Home Sweet Home: Working from home and employee performance during the COVID-19 pandemic in the UK

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Abstract: In 2020, the COVID-19 pandemic forced governments in many countries to ask employees to work from home (WFH) where possible. Using representative data of the employed respondents from the UK, we find that the pandemic-led increases in WFH frequency are associated with a higher self-perceived hourly productivity, notably among female employees working in occupations conducive to WFH. Interestingly, changes in WFH frequency are unrelated to the respondents' weekly working hours (and weekly wages) during the same period. We then perform effect heterogeneity analysis by separately focusing on males and females working in WFH feasible occupations. For males, we find that the WFH-productivity correlation is stronger among those who commuted larger distances (and spent longer commuting time) to the office before the pandemic. For females, while we observe a stronger WFH-productivity correlation among those with higher autonomy over work pace, a weaker correlation is found among mothers with school-age children, mainly due to increased homeschooling needs during the pandemic. Finally, looking at the future of WFH, we show that employees' recent WFH experience and subsequent hourly productivity are intimately associated with their desire to undertake WFH in the future.

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1 Introduction

Nowadays, many firms allow their employees the possibility to work from home (WFH). Although WFH has become a reality for some, many employers were hesitant until recently, citing suspicions about employees' misuse of freedom over assigned work, resulting in an increased risk of "shirking from home". The COVID-19 pandemic in 2020, however, dramatically changed this pattern. In response to increasing infections and deaths, in mid-March 2020, many European governments called for social distance measures to slow the virus' spread, including restrictions on going to work. By the end of Spring of 2020, about half of the employed population worked exclusively from home in many Western countries (Brynjolfsson et al., 2020; Bonacini et al., 2021b; Dingel & Neiman, 2020; Felstead & Reuschke, 2020; Schröder et al., 2020; Kunze et al., 2020). This 'forced' innovation of WFH comes close to a "natural experiment", allowing social scientists to analyze the WFH's impact on employee performance. With the prospects that WFH is expected to remain in practice even after the pandemic ends (Barrero et al., 2021), a comprehensive assessment of employees' WFH performance gains policy relevance.

In theory, WFH—which increases employees' authority over working time, pace, and workplace—can be thought of as a principal-agent problem as the worker (agent) has fewer incentives to maximize the firm's value than the owner (principal) (Aghion & Tirole, 1997; Bloom & Van Reenen, 2011). It follows that workers may exploit this increased authority, resulting in increased shirking, hindering teamwork, and lowering performance. In contrast, increased work authority may lead to more intrinsic motivation (Deci & Ryan, 2000; Blau, 2017; Delfgaauw & Dur, 2008), a pertinent determinant of employee productivity (Becchetti et al., 2013). The empirical research on the topic also finds that increasing workers' authority enhances their performance (Eaton, 2003; Lyness et al., 2012; Kelliher & Anderson, 2010; Beckmann et al., 2017; Bloom et al., 2015; Rupietta & Beckmann, 2018).

In this paper, we empirically investigate the relationship between the increased WFH frequency during the COVID-19 pandemic and employee performance. Our analysis uses the novel *Understanding Society COVID-19 survey data* from the UK. Depending on the availability of outcome variables, the baseline estimation sample consists of employed respondents interviewed in September 2020 (*wave 5*) and March 2021 (*wave 7*). Using the information on their WFH behavior before and during the COVID-19 pandemic, we construct our primary explanatory variable of interest, indicating the change in the respondents' WFH frequency. Similarly defined outcome variables record the changes in work performance in the same period, measured in changes in their self-reported hourly productivity and weekly hours worked. The baseline estimation model investigates whether increases in WFH frequency are associated with changes in the respondents' work performance. Our results show that increases in WFH frequency during the pandemic are associated with higher self-perceived hourly productivity, whereas they are unrelated to changes in weekly hours worked.[1] The association is robust to including a battery of control variables indicating a range of demographic, household-level, and job-related characteristics.

Further subsample analysis suggests that the positive WFH-productivity association primarily applies to employees, especially females, working in occupations with higher WFH feasibility. Workers in low WFH feasibility occupations do not show a similar positive association on average. After that, we restrict the estimation sample to those working in occupations with high WFH feasibility and study whether the association varies with essential individual characteristics. We find that the WFH-productivity association is stronger among females who report higher autonomy over work pace and weaker among females caring for school-age children, mainly due to increased homeschooling needs because of school closures. For males, we find that the correlation is higher among those who commuted larger distances (and spent longer commuting time) to the office in the pre-pandemic period.

Our paper makes the following contributions to the literature. First, separate from existing research investigating the relationship between voluntarily taken WFH and employee performance (Bloom et al., 2015; Rupietta & Beckmann, 2018), our results indicate the existence of a modest positive effect of WFH on employee performance even when WFH is 'forced' by the government. Second, the study on WFH and employee performance during the pandemic in the UK is still rare. For instance, using data similar to this paper, Etheridge et al. (2020) report mean productivity changes for individuals working from home and find that employees working more from home during June 2020 reported higher WFH productivity. Different from their approach, our analysis considers

[1] The finding that employees' WFH frequency changes are unrelated to their weekly working hours needs further elaboration. The existing evidence shows that employees increase work efforts, typically measured in hours worked, in times of macroeconomic crisis (Senney & Dunn, 2019). As the COVID-19 pandemic also brought about the economic recession in the UK, our findings contradict earlier research on the topic.

all employees, including those who never worked from home during the pandemic. Further, instead of showing means, we isolate the effect of WFH on productivity by controlling for the pandemic severity (weekly COVID-death rates) and individual and job characteristics that could influence the selection into WFH frequency and productivity changes. Moreover, we use several measures for performance, and our analysis spans a much larger time horizon to shed light on the persistence of performance effects induced by increased WFH frequency. Finally, in place of a continuous measure of the change in WFH frequency, we perform additional analysis by employing a set of dummy variables indicating all possible jumps in WFH frequencies between the baseline and pandemic periods. In this regard, our use of a dedicated and large control group of employees in the empirical analysis – those who observe no change in their WFH behavior or have never taken WFH before/during the pandemic – helps us capture the general effects of the pandemic on labor market outcomes that are unrelated to the WFH frequency and sets the paper apart from emerging literature on the topic (Etheridge et al., 2020; Lee & Tipoe, 2020; Feng & Savani, 2020; Kunze et al., 2020).

As the pandemic continues to rage worldwide and is likely to result in structural changes in the labor market permanently affecting work environments (Baert et al., 2020; Kunze et al., 2020), we further investigate whether employees' recent WFH experience relates to their desire to undertake WFH in the future. We find that increases in WFH frequency and subsequent WFH productivity are intimately associated with the respondents' willingness to perform more WFH in the future, a finding particularly relevant for policymakers and employers aiming to expand flexible WFH arrangements. Our findings also call attention to mitigating policies aimed at curing the adverse differential experience of WFH. The results suggest that necessary support for WFH takers, especially always-open childcare facilities for working mothers, should also be considered.

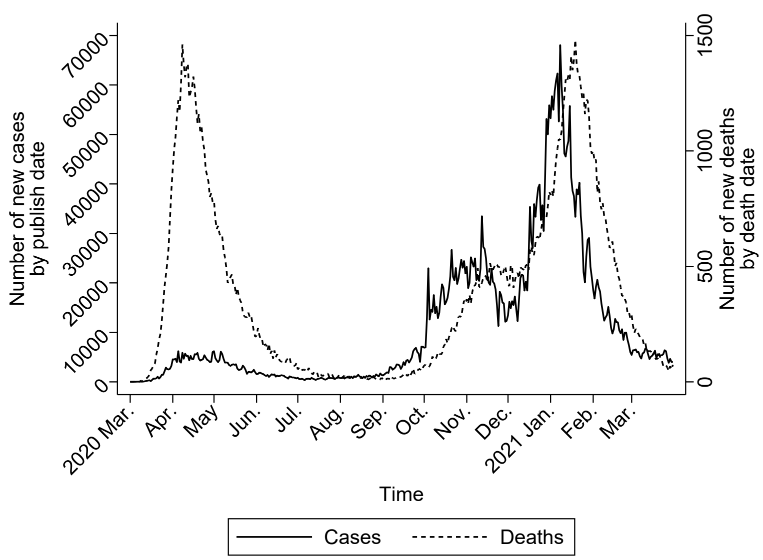
The remainder of the paper is set up as follows. The next section elaborates on the UK's COVID-19 pandemic situation, reviews related literature, and enlists theoretical foundations of our expected results. Section 3 describes the data sources we employ, defines variables used in the empirical analysis, and outlines our estimation strategy. In Section 4, we present and interpret our results. Finally, Section 5 concludes our findings.

2 Background

2.1 COVID-19 pandemic and government restrictions in the UK

In mid-March of 2020, Europe overtook China as the active center of the COVID-19 pandemic, with many European countries reporting increased infections and deaths. Figure 1 shows how the pandemic evolved in the UK.[2] The number of deaths per 100,000 population jumped dramatically in March 2020 and January 2021. Following other countries, Britain responded to the worsening pandemic by calling for social distance measures to slow the spread of the virus. As announced on 23 March by the British prime minister Boris Johnson, the measures included wide-ranging restrictions on freedom of movement, enforceable in law, under a stay-at-home order (BBC News, 2020).

Figure 1: **Number of COVID-19 cases and deaths in the UK**



Data source: The official UK Government website for data and insights on Coronavirus (COVID-19).
Notes: This figure shows the number of new cases by publish date and deaths by death date from March 2020 to March 2021 in the UK.

Figure 2 shows the daily variation in government-imposed COVID-19 restrictions in the UK, presented separately for four constituent countries, i.e., England, Scotland, Northern Ireland, and

[2] Information on the number of cases and deaths during the COVID-19 pandemic is provided by UK Government at `https://coronavirus.data.gov.uk/`.

Wales, respectively.[3,4] In subfigure (a), we plot the evolution of the government stringency index, a composite measure indicating different restrictions, including school closures, workplace closures, and travel bans. The index is scaled from 0 (*no restrictions*) to 100 (*strictest restriction*). The figure confirms the earlier observation that the country imposed stringent restrictions (≈ 80) around mid-March. The general stringency remained high in the following months with some regional variation. In subfigures (b) and (c), we show the evolution of the two additional indexes indicating government-imposed workplace and school closures, respectively. The index on workplace closures captures the following four restriction levels: 0 (*no restrictions*), 1 (*recommend closing or work from home*), 2 (*require closing or WFH for some sectors or categories of workers*), and 3 (*require closing or WFH for all-but-essential workplaces*). The figure shows that the highest workplace restrictions (level 3) were imposed starting in late March until May of 2020, followed by level 2 in the summer of 2020, and level 3 was in force again from the winter of 2020 till the beginning of 2021. Similar to the workplace restrictions index, restrictions on school closures also have four levels: 0 (*no restrictions*), 1 (*recommend closing schools or keeping schools open with alterations resulting in significant differences compared to non-COVID-19 operations*), 2 (*require closing only at some levels or categories*), and 3 (*require closing all levels*). Subfigure (c) shows that all schools were closed from mid-March to the end of May 2020 and January and February 2021. We exploit this variation in school closures in the empirical analysis.

