(10.73)	(8.22)			
Age FEs	*No*	*No*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*No*	*No*	*No*	*No*	*Yes*
Occupation clusters	99	99	99	99	99
R2	0.08	0.08	0.09	0.12	0.11
Observations	18,300	18,300	18,300	18,300	18,297

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 4: 2nd stage, 2019-2021

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Real wage growth 2019-2022		
	OLS	IV	IV	IV	IV
WFH share post-2020	0.049***	0.067***	0.068**	0.076***	0.079***
	(2.71)	(2.88)	(2.60)	(3.00)	(3.02)
Real wage growth 2015-16	0.093***	0.092***	0.049***	0.056***	0.050***
	(7.14)	(7.27)	(4.08)	(5.00)	(4.52)
Real wage growth 2016-17	0.033*	0.032*	−0.013	0.009	0.012
	(1.84)	(1.80)	(−0.79)	(0.58)	(0.83)
Real wage growth 2017-18	−0.105***	−0.104***	−0.142***	−0.096***	−0.095***
	(−5.86)	(−5.92)	(−9.33)	(−6.18)	(−5.76)
Real wage growth 2018-19	−0.360***	−0.360***	−0.393***	−0.339***	−0.339***
	(−14.47)	(−14.67)	(−17.91)	(−17.40)	(−18.76)
Male			−0.021***	−0.001	−0.002
			(−4.81)	(−0.28)	(−0.52)
2020: Furloughed				−0.000	−0.003
				(−0.11)	(−0.62)
2020: Missing furlough info				0.013**	0.009*
				(2.51)	(1.72)
2021: Furloughed				−0.029***	−0.035***
				(−4.89)	(−6.08)
2021: Missing furlough info				0.002	0.005
				(0.09)	(0.27)
2019: Part-time				0.077***	0.076***
				(11.04)	(11.32)
2019: Multiple jobs				−0.108***	−0.106***
				(−10.57)	(−12.13)
Constant	0.008	0.004			
	(1.33)	(0.56)			
Age FEs	*No*	*No*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*No*	*No*	*No*	*No*	*Yes*
Occupation clusters	103	103	103	103	103
R2	0.06	0.06	0.07	0.10	0.09
Observations	18,300	18,300	18,300	18,300	18,295

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 5: 2nd stage, 2019-2022

2019 and 2022. Hence, we conclude that the increase in working from home since 2020 has accounted for 0.079 x 18 = 1.4 percentage points of real wage growth between 2019 and 2022 (53% of the total).

4.1 Robustness

Tables B.1 and B.2 in Appendix B show that our results are robust to a number of alternative specifications. For ease of reference, Column 1 shows our baseline estimates (Column 5 in Tables 4 and 5).

Column 2 considers the case where the remote work variable is specified as the change in the WFH share for employee i in occupation $o(i)$: $\Delta wfh_{t,o(i)} = wfh^{post}_{t,o(i)} - wfh^{pre}_{t,o(i)}$. Given the affine relationship between remote work pre- and post-2020 shown in Figure 3, it is no surprise that $wfh^{pre}_{t,o(i)}$ is a good instrument also for the change in remote work $\Delta wfh_{t,o(i)}$. However, the F-statistic of the first stage is lower (around 23 vs. our baseline value of 65 to 67 in 2021 and 2022), hence our conservative choice of specifying the WFH variable in levels rather than differences.

The remaining Columns 3 to 5 show other specifications where we interact the remote work variable $wfh^{post}_{t,o(i)}$ with indicators of whether the employee in year t is in a new job, whether she is working more than one job, or is a woman, respectively.[13] In each case, the uninteracted coefficient estimate is close to the baseline value of Column 1 and the interaction coefficient is generally not significantly different from 0.

5 Extensions

In this section, we would like to understand to what extent higher wage growth with remote work is driven by productivity or hours worked.

