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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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ABSTRACT

In 2020, many governments responded to the COVID-19 pandemic by encouraging employees to work from home (WFH). Analyzing representative data from the UK, we find that the pandemic-led increases in WFH frequency are associated with a higher self-perceived hourly productivity among employed respondents. Interestingly, changes in WFH frequency are unrelated to the respondents' weekly working hours and weekly wages during the same period. While the WFH-productivity association is more substantial in non-lockdown months, it is inexistent during the months with strict lockdowns, indicating that lockdown measures inhibited the baseline association. The WFH-productivity association is weaker among parents with increased homeschooling needs due to school closures implemented during lockdowns. In addition, the effect heterogeneity analysis identifies the role of crucial job-related characteristics in the baseline association. Finally, looking at the future of WFH, we show that employees' recent WFH experiences and subsequent changes in hourly productivity are intimately associated with their desires to WFH in the future.

1. Introduction

Now, many firms give their employees the option to work from home (WFH). Although a WFH arrangement has become a reality for some, many employers were hesitant to provide this option until recently, citing suspicions about employees' misuse of freedom over assigned work and the resulting increased risk of "shirking from home." The onset of 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 the spring of 2020, about half of the employed population in many Western countries worked exclusively from home (Bonacini et al., 2021b; Brynjolfsson et al., 2020; Dingel and Neiman, 2020; Felstead and Reuschke, 2020; Kunze et al., 2020; Schröder et al., 2020). This 'forced' innovation of WFH, though not a perfect "natural experiment" as not all employees could feasibly take up WFH, allowed social scientists to analyze the relationship between WFH and employee performance. With WFH expected to remain in practice even after the pandemic ends (Barrero et al., 2021), a comprehensive assessment of employees' WFH performance is relevant to establishing future policies.

In theory, WFH should increase employees' authority over working time, pace, and workplace. Following this line of argument, some existing research suggests that increasing workers' authority over delegated tasks can positively influence their performance (Eaton, 2003; Kelliher and Anderson, 2010; Lyness et al., 2012) and that there is a positive link between WFH and employee performance, e.g., hourly productivity (Bloom et al., 2015) and work effort (Beckmann et al., 2017; Bloom et al., 2015; Rupietta and Beckmann, 2018). Furthermore, an individual's job-related and household characteristics play an important role in the productivity association, which we consider in our attempt to understand the relationship between WFH and employee performance. For instance, the use of technology at work can determine the nature of the expected relationship. The employers' ability to monitor worker efforts can vary between high-tech and low-tech sectors. Also, the degree of oversight may differ by the nature of the occupation and job function. For example, in the case of customer service call centers, employers can monitor operators' work efforts in real time (e.g., the number of calls taken, length of calls, and ratings from end of call surveys), while such oversight is not readily available in sectors that do not use similar monitoring tools. Similarly, individuals' household characteristics (e.g., number of children, household size, availability of a separate working room, stable internet) can determine how effectively they can work from home. For instance, parents of school-age children may find it more challenging to concentrate on their work than their childless counterparts, especially during pandemic-led school closures.

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Using the novel *Understanding Society COVID-19 survey data* from the UK, this paper investigates whether employees' WFH frequency is associated with their work performance during the COVID-19 pandemic. Dependent on the availability of outcome variables, the baseline estimation sample consists of employed respondents interviewed in the following three COVID-19 survey waves: 5 (September 2020), 7 (January 2021), and 9 (September 2021). Using the information on their WFH behavior, we construct our primary explanatory variable of interest, a dummy variable indicating the increase in the respondents' WFH frequency during the pandemic compared to the baseline period in January/February 2020. The primary outcome variable reflects the change in work performance in the same period, measured by the change in their self-reported hourly productivity. Other outcomes include employees' weekly hours worked and weekly wages (net payments).

The baseline estimation model investigates whether increases in WFH frequency are associated with changes in the respondents' work performance. The results show that increases in WFH frequency during the pandemic are positively related to hourly productivity. In contrast, we find that increases in WFH are unrelated to changes in weekly hours worked and wages. Further subsample analyses suggest that the positive WFH-productivity association primarily applies to employees surveyed in months when strict lockdown measures were not imposed. Furthermore, the positive association with productivity becomes weaker for parents with homeschooling needs during school closures. We then investigate the effect of heterogeneity in the baseline relationship. Concerning gender differences, we find that females show a stronger WFH-productivity association if they work in more WFH-feasible jobs or have higher autonomy over their work pace and hours. Meanwhile, male employees who previously had a longer commute to their jobs exhibit increased productivity when beginning to WFH during the lockdown.

Although COVID-19-related increases in WFH offer an appropriate setting for studying the association between WFH and hourly productivity, selection into WFH may distort our findings. In particular, not all employees were forced to WFH, and those who were asked to do it were not necessarily working from home during the entire pandemic period, i.e., more employees were asked to WFH during lockdown months than in months when strict lockdowns were not imposed. Moreover, as performance measures and WFH behavior are only available for the employed during the pandemic, our results may be representative of a selective group. We exploit the richness of the data to visit the extent of selection in this context. Based on the available data and our analysis, we suggest that the estimates presented in this paper should not be interpreted as causal estimates of WFH's impact on employee performance but simply as correlations.

Our paper makes the following contributions to existing literature. First, we contribute to the emerging literature investigating the connection between WFH and employee performance. To this end, in addition to the pre-pandemic research demonstrating the link between voluntarily-taken WFH and employee performance (Beckmann et al., 2017; Bloom et al., 2015; Rupietta and Beckmann, 2018), we contribute to the small yet growing body of literature on the topic that emerged during the COVID-19 pandemic (Adrjan et al., 2021; Baert et al., 2020; Bonacini et al., 2021b; Etheridge et al., 2020; Felstead and Reuschke, 2020; Feng and Savani, 2020; Kunze et al., 2020; Lee and Tipoe, 2020). Our results indicate the existence of a modest positive association between WFH and employee productivity even when WFH is introduced by the government. Second, WFH and employee performance during the pandemic in the UK is still rarely studied. For instance, using data similar to the data analyzed in this paper, Etheridge et al. (2020) report mean hourly productivity changes for individuals working from home and find that they reported higher WFH productivity in June 2020.[1] Different from their approach, our analysis considers all employees, including those who never worked from home during the pandemic. In this regard, our use of a dedicated and large reference group of employees in the empirical analysis — those who observe no change in their WFH behavior or have never participated in WFH before and during the pandemic — helps us capture the general effects of the pandemic on labor market outcomes and sets the paper apart from emerging literature on the topic (Feng and Savani, 2020; Kunze et al., 2020; Lee and Tipoe, 2020). Third, we use three measures for performance and mainly focus on hourly productivity. Our analysis spans a relatively large time horizon, approximately one and a half years after the outbreak of the pandemic, which sheds some light on the persistence of a higher performance induced by increased WFH frequency. We also describe how the links between WFH and hourly productivity differ across observation periods (lockdown and non-lockdown), demographic groups (gender and parenthood) and job-related characteristics (WFH feasibility, work autonomy, and commutes).