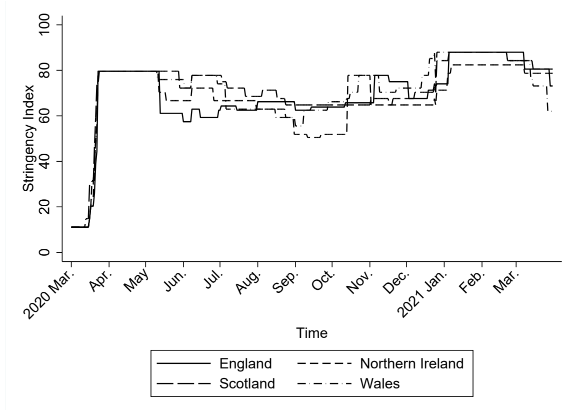
Early evidence suggests that the stringency measures were effective in restricting population movements. To show this, using *Google Mobility* data, we plot in Figure 3 the 7-day average of changes in workplace and residence place mobility during the pandemic compared to the baseline period in the UK.[5] It is clear that the country observed a considerable reduction in employees' mobility at the workplace, and the mobility at the place of residence increased consequently. This observation is in line with the early estimates by Felstead & Reuschke (2020), who find an eight-fold increase in those reporting to work exclusively from home (from 5.7% in January/February to

[3] The data are extracted from Coronavirus government tracker. More information can be found at `https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker`.

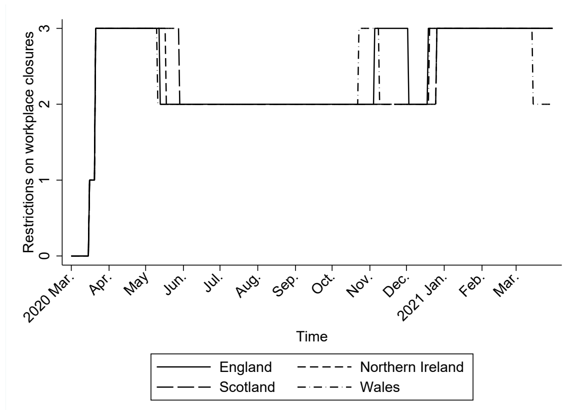
[4] These restrictions also had economic costs for the country, and the estimates suggest that they reduced the UK GDP by 20.4% in the second quarter of 2020 (Office for National Statistics, 2020).

[5] We obtain this data from *Community Mobility Reports* compiled by Google and are accessible at `https://www.google.com/covid19/mobility/`. A baseline-day value is the value for that day of the week, which is the median value from the 5-week period of 3. January to 6. February 2020. We calculated the last-7-day average ourselves. A negative value represents a decrease in mobility, and a positive value means an increase in mobility.

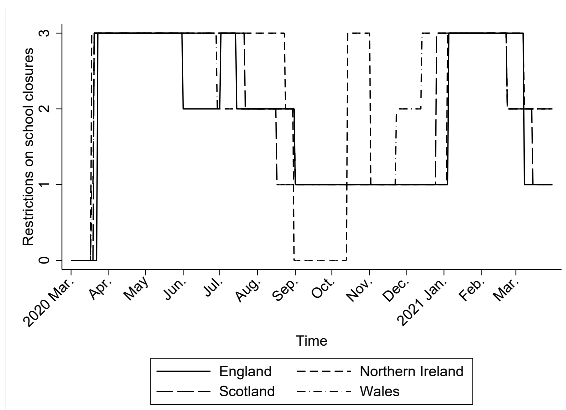
Figure 2: **Government restrictions during the COVID-19 pandemic in the UK**



(a) Government stringency index



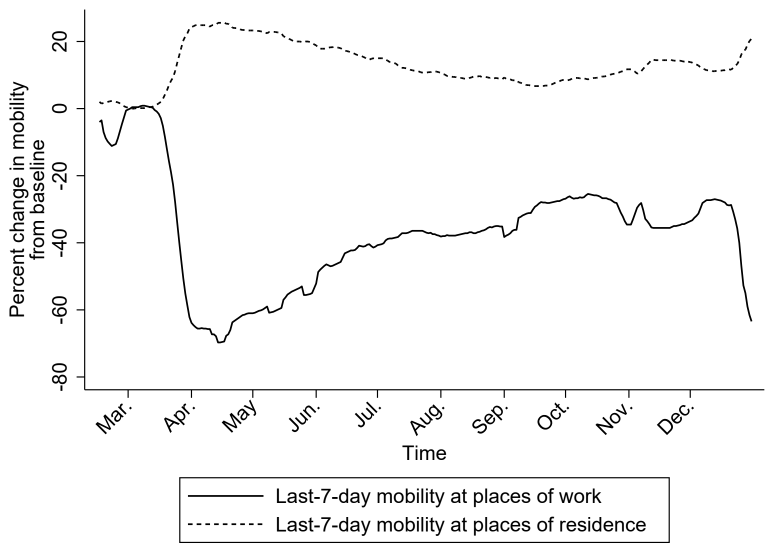
(b) Restrictions on workplace closures



(c) Restrictions on school closures

Data source: Coronavirus government response tracker.
Notes: This figure shows the government restrictions from March 2020 to March 2021 in England, Scotland, Northern Ireland, and Wales. Panel (a) shows the stringency index, Panel (b) restrictions on workplace closures, and Panel (c) restrictions on school closures.

Figure 3: **Last-7-day average mobility change at workplace and residence place in the UK**



Data source: COVID-19 community mobility reports, own calculation.
Notes: This figure shows the last-7-day average mobility change at workplace and residence place from March to December 2020 in the UK. This percentage change compares the mobility of people at work or at home for the report date to the baseline day.

43.1% in April, remaining high in June (36.5%)).[6] By the summer of 2020, however, the workplace restrictions were marginally relaxed and workplace mobility gradually improved (*see* figures 2b and 3). In the following subsection, we summarize the existing research and motivate how WFH relates to employee performance.

2.2 Working from home and employee performance

Baseline relationship

As WFH increases employees' freedom and control on job tasks, pace, and place, we first summarize economic theory research that studies how increased workers' work autonomy (also referred to as the intra-firm decentralization of power) affects employee performance (Aghion & Tirole, 1997; Bloom & Van Reenen, 2011). The researchers propose a principal-agent problem, where workers (agents) make decisions on behalf of the employer (principal). While increased work autonomy may decrease workers' performance as they (agent) have weaker incentives to maximize the firm value

[6] Also, *see* Brynjolfsson et al. (2020); Bonacini et al. (2021b); Dingel & Neiman (2020); Felstead & Reuschke (2020); Schröder et al. (2020); Kunze et al. (2020).

than the principal (employer), giving rise to increased shirking possibilities, the authors propose many sources with which decentralization can also benefit firms. Bloom & Van Reenen (2011, pp. 1751–1752) indicate that decentralization may help firms reduce costs of information transfer and communication, increase their speed of response to market changes, and increase workers' job satisfaction resulting in improved employee involvement, greater information sharing, and greater participation of lower-level staff.

The productivity-enhancing effect of increasing employees' work autonomy (decentralization) finds strong support in empirical research. Researchers find that the newly found authority, which we assume to be the consequence of allowing the WFH possibility to workers, may motivate workers to act in their own best interests and become more motivated and committed to their employers, increasing intrinsic motivation and reciprocal behavior (Deci & Ryan, 2000; Delfgaauw & Dur, 2008; Ellingsen & Johannesson, 2008; Blau, 2017). Moreover, Beckmann et al. (2017) show that granting employees autonomy over working time induces intrinsic motivation and reciprocal behavior. This finding directly contrasts employers' fears that employees would perform worse due to a lack of accountability when working from home. In the context of a large Italian company, Angelici & Profeta (2020) also find that work flexibility (in terms of location and time) increases worker productivity and well-being.

More related to the paper's scope, recent research investigates whether allowing the WFH possibility to employees, which increases their autonomy over working time, pace and place, is equally effective for firms than traditional onsite (office) working. Prominently, using a Randomized Controlled Trial (RCT) with call center workers in China, Bloom et al. (2015) show that employees switching to WFH observed an increase in their performance by 13%. Of the 13% increase in overall performance, an improvement of 9% is attributed to productivity change per shift (primarily due to a quieter and more convenient working environment) and 4% is due to longer minutes per day because of fewer breaks and sick days taken by employees while working from home. To shed more light on our paper's expected results, we refer to Bloom et al. (2015) and provide the following two opposing arguments concerning the WFH's impact on employees' performance, measured in hourly productivity and weekly hours.

First, we expect a relatively quieter and convenient work environment to increase the employees' WFH performance. More directly, WFH saves individuals time spent commuting to and from the office (Rubin et al., 2020).[7] In the UK, average daily commute was nearly one hour in 2018 (Trades Union Congress, 2021). Also, employees now save the time spent on multiple coffee breaks taken at the office. These arguments suggest that employees can now concentrate better and devote more time to work, indicating a qualitative and quantitative increase in working time, and should observe improved work performance during WFH. Second, in the opposite direction, forced WFH may be detrimental to employee performance for the following reasons. For instance, time saved due to WFH should make shirking and taking breaks more attractive, which employees can spend watching TV or playing video games. Lower access to supervisor support and teamwork can also hamper accountability and efficiency of working from home.

During the COVID-19 pandemic, when WFH was not always optional but necessary, social scientists devoted new research to studying the nature of changed working arrangements of the employed. This research investigated whether the employee work performance and general well-being were affected. According to this research, in line with the earlier assumption, WFH increased workers' work autonomy. Using British data, for instance, Pelly et al. (2021) provide evidence that homeworkers felt more engaged and autonomous during the pandemic. Concerning changed working arrangements, using data from Luxembourg, Hauret & Martin (2020) show that WFH workers extensively used digital tools to enhance communication, and those who had the pre-pandemic experience of using these tools reported even larger increases in their usage frequency during the lockdown. Others asked whether the pandemic-led changes in working arrangements affected employee performance. Using data on 700 telecommuting employees in Germany, Kunze et al. (2020) find that WFH increased perceived productivity and commitment during the pandemic. Etheridge et al. (2020) find that employees working more from home during the pandemic reported higher WFH productivity. Concerning the changes in working hours during the pandemic, the evidence is rather mixed (Kunze et al., 2020; Lee & Tipoe, 2020; The Economist, 2020).