To this end, letting $f(i)$ denote the firm employing worker i, we introduce time-by-firm fixed effects[14] in Equations 2 and 3, which become

$$\text{1st stage: } wfh^{post}_{t,i} = \kappa^{firm}_{2019,f(i)} + \kappa^{firm}_{t,f(i)} + \gamma_t wfh^{pre}_{t,o(i)} + X'_{t,i}\theta_t + u_{t,i} \tag{4}$$

$$\text{2nd stage: } \Delta^{t-2019} \log w_{t,i} = \alpha^{firm}_{2019,f(i)} + \alpha^{firm}_{t,f(i)} + \beta_t \widehat{wfh^{post}_{t,o(i)}} + X'_{t,i}\delta_t + \epsilon_{t,i} \tag{5}$$

Since the firm fixed effects capture common changes in wages within each firm – including changes due to firm productivity – our coefficients of interest $\{\beta_t\}_{t\in\{2021,2022\}}$ end up cap-

[13] In each case we instrument the endogenous variables $wfh^{post}_{t,o(i)}$ and $wfh^{post}_{t,o(i)} \times \mathbb{I}_t\{\dots\}$ with $wfh^{pre}_{t,o(i)}$ and $wfh^{pre}_{t,o(i)} \times \mathbb{I}_t\{\dots\}$.

[14] For 2019 and year t, since employees may be switching firms.

turing only changes in (weekly) wages due to changes in employees' productivity or hours worked. In practice, introducing firm fixed effects comes at the expense of losing around 40% of our sample, since for some firms we only have one employee in the sample.

A clarification is in order. Since our starting point for real wages are money wages, productivity has to be intended as "measured" productivity, reflecting either output productivity or relative bargaining power of firms and workers in the labor market. Based on our data alone, we cannot disentangle the two components.

Furthermore, since our measure of wage growth from ASHE is weekly, it includes changes in weekly hours worked. One way to address this issue and isolate productivity is to use hourly wage growth. Alternatively, since hours worked of employees who are not paid by the hour may be imperfectly measured, we also look at the separate effect of part-time work in 2021 and 2022.

Tables 6 and 7 show the results from these extensions. Column 1 reports our baseline estimates from Tables 4 and 5 for ease of comparison. Column 2 introduces firm fixed effects, as in Equations 4 and 5. With fixed effects, the impact of remote work on wage growth decreases by 45% for 2021 (from 6.2 to 3.4 bps for a 1 percentage point higher share of remote work) and by 34% for 2022. This suggests that more than half of the total effect of WFH on wage growth is driven by changes in workers' productivity or their hours worked.

Column 3 shows our estimates using hourly wage growth, but no firms fixed effects. Compared to Column 1, the estimates of the impact of remote work on hourly wages are lower than for weekly wages, suggesting that part of the effects we detect go through employees in higher WFH occupations working relatively more hours.

Column 4 introduces firm fixed effects in the hourly wage growth estimation. For 2021, this reduces the impact of remote work from 6.2 bps to 3.2 bps for an increase in the WFH share of 1 percentage point. By 2022, the coefficient on remote work becomes non-significantly different from 0. Our interpretation – considering also the estimation in Column 2 – is that, by 2022, the increase in weekly wages with higher WFH is driven by firm factors (34%, accounting for the decrease from 0.079 to 0.052 in the estimated coefficient) and hours worked (accounting for the remaining 66%), but not by employees' productivity.