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 experiences relate to their desires to 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 experiences of WFH arrangements. The results suggest that necessary support for those who WFH, especially always-open childcare facilities for working parents, should 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 discusses the 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 with our findings.

2. Background and existing research

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, reporting the number of daily infections and daily deaths between March 2020 to September 2021. The three gray bars depict the periods observed in the empirical analysis. The figure shows that daily deaths jumped dramatically in March 2020 and January 2021, and the number of cases was extremely high at the beginning of 2021. Following other countries, Britain responded to the worsening pandemic by calling for social distancing measures to slow the spread of the virus. These measures included wide-ranging restrictions on freedom of movement, enforceable in law, under a stay-at-home order (BBC News, 2020).

In Fig. 2, we show 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 Wales, respectively (for a description of the data, see Appendix B).[2] In subfigure (a), we plot a composite index indicating the government restrictions, including school closures, workplace closures, and restrictions on gatherings. The index is scaled from 0 (*least stringent*) to 100 (*most stringent*). The subfigure affirms that the government stringency index increased from around 10 in early March to about 80 by mid-March 2020. In the

[1] Also see Felstead and Reuschke (2020).

[2] The pandemic and consequent 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).

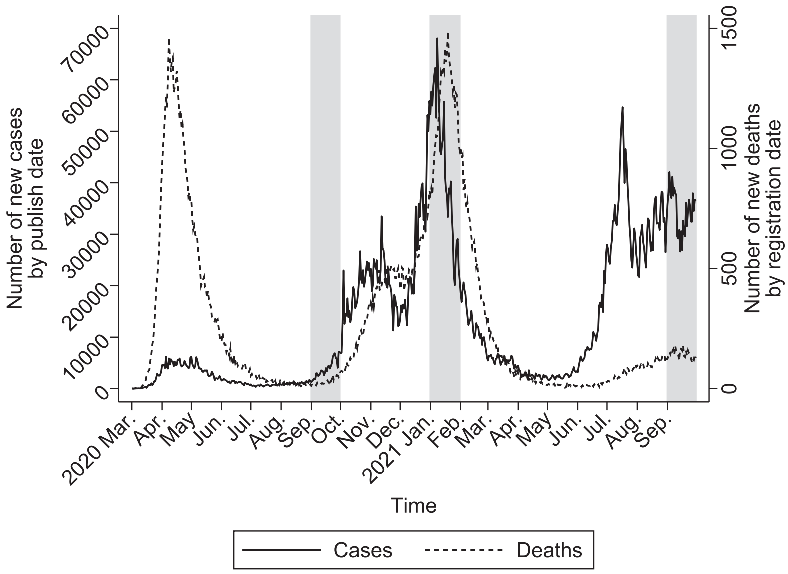
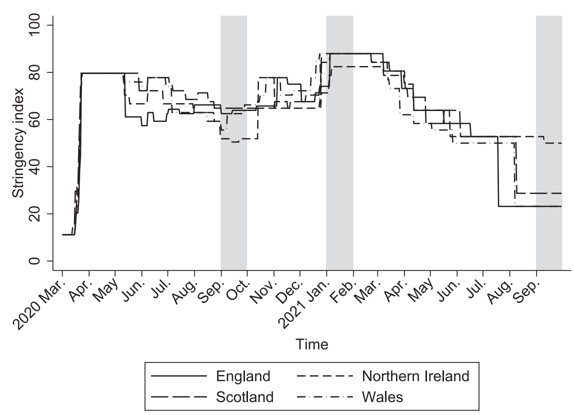
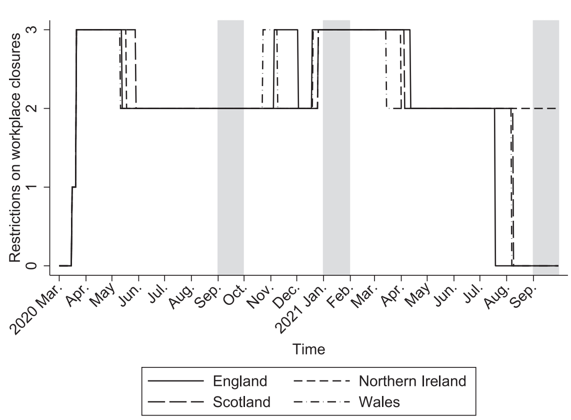


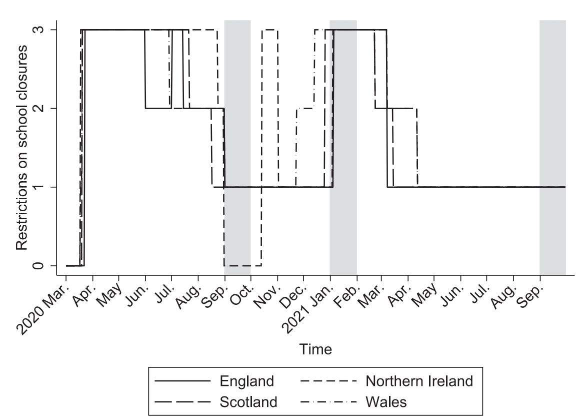
Fig. 1. Number of COVID-19 cases and deaths in the UK. Data source: The official UK Government website for data and insights on Coronavirus (COVID-19). https://coronavirus.data.gov.uk. *Notes:* This figure shows the number of new cases by publish date and deaths by registration date from March 2020 to September 2021 in the UK. The three gray bars depict the periods we observe in the empirical analysis.



(a) Government stringency index



(b) Restrictions on workplace closures



(c) Restrictions on school closures

Fig. 2. Government restrictions during the COVID-19 pandemic in the UK. Data source: COVID-19 government response tracker. *Notes:* This figure shows the government restrictions from March 2020 to September 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. The three gray bars depict the periods we observe in the empirical analysis.