The role of job characteristics

The employees' job characteristics are crucial considerations in the analysis of their WFH takeup and WFH performance. Several job-related characteristics, such as job's WFH feasibility, level of interaction needed to perform work, and the availability of amenities at home (separate workroom,

[7] Additionally, they find that the saved commuting time induced satisfaction among employees, especially among those who commuted by car.

appropriate electronics, etc.), are pertinent for employees to continue working unhindered without skimping on work during WFH. In this regard, the results of Felstead & Reuschke (2020) indicate that job's WFH feasibility was essential in determining WFH productivity during the COVID-19 lockdowns. Others discuss how WFH productivity is different based on job types. Dutcher (2012) shows that WFH's productive effect predominantly exists among workers performing creative tasks, which generally is a feature of WFH feasible occupations. In contrast, they find that WFH is counter-productive for workers dealing with dull tasks. For the UK, Etheridge et al. (2020) find that the self-perceived WFH productivity is higher among workers in industries that are more suitable for home office and lower among those in low-paying jobs.

The role of household characteristics

Many demographic and household characteristics are also pertinent determinants of WFH takeup and performance. Researchers find that male, older, and high-paid employees report higher WFH possibility (Adams-Prassl et al., 2020; Bonacini et al., 2021b; Dingel & Neiman, 2020). Others highlight the role of the respondents' gender and childcare needs in WFH performance. Etheridge et al. (2020) estimate that the average WFH productivity declined for women during the pandemic. Cui et al. (2020) show that the productivity of female academics dropped by 13.2 percent relative to that of male academics ten weeks after the lockdown in the United States. There is also evidence of an increase in the gender wage gap in occupations with a high level of WFH feasibility (Bonacini et al., 2021a).

WFH might have been particularly cumbersome for parents with childcare responsibilities, especially in the aftermath of the forced closure of schools and childcare during the COVID-19 lockdowns, compared to employees without children. For the UK, Panel (c) of Figure 2 shows that the country implemented two distinct school closures between March and May 2020 and between January and March 2021. Accordingly, the closure of childcare facilities and schools, a "disruptive exogenous shock" to family life (Huebener et al., 2021), increased the need for private childcare (Alon et al., 2020), which increased parents' time spent in childcare. Andrew et al. (2020) formally show that, in response, parents' time spent on childcare increased by 3.5 hours per day during the first lockdown, while working time decreased by 3.5 hours, partly driven by large employment losses. Using data from Germany, Arntz et al. (2019) record that childless employees worked an extra hour per week of unpaid overtime in WFH.

Furthermore, researchers show that increased childcare responsibilities had a disproportionate adverse impact on working mothers, who observed a relative reduction in their employment outcomes during the pandemic. Gallen (2018) show that mothers are still the primary childcare givers in Western countries, which explains why women are less productive than men, mainly visible among parents. New research also finds that the COVID-19 situation translated into a relative increase in females' time spent in childcare and housework. Andrew et al. (2020) find that mothers worked two hours per weekday less than fathers, increasing their time spent in childcare and housework. For the US, Zamarro & Prados (2021) show that mothers reduced working hours more and have an increased probability of transitioning out of employment. In contrast, for Germany, Kreyenfeld & Zinn (2020) do not find evidence of the gender gap in childcare as they show that fathers and mothers expanded their time spent on childcare to similar degrees.

Finally, we summarize the research discussing the welfare implications and future of WFH. Research suggests that workers undertook excessive workloads after switching to WFH, resulting in exhaustion (Kunze et al., 2020). Simultaneously, it is worth noting that breaks at home might be less enjoyable as social interactions are lower than working from the office. Extended stays at home may increase boredom, worsening the individuals' mental health (Etheridge & Spantig, 2020). Worsened mental health may also have an additional adverse impact on employees' WFH productivity. Therefore, the welfare impact of WFH needs serious consideration. Nonetheless, there is some evidence that the forced WFH experience during the COVID-19 induced desire to take up more WFH in the future (Kunze et al., 2020).

3 Data and methodology

3.1 Data and variables

3.1.1 Data source and sample restrictions

Our empirical investigation employs the high-quality individual-level longitudinal data of the *Understanding Society* from the UK (University of Essex, Institute for Social and Economic Research, NatCen Social Research, Kantar Public, 2020). Initially starting in 2009 (*wave 1*), the survey records detailed information on approximately 40,000 British households annually. In the Spring of 2020, when the COVID-19 pandemic began in the UK, the survey asked respondents to complete supplementary web-based surveys since April 2020 (University of Essex, Institute for Social and Economic Research, 2020). These special waves (referred to as *COVID-19 waves*) covered various questions on the welfare of individuals, families, and communities in the country.[8] These waves contain detailed information on individuals' time-invariant characteristics, such as birth year and gender. We source the information absent in COVID-19 survey waves and roughly constant over a short period (e.g., individual's occupation, industry, region (rural/urban), and the number of children under 16) from waves nine and ten (2017–2019) of primary survey data. Subsequent sections define and motivate the choice of variables used.

Given the paper's focus on studying the association between the changes in the respondents' WFH frequency and working performance, we restrict the estimation sample to working-age respondents, i.e., 18 and 65 years. Furthermore, we limit the analysis to those respondents who reported being paid employees (or self-employed) in the baseline period (before the pandemic, in January/February 2020) and during the pandemic. Depending on the availability of self-reported hourly productivity, our analysis uses COVID-19 waves five and seven, conducted in September 2020 and January 2021, respectively.[9,10] Now, we discuss the exceptional group of individuals who reported decreased WFH frequency during the pandemic. While we omit these individuals from the baseline sample as we suspect them to behave differently from others, in a robustness check, we confirm that the central message of the paper does not depend on this exclusion.[11] Finally, to restrict the sample, we use the information on reasons for a reported drop in their working hours. We omit individuals reporting zero working hours or those who report changes in their working hours for the following reasons: laid-off by employers, taking paid leave, or taking sick leave.[12]

[8]For more information on the COVID-19 survey waves, see `https://www.understandingsociety.ac.uk/documentation/COVID-19`.

[9]We ignore wave three, used by Etheridge et al. (2020), because it collects hourly productivity information of only a subsample of the employed population, primarily only those working from home, and omits those who did not undertake WFH during this period, the group which is, however, of our particular interest.

[10]While baseline estimation employs the sample of individuals reporting data on all outcome variables, we now test the main results' robustness by employing all available information for distinct outcomes in waves one to eight. For instance, we re-estimate the model for hourly productivity changes by adding the information present in wave three, whereas, for the changes in working hours, we employ all COVID-19 waves (one–eight). Table A-1 and Table A-2 in the appendix present the results, which we confirm to be qualitatively similar to the ones discussed in subsection 4.1.

[11]The results are presented in Table A-3 in the appendix.

[12]We also drop individuals who reported too large values in their weekly working hours (>60 hours) in the baseline or current period. These amount to about 1% of the sample.

Consequent to sample restrictions noted above, the baseline estimation sample consists of information on 3,056 individuals with 4,814 observations, including information on all dependent and essential independent variables. In Table 1, we report the summary statistics of the variables used. Beyond overall sample means and standard deviations as presented in columns (1)–(2), columns (3)–(6) separately report information of individuals who reported increases in WFH frequency and those who did not observe any changes in their WFH frequency (columns (5)–(6)) during the pandemic. Next, we define and describe the variables of interest.

3.1.2 Changes in working from home frequency

The primary explanatory variable is the change in the respondents' frequency of working from home (ΔWFH). Individuals respond to the following survey question: *"During the last four weeks how often did you work at home?"*. Their answers can be 1 (*always*), 2 (*often*), 3 (*sometimes*) and 4 (*never*). A similarly defined question also records the respondents' pre-COVID-19 WFH behavior by retrospectively asking them to report how often they took up WFH in January and February 2020, which we refer to as the baseline WFH behavior. Using this information, we construct ΔWFH by performing the following two steps. First, we reverse individual responses to the two questions above so that larger values of the new variables correspond to higher frequencies of WFH, i.e., 1 (*never*) to 4 (*always*). Second, we take the difference in WFH frequencies between the current and baseline period to compute the change in the frequency, i.e., $\Delta WFH = WFH - WFH_{baseline}$.

The descriptive statistics presented in Table 1 show that UK respondents reported increases in their WFH frequency during the pandemic. The mean of ΔWFH is 0.9088, equivalent to about a one-step increase in their WFH take-up during the pandemic. However, it is noteworthy that not all increases in WFH frequency are comparable. A one-step increase from *never* to *sometimes* may bring about different changes in working performance compared to the increase from *often* to *always*. To ease the interpretation of the results of our estimation model, we employ the z-standardized ΔWFH with a mean of zero and standard deviation of one and discuss the effects associated with a one-standard-deviation change in ΔWFH. Alternatively, we employ a set of dummy variables indicating all possible changes in WFH frequency between the baseline and the current period in a robustness check. We elaborate on these results in section 4.