Columns 5 and 6 show the estimates when we introduce in the regression – without and with firm fixed effects, respectively – a dummy variable for whether the employee worked part-time in year t. The results are similar as with hourly wages. Let us focus on Column 5 first. The impact of remote work on real wage growth, controlling for the work pattern, is lower, which means that a portion of the effect of remote work on wage growth goes through the probability that an employee works part-time. Since the coefficient for part-time work is negative[15], we would expect that the impact of remote work on the probability of working part-time in year t is negative.[16] And this is shown in Table 8, where we find that a 1 percentage point higher WFH share reduces the probability of working part-time by 0.07 percentage points in 2021 and 0.12 percentage points in 2022. Given the 42 percentage point difference in WFH share between top and bottom occupations by remote work, this translates into a 5 percentage point higher probability of working part-time at the bottom – which is sizeable considering that, on average, 19% of workers in our data work part-time (Table 1). In Column 6, we add firm fixed effects to the regressions with the year t part-time control. The coefficients on remote work turn non significant, as for hourly wages.

Putting everything together, our analyses show that more than half of the total impact of remote work on real wage growth in both 2021 and 2022 is due to relatively more hours worked by employees in higher WFH occupations – in particular due to a lower probability of working part time – with the remaining share due to firm-level factors.

6 Conclusion

How does remote work affect wages? This is a crucial question given the staggering increase in working from home since the Covid-19 pandemic, in particular in the UK. We answer it by combining information from two UK microdatasets and leveraging an important feature of the data: remote work in a given occupation before 2020 is a sufficient statistic for remote work after 2020. This allows us to instrument post-2020 remote work and address concerns about its endogeneity with respect to wages.

We unveil a positive impact of remote work on real weekly wage growth. We also argue that hours worked play an important role in explaining the increase in wage growth with remote work. Specifically, more working from home reduces the probability of workers relying on part-time work, thereby increasing weekly wages relative to 2019.

Our results suggest that the effects of remote work on wages operate in large part by enabling more work-life balance, thus reducing the need for workers to use part-time work. Future research could shed light on the implications of this channel for labor-market tightness in different occupations and for consumption inequality.

[15] As expected, since other things equal – and in particular whether an employee was working part-time in 2019 – part-time work in t means fewer hours worked and thus lower wage growth.

[16] Suppose the true data-generating process of wage growth is $\Delta \log w = f(pt(wfh), wfh)$ where pt denotes if a worker is employed part-time. Then the impact of remote work is $\frac{d\Delta \log w}{dwfh} = \frac{\partial f}{\partial pt}\frac{\partial pt}{\partial wfh} + \frac{\partial f}{\partial wfh}$. Now, suppose we estimate a different DGP, $\Delta \log w = g(wfh)$, where $\frac{d\Delta \log w}{dwfh} = \frac{\partial g}{\partial wfh}$. We know $\frac{\partial g}{\partial wfh} > \frac{\partial f}{\partial wfh}$, hence $\frac{\partial f}{\partial pt}\frac{\partial pt}{\partial wfh} = \frac{\partial g}{\partial wfh} - \frac{\partial f}{\partial wfh} > 0$. Since we also know $\frac{\partial f}{\partial pt} < 0$, $\frac{\partial pt}{\partial wfh}$ must be negative.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Weekly wage growth 2019-2021		Hourly wage growth 2019-2021		Weekly wage growth 2019-2021	
WFH share post-2020	0.062***	0.034***	0.055***	0.032**	0.046***	0.014
	(4.00)	(2.76)	(4.07)	(2.16)	(3.15)	(0.97)
Real wage growth 2015-16	0.028**	0.023*	0.008	0.009	0.027**	0.020*
	(2.52)	(1.84)	(0.68)	(0.62)	(2.44)	(1.75)
Real wage growth 2016-17	−0.004	−0.012	−0.015	−0.018	−0.005	−0.012
	(−0.37)	(−0.78)	(−1.38)	(−1.26)	(−0.43)	(−0.93)
Real wage growth 2017-18	−0.117***	−0.103***	−0.107***	−0.127***	−0.112***	−0.096***
	(−6.64)	(−4.76)	(−10.44)	(−8.12)	(−7.85)	(−4.95)
Real wage growth 2018-19	−0.339***	−0.308***	−0.307***	−0.314***	−0.327***	−0.303***
	(−16.58)	(−14.22)	(−19.40)	(−17.37)	(−18.19)	(−14.26)
Male	−0.001	−0.002	−0.006***	−0.005**	−0.014***	−0.012***
	(−0.51)	(−0.62)	(−3.22)	(−2.42)	(−6.63)	(−4.57)
2020: Furloughed	−0.017***	−0.015*	−0.019***	−0.016**	−0.016***	−0.010
	(−4.00)	(−1.70)	(−6.55)	(−1.99)	(−3.72)	(−1.10)
2020: Missing furlough info	−0.005	−0.002	−0.003	0.009	−0.001	0.002
	(−1.38)	(−0.17)	(−0.97)	(1.15)	(−0.47)	(0.21)
2021: Furloughed	−0.062***	−0.027*	−0.050***	−0.037***	−0.058***	−0.028**
	(−10.97)	(−1.98)	(−11.16)	(−2.85)	(−10.84)	(−2.04)
2021: Missing furlough info	0.011		−0.002		0.006	
	(0.75)		(−0.20)		(0.45)	
2019: Part-time	0.049***	0.039***			0.214***	0.196***
	(11.07)	(9.03)			(15.05)	(20.66)
2019: Multiple jobs	−0.087***	−0.072***			−0.075***	−0.072***
	(−9.17)	(−5.34)			(−9.68)	(−5.12)
Growth in basic paid hours 2015-16			0.029***	0.013		
			(3.83)	(1.22)		
Growth in basic paid hours 2016-17			0.065***	0.053***		
			(7.59)	(6.35)		
Growth in basic paid hours 2017-18			0.099***	0.125***		
			(9.30)	(9.78)		
Growth in basic paid hours 2018-19			0.181***	0.201***		
			(18.53)	(13.31)		
2021: Part-time					−0.222***	−0.205***
					(−16.85)	(−19.10)
Age FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*
Firm FEs	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Occupation clusters	99	99	99	99	99	99
R2	0.11	0.10	0.09	0.09	0.22	0.20
Observations	18,297	11,512	18,296	11,512	18,297	11,512