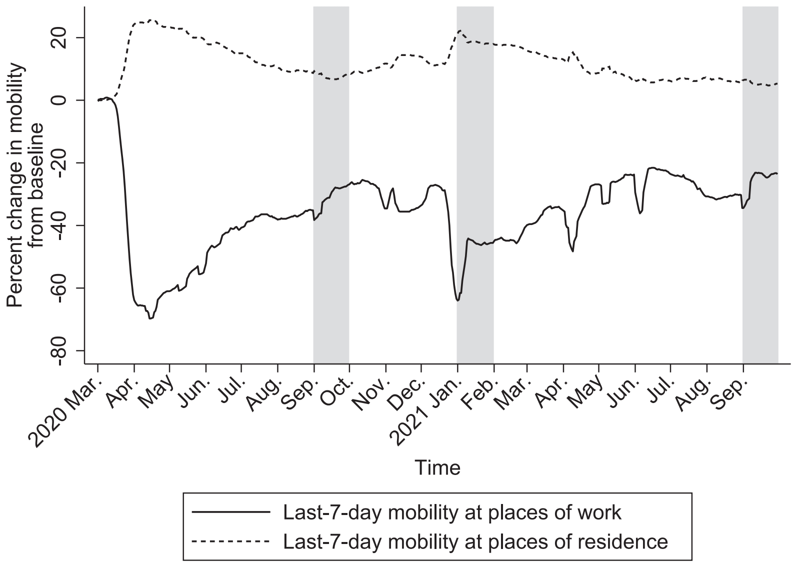


Fig. 3. Last-7-day average mobility change at workplace and residence place in the UK. Data source: COVID-19 community mobility reports, own calculation. *Notes:* This figure shows the last-7-day average mobility change at workplace and residence place from March 2020 to September 2021 in the UK. The data depicts the percentage change in the mobility compared to the baseline value. The three gray bars depict the periods we observe in the empirical analysis.

following months, the index remained high with some regional variations and decreased gradually in 2021. In subfigures (b) and (c), we illustrate the evolution of government-imposed workplace and school closures, respectively. Subfigure (b) shows that the highest workplace restrictions (level 3) were imposed from 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 until the beginning of 2021. Similarly, subfigure (c) shows that all schools were closed (level 3) from mid-March to the end of May 2020 and in January and February 2021. We exploit this variation in school closures later in the empirical analysis.

Early evidence suggests that stringency measures were effective in restricting population movements. To demonstrate this, we plot in Fig. 3 the last-7-day average of changes in workplace and place of residence mobility during the pandemic compared to the baseline pre-pandemic period in the UK using *Google Mobility* data (also see Appendix B for more information). A positive value indicates an increase in mobility, while a negative value implies a decrease. We observe that the UK experienced a considerable reduction in employees' mobility at the workplace, especially in the lockdown periods, while the mobility at the place of residence increased. This observation is in line with the early estimates by Felstead and Reuschke (2020), who find an eight-fold increase in those reporting to work exclusively from home in 2020 (from 5.7% in January/February to 43.1% in April, remaining high in June 2020 (36.5%)).[3] In the following subsection, we summarize the existing research and explain how WFH relates to employee performance.

2.2. Literature review

2.2.1. WFH frequency and employee performance

WFH increases employees' freedom and control over job tasks, pace, and location, also referred to as the intra-firm decentralization of power. The implications of this decentralization of power within the firm can be considered a principal-agent problem as workers (agents) make decisions on behalf of the employer (principal) while working from home (Aghion and Tirole, 1997; Bloom and Van Reenen, 2011). On the one hand, increased work autonomy may decrease workers' performance as they (agents) have weaker incentives to maximize the firm's value than the principal (employer), giving rise to increased shirking possibilities. In contrast, some studies show that decentralization can also benefit firms. For instance, Bloom and Van Reenen (2011) propose that this decentralization can help firms reduce the costs of information transfer and communication, increase their speed in responding to market changes, and increase workers' job satisfaction. Other researchers find a positive relationship between flexible work arrangements and productivity, measured by absenteeism (Koopman et al., 2002) and output per hour (Golden, 2012). Moreover, providing the option to WFH to workers may encourage them to act in their own best interest and remain committed to their employers, increasing employees' intrinsic motivation and reciprocal behavior (Beckmann et al., 2017; Blau, 2017; Deci and Ryan, 2000; Delfgaauw and Dur, 2008; Ellingsen and Johannesson, 2008).

More related to this paper's scope, recent research investigates whether allowing the WFH option to employees is equally effective for firms as traditional onsite (office) working. Prominently, using a Randomized Controlled Trial 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 this increase in overall performance, an improvement of 9% is attributed to changes in productivity per shift (primarily due to a quieter and more convenient working environment) and 4% is due to working more 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 other pre-pandemic research on the impact of WFH on employees' performance measured in productivity, working hours, and wages. We also summarize the findings from the recent pandemic-related research on the topic.

First, we expect a relatively quieter and convenient work environment to increase employees' WFH performance. In the UK, the average daily commute was nearly one hour in 2018 (Trades Union Congress, 2021).[4] If employees work from home, the saved commuting time can be devoted to working, and stressful commuting, if any, can be avoided. Also, employees can save the time spent on multiple coffee breaks taken at the office. These arguments suggest that employees can concentrate better and devote more time to work when working from home, indicating a qualitative and quantitative increase in working time and improved work performance. On the other hand, WFH requirements may be detrimental to employee performance. For instance, time saved due to WFH could make shirking and taking breaks more

[3] Also see Brynjolfsson et al. (2020), Dingel and Neiman (2020), Felstead and Reuschke (2020), Schröder et al. (2020), Kunze et al. (2020), and Bonacini et al. (2021b).

[4] An international online survey found that WFH saved individuals time spent commuting to and from the office during the COVID-19 pandemic (Rubin et al., 2020).

attractive, and less access to supervisor support and teamwork can also hamper accountability and the efficiency of WFH (Bloom et al., 2015). In this case, WFH may have a negative impact on hourly productivity and working hours. Therefore, the cumulative effect of WFH on productivity and working hours may be minimal.

In addition to productivity and working hours, wages are another measure of employee performance. First, wages and employee performance, measured by gross value added, have a positive correlation (Gunawan and Amalia, 2015). In terms of efficiency wages, the amount of wages reflects the size of the output produced by employees. Therefore, if WFH is positively or negatively correlated with productivity or working hours, wages may also be affected in the same way. Second, increased WFH induces either a wage penalty or a wage premium (Arntz et al., 2022). If WFH is costly for the employer and only serves to arrange workers' work/family balance, a wage penalty may occur. In contrast, if WFH is not costly for the firm and increases worker productivity, it may induce a wage increase. Third, most occupations, particularly those open to WFH, pay hourly or by salary rather than piecemeal. Wage increases typically occur annually or as a result of a promotion. Thus, for workers who work roughly the same number of hours, their wages should not change. Fourth, the signaling effect, found in experimental studies (Bloom et al., 2015), states that absent workers are often overlooked for promotion and, thus, wage increases. Hence, productivity increases do not necessarily directly relate to wage increases in a short period.

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. 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 and 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 technology usage during the lockdown. More applicable to this study, others asked whether the pandemic-led changes in working arrangements affected employee performance. Kunze et al. (2020) find that WFH increased perceived productivity and commitment in Germany during the pandemic. Etheridge et al. (2020) show that UK employees working more from home during the pandemic reported higher hourly WFH productivity.[5] With respect to the changes in working hours during the pandemic, Kunze et al. (2020) and The Economist (2020) show an excessive workload for WFH employees, while Lee and Tipoe (2020) find that the time-use rather shifted away from work-related activities in the UK. Some evidence suggests that managers also welcome the productive use of WFH. For instance, Adrjan et al. (2021) shows for OECD countries that around 60% of managers think that workers work more and more productively in a teleworking environment — a result that is also consistent with findings from Barrero et al. (2021) for the US and Taneja et al. (2021) from the UK.