Table 1: **Summary statistics**

	(1)	(2)	(3)	(4)	(5)	(6)
	All		ΔWFH **>0**		ΔWFH**=0**	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Main explanatory variable						
$\Delta WFH = WFH - WFH_{baseline}$	0.9088	1.1182	1.9734	0.7834	0	0
Outcome variables						
$\Delta PROD$	3.1717	0.9139	3.2312	1.0383	3.1210	0.7892
$\Delta PRODQ$	0.1468	1.1950	0.2046	1.3576	0.0976	1.0340
$\Delta PRODM$	1.5321	15.3087	2.1799	17.2474	0.9790	13.4127
$\Delta HOURS = HOURS - HOURS_{baseline}$	0.1809	7.0482	-0.0291	6.9737	0.3602	7.1075
Individual-level control variables						
Age	43.7556	11.8550	42.7723	11.2335	44.5949	12.3010
Female (0/1)	0.5045	0.5000	0.5298	0.4992	0.4830	0.4998
Live with a partner (0/1)	0.7000	0.4583	0.7240	0.4471	0.6795	0.4668
Number of children	0.6313	0.9409	0.6630	0.9166	0.6043	0.9605
Urban (0/1)	0.7672	0.4227	0.7758	0.4171	0.7598	0.4273
Key sector workers (0/1)	0.5438	0.4981	0.5644	0.4959	0.5263	0.4994
Log income	6.1282	0.6710	6.3563	0.6276	5.9336	0.6451
COVID-19 weekly death rates	6.2132	6.8698	7.3234	7.0904	5.2655	6.5293
Working hours changed for specific reasons (0/1)	0.4077	0.4914	0.3783	0.4851	0.4327	0.4956
Firm size						
1–2	0.0229	0.1495	0.0327	0.1780	0.0144	0.1192
3–9	0.1024	0.3032	0.0587	0.2352	0.1397	0.3468
10–24	0.1277	0.3337	0.0899	0.2861	0.1599	0.3666
25–49	0.1328	0.3394	0.0882	0.2837	0.1709	0.3765
50–99	0.1123	0.3158	0.1053	0.3070	0.1183	0.3231
100–199	0.1216	0.3268	0.1061	0.3081	0.1348	0.3415
200–499	0.1190	0.3239	0.1396	0.3467	0.1015	0.3020
500–999	0.0616	0.2405	0.0751	0.2637	0.0501	0.2181
1000 or more	0.1997	0.3998	0.3042	0.4602	0.1105	0.3135
Qualification						
University higher degree	0.1735	0.3787	0.2730	0.4456	0.0886	0.2843
First degree or equivalent	0.2169	0.4122	0.3110	0.4630	0.1367	0.3436
Diploma in higher education	0.0746	0.2628	0.0706	0.2562	0.0780	0.2682
Teaching qual. not PGCE	0.0067	0.0816	0.0067	0.0816	0.0067	0.0817
Nursing/other med. qual.	0.0147	0.1202	0.0084	0.0913	0.0200	0.1400
Other higher degree	0.0014	0.0373	0.0022	0.0467	0.0007	0.0267
A level	0.0859	0.2803	0.0825	0.2752	0.0889	0.2846
Welsh baccalaureate	0.0005	0.0218	0.0002	0.0153	0.0007	0.0261
Intl. baccalaureate	0.0008	0.0287	0.0015	0.0390	0.0002	0.0152
AS level	0.0246	0.1550	0.0240	0.1530	0.0252	0.1567
Highers (scot)	0.0101	0.1002	0.0104	0.1016	0.0099	0.0989
Cert 6th year studies	0.0025	0.0499	0.0010	0.0314	0.0038	0.0614
GCSE/O level	0.2289	0.4202	0.1415	0.3486	0.3035	0.4599
CSE	0.0417	0.2000	0.0125	0.1113	0.0667	0.2495
Standard/o/lower	0.0078	0.0878	0.0022	0.0470	0.0125	0.1112
Other school cert	0.0043	0.0654	0.0011	0.0332	0.0070	0.0835
None of the above	0.1050	0.3066	0.0512	0.2204	0.1510	0.3581
Supplementary analysis						
Commuting distance (miles): $ComDis$	10.9472	16.8004	13.1662	19.7871	9.0529	13.4641
Commuting time (minutes): $ComTime$	27.9856	21.5606	34.0188	24.4386	22.8354	17.1580
Work autonomy over work pace (categories 1–4)	3.0487	0.9519	3.1812	0.9167	2.9355	0.9669
Having children (0/1)	0.3604	0.4802	0.3895	0.4877	0.3357	0.4723
School closures (0/1): $SchClose$	0.4546	0.4980	0.5312	0.4991	0.3892	0.4877
Childcare responsibility (categories 1–3)	1.9078	0.7321	2.0620	0.7097	1.7462	0.7209
Government restrictions	74.5728	12.2211	76.4568	12.2409	72.9644	11.9742
Concentration (0/1)	0.8068	0.3949	0.7663	0.4233	0.8412	0.3656
Number of individuals	3,056		1,642		1,692	
Number of observations	4,814		2,464		2,350	

Note: This table shows the weighted summary statistics of the estimation sample. Columns (1)–(2) show statistics for the whole sample of 4,814 observations, columns (3)–(4) for 2,464 observations who reported increased WFH frequency, and columns (5)–(6) for 2,350 observations who did not report any increase in WFH frequency.

3.1.3 Dependent variables: Changes in working performance

Changes in hourly productivity

We measure employee performance using two sets of outcome variables. First, we employ two variables recording the respondents' self-reported change in productivity per hour. In COVID-19 waves five and seven, respondents were asked the following question: *"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?"*. The answer to this question can be 1 (*much more done*), 2 (*a little more done*), 3 (*about the same done*), 4 (*a little less done*), and 5 (*much less done*).[13] We re-scale the responses so that higher values indicate larger increases in hourly productivity. The newly generated variable, $\Delta PROD$, ranges from 1 - *much less done* to 5 - *much more done*, which is z-standardized when applied in the estimation model.

It is worth mentioning that individuals may have different conceptions about what "a little/much less/much more" means. Two individuals with a similar answer may behave differently, making the objective measure of the productivity change desirable. To partially address this issue, we employ the survey question asking respondents to quantify the changes in their hourly productivity and clarify their expected changes in productivity in minutes. For example, the respondents reporting decreases in hourly productivity during the pandemic are asked to answer the following question: *"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: (1) Between 45 minutes and an hour; (2) Between 30 and 45 minutes; (3) Less than 30 minutes?"*. Similarly, the respondents reporting increases in hourly productivity are asked the following question: *"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: (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?"*. Using this information, we generate a categorical outcome variable, $\Delta PRODQ$, which takes the value of 0 if individuals reported no changes in the hourly productivity. A positive value of this variable indicates an increase in productivity, and a

[13] A data issue concerning the time difference in the phrasing of the questions recording our variables of interest is worth mentioning. The survey question recording WFH frequency asks respondents to report their behavior for "the last four weeks". In contrast, the survey question for productivity includes the phrasing "these days". For the simplicity of our results' interpretation, we assume that individuals' behavior remains relatively constant during the two time periods, an assumption we extend to our investigation of the changes in working hours "last week".

negative value means a decrease. In other words, for the tasks currently done within one hour, $\Delta PRODQ$ equals 1 if the respondent previously needed 15 minutes more, 2 if 15–30 minutes more, and 3 if more than 30 minutes. Correspondingly, in terms of decreased productivity, $\Delta PRODQ$ equals -1 if the individual previously needed 45–60 minutes, -2 if 30–45 minutes, and -3 if less than 30 minutes.

To put the newly created variable $\Delta PRODQ$ in perspective of the original hourly productivity indicator $\Delta PROD$, in Table A-4 in the appendix, we show the cross-distribution frequency of $\Delta PROD$ against $\Delta PRODQ$. Taking "(2) little less" of $\Delta PROD$ as an example, 299 observations report that they previously needed 15 minutes less, but 214 observations report to have required 15–30 minutes less, and 55 observations used less than 30 minutes. As the new variable brings clarity on the issue arising from individuals' differential conceptions of the meaning of what different steps in $\Delta PROD$ (e.g., "little less") mean, our baseline analysis employs $\Delta PRODQ$ as our primary productivity measure.[14] Like $\Delta PROD$, we z-standardize $\Delta PRODQ$ before using it in our baseline regression model. The statistics presented in Table 1 report that, on average, British respondents reported an increase in hourly productivity during the pandemic, compared to the baseline period, and the increase is larger for individuals who reported more WFH, i.e., $\Delta WFH > 0$. This difference is more pronounced if quantified productivity changes are applied, i.e., $\Delta PRODQ$.

Changes in weekly working hours

We employ the respondents' change in weekly working hours ($\Delta HOURS$) as the second measure of employee performance. Generally construed as an input measure, working hours may also indicate worker's performance as more time is spent on work-related activities, likely increasing worker's output (Bell & Freeman, 2001). Alternatively, noteworthily, given the number of tasks and output

[14] Using this information, we generate an additional measure of the quantified productivity, which allows us to estimate the productivity change in minutes, easing the interpretation of the sizes of the coefficients. To do this, we average the information in minutes of changes in hourly productivity and construct $\Delta PRODM$, which equals 0 if the productivity remains the same. If the respondent needed 45–60 minutes previously, the variable takes the value of -7.5, indicating a reduction of 7.5 minutes in hourly productivity. Similarly, the variable takes the values of -22.5 and -45 if the respondent needed 30–45 minutes and less than 30 minutes less than previously, respectively. For productivity increases, the opposite of the logic above applies. That is, we assign 7.5 to the variable if individuals needed 15 minutes more previously, 22.5 if 15–30 minutes more, and 45 (at least) if more than 30 minutes. For individuals with the largest increase in productivity, it is unclear what the average number of minutes should be. To be symmetric to the productivity decrease, we assign 45 minutes to them. As per Table 1, the mean of $\Delta PRODM$ for individuals doing more WFH is 2.1799 (minutes), indicating an increase in productivity by 3.63% (= 2.1799/60). Table A-5 report the results estimated using this variable, which we confirm to be qualitatively similar to the results estimated using our main dependent variable, i.e., $\Delta PRODQ$.

remains constant, the decrease in working hours due to increases in hourly productivity may also indicate a better employee performance. These opposite interpretations support our attempt at investigating hourly productivity and hours worked together. The survey question asks: *"How many hours did you work, as an employee or self-employed, last week?"*. A similarly defined question records the respondents' baseline weekly working hours, i.e., pre-COVID-19 behavior in January and February 2020. The question asks: *"During January and February 2020, how many hours did you usually work per week? Please include all jobs and self-employment activities"*. We construct our outcome variable $\Delta HOURS$ by taking the difference in weekly working hours between the current and baseline period.

The statistics presented in Table 1 show that UK respondents, on average, reported a very small increase in their working hours during the pandemic (see column (1)), which is contradictory to the evidence from other countries (see Schröder et al., 2020). Interestingly, individuals observing an increase in their WFH frequency during the pandemic reported on average a slight decrease in working hours (column (3)), while those reporting no change in their WFH frequency show an increase in working hours (column (5)). Like outcomes noted above, we z-standardize $\Delta HOURS$ when estimating the regression model.

3.1.4 Control variables

The first set of control variables include the respondent's demographic characteristics. These include the respondents' age, gender, couple status (whether living with a partner or not), number of children, urban/rural residence, and 12 dummy variables for the UK NUTS-1 regions. We also apply a set of dummy variables indicating their highest educational qualification. As COVID-19 waves do not record the individuals' education, we obtain this information from waves nine and ten of the primary survey data collected in the pre-pandemic period.

Additionally, we include a set of covariates indicating the respondents' labor market characteristics, which may be associated with their WFH frequency and working performance. First, we control for the effect associated with the respondents' industry and occupation of work. To do so, we generate dummy indicators, amounting to 20 industry and 26 occupation dummies.[15] Moreover, we generate a dummy variable for being a key worker representing workers employed in essential

[15] The list of industries and occupations is reported in Table A-6.

sectors as listed in the survey questionnaire, which include: health and social care, education and childcare, key public services, local and national government, food/other necessary goods, public safety/national security, transport, and utilities, communications and financial services.[16] We use 9 dummy variables indicating the firm size of their employment. Finally, we consider the respondents' pre-COVID performance with the logarithm of monthly gross pay obtained from waves nine and ten of the primary survey data. Next, we control for the severity of the pandemic in the main specification. That is, we employ the weekly deaths by registration date per 100,000 population at the NUTS-1 level. Moreover, we exploit the respondents' self-reported reasons why their working hours changed more than one hour during the pandemic compared to the latest survey. These reasons include caring for children, changed employer, avoiding the risk of becoming sick, and so on. We control for the effect of such changes on employee performance using a single dummy variable together representing these reasons. This variable is relevant since the event may affect respondents' working hours and productivity, which could also change their WFH frequency. Finally, we account for wave fixed effects and wave-industry-specific fixed effects.

Now we discuss the summary statistics of control variables shown in Table 1. Comparing the mean of *age* and $female$ in groups with $\Delta WFH > 0$ and $\Delta WFH = 0$, respectively, we note that young and female employees are more likely to increases their WFH frequency. It may be easier for young workers to learn how to use necessary software to communicate with colleagues. Women may have to spend more time at home to take care of children, which is corroborated by the evidence that individuals doing more WFH have, on average, more children (see the mean of *number of children*). Notably, we observe that individuals residing in areas worse affected by the pandemic, denoted by higher COVID-19-related deaths in their region of residence, reported larger increases in WFH take-up, another evidence that the pandemic induced increased WFH frequency among the employed.