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 6: 2nd stage with firm FEs, hourly wage growth, and year-*t* work pattern, 2019-2021

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Weekly wage growth 2019-2022		Hourly wage growth 2019-2022		Weekly wage growth 2019-2022	
WFH share post-2020	0.079***	0.052**	0.039*	0.001	0.047*	0.014
	(3.02)	(2.45)	(1.79)	(0.05)	(1.76)	(0.56)
Real wage growth 2015-16	0.050***	0.023	0.020*	0.017	0.047***	0.017
	(4.52)	(1.66)	(1.82)	(0.94)	(5.04)	(1.20)
Real wage growth 2016-17	0.012	0.034*	−0.016	−0.004	−0.002	0.016
	(0.83)	(1.66)	(−1.11)	(−0.18)	(−0.15)	(0.88)
Real wage growth 2017-18	−0.095***	−0.063***	−0.109***	−0.105***	−0.098***	−0.065***
	(−5.76)	(−2.92)	(−7.04)	(−5.69)	(−6.86)	(−3.10)
Real wage growth 2018-19	−0.339***	−0.328***	−0.305***	−0.314***	−0.324***	−0.323***
	(−18.76)	(−13.65)	(−18.66)	(−15.48)	(−19.74)	(−12.74)
Male	−0.002	−0.011***	−0.011***	−0.014***	−0.021***	−0.022***
	(−0.52)	(−3.82)	(−3.29)	(−3.84)	(−5.39)	(−7.54)
2020: Furloughed	−0.003	0.001	−0.005	−0.001	0.001	0.008
	(−0.62)	(0.05)	(−1.28)	(−0.07)	(0.18)	(0.65)
2020: Missing furlough info	0.009*	0.007	0.012***	0.021**	0.013***	0.015
	(1.72)	(0.57)	(3.60)	(2.19)	(2.70)	(1.48)
2021: Furloughed	−0.035***	−0.013	−0.011**	−0.020	−0.029***	−0.018
	(−6.08)	(−0.84)	(−2.28)	(−1.62)	(−5.43)	(−1.17)
2021: Missing furlough info	0.005	0.032	−0.005	−0.017	0.006	0.033
	(0.27)	(1.54)	(−0.43)	(−1.06)	(0.33)	(1.60)
2019: Part-time	0.076***	0.067***			0.257***	0.232***
	(11.32)	(9.71)			(20.90)	(27.42)
2019: Multiple jobs	−0.106***	−0.087***			−0.097***	−0.093***
	(−12.13)	(−7.12)			(−11.22)	(−7.65)
Growth in basic paid hours 2015-16			0.025*	0.009		
			(1.92)	(0.53)		
Growth in basic paid hours 2016-17			0.071***	0.058***		
			(5.57)	(2.96)		
Growth in basic paid hours 2017-18			0.114***	0.118***		
			(9.56)	(9.95)		
Growth in basic paid hours 2018-19			0.190***	0.199***		
			(17.42)	(10.30)		
2022: Part-time					−0.264***	−0.231***
					(−24.23)	(−22.21)
Age FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*
Firm FEs	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Occupation clusters	103	103	103	103	103	103
R2	0.09	0.09	0.07	0.07	0.23	0.21
Observations	18,295	11,409	18,295	11,409	18,295	11,409