2.2.2. The role of household characteristics

Many demographic and household characteristics are also pertinent determinants of WFH take-up and performance. The existing research highlights gender as an important determinant of WFH and identifies having children and childcare needs as a primary driver for the gender gap in WFH performance. While women value WFH opportunities more than men, especially if they have young children (Mas and Pallais, 2017), researchers find that men more often report working in WFH-feasible jobs (Adams-Prassl et al., 2022; Bonacini et al., 2021b; Dingel and Neiman, 2020).[6] Bonacini et al. (2021a) finds an increase in the gender wage gap in occupations with a high WFH feasibility in the Italian labor market using pre-pandemic data. Cui et al. (2022) show that the productivity of female academics dropped by 13.2% relative to that of male academics ten weeks after the lockdown in the United States.

WFH can be particularly cumbersome for parents with childcare responsibilities compared to employees without children, especially in the aftermath of the forced closure of schools and childcare facilities during the COVID-19 lockdowns. Accordingly, the closure of schools and childcare facilities, a "disruptive exogenous shock" to family life (Huebener et al., 2021), increased the need for private childcare (Alon et al., 2020) and employees' time spent parenting. Andrew et al. (2020) show for the UK that parents' time spent providing childcare increased by 3.5 h per day during the first lockdown, while working time decreased equally, partly driven by large employment losses. Using pre-pandemic data from Germany, Arntz et al. (2022) record that childless employees worked more overtime when taking up WFH while higher wages were limited to parents.

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. Mothers are still the primary childcare givers in Western countries, which explains why women are less productive than men, mainly apparent among respondents with children (Gallen, 2018). New research also finds that the COVID-19 situation translated into a relative increase in mothers' time spent providing childcare and performing housework, a decrease in working hours, and a higher probability of job loss (Andrew et al., 2020; Sevilla and Smith, 2020; Zamarro and Prados, 2021). In contrast, for Germany, Kreyenfeld and Zinn (2021) do not find evidence of the gender gap in childcare as they show that fathers and mothers expanded their time spent providing childcare to similar degrees. For Spain, although mothers spent more hours than fathers providing childcare before the lockdown, there was no gender gap in increases in providing childcare during the lockdown (Farré et al., 2020).

2.2.3. The role of job characteristics

The employees' job characteristics are also crucial considerations in the analysis of their WFH take-up and WFH performance. Several job-related characteristics, such as the job's WFH feasibility, including the availability of amenities at home (separate workroom, appropriate electronics, etc.), the type of tasks, and the level of interaction needed to perform work, are pertinent for employees to continue working unhindered without skimping on work during WFH. For example, Angelici and Profeta (2020) collect Italian data for 2017/18 and find that work flexibility (in terms of location and time) increases worker productivity and well-being. Other pre-pandemic studies also show a positive relationship of work flexibility with self-reported productivity in European companies (Riedmann et al., 2006) and output per hour (Golden, 2012). For the pandemic period, Etheridge et al. (2020) demonstrate a positive correlation between the WFH feasibility and change in hourly productivity in the UK.

Whether employees are productive at home also depends to some degree on the employer's ability to monitor worker effort or output as well as the type of tasks. Simple and repetitive tasks can still be monitored in near real time by their employers, but sophisticated work is much more difficult to monitor. Dutcher (2012) shows that WFH's productive effect predominantly exists among US workers performing creative tasks, which generally is a feature of WFH-feasible occupations. In contrast, WFH is counter-productive for workers dealing with less complex tasks.

Moreover, the loss of social interaction might harm productivity as interactions produce knowledge spillovers between workers, induce

[5] For Japan, Morikawa (2022) finds that the WFH productivity has improved over time, but it is still lower than the productivity of working at the office. These results may not be transferable to the UK due to differences in working culture between these two countries.

[6] Researchers also show that younger and high-paid employees report a higher WFH possibility (Adams-Prassl et al., 2022; Bonacini et al., 2021b; Dingel and Neiman, 2020).

peer pressure and, thus, a feeling of guilt, and increase individual productivity (Cornelissen et al., 2017). This context only applies to occupations where the simple repetitive nature of tasks makes the output more readily available to coworkers. As such factors are often occupation and industry-specific, we consider individuals' occupation and industry of work and self-reported autonomy over working hours and pace later in our empirical investigation. In-person interactions (synchronous communication) are best suited to communicate complex and explain the meaning of information, while asynchronous communication channels, such as emails, are better suited for converging information (Daft and Lengel, 1986; Dennis et al., 2008). Yang et al. (2022) find for US employees an overall decrease in synchronous communication due to increased time in home offices after the outbreak of the COVID-19 pandemic making it challenging to convey the meaning of complex information.

In the end, commuting time is considered the price to be paid for working from the office (de Graaff and Rietveld, 2007). Le Barbanchon et al. (2021) show that women valued short commutes more than men during the pandemic. During the lockdown, as noted earlier, commutes to the office saw a significant decrease. The saved commuting time can be used to work, which may be more pronounced for employees who had to commute over long distances or periods of time before the lockdown. Moreover, employees can avoid the stress of long commutes and get immersed in work quickly. Therefore, the relationship between WFH take-up and employee performance may differ by the commutes, which we study in detail in later sections.

3. Data, variables and methodology

3.1. Data source

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, 2021b). Initially starting in 2009, the Understanding Society dataset records detailed information on approximately 40,000 British households annually. In the spring of 2020, the survey conducted supplementary web-based questionnaires to capture the changing impact of the COVID-19 pandemic (University of Essex, Institute for Social and Economic Research, 2021a). Between April 2020 and September 2021, the survey completed nine rounds (referred to as *COVID-19 waves*), covering various questions on the welfare of individuals, families, and communities in the country.[7] In particular, the *COVID-19 waves* record included respondents' self-reported changes in hourly productivity and WFH frequency, the main variables of interest for our analysis. Depending on these variables' availability, our estimation sample considers the following COVID-19 survey waves (month conducted): wave 5 (September 2020), wave 7 (January 2021), and wave 9 (September 2021).[8]

3.2. Changes in working from home frequency

The primary explanatory variable is the change in the respondents' frequency of working from home (*WFH increase*). Individuals respond to the following survey question: *"During the last four weeks how often did you work at home?"* The possible answers are 1 (*always*), 2 (*often*), 3 (*sometimes*) and 4 (*never*). The same question also records the respondents' pre-COVID-19 WFH behavior by 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 our WFH measurement by performing the following 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 frequency between the current and baseline period to compute the change in the frequency, i.e., $\Delta WFH = WFH - WFH_{baseline}$. Finally, we generate a dummy indicator, *WFH increase*, that equals one if individuals report increases in WFH frequency, and zero otherwise.