[16]Additionally, we also employ the industry information of individuals and define that an employee is a key worker if they work in the following industries: Accommodation and food service activities; financial and insurance activities; public administration and defense; compulsory social security; education; and human health and social work activities.

3.2 Empirical strategy

3.2.1 Main specification

To study the association between changes in the respondents' WFH frequency and employee performance, we estimate the following model:

$$\Delta Y_{it} = \alpha_0 + \alpha_1 \Delta WFH_{it} + \boldsymbol{X'_{it}}\,\boldsymbol{\beta} + \lambda_t + \varepsilon_{it}, \tag{1}$$

where ΔY_{it} denotes the change in employee performance, indicated by changes in their hourly productivity ($\Delta PROD_{it}$ or $\Delta PRODQ_{it}$) and weekly working hours ($\Delta HOURS_{it}$), of individual i interviewed in wave t. ΔWFH_{it} represents the change in self-reported WFH frequency of individual i in the last four weeks. $\boldsymbol{X_{it}}$ is a vector of individual characteristics in levels shown in Table 1. Notably, these include the respondent's age and quadratic term, gender, residence status (currently living with a partner), urban region, number of children under 16 in the household, and a set of dummy variables for the highest educational qualification. The vector also includes a regional measure of the pandemic intensity, log of pre-pandemic wage income, several job-related characteristics (dummy indicators representing the firm size of their employer, occupation and industry dummies, key-sector workers, and having an increase or a decrease in working hours by more than one hour), and region fixed effects. λ_t represents wave fixed effects and ε_{it} is the error term. Additionally, we include the industry-wave fixed effects in the model, since employees in different industries may be affected by the pandemic to different extent, and this difference may also change across waves (time).

We estimate the model using Ordinary Least Squares (OLS). The standard errors are clustered at the individual level to account for serial correlation of an individual. To consider different selection probabilities of individuals, following Crossley et al. (2021), we apply individual cross-sectional weights, provided in each wave of the Understanding Society COVID-19 study, in all regressions. Estimating the WFH-performance correlation in first differences rather than in levels allows us to control for time-invariant (un-)observable factors correlated with employee performance and WFH frequency, such as individuals' personality traits or ability. In addition to the estimates for the entire sample, we show separate estimates for male and female subsamples and employees with a low and high WFH feasibility, respectively.

Nevertheless, the interpretation of α_1 needs careful discussion. First and foremost, it is noteworthy that not all respondents were forced to work from home. The first lockdown in the UK came into force on March 26th, 2020. By September 2020, most strict measures eased, which is when the survey wave five was collected. On January 6th, 2021, the country entered the third national lockdown, the month when the wave seven was collected. As the lockdowns were not always in place when our estimation sample was collected, especially in wave five, WFH was not forced to all employees and not all the time. Therefore, we suggest that the estimate α_1 should be interpreted as the correlation between the change in WFH frequency and employee performance. Second, selecting into WFH may be correlated with the ability of working from home unhindered. If high-ability individuals self-select into WFH (and can increase their performance more than others), the estimated WFH-performance relationship could be more representative for 'better' employees. However, WFH takers may also be adversely selected if 'better' workers want to stay in the office (Emanuel & Harrington, 2021). In this case, our model may underestimate the causal impact.

3.2.2 Supplementary analysis

As noted earlier, numerous variables may intervene in the WFH-performance relationship, and their intervention may be more pronounced in subgroups of employees. Therefore, we perform supplementary analysis using additional information present in the survey or from other sources. First, WFH may not be feasible for all employees, and the forced WFH may adversely affect the work performance of those who find WFH infeasible. To test this, we consider external measures of the WFH feasibility at the occupation and industry level sourced from Adams-Prassl et al. (2020).[17] To be precise, we apply the mean of WFH feasibility scores of the occupations listed in Adams-Prassl et al. (2020), this is, a mean of 30, as the cutoff point to divide the estimation sample. We refer to occupations as *high WFH feasibility occupations* if their WFH feasibility$\geq$30 and those working in occupations with WFH feasibility$<$30 as *low WFH feasibility occupations*. The regression model is then re-estimated separately on both subgroups. We perform a similar

[17] For this application, we first transfer our 26 occupations, classified according to the 3-digit ISCO-88, to SOC00 classification, and then re-code it to SOC18 classification, which is the occupation classification used in Adams-Prassl et al. (2020). The industry classification is the same as in Adams-Prassl et al. (2020). However, our sample lacks information on individuals working in the following industry groups: *extraterritorial organisations* and *other*.

analysis using the WFH feasibility information of the individual's industry (mean of 46). We also apply the self-reported WFH flexibility recorded in the Understanding Society dataset, which indicates whether the employer allows flexible working arrangements, including WFH possibilities. We exploit these variables to investigate whether and how the WFH-performance relationship differs across subsamples.

Second, we consider the role of commuting distance (and commuting time) and self-reported autonomy over the pace of work in determining the heterogeneity in the baseline relationship. We employ the commuting distance and commuting time obtained from waves nine and ten (2017–2019) of the primary survey data. The survey measures commuting distance in miles and commuting time in minutes. As noted earlier, employees, who used to commute for longer times or distances before the pandemic, can now save commuting time due to workplace restrictions. The increased WFH frequency should help them avoid the stress of commuting long distances, improving their work performance. Additionally, we investigate whether the WFH-performance association differs between employees with more or less autonomy over the pace of work, a variable borrowed from wave ten of the primary survey data. For this analysis, we generate a dummy variable, *work autonomy*, that takes the value of one if the individual reported *a lot* or *some* autonomy over the pace of work and zero if only *a little* or *no* autonomy is reported, and re-estimate the regressions separately on both subsamples. In the analysis, focusing on individuals for whom WFH is feasible, we control for the aforementioned job-related characteristics and include interaction terms between ΔWFH and these new variables in the model.

Third, following the estimation strategy introduced above, we analyze the heterogeneous effects by family characteristics. In particular, we employ four variables indicating the respondents' family structure and life, including information on having children, self-reported childcare responsibility, and an indicator for the government-imposed school closures. Using the continuous variable indicating the number of children under 16 in the household, we generate a dummy variable representing whether the respondents have children. We also use the information on the number of children as a continuous variable. During the lockdowns, schools were momentarily closed in most UK regions, which may increase demand for childcare and homeschooling, adversely affecting parents' WFH performance differently. To study this, we use the stringency index denoting the level of restrictions on school closures in a region. The index has three stringency levels, one to three, during the estimation period, where level three indicates the strictest regulation. We generate a dummy variable using this information, which takes one if levels two or three were imposed and zero otherwise. The final variable relates to the level of self-reported childcare responsibility, which takes the following three values: 1 (individual's partner or other relatives are responsible for the child), 2 (if both partners are equally responsible), and 3 (if the respondent always or usually takes the childcare responsibility). We expect that individuals who take more childcare responsibilities record reduced work performance.

Fourth, we give special attention to the role of pandemic severity in the baseline relationship and then study the WFH prospects. We employ two externally sourced variables for this analysis. We first include an interaction term between the ΔWFH and the weekly COVID-19-related death rate by registration dates in the model. Furthermore, we employ the government stringency index discussed earlier and include its interaction with ΔWFH in the regression model. Beyond region-level pandemic severity, we use the individuals' self-reported ability to concentrate during the pandemic to account for the mental distress induced by the pandemic, which may determine their WFH frequency and performance while working from home. To test this hypothesis, we use the following survey question: *"The next questions are about how you have been feeling over the last few weeks. Have you recently been able to concentrate on whatever you're doing?"*. The individual responses to this question are as follows: *(1) Better than usual; (2) Same as usual; (3) Less than usual; and (4) Much less than usual.* Using this information, we create a dummy, *concentration*, for individuals stating that they concentrate better (1) or the same as usual (2). We include the variable *concentration* and its interaction with ΔWFH in the model. Employees who have at least the same concentration at home as in the office may perform better than those who do more WFH but cannot concentrate well.

Finally, we close our investigation by bringing attention to the future of WFH in the modern workplace. That is, we analyze the determinants of the willingness to undertake WFH in the future with the question: *"Once social distancing measures are fully relaxed and workplaces fully go back to normal, how often would you like to work from home?"*. Four answers are possible: *always*, *often*, *sometimes*, and *never*. This continuous variable is z-standardized. Individuals taking more WFH during the pandemic and having good performance, e.g., reporting higher productivity, may be more willing to continue with WFH regularly.

4 Results

4.1 Main results

Table 2 presents the main results. The organization of the table is as follows. In Panel I, we report the results of the two hourly productivity measures motivated earlier ($\Delta PROD$ and $\Delta PRODQ$), whereas Panel II shows the estimates for the changes in weekly working hours ($\Delta HOURS$). In column (1), we show the results estimated using the entire baseline estimation sample, whereas columns (2) and (3) depict the results separately for female and male subsamples. The results suggest that increases in the WFH frequency are associated with modest increases in both measures of hourly productivity but uncorrelated with weekly working hours.[18] In other words, although, on average, employees taking more WFH are more productive, their working hours do not change significantly in response to changes in WFH frequency. In terms of magnitude, a one standard deviation increase in the WFH frequency is associated with a 0.09 (0.073) standard deviation increase in hourly productivity $\Delta PROD$ ($\Delta PRODQ$). Furthermore, in columns (2)–(3), we find that females show a stronger WFH-productivity association than males, both in magnitude and significance.

Beyond highlighting the productive impact of the 'forced' WFH during the COVID-19 lockdowns, our analysis demands a thorough discussion of its many results and WFH prospects. First, we attempt to put our baseline results in the perspective of the existing research. Our results suggest a positive association between the employees' WFH frequency and their productivity per hour, a finding consistent with other research on the topic (Bloom et al., 2015; Etheridge et al., 2020). However, the main criticism of our results is the self-reporting nature of the hourly productivity measures, which we attempt to address in two ways. First, we test whether the weekly wages (net payment), an alternative measure of performance, share a similar relationship with changes in WFH frequencies. The results reported in Table A-8 do not report a statistically significant WFH-wages association. We argue that no changes in weekly wages may be indicative of the

[18]Employees' baseline WFH frequency may be a crucial determinant of their WFH behavior during the pandemic and subsequent work performance due to their pre-pandemic familiarity with working from home. While those with baseline WFH experience are likely to take up more WFH during the pandemic, Emanuel & Harrington (2021) highlight that better-performing employees preferred to working more from the office in the pre-pandemic period. To account for the role of baseline WFH experience, we control for a set of dummy variables indicating the baseline WFH frequency in the baseline model. Table A-7 in the appendix presents the results, which provide further supporting evidence of the main findings.