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 7: 2nd stage with firm FEs, hourly wage growth, and year-*t* work pattern, 2019-2022

	(1)	(2)
Dependent variable:	Working part-time in 2021	Working part-time in 2022
WFH share post-2020	-0.073^{**}	-0.119^{***}
	(-2.08)	(-2.85)
Real wage growth 2015-16	-0.008	-0.011
	(-0.54)	(-0.76)
Real wage growth 2016-17	-0.002	-0.055^{**}
	(-0.09)	(-2.30)
Real wage growth 2017-18	0.026	-0.010
	(0.88)	(-0.42)
Real wage growth 2018-19	0.056^{**}	0.057^{**}
	(2.49)	(2.32)
Male	-0.059^{***}	-0.070^{***}
	(-8.49)	(-10.54)
2020: Furloughed	0.007	0.012
	(1.01)	(1.28)
2020: Missing furlough info	0.016^{**}	0.016^{**}
	(2.23)	(2.16)
2021: Furloughed	0.018^{*}	0.022^{*}
	(1.93)	(1.94)
2021: Missing furlough info	-0.022	0.004
	(-0.94)	(0.18)
2019: Part-time	0.743^{***}	0.685^{***}
	(46.06)	(38.81)
2019: Multiple jobs	0.056^{**}	0.034
	(2.06)	(1.29)
Age FEs	*Yes*	*Yes*
Local authority & sector FEs	*Yes*	*Yes*
Occupation clusters	99	103
R2	0.60	0.52
Observations	18,297	18,295

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table 8: Impact of remote work on probability of working part-time in 2021 and 2022