3.3. Changes in employee performance

3.3.1. Changes in hourly productivity

We first measure employee performance using variables recording the respondents' self-reported change in productivity per hour. In surveys conducted in September 2020, January 2021, and September 2021, i.e., *COVID-19 waves 5, 7, and 9*, 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*).[9] We re-scale the responses and generate a variable, $\Delta PROD$, with higher values indicating larger increases in hourly productivity. We further generate a categorical variable, $\Delta PRODC$, taking the value of -1 (*little/much less done*), 0 (*about the same done*), and 1 (*little/much more done*), as our main outcome variable.

To test the construct validity of self-perceived hourly productivity changes, we show that the measure correlates to a measure of mental well-being (see Table C-1), a variable that is empirically shown to relate to productivity because employees, in general are better off when they are more productive (Greenberg et al., 2003). Second, we show that our measure of productivity changes positively correlates to the change in gross values added at the industry level, an official and objective measure (see Figure C-1). For a more detailed discussion on the construct validity of productivity, see Appendix C.

3.3.2. Changes in weekly working hours and wages

We employ the respondents' change in weekly working hours ($\Delta HOUR$) and change in weekly wages ($\Delta WAGE$) as alternative measures of employee performance. Generally construed as an input measure, working hours can also indicate workers' performance as more time is spent on work-related activities, likely increasing workers' output (Bell and Freeman, 2001). Alternatively, given that the number of tasks and output 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 poses the question: *"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/February 2020. The question is: *"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 $\Delta HOUR$ by taking the difference in weekly working hours between the current and baseline period.

To calculate the change in wages, we employ the following survey question: *"What is your usual take-home pay/earnings now?"* A similarly

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

[8] We ignore *COVID-19 wave 3* because it collects hourly productivity information of 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. Although waves 5, 7, and 9 were surveyed in the three months as mentioned above, fewer than 10 percent of the observations are also visible for the subsequent month (i.e., October 2020, February, and October 2021.)

[9] The survey question recording WFH frequency asks respondents to report their behavior for "the last four weeks". In contrast, the survey question for hourly 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".

formulated question also records the net payment in January and February 2020. We first transform the payment into a weekly measure and then calculate the difference between the current and baseline period, $\Delta WAGE$.

3.4. Control variables

Taking up WFH is usually not exogenous but related to some individual characteristics. Although many employees were forced to WFH during the lockdown, individuals observed in the non-lockdown period could choose to WFH if feasible. Therefore, it is essential to control for relevant factors correlated with WFH frequency, especially those affecting employee performance. The first set of control variables considers the respondents' demographic characteristics. These include the respondents' age, gender, cohabitation status with a partner (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 the *main waves 9* to *11* of the primary survey data conducted between 2017 and 2020.

To account for different job factors, we include a set of covariates reflecting the respondents' labor market characteristics. First, we control for the effects associated with the respondents' industry and occupation of work. To do so, we generate dummy indicators amounting to 20 industry and 26 occupation dummies.[10] Moreover, we generate a dummy variable for being a key worker representing workers employed in essential 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.[11] Furthermore, we use nine dummy variables for the firm size. Finally, we consider the respondents' pre-COVID-19 performance using the logarithm of monthly gross pay obtained from the *main waves 9–11* (surveyed in 2017–2020).

Next, we consider the severity of the pandemic in the main specification. That is, we employ the weekly death rates. To do this, we employ the latest weekly deaths by registration date per 100,000 population at the UK NUTS-1 level available to the respondent at the time of the interview as control variables. For example, for the respondents interviewed between September 19, and 25, 2020, we assign the weekly death rates published on September 18, 2020.[12] Finally, we account for wave fixed effects and wave-industry-specific fixed effects.

In addition, *COVID-19 waves* contain detailed information on individuals' time-invariant characteristics, such as birth year and gender. We source the information absent in *COVID-19 waves* from the data in the *main waves 9–11*. The gathered information is assumed to be roughly constant over a short period and includes the individual's occupation, industry, region (rural/urban), and the number of children under 16.

3.5. Sample restriction and descriptive statistics

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., between 18 and 65 years. Moreover, we limit the analysis to those who reported being paid employees (or self-employed) before the pandemic, i.e., January/February 2020 (referred to as the baseline period), and during the pandemic. Furthermore, we drop one exceptional group of individuals who reported decreased WFH frequency during the pandemic because we suspect them to behave differently from others. Nevertheless, in a robustness check, we re-estimate the baseline model by adding this special group to the sample. We confirm that the central message of the paper does not depend on this sample restriction. Finally, we omit individuals reporting zero working hours or zero net payments as well as individuals who reported changes in their working hours for the following reasons: laid-off by employers, taking paid leave, or taking sick leave.[13,14] Due to these sample restrictions, the estimation sample consists of information on 3846 individuals with 8409 observations.

This sample restriction could suffer from potential self-selection due to the fact that low-productivity workers may be the first to be terminated. Moreover, suppose the relationship between the WFH frequency and employee performance is smaller for less-productive individuals who were fired or laid-off by the employer during the pandemic than for the more-productive ones who remained working. In that case, our results may overestimate the overall average effect among the whole population. While we cannot assess whether individual-level differences in productivity drive the sample selection issue due to a lack of data, we test whether those in our sample are structurally different in their individual-level characteristics. We begin our analysis by investigating whether those who became unemployed during the pandemic differed from their employed counterparts. These two groups of employees were employed in January/February 2020. In Table A-2, we show the difference in relevant variables between the two groups. We also apply the two-sample KS test to check whether the distribution of these variables differs between the employed and the unemployed samples. Our results suggest that most demographic variables have different distributions between the two samples while the occupation and industry variables show similar distributions. However, those who recently became unemployed are a little less educated and have fewer children, less autonomy at the workplace, and lower wages before the pandemic. Importantly, they also show less WFH frequency and fewer working hours in the baseline period.

Although employed and unemployed individuals show different characteristics, some employees may be more likely to lose their jobs than others, especially during the pandemic. Therefore, we ask whether the unemployed during the pandemic differed from those before the pandemic. This concern is particularly notable as the pandemic-caused economic downturn increased unemployment by approx. 20% (Office for National Statistics, 2020). To do this, we compare the following two groups of unemployed individuals: (1) individuals employed in 2018 and unemployed in 2019, and (2) individuals employed in 2019 and unemployed in 2020 (see Appendix D for more information). In Ta-

[10] The list of industries and occupations is reported in Table A-1.

[11] 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.

[12] Our results are robust to using contemporaneous (i.e., deaths occurring during the week of the interview) and 2-week lagged death rates. The weekly death rate is also available at the NUTS-3 level for most counties/districts. We re-estimate the baseline model with the death rate at the county/district level, and the results remain virtually unchanged (not shown here).