Table 2: **Work from Home and employee performance**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline			**Occupation WFH feasibility**					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
I. Changes in hourly productivity									
Dependent variable: $\Delta PROD$									
ΔWFH	0.090***	0.114***	0.078*	0.032	0.092	0.025	0.111***	0.124***	0.105**
	(0.029)	(0.034)	(0.046)	(0.064)	(0.061)	(0.105)	(0.031)	(0.038)	(0.047)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354
Dependent variable: $\Delta PRODQ$ **(Main outcome)**									
ΔWFH	0.073**	0.104***	0.052	0.043	0.104	-0.048	0.085***	0.100***	0.079
	(0.031)	(0.032)	(0.052)	(0.065)	(0.066)	(0.108)	(0.032)	(0.035)	(0.052)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354
II. Changes in weekly working hours									
Dependent variable: $\Delta HOURS$									
ΔWFH	-0.058	-0.070	-0.015	-0.294***	-0.335***	-0.152	0.004	0.003	-0.007
	(0.037)	(0.043)	(0.052)	(0.085)	(0.095)	(0.092)	(0.035)	(0.035)	(0.060)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354

Note: This table shows the correlation between the change in WFH frequencies and the change in productivity ($\Delta PROD$), quantified productivity ($\Delta PRODQ$), and working hours ($\Delta HOURS$). Control variables include age, age^2, female, living with a partner, living in the urban area, dummy variables for qualifications, number of children, the weekly COVID-19 death rate, dummy variables for firm size, having changes in working hours, being key-sector workers, the logarithm of income before the pandemic, occupation dummies, and industry dummies. Region, wave and industry-wave fixed effects are controlled for. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

economic crisis the pandemic brought. One can also expect the productivity increases during the pandemic to translate into improved job security and increased possibilities of promotions in the future. Second, we refer to surveys highlighting that the possibility of exaggerated self-reporting is lower than conventionally thought. For instance, according to The Economist (2020), the increased WFH productivity cannot be explained away by employees' exaggerated self-reporting of their productivity. The article cites a survey by *PricewaterhouseCoopers (PwC)*, which reported that 44% of American bosses think that their employees have become more productive during the pandemic, while only 28% of workers agreed.

Our baseline result shows that employees doing more WFH have no significant changes in weekly working hours, an indicator of their work effort, which is somewhat at odds with the existing literature. For instance, Rupietta & Beckmann (2018) show that employees increase their work effort when they undertake WFH in normal times. According to The Economist (2020), researchers at *Atlassian*, a developer of workplace software, found that employees in industrialized countries were logged into the software on average 30 minutes longer during the lockdown than before. They show that employees made better use of their increased work authority by working more in the evening. However, this proxy of working hours, the time between the first and the last interaction with the software, may overestimate the true number of hours, as breaks are completely ignored. In contrast, Lee & Tipoe (2020), using a sample of 1,036 individuals, find that the employees working from home reduced work-related activities during the UK lockdown.

As motivated in Section 3.2.2, not all occupations are WFH feasible, and employees' work performance may differ depending on their ability to perform WFH uninterrupted. Therefore, using data from Adams-Prassl et al. (2020) about the WFH feasibility at the occupation level, we now investigate whether the WFH-performance relationship differs in high and low WFH feasibility occupations. Columns (4)–(9) show the results separately for both groups, including the within-group gender difference. The results in columns (4)–(6) indicate no significant correlation between the changes in WFH frequency and the measures of hourly productivity for employees working in occupations with low feasibility. However, for weekly hours worked, we find a statistically significant and negative correlation, especially among females. These results indicate that, for employees working in low WFH feasibility occupations, the more often WFH is taken, their inability to perform many tasks at home reduces weekly hours worked, while hourly productivity remains unchanged. In columns (7)–(9), we observe the WFH-performance relationship for those working in high WFH feasibility occupations. The results show that ΔWFH shares a positive and statistically significant relationship with the employees' hourly productivity measures, whereas no evidence of the ΔWFH-$\Delta HOURS$ relationship is found. In other words, employees observed increased hourly productivity in responses to increases in WFH frequency in occupations where work tasks are suitable to perform at home. Notably, working hours are not associated with the increases in WFH frequency.

4.2 Alternative measures of WFH frequency and feasibility

Now, we employ alternative measures of the dependent and independent variables and vary the estimation sample. We begin our investigation by employing the following two alternative measures of WFH feasibility. First, we consider the self-reported information on the firm's WFH flexibility provided by employees surveyed by the Understanding society. Second, we use the industry-level WFH feasibility information sourced from Adams-Prassl et al. (2020). Table A-9 in the appendix presents the estimation results, which are qualitatively similar to the main results.

Next, we pay special attention to different jumps in WFH frequency of employees during the pandemic. The primary motivation behind this analysis is the possibility that performance measures may respond differently to similar jumps in WFH frequency, i.e., changes in hourly productivity may be different for individuals who increased their WFH frequency from "never" to "sometimes" compared to those who changed from "sometimes" to "often". It is also reasonable to assume that the ΔWFH-$\Delta PRODQ$ association differs depending on individuals' previous experience and familiarity with WFH, further deeming this investigation necessary. In response, in place of the baseline explanatory variable ΔWFH, we employ a set of dummy variables indicating 10 distinct jumps in WFH frequencies, i.e., never–never, never–sometimes, never–often, never–always, sometimes–sometimes, sometimes–often, sometimes–always, often–often, often–always, always–always. We use "never–never" as the reference group, which is also the biggest group in the sample and can also capture the general effects of the pandemic on labor market outcomes that are unrelated to WFH. The results are presented in Table A-10 in the appendix. We observe the largest increase in hourly productivity for individuals switching their WFH frequency from "sometimes" to "often", followed by "never" to "always" or from "sometimes" to "always". Notably, these results are entirely driven by the female subsample, as shown in column (2), whereas the hourly productivity of males does not respond to changes in WFH frequency. A similar pattern of results is observed for individuals working in occupations with high WFH feasibility. Concerning weekly working hours, similar to the main results in Table 2, employees in occupations with low WFH feasibility show a negative correlation between WFH frequencies and working hours. However, for employees with high WFH feasibility, we observe no significant correlations.

4.3 Heterogeneous effects

This subsection analyzes the heterogeneous effects in the WFH-work performance relationship. For this investigation, we restrict the sample to employees working in occupations with high WFH feasibility. We limit the scope of our discussion of hourly productivity results to discussing those estimated using quantified hourly productivity ($\Delta PRODQ$). We omit the discussion of the results estimated using the other measure of hourly productivity ($\Delta PROD$) to save space and avoid repetition given their qualitative familiarity with the $\Delta PRODQ$ results.

4.3.1 Job-related characteristics

We begin our investigation of heterogeneous effects by considering job-related characteristics. In addition to WFH feasibility considered earlier, we now focus on the respondents' commuting distance and commuting time to work and work autonomy, as motivated in subsection 3.2.2. Columns (1)–(3) in Table 3 initiates the investigation by considering the role of employees' commuting distance. We find that individuals who previously commuted longer distances to work reported a stronger association between WFH frequency and productivity. This association is mainly present among male respondents, whereas the analysis of the female subsample does not highlight such a role played by commuting distance. A similar pattern of results is observed for effect associated with the time spent in commuting in the pre-pandemic period (columns (4)–(6)). In line with earlier discussions, we conclude that individuals who previously spent more time commuting became more productive when taking more WFH, potentially due to time saved for commuting reducing stress and enabling employees to concentrate better on the job tasks.

Table 3: **Heterogeneous effects I: Job-related characteristics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Commuting distance			**Commuting time**			**Autonomy over work pace**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: $\Delta PRODQ$									
ΔWFH	0.025	0.104**	-0.056	-0.014	0.153***	-0.173**	-0.087	-0.152	0.046
	(0.040)	(0.042)	(0.067)	(0.050)	(0.053)	(0.081)	(0.088)	(0.093)	(0.192)
$\Delta WFH \times ComDis$	0.005**	-0.000	0.010***						
	(0.003)	(0.003)	(0.003)						
$\Delta WFH \times ComTime$				0.003**	-0.002	0.007***			
				(0.001)	(0.002)	(0.002)			
Reference category: *None*									
$\Delta WFH \times A\ little$							0.270**	0.236**	0.250
							(0.111)	(0.120)	(0.221)
$\Delta WFH \times Some$							0.134	0.271***	-0.045
							(0.100)	(0.105)	(0.204)
$\Delta WFH \times A\ lot$							0.210**	0.319***	0.045
							(0.096)	(0.100)	(0.207)
Observations	3,329	1,975	1,354	3,329	1,975	1,354	3,329	1,975	1,354

Note: This table shows heterogeneous associations between the WFH frequency and the hourly productivity for employees with high occupation WFH feasibility by characteristics of the work, i.e., commuting distance in columns (1)–(3), commuting time in columns (4)–(6), and autonomy over work pace in columns (7)–(9). Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Next, we discuss the role of autonomy over work pace enjoyed by the employees. Columns (7)–(9) show the results. With "no autonomy" individuals as the reference group, our results broadly show that more autonomy over work pace strengthens the ΔWFH-$\Delta PRODQ$ association, especially among female workers. The size of the coefficients becomes larger if female employees' level of work autonomy is higher. Thus, employees with a greater work autonomy, measured in the pre-pandemic period, benefit especially from working more from home. In our attempt to explain these results, we argue that employees with higher autonomy over work pace in the pre-pandemic period needed less coordination with their supervisors or colleagues while managing pandemic-era WFH restrictions and were quick to benefit from working from home.

4.3.2 Household characteristics: School closures and childcare responsibilities

This subsection considers the role of having children and increases in childcare needs due to school closures implemented during the COVID-19 lockdowns. The analysis begins by investigating the heterogeneous impact associated with having children. Columns (1)–(3) in Table 4 employ a dummy variable indicating whether an employee has children between the age of 0 and 16 in the household. The results report that having children weakens WFH productivity gains reported earlier, but only for females. In columns (4)–(6), we use the number of children as a continuous variable and find that female employees with more children report weaker ΔWFH-$\Delta PRODQ$ association.