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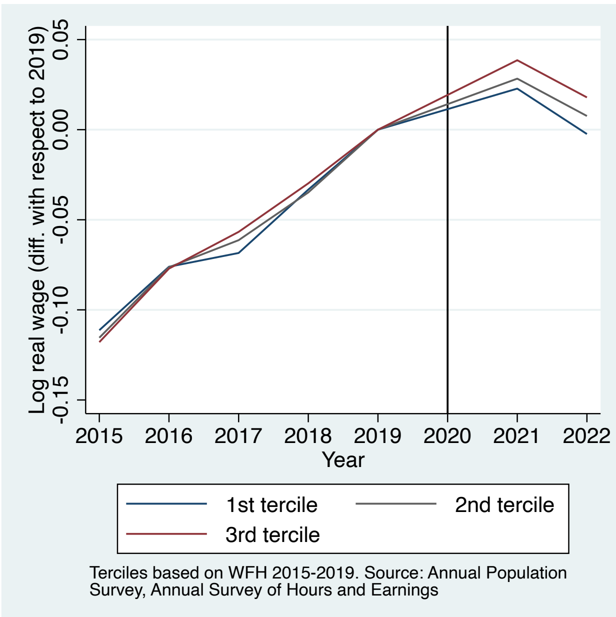
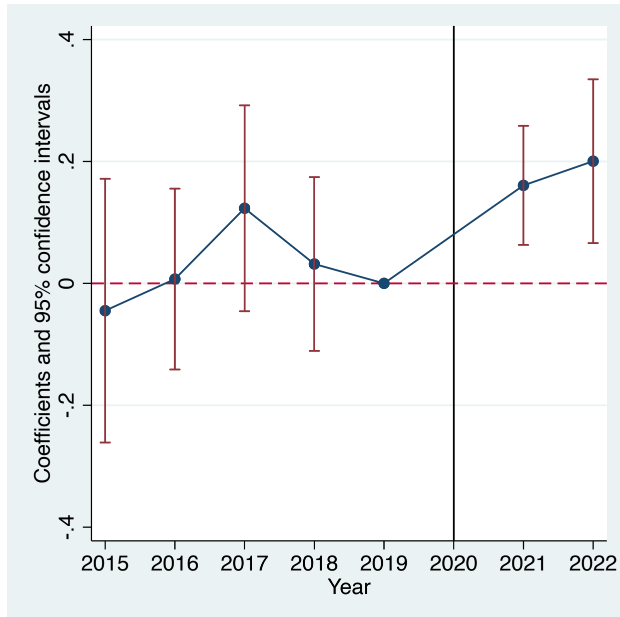
Appendix

A Additional Figures



(a) Trends in real wages by WFH pre-2020



(b) Event analysis of wages on WFH pre-2020

Figure A.1: Assessment of pre-trends (based on 2021 occupations)

B Additional Tables

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Real wage growth 2019-2021		
	Baseline	Δ WFH share	Job switchers	Multiple jobs	Gender
WFH share post-2020	0.062***		0.057***	0.067***	0.069***
	(4.00)		(3.72)	(4.35)	(2.90)
Real wage growth 2015-16	0.028**	0.029**	0.029**	0.026**	0.029**
	(2.52)	(2.54)	(2.53)	(2.41)	(2.54)
Real wage growth 2016-17	−0.004	−0.004	−0.003	−0.005	−0.004
	(−0.37)	(−0.40)	(−0.27)	(−0.46)	(−0.36)
Real wage growth 2017-18	−0.117***	−0.117***	−0.117***	−0.131***	−0.117***
	(−6.64)	(−6.66)	(−6.64)	(−7.09)	(−6.66)
Real wage growth 2018-19	−0.339***	−0.339***	−0.341***	−0.331***	−0.339***
	(−16.58)	(−16.54)	(−16.87)	(−15.36)	(−16.59)
Male	−0.001	−0.000	−0.002	−0.001	0.001
	(−0.51)	(−0.11)	(−0.67)	(−0.40)	(0.14)
2020: Furloughed	−0.017***	−0.016***	−0.016***	−0.018***	−0.017***
	(−4.00)	(−3.80)	(−3.72)	(−4.39)	(−4.00)
2020: Missing furlough info	−0.005	−0.005	0.000	−0.003	−0.005
	(−1.38)	(−1.34)	(0.11)	(−0.93)	(−1.38)
2021: Furloughed	−0.062***	−0.062***	−0.064***	−0.061***	−0.062***
	(−10.97)	(−10.88)	(−11.14)	(−11.12)	(−10.99)
2021: Missing furlough info	0.011	0.012	0.009	0.017	0.010
	(0.75)	(0.84)	(0.70)	(1.18)	(0.75)
2019: Part-time	0.049***	0.050***	0.048***	0.044***	0.049***
	(11.07)	(10.95)	(11.13)	(10.91)	(11.04)
2019: Multiple jobs	−0.087***	−0.086***	−0.086***	−0.187***	−0.087***
	(−9.17)	(−9.18)	(−8.72)	(−16.08)	(−9.15)
Change in WFH share post-2020		0.107***			
		(3.64)			
2021: New job × WFH share post-2020			0.125*		
			(1.73)		
2021: New job			−0.078***		
			(−4.08)		
2021: Multiple jobs × WFH share post-2020				−0.051	
				(−0.76)	
2021: Multiple jobs				0.251***	
				(15.23)	
Male × WFH share post-2020					−0.010
					(−0.46)
Age FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Occupation clusters	99	99	99	99	99
R2	0.11	0.11	0.12	0.16	0.11
Observations	18,297	18,297	18,297	18,297	18,297