[13] Note that the information on the reasons for decreased working hours is not available in the *COVID-19 wave 9* (conducted in September 2021). Using the main survey waves 9–11, we find that the share of employees who were laid off, taking paid leave, or taking sick leave was 3.43% in 2018 and 2019, and it increased to 9% in 2020 and 2021. Then, we check whether these employees differ before and during the pandemic by observing their characteristics in the pre-COVID period, including age, gender, qualification, living with a partner, the number of children, living in an urban area, the number of hours worked, and the logarithm of weekly gross payment. Our results (not depicted and available upon request) suggest that, compared to employees who were laid off, taking paid leave, or taking sick leave in 2018 and 2019, the ones observed in 2020 and 2021 were younger and even earned more and worked longer.

[14] We also drop individuals who reported too large values in their weekly working hours (>60 h) in the baseline or current period. These amount to about 1% of the sample. If we include individuals working over 60 h in the regression, our results remain virtually unchanged (results not depicted).

Table 1
Summary statistics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All		*WFH increase* = 1		*WFH increase* = 0		(3) - (5)
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Difference in means
Main explanatory variable							
$\Delta WFH \approx WFH - WFH_{baseline}$ (0/1/2/3)	0.8440	1.0761	1.8954	0.7794	0.0000	0.0000	
WFH increase (0/1) **[main explanatory var.]**	0.4453	0.4970	1.0000	0.0000	0.0000	0.0000	
Outcome variables							
$\Delta PROD$ (1/2/3/4/5)	3.2275	0.8973	3.3468	1.0325	3.1318	0.7584	0.2150***
$\Delta PRODC$ (−1/0/1), **[main outcome var.]**	0.1351	0.6079	0.2068	0.6997	0.0775	0.5155	0.1293***
$\Delta HOUR \approx HOUR - HOUR_{baseline}$	0.1826	6.7767	0.3247	6.4895	0.0685	6.9973	0.2562
$\Delta WAGE \approx WAGE - WAGE_{baseline}$	9.7138	184.8581	15.7661	174.4603	4.8489	192.6910	10.9172**
Control variables							
Age	43.6596	11.7685	42.8901	11.2350	44.2773	12.1458	-1.3872***
Female	0.5198	0.4996	0.5388	0.4986	0.5046	0.5000	0.0341**
Live with a partner	0.7052	0.4560	0.7312	0.4434	0.6844	0.4648	0.0468***
Urban	0.7634	0.4250	0.7686	0.4218	0.7592	0.4276	0.0093
Number of children	0.6187	0.9087	0.6667	0.9070	0.5801	0.9083	0.0866***
COVID-19 weekly death rates	4.9122	6.3397	5.8712	6.8199	4.1423	5.8135	1.7289***
Log income	6.1508	0.6793	6.3759	0.6422	5.9701	0.6540	0.4058***
Key sector workers	0.6905	0.4623	0.6579	0.4745	0.7166	0.4507	-0.0587***
Firm size							
1–2	0.0300	0.1707	0.0295	0.1693	0.0304	0.1718	-0.0009
3–9	0.0961	0.2948	0.0610	0.2394	0.1243	0.3299	-0.0633***
10–24	0.1352	0.3419	0.0855	0.2797	0.1750	0.3800	-0.0895***
25–49	0.1203	0.3253	0.0677	0.2513	0.1625	0.3689	-0.0948***
50–99	0.1095	0.3122	0.0992	0.2989	0.1177	0.3223	-0.0185**
100–199	0.0990	0.2987	0.0935	0.2911	0.1034	0.3045	-0.0099
200–499	0.1067	0.3087	0.1197	0.3246	0.0963	0.2950	0.0234**
500–999	0.0640	0.2447	0.0852	0.2793	0.0469	0.2114	0.0383***
1000 or more	0.2393	0.4267	0.3586	0.4797	0.1435	0.3506	0.2151***
Supplementary analysis							
Commuting distance (miles)	10.9989	17.9281	13.6468	21.8588	8.8733	13.6307	4.7735***
Commuting time (minutes)	28.1837	21.7273	34.3973	24.3678	23.1958	17.8489	11.2015***
Work autonomy over work pace (categories 1–4)	3.0317	0.9897	3.1706	0.9400	2.9201	1.0143	0.2505***
Work autonomy over work hours (categories 1–4)	2.4151	1.1617	2.7890	1.0771	2.1149	1.1400	0.6741***
Having children (0/1)	0.3688	0.4825	0.4010	0.4902	0.3428	0.4747	0.0582***
School closures (0/1)	0.3134	0.4639	0.3813	0.4858	0.2589	0.4381	0.1224***
# of observations	8,409		4,085		4,324		
Wave 5 (September 2020)	2,917		1,309		1,608		
Wave 7 (January 2021)	2,604		1,517		1,087		
Wave 9 (September 2021)	2,888		1,259		1,629		
# of respondents	3,846		2,105		2,336		

Note: This table shows the summary statistics of the estimation sample. Cross-sectional weights are applied. Columns (1)–(2) show statistics for the whole sample of 8409 observations, columns (3)–(4) for 4085 observations who reported increased WFH frequency, and columns (5)–(6) for 4324 observations who did not report any increase in WFH frequency. Column (7) depicts the difference in means between column (3) and column (5).

ble D-1, we report the coefficients estimated by regressing individual-level characteristics on the dummy variable for being unemployed during the pandemic (group 2). The results do not indicate any notable differences between these two groups. Notably, we do not find differences concerning their industries and occupations of work. Therefore, we conclude that the structure of employees losing jobs is similar before and during the pandemic, and our sample restriction may not face a severe selection problem.[15]

In Table 1, we report the summary statistics for the estimation sample. Beyond overall sample means and standard deviations as presented in columns (1)–(2), columns (3)–(6) separately document information of individuals who reported increases in WFH frequency and those who did not observe any changes in their WFH frequency during the pandemic compared to the baseline period. Column (7) shows the difference in means between columns (3) and (5). Additionally, in Table A-1, we report the descriptive statistics for all qualification, occupation, and industry groups.

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 0.8440, equivalent to about a one-step increase in their WFH frequency 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*.[16] Therefore, using the dummy variable indicating the increased WFH frequency, i.e., *WFH increase*, estimates the average difference in employee performance between individuals who increased their WFH frequency and those who maintained their WFH frequency.

Moreover, on average, respondents reported an increase in hourly productivity during the pandemic compared to the baseline period, which is significantly larger for individuals who reported increased WFH frequency.[17] The overall sample also shows an increase in employees'

[15] We also do one robustness check by observing individuals who had unemployment experience from 2015 to 2019 or ever reported to be unemployed in at least one COVID wave. Using this small and restricted sample, we run the baseline regression model. We find a positive correlation between changes in WFH frequency and changes in hourly productivity in most specifications (see Appendix D for more information).

[16] We show in an additional test that our results are robust when we include dummies for all different transitions in WFH.

[17] 12.72% of the observations report a decrease in productivity (including 2.84% saying "get much less done"), 60.2% no changes, and 27.08% an increase

working hours during the pandemic, which is in line with the evidence from other countries (see Schröder et al., 2020).[18] Individuals observing an increase in their WFH frequency during the pandemic reported, on average, a larger increase in working hours than those reporting no changes in their WFH take-up. However, the difference in the means is not statistically significant. Furthermore, weekly wages increased during the pandemic for both groups of employees, but with a larger increase for those who worked from home more often.[19] Similar to hourly productivity, individuals experiencing an increase in WFH frequency also reported higher wages.