Table 4: **Heterogeneous effects II: School closures and childcare**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	With or without children						**With children**					
	Having children			**Number of children**			**School closures**			**Childcare responsibility**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: $\Delta PRODQ$												
ΔWFH	0.115***	0.134***	0.121**	0.120***	0.138***	0.121**	0.102	0.215***	0.000	0.079	0.146	0.095
	(0.033)	(0.040)	(0.051)	(0.032)	(0.039)	(0.049)	(0.062)	(0.077)	(0.091)	(0.090)	(0.212)	(0.112)
$\Delta WFH\times$ *Having children*	-0.095	-0.115*	-0.113									
	(0.058)	(0.062)	(0.091)									
$\Delta WFH\times$ *Number of children*				-0.060*	-0.072**	-0.064						
				(0.035)	(0.035)	(0.051)						
$\Delta WFH\times$ *SchClose*							-0.135*	-0.200*	-0.039			
							(0.076)	(0.107)	(0.113)			
Reference category: *Partner is responsible*												
$\Delta WFH\times$ *Both equally*										-0.165	-0.128	-0.205
										(0.105)	(0.229)	(0.141)
$\Delta WFH\times$ *My responsibility*										0.014	0.017	0.036
										(0.141)	(0.218)	(0.584)
Observations	3,329	1,975	1,354	3,329	1,975	1,354	1,250	699	551	1,030	532	498

Note: This table shows heterogeneous associations between the WFH frequency and the hourly productivity for employees with high occupation WFH feasibility by school closures and family characteristics, i.e., having children in columns (1)–(3), number of children (4)–(6), school closures in columns (7)–(9), and the childcare responsibility in columns (10)–(12). Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Next, in columns (7)–(12), we restrict our investigation to parent respondents only and study whether school closures and the resultant increases in childcare responsibilities affect the relationship. In columns (7)–(9), we find that stronger school closure restrictions, i.e., closing at some levels or all levels, weaken the ΔWFH-$\Delta PRODQ$ association, however, only for mothers but not fathers. These results align with the findings of existing literature showing that mothers' work performance was particularly affected during the pandemic. Finally, we study the role played by childcare responsibilities. The results presented in columns (10)–(12) report that the increases in the parent respondents' childcare responsibilities do not intervene in the WFH-performance relationship. In conclusion, it seems that the adverse effect on female WFH productivity is not due to increased childcare responsibilities during the pandemic. However, it is possible that having children at home may be disproportionately more stressful to females due to increased distractions at their new workplace (home).

4.3.3 Pandemic severity and the ability to concentrate

Now we discuss the intervening role of pandemic severity in the baseline relationship. Employees in regions with a high risk of contracting the virus may experience heightened mental stress, reducing their work performance. For this analysis, we consider two measures of the COVID-19 pandemic severity, i.e., death rates and the government stringency index in the employees' region of residence. The results presented in columns (1)–(3) of Table 5 suggest that the increased death rates do not affect the ΔWFH-$\Delta PRODQ$ relationship significantly. Similarly, when we investigate the impact of government restrictions, the association with hourly productivity does not vary with the stringency index.

Table 5: **Heterogeneous effects III: COVID-19 pandemic severity**

	(1)	(2)	(3)	(4)	(5)	(6)
	Death rates			**Government restrictions**		
	All	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: $\Delta PRODQ$						
ΔWFH	0.142***	0.158***	0.128**	0.345**	0.391**	0.146
	(0.033)	(0.044)	(0.053)	(0.138)	(0.191)	(0.192)
$\Delta WFH \times$ *Death rates*	-0.005	-0.005	-0.003			
	(0.004)	(0.004)	(0.005)			
$\Delta WFH \times$ *Government restrictions*				-0.003	-0.004	-0.001
				(0.002)	(0.003)	(0.003)
Observations	3,329	1,975	1,354	3,329	1,975	1,354

Note: This table shows heterogeneous associations between the WFH frequency and changes in hourly productivity for employees with high occupation WFH feasibility by the COVID-19 pandemic severity, i.e., death rates in columns (1)–(3) and government restrictions in columns (4)–(6). Control variables are the same as in the baseline specification. Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

As motivated in Section 3.2.2, we now study the role of individuals' concentration ability in explaining the heterogeneity in the baseline results. The results reported in Table A-11 in the appendix suggest that those who can concentrate better than or the same as usual report higher increases in productivity if they take WFH more often. Thus, our main results, a positive ΔWFH-$\Delta PRODQ$ relationship, can partly be explained by employees that can concentrate, an essential determinant of their WFH performance, which may equally apply to male and female employees.[19]

4.4 Working from home in the future

We end our discussion by shedding some light on the future of WFH. As many expect WFH to "stick" (Dingel & Neiman, 2020), a formal analysis of employees' willingness to continue WFH in the future (*desired WFH*) has not been conducted. The results presented in Table A-12 investigate whether employees' current WFH frequency and work performance measures are associated with their desired WFH. The outcome variable indicates the respondents' self-reported desired WFH frequency once social distancing measures are relaxed and workplaces go back to normal. The results in columns (1)–(3) show that the increased current WFH frequency is positively associated with individuals' willingness to continue WFH in the future. Columns (4)–(6) reveal whether work performance has an independent association with the new outcome variable. We find evidence that the self-reported improvement in employees' productivity is positively associated with the willingness to do WFH in the future, but changes in working hours show no significant effect.

5 Conclusion

The 2020 COVID-19 pandemic affected lives all around the world. While responding to the pandemic, many countries imposed "lockdowns" and enforced workplace restrictions, forcing a vast number of employees to work from home, which presented a great challenge for employers and employees alike. Using representative data from the UK, we showed that the increased frequency of working from home is associated with a higher self-perceived productivity per hour, prominently among females working in occupations conducive to working from home. Furthermore, we found that the positive association between WFH and hourly productivity is stronger among males who previously commuted longer distances to work and females who experience higher autonomy over work pace. Essentially, the WFH-productivity association is weaker among mothers living with

[19] Our main results hold when we include a set of dummy variables indicating the change in concentration ability (i.e., better than usual, same as usual, less than usual, and much less than usual) as covariates in the model. Results are available upon request.

school-age children, which we demonstrated to be driven by increased homeschooling needs due to pandemic-led school closures, and should draw the attention of policymakers. Notably, changes in WFH frequency are unrelated to the respondents' weekly working hours (and weekly wages) during the same period.

As the world economy is slowly recovering from the pandemic, many predict that the changes in working arrangements (increased use of technology and working from home) observed during this pandemic will stay with us. In this regard, the results presented in this paper shed a positive light on the alternative working arrangement of working from home. In addition to highlighting the positive association between WFH and hourly productivity, we demonstrated that increased WFH frequency during the pandemic is associated with higher intentions to take up WFH in the future, firmly establishing WFH as an alternative to the conventional office setting.

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Home Sweet Home: Working from home and employee performance during the COVID-19 pandemic in the UK

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Supplementary material

Supplementary appendix

Table A-1: **Hourly productivity: Including wave three**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Occupation WFH feasibility					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: ($\Delta PRODQ$)									
ΔWFH	0.072**	0.104***	0.046	0.046	0.107	-0.042	0.082***	0.099***	0.071
	(0.029)	(0.032)	(0.049)	(0.066)	(0.068)	(0.108)	(0.030)	(0.034)	(0.049)
Observations	5,487	3,238	2,249	1,587	946	641	3,900	2,292	1,608

Note: This table shows the correlation between changes in the WFH frequency and changes in hourly productivity using data from waves three, five and seven in the COVID-19 survey. Note that wave three excludes individuals working completely from office. Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-2: **Weekly hours: Using waves one to eight**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Occupation WFH feasibility					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: ($\Delta HOURS$)									
ΔWFH	-0.015	-0.033	0.012	-0.105**	-0.124**	-0.052	0.010	-0.008	0.017
	(0.018)	(0.025)	(0.023)	(0.043)	(0.056)	(0.050)	(0.018)	(0.025)	(0.026)
Observations	20,609	12,192	8,417	6,447	3,791	2,656	14,162	8,401	5,761

Note: This table shows the correlation between changes in the WFH frequency and changes in weekly working hours using data from waves one to eight in the COVID-19 survey. Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-3: **Larger sample: Including employees with decreases in WFH frequency**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
				Occupation WFH feasibility					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
I. Changes in hourly productivity									
Dependent variable: ($\Delta PRODQ$)									
ΔWFH	0.048	0.086***	0.008	0.077	0.135**	-0.055	0.042	0.062*	0.025
	(0.030)	(0.031)	(0.053)	(0.059)	(0.063)	(0.088)	(0.032)	(0.033)	(0.055)
Observations	4,976	2,967	2,009	1,536	912	624	3,440	2,055	1,385
II. Changes in weekly working hours									
Dependent variable: ($\Delta HOURS$)									
ΔWFH	-0.093**	-0.057	-0.113	-0.361***	-0.300***	-0.468**	-0.016	0.004	-0.047
	(0.043)	(0.038)	(0.071)	(0.110)	(0.089)	(0.206)	(0.036)	(0.032)	(0.062)
Observations	4,976	2,967	2,009	1,536	912	624	3,440	2,055	1,385

Note: This table shows the correlation between changes in the WFH frequency and changes in hourly productivity as well as weekly working hours using a larger sample including employees with a decrease in the WFH frequency during the pandemic. Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-4: **Different measures of productivity changes**

		$\Delta PROD$				
		(1) Much less	(2) Little less	(3) Same	(4) Little more	(5) Much more
	-3	72	55	0	0	0
	-2	74	214	0	0	0
	-1	27	299	0	0	0
$\Delta PRODQ$	0	0	0	2,825	0	0
	1	0	0	0	374	199
	2	0	0	0	238	248
	3	0	0	0	46	143

Note: In this table, we tabulate the distribution of $PROD$ and $PRODQ$ for 4,814 observations. $\Delta PROD$ has five values, ranging from 1 (much less) to 5 (much more). $PRODQ$ has seven values. Zero means no changes in the productivity, negative values indicate decreases in the productivity and positive values are for increases in the productivity. The definition in detail can be found in Section 3.2.

Table A-5: **Hourly productivity: Quantified in minutes**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline sample			**Occupation WFH feasibility**					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: $\Delta PRODM$									
ΔWFH	0.941**	1.481***	0.556	0.473	1.620	-1.769	1.112**	1.342***	1.045
	(0.479)	(0.476)	(0.832)	(1.015)	(1.021)	(1.725)	(0.500)	(0.510)	(0.829)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354

Note: This table shows the correlation between changes in the WFH frequency and changes in hourly productivity measured in minutes. Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-6: **The list of occupations and industries**

Occupation	**Industry**
Legislators and senior officials	Agriculture, forestry and fishing
Corporate managers	Mining and quarrying
Managers of small enterprises	Manufacturing
Physical, mathematical and engineering science professionals	Electricity, gas, steam and air conditioning supply
Life science and health professionals	Water supply; Sewerage, waste management and remediation activities
Teaching professionals	Construction
Other professionals	Wholesale and retail trade; Repair of motor vehicles and motorcycles
Physical and engineering science associate professionals	Transportation and storage
Life science and health associate professionals	Accommodation and food service activities
Teaching associate professionals	Information and communication
Other associate professionals	Financial and insurance activities
Office clerks	Real estate activities
Customer services clerks	Professional, scientific and technical activities
Personal and protective services workers	Administrative and support service activities
Models, salespersons and demonstrators	Public administration and defence; Compulsory social security
Skilled agricultural and fishery workers	Education
Extraction and building trades workers	Human health and social work activities
Metal, machinery and related trades workers	Arts, entertainment and recreation
Precision, handicraft, craft printing and related trades workers	Other service activities
Other craft and related trades workers	Activities of households as employers
Stationary plant and related operators	
Machine operators and assemblers	
Drivers and mobile plant operators	
Sales and services elementary occupations	
Agricultural, fishery and related labourers	
Labourers in mining, construction, manufacturing and transport	