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table B.1: Alternative specifications, 2nd stage, 2019-2021

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Real wage growth 2019-2022				
	Baseline	Δ WFH share	Job switchers	Multiple jobs	Gender
WFH share post-2020	0.079***		0.076***	0.084***	0.093***
	(3.02)		(2.94)	(3.19)	(2.80)
Real wage growth 2015-16	0.050***	0.051***	0.051***	0.042***	0.050***
	(4.52)	(4.59)	(4.54)	(4.01)	(4.59)
Real wage growth 2016-17	0.012	0.012	0.013	0.010	0.013
	(0.83)	(0.81)	(0.84)	(0.71)	(0.85)
Real wage growth 2017-18	−0.095***	−0.094***	−0.095***	−0.101***	−0.094***
	(−5.76)	(−5.75)	(−5.76)	(−5.92)	(−5.80)
Real wage growth 2018-19	−0.339***	−0.339***	−0.339***	−0.327***	−0.339***
	(−18.76)	(−18.79)	(−18.81)	(−17.25)	(−18.89)
Male	−0.002	−0.001	−0.002	−0.002	0.003
	(−0.52)	(−0.19)	(−0.55)	(−0.36)	(0.30)
2020: Furloughed	−0.003	−0.001	−0.003	−0.002	−0.003
	(−0.62)	(−0.31)	(−0.60)	(−0.50)	(−0.64)
2020: Missing furlough info	0.009*	0.009*	0.009*	0.011**	0.009*
	(1.72)	(1.75)	(1.79)	(2.11)	(1.73)
2021: Furloughed	−0.035***	−0.034***	−0.035***	−0.033***	−0.034***
	(−6.08)	(−6.00)	(−6.15)	(−6.01)	(−6.04)
2021: Missing furlough info	0.005	0.007	0.005	−0.000	0.005
	(0.27)	(0.36)	(0.25)	(−0.01)	(0.26)
2019: Part-time	0.076***	0.077***	0.076***	0.073***	0.077***
	(11.32)	(11.24)	(11.37)	(11.02)	(11.53)
2019: Multiple jobs	−0.106***	−0.106***	−0.106***	−0.191***	−0.106***
	(−12.13)	(−12.08)	(−12.22)	(−15.24)	(−12.07)
Change in WFH share post-2020		0.134***			
		(2.86)			
2022: New job × WFH share post-2020			0.065		
			(0.71)		
2022: New job			−0.029		
			(−1.29)		
2022: Multiple jobs × WFH share post-2020				−0.017	
				(−0.22)	
2022: Multiple jobs				0.245***	
				(16.81)	
Male × WFH share post-2020					−0.024
					(−0.70)
Age FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Local authority & sector FEs	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Occupation clusters	103	103	103	103	103
R2	0.09	0.09	0.09	0.13	0.09
Observations	18,295	18,295	18,295	18,295	18,295

t-statistics in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.01$

Table B.2: Alternative specifications, 2nd stage, 2019-2022