From Table 1, we also note that young and female employees are more likely to increase 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 reporting increases in WFH resided in areas affected worse by the pandemic, denoted by higher COVID-19-related death rates in their regions of residence, further evidence that the pandemic induced increased WFH frequency among the employed.

3.6. Empirical strategy

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

$$\Delta Y_{it} = \alpha_0 + \alpha_1 WFH\ increase_{it} + \boldsymbol{X}_{it}' \beta + \lambda_t + \varepsilon_{it}, \quad (1)$$

where ΔY_{it} denotes the change in employee performance of individual i between wave t and the baseline period, indicated by changes in their hourly productivity ($\Delta PRODC_{it}$), weekly working hours ($\Delta HOUR_{it}$), and weekly wages ($\Delta WAGE_{it}$). $WFH\ increase_{it}$ represents a dummy variable reporting whether an individual worked more from home in the last four weeks compared to the baseline period. $\boldsymbol{X}_{it}$ 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), living in the urban region, number of children under 16 in the household, and a set of dummy variables for the highest educational qualification and the place of residence. The vector also includes a regional measure of the pandemic severity, the logarithm of pre-pandemic wage income, and several job-related characteristics (i.e. dummy variables for the firm size, occupation, industry, and key-sector workers). 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 a different extent, and this difference may also change across waves.

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 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. Moreover, our analysis considers the performance of employees who worked and never worked from home during the pandemic, a significant difference from Etheridge et al. (2020). The use of individuals who observe no change in WFH frequency, including a large group of employees having never made use of WFH before and during the pandemic (about 44% of the estimation sample), accounts for the general effects of the pandemic on the labor market outcomes. The pandemic may have an independent impact on employee performance even when the WFH behavior is the same as in the pre-pandemic period. Therefore, we consider that the estimate on the dummy variable for the increased WFH frequency, α_1, captures the change in the outcome variable related to the increase in WFH frequency. However, we must be careful with the interpretation of α_1 because the decision to take up WFH may be endogenous.

In addition to the estimates for the entire sample, we show estimates for male and female subsamples and results for each wave separately. Since the outcome variable is a categorical variable, to check the robustness of the OLS estimates, we also apply Ordered Probit estimations. Using an Ordered Probit model eases the interpretation of coefficients, i.e. whether the change in WFH frequency is associated with the probability of an increased, decreased, or unchanged productivity.

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. In September 2020, when the *COVID-19 wave 5* was collected, most strict measures eased. On January 6th, 2021, the country entered the third national lockdown, the month when the *COVID-19 wave 7* data was collected. When data for the *COVID-19 wave 9* were collected in September 2021, the UK had eased lockdown measures again. As the lockdowns were not always in place when our estimation sample was collected, especially in *COVID-19 waves 5* and *9* (September 2020 and September 2021), not all employees were forced to WFH and was not required all the time. Therefore, as mentioned above, we suggest that the estimate α_1 should be interpreted as the correlation between the change in WFH frequency and employee performance. Second, as discussed in Section 3.5, choosing to 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 of "better" employees and may overestimate the causal impact. However, WFH takers may also be adversely selected if "better" workers want to stay in the office (Emanuel and Harrington, 2021). In this case, our model may underestimate the causal impact. In terms of endogeneity of WFH mentioned above, we apply the bounding approach in Oster (2019) and discuss the relevance of unobservables. Third, as detailed in Section 3.5, our results are representative for the employed population during the pandemic. Considering all these facts, we suggest that the estimates presented in this paper should not be interpreted as causal estimates of the WFH's impact on employee performance but simply as correlations.

4. Results

4.1. Main results

Table 2 presents the main results. In Panel (A), we report the estimated results using the entire available sample. In Panels (B)–(D), we present our estimates using wave-specific subsamples. In each panel, columns (1)–(3) report the results of the OLS model, whereas, in columns (4)–(9), we report the coefficients and marginal effects estimated using the Ordered Probit model.

(including 13.3% saying "get much more done") compared to the pre-COVID-19 period.

[18] Notably, $\Delta HOUR$ reports a very large variation that needs further elaboration. To do this, we regress $\Delta HOUR$ on the explanatory variables one by one and underline the drivers of this variation. Besides notable demographic and labor market characteristics, we find that a large variation in $\Delta HOUR$ is explained by high heterogeneity in industries and occupations.

[19] We also observe a large difference in wage growth that we attempt to explain by regressing it on control variables. Wage growth is associated with, among others, younger age, being single, having high qualifications, having children, and a high pre-pandemic income. In the wage regression in Table A-3, we control for all the shown characteristics. Hupkau and Petrongolo (2020) show that earnings in the UK fell by 9.5% or £36 in May 2020 compared to January 2020, a period that is, however, much earlier than our observation period.

Table 2
WFH and hourly productivity (OLS & Ordered Probit estimates).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OLS			Ordered Probit					
	All	Female	Male	All		Female		Male	
				Coefficient	Marginal effect	Coefficient	Marginal effect	Coefficient	Marginal effect
Dependent variable: $\Delta PRODC$									
Panel (A): All waves									
WFH increase (0/1)	0.138***	0.150***	0.123***	0.270***		0.291***		0.254***	
	(0.025)	(0.032)	(0.037)	(0.049)		(0.061)		(0.077)	
$\Delta PRODC = -1$					-0.053***		-0.058***		-0.045***
					(0.009)		(0.012)		(0.013)
$\Delta PRODC = 0$					-0.032***		-0.033***		-0.030***
					(0.007)		(0.008)		(0.011)
$\Delta PRODC = 1$					0.085***		0.091***		0.076***
					(0.016)		(0.019)		(0.023)
Observations	8409	4931	3478	8,409		4,931		3,478	
Panel (B): September 2020 (wave 5)									
WFH increase (0/1)	0.176***	0.224***	0.136**	0.357***		0.453***		0.293**	
	(0.037)	(0.047)	(0.055)	(0.074)		(0.094)		(0.117)	
$\Delta PRODC = -1$					-0.064***		-0.081***		-0.049***
					(0.013)		(0.016)		(0.019)
$\Delta PRODC = 0$					-0.045***		-0.059***		-0.034**
					(0.012)		(0.015)		(0.016)
$\Delta PRODC = 1$					0.110***		0.140***		0.083**
					(0.023)		(0.030)		(0.034)
Observations	2917	1733	1184	2,917		1,733		1,184	
Panel (C): January 2021 (wave 7, lockdown)									
WFH increase (0/1)	0.054	0.027	0.071	0.101		0.053		0.141	
	(0.043)	(0.055)	(0.068)	(0.077)		(0.096)		(0.128)	
$\Delta PRODC = -1$					-0.025		-0.013		-0.032
					(0.019)		(0.024)		(0.029)
$\Delta PRODC = 0$					-0.005		-0.002		-0.007
					(0.004)		(0.005)		(0.007)
$\Delta PRODC = 1$					0.030		0.016		0.039
					(0.023)		(0.029)		(0.035)
Observations	2604	1521	1083	2,604		1,521		1,083	
Panel (D): September 2021 (wave 9)									
WFH increase (0/1)	0.188***	0.200***	0.159***	0.400***		0.425***		0.370***	
	(0.035)	(0.045)	(0.051)	(0.074)		(0.096)		(0.114)	
$\Delta PRODC = -1$					-0.056***		-0.062***		-0.044***
					(0.009)		(0.013)		(0.013)
$\Delta PRODC = 0$					-0.074***		-0.074***		-0.068***
					(0.016)		(0.020)		(0.024)
$\Delta PRODC = 1$					0.130***		0.136***		0.112***
					(0.025)		(0.031)		(0.036)
Observations	2888	1677	1211	2,888		1,677		1,211	