Table A-7: **Controlling for baseline WFH frequency**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline sample			**Occupation WFH feasibility**					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
I. Changes in hourly productivity									
Dependent variable: ($\Delta PRODQ$)									
ΔWFH	0.075**	0.112***	0.042	0.021	0.088	-0.088	0.083**	0.106***	0.066
	(0.031)	(0.033)	(0.054)	(0.066)	(0.066)	(0.110)	(0.033)	(0.035)	(0.055)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354
II. Changes in weekly working hours									
Dependent variable: ($\Delta HOURS$)									
ΔWFH	-0.058	-0.074*	-0.016	-0.293***	-0.333***	-0.121	0.004	-0.006	-0.009
	(0.037)	(0.043)	(0.055)	(0.086)	(0.097)	(0.102)	(0.037)	(0.037)	(0.066)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354

Note: This table shows the correlation between changes in the WFH frequency and changes in hourly productivity as well as weekly working hours. Control variables are the same as in the baseline specification. Additionally, we control for the baseline WFH frequency using a set of dummy variables. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-8: **Weekly wages**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline sample			**Occupation WFH feasibility**					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
Dependent variable: $\Delta WAGE$									
ΔWFH	0.445	4.452	-6.388	2.540	-0.007	11.810	-1.829	3.074	-11.087
	(4.332)	(3.777)	(7.524)	(6.436)	(8.992)	(8.709)	(5.157)	(3.947)	(8.379)
Observations	4,785	2,845	1,940	1,475	875	600	3,310	1,970	1,340

Note: This table shows the correlation between changes in the WFH frequency and changes in weekly wages. Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-9: **Additional WFH feasibility measures**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Self-reported WFH feasibility of the firm						**Industry WFH feasibility**					
	Low			**High**			**Low**			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
I. Changes in hourly productivity												
Dependent variable: $\Delta PROD$												
ΔWFH	0.082**	0.090**	0.069	0.116***	0.165***	0.109*	0.085**	0.076*	0.099	0.108***	0.175***	0.067
	(0.038)	(0.042)	(0.056)	(0.041)	(0.055)	(0.058)	(0.041)	(0.043)	(0.069)	(0.035)	(0.051)	(0.053)
Observations	3,277	2,002	1,275	1,485	826	659	3,198	2,022	1,176	1,616	836	780
Dependent variable: $\Delta PRODQ$												
ΔWFH	0.053	0.081**	0.012	0.114**	0.151***	0.107*	0.054	0.071*	0.039	0.101***	0.157***	0.083
	(0.039)	(0.041)	(0.062)	(0.045)	(0.058)	(0.065)	(0.043)	(0.041)	(0.079)	(0.037)	(0.052)	(0.053)
Observations	3,277	2,002	1,275	1,485	826	659	3,198	2,022	1,176	1,616	836	780
II. Changes in weekly working hours												
Dependent variable: $\Delta HOURS$												
ΔWFH	-0.069	-0.086**	-0.050	0.034	0.040	0.068	-0.102*	-0.156***	-0.007	0.028	0.073	-0.010
	(0.045)	(0.043)	(0.073)	(0.034)	(0.042)	(0.054)	(0.053)	(0.059)	(0.077)	(0.035)	(0.045)	(0.058)
Observations	3,277	2,002	1,275	1,485	826	659	3,198	2,022	1,176	1,616	836	780

Note: This table shows the correlation between changes in the WFH frequency and changes in hourly productivity as well as weekly working hours with alternative measures of the WFH feasibility. Control variables are the same as in the baseline specification. Data on the industry WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-10: **Dummy variables for changes in WFH frequency**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline sample			**Occupation WFH feasibility**					
				Low			**High**		
	All	**Female**	**Male**	**All**	**Female**	**Male**	**All**	**Female**	**Male**
I. Changes in hourly productivity									
Dependent variable: ($\Delta PRODQ$)									
Reference category: *Never – Never*									
Never – Sometimes	-0.047	0.112	-0.245*	-0.125	0.228	-0.554***	0.051	0.063	-0.032
	(0.090)	(0.094)	(0.126)	(0.172)	(0.154)	(0.206)	(0.087)	(0.115)	(0.125)
Sometimes – Sometimes	0.115	0.141	-0.061	0.097	-0.046	-0.175	0.114	0.166	-0.047
	(0.120)	(0.135)	(0.190)	(0.257)	(0.257)	(0.340)	(0.127)	(0.134)	(0.230)
Never – Often	0.049	-0.002	0.065	-0.428*	-0.327	-0.660	0.151	0.081	0.208
	(0.105)	(0.124)	(0.177)	(0.243)	(0.290)	(0.476)	(0.111)	(0.134)	(0.181)
Sometimes – Often	0.329***	0.395***	0.127	0.563**	0.492*	0.285	0.278***	0.314**	0.231
	(0.113)	(0.134)	(0.182)	(0.275)	(0.279)	(0.424)	(0.106)	(0.144)	(0.176)
Often – Often	0.120	-0.046	0.195	0.305	0.499	0.150	0.058	-0.162	0.199
	(0.151)	(0.234)	(0.206)	(0.319)	(0.506)	(0.257)	(0.169)	(0.259)	(0.244)
Never – Always	0.213**	0.327***	0.093	0.173	0.316	0.049	0.218**	0.285***	0.151
	(0.092)	(0.096)	(0.158)	(0.209)	(0.208)	(0.363)	(0.095)	(0.102)	(0.165)
Sometimes – Always	0.297***	0.402***	0.143	0.632***	0.392	0.615*	0.308***	0.406***	0.171
	(0.097)	(0.103)	(0.139)	(0.219)	(0.303)	(0.322)	(0.094)	(0.104)	(0.141)
Often – Always	0.112	0.302	-0.051	1.232**	1.576*	0.409	0.041	0.153	-0.085
	(0.150)	(0.227)	(0.200)	(0.609)	(0.943)	(0.360)	(0.148)	(0.218)	(0.212)
Always – Always	0.071	0.598	-0.467	2.814***	3.260***		-0.043	0.239	-0.332
	(0.279)	(0.442)	(0.287)	(0.345)	(0.405)		(0.232)	(0.372)	(0.263)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354
II. Changes in weekly working hours									
Dependent variable: ($\Delta HOURS$)									
Reference category: *Never – Never*									
Never – Sometimes	-0.180	-0.092	-0.220	-0.476**	-0.139	-0.833***	0.028	-0.106	0.178
	(0.110)	(0.113)	(0.178)	(0.194)	(0.176)	(0.309)	(0.110)	(0.154)	(0.143)
Sometimes – Sometimes	-0.386***	-0.344*	-0.362*	-0.697**	-0.442	-1.258**	-0.249	-0.317	-0.129
	(0.145)	(0.180)	(0.197)	(0.305)	(0.329)	(0.596)	(0.160)	(0.224)	(0.188)
Never – Often	-0.093	-0.200*	0.111	-0.465**	-0.732***	-0.078	0.079	0.008	0.184
	(0.094)	(0.106)	(0.171)	(0.232)	(0.280)	(0.383)	(0.109)	(0.119)	(0.193)
Sometimes – Often	-0.090	-0.086	-0.181	0.024	-0.080	-0.264	-0.032	-0.079	0.012
	(0.087)	(0.108)	(0.136)	(0.137)	(0.177)	(0.239)	(0.113)	(0.150)	(0.158)
Often – Often	-0.083	-0.183	-0.119	0.171	0.386	-0.578	-0.027	-0.303	0.051
	(0.141)	(0.246)	(0.180)	(0.476)	(0.444)	(0.615)	(0.159)	(0.293)	(0.200)
Never – Always	-0.226**	-0.242*	-0.137	-0.870***	-0.954***	-0.169	-0.040	-0.071	-0.057
	(0.111)	(0.128)	(0.161)	(0.312)	(0.336)	(0.199)	(0.109)	(0.111)	(0.193)
Sometimes – Always	-0.141	-0.170	-0.066	-0.302	-0.631	-0.111	-0.036	-0.110	-0.007
	(0.087)	(0.106)	(0.128)	(0.285)	(0.492)	(0.279)	(0.098)	(0.115)	(0.153)
Often – Always	-0.069	-0.177	-0.019	-0.246	-0.033	0.099	0.034	-0.168	0.083
	(0.095)	(0.152)	(0.144)	(0.167)	(0.323)	(0.389)	(0.109)	(0.171)	(0.163)
Always – Always	-0.119	-0.022	-0.167	-0.719*	-0.165		-0.060	-0.018	-0.217
	(0.279)	(0.262)	(0.510)	(0.397)	(0.390)		(0.273)	(0.260)	(0.504)
Observations	4,814	2,858	1,956	1,485	883	602	3,329	1,975	1,354

Note: This table shows the correlation between changes in the WFH frequency and changes in hourly productivity as well as the weekly working hours. Changes in WFH frequencies are measured by a set of dummy variables. Control variables are the same as in the baseline specification. Data on the occupation WFH feasibility source from Adams-Prassl et al. (2020). Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-11: **Heterogeneous effects by concentration**

	(1)	(2)	(3)
	All	**Female**	**Male**
Dependent variable: ($\Delta PRODQ$)			
ΔWFH	-0.012	0.064	-0.053
	(0.062)	(0.069)	(0.106)
Concentration	0.380***	0.346***	0.506***
	(0.067)	(0.079)	(0.109)
$\Delta WFH \times Concentration$	0.154**	0.059	0.212*
	(0.065)	(0.073)	(0.110)
Observations	3,276	1,941	1,335

Note: This table shows heterogeneous associations between the WFH frequency and changes in hourly productivity for employees with high occupation WFH feasibility by concentration changes during the pandemic. *Concentration* takes value of one if the individual's concentration remains the same as or better than usual, and zero otherwise. Control variables are the same as in the baseline specification. Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.

Table A-12: **Desired WFH frequency in the future**

	(1)	(2)	(3)	(4)	(5)	(6)
	All	**Female**	**Male**	**All**	**Female**	**Male**
Outcome: Desired WFH frequency in the future ($FutWFH$)						
ΔWFH	0.154***	0.141***	0.170***	0.141***	0.128***	0.152***
	(0.027)	(0.034)	(0.040)	(0.026)	(0.033)	(0.038)
$\Delta PRODQ$				0.231***	0.226***	0.245***
				(0.021)	(0.029)	(0.033)
$\Delta HOURS$				-0.010	0.009	-0.059
				(0.026)	(0.025)	(0.051)
Observations	2,760	1,625	1,135	2,760	1,625	1,135

Note: This table shows impact of possible predictors on willingness to continue WFH in the future ($FutWFH$, z-standardized). Desired WFH frequency in the future originally has four values. It takes one if the individual will never work from home, two if sometimes, three if often, and four if always. Other covariates are the same as in the baseline specification. We apply OLS estimation for all specifications. Robust standard errors (clustered at the individual-level) in parentheses: *** p<0.01, ** p<0.05, * p<0.1.