Note: This table shows OLS (columns (1)–(3)) and Ordered Probit (columns (4)–(9)) estimation results on the correlation between the increase in WFH frequency and the change in hourly productivity ($\Delta PRODC$). Panel (A) depicts the average correlation over three waves, and the associations for each wave are shown in Panel (B)–(D). Control variables include age, age^2, female, living with a partner, living in the urban area, dummy variables for qualifications, number of children, COVID-19 weekly death rates at the regional level, dummy variables for firm size, 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. Standard errors (clustered at the individual-level) in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The main results of the baseline specification presented in column (1) of Panel (A) suggest that increases in WFH frequency during the pandemic are associated with a rise in the hourly productivity by 0.138 points.[20] In columns (2) and (3), we present the results separately for the female and male subsamples. The relationship is positive and statistically significant for both subsamples. Concerning the estimates from the Ordered Probit regressions, increases in WFH frequency are positively correlated with the individuals' likelihood of reporting increased hourly productivity and negatively associated with the probability of a lower or unchanged hourly productivity. In terms of magnitude, an increase in WFH frequency is associated with a higher likelihood of reporting increased hourly productivity by 8.5 percentage points. Similar magnitudes are observed among the female and male subsamples.

We now discuss the wave-specific results shown in Panels (B)–(D) of Table 2. Panels (B) and (D) report findings similar to those noted above. Interestingly, however, we observe an insignificant relationship in Panel (C) for the subsample using data conducted in January 2021 when the UK was in lockdown. We attempt to explain this finding by arguing for the pertinent role of lockdown-specific factors responsible for weakening the relationship between WFH and hourly productivity. For instance, firms may experience big challenges when a large number of employees work from home, not only their own employees, but also those in partner firms. Organizations may need to be rearranged. Moreover, school closures imposed during the lockdown might have increased childcare and homeschooling needs among parents, substantially affecting the relationship of interest. In the following subsection, we revisit this concern in more detail.

[20] We additionally employ STATA command *dfbeta* to demonstrate whether certain industries are driving the result. Our results underline the pertinence of many essential occupations (corporate managers, teaching professionals, office clerks, personal and protective services workers, and other associate professionals) and industries (education, human health and social work activities) in driving our findings.

Our results indicate a positive WFH-productivity association, which is in line with other research on the topic (Bloom et al., 2015). However, unlike existing research, the self-reporting nature of hourly productivity needs further exploration. Therefore, we apply two more objective measures of employee performance. We consider individuals' weekly working hours as an indicator of their work effort (see Bloom et al., 2015). In addition, we also consider weekly wages (net payments), a measure of remuneration employees receive for their work effort. Panels (A) and (B) of Table A-3 present the results.

We find that WFH increases are, on average, not associated with employees' working hours, except for the weakly significant and negative association during the lockdown wave (column (7)). This is somewhat at odds with the existing literature studying the relationship in the pre-pandemic period (see Rupietta and Beckmann, 2018). Researchers at *Atlassian*, a developer of workplace software, find that employees in industrialized countries were logged into the software on average 30 min longer, especially in the evening, during the pandemic compared to before (The Economist, 2020). In contrast, Lee and Tipoe (2020) find that employees working from home reduced work-related activities during the UK lockdown. Moreover, as discussed in Section 2.2.1, the saved commuting time can be devoted to working. However, the increased productivity may lead to reduced working time if the number of tasks remains the same. In this context, the total number of weekly working hours of individuals working from home may not differ from that of employees working in the office.

Results in Panel (B) follow a similar pattern to earlier results. WFH increases are not associated with employees' weekly wages, except for a (weakly significant) mild increase in wages for male employees. The results may indicate the economic uncertainty and costs of the pandemic. As discussed in Section 2.2.1, the effect of WFH on wages is ambiguous. However, one may expect hourly productivity increases during the pandemic to translate into improved job security and increased possibilities of promotions in the future.

4.2. Alternative measures of hourly productivity and WFH frequency

4.2.1. Hourly productivity

We employ the following two alternative productivity measurements available in the dataset. First, we use a continuous measurement indicating the change in self-perceived hourly productivity ranging between 1 (*get much less done*) to 5 (*get much more done*) ($\Delta PROD$). However, individuals may have different perspectives about what "a little/much less/much more" means. Therefore, second, we consider a more objective measure of the productivity change, $\Delta PRODQ$, a quantified measure considering the time when tasks are done (see Appendix E for more information). This variable ranges from -3 (if less than 30 min needed before the pandemic to finish a task) to 3 (if more than 30 min needed before the pandemic to finish a task). Table A-4 presents the estimation results for both measurements that are very similar to the main specification.

4.2.2. WFH frequency

Next, we employ alternative measurements of the main explanatory variable, changes in WFH frequency. We pay special attention to different transitions in the WFH frequency of employees during the pandemic. The primary motivation behind this analysis is the possibility that performance measures may respond differently to similar transitions in the 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 association between the change in WFH and hourly productivity differs depending on individuals' previous experience and familiarity with WFH, further deeming this investigation necessary. Thus, in place of the main explanatory variable $WFH\ increase$, we employ three dummy variables indicating a 1-unit, 2-unit, and 3-unit increase in WFH. The results are depicted in Table A-5, and our main findings remain virtually unchanged. The association with a 1-unit increase is relatively smaller than the one with 2-unit or 3-unit increase.

Moreover, we use a set of dummy variables indicating 10 distinct transitions in WFH frequency, i.e., never–never (44.50% of the sample), never–sometimes (8.54%), never–often (6.34%), never–always (11.82%), sometimes–sometimes (4.85%), sometimes–often (6.01%), sometimes–always (12.59%), often–often (1.42%), often–always (3.28%), always–always (0.65%). We observe that about one half of the observations did not work from home before and during the pandemic. Moreover, the second largest group of observations reported their WFH frequency to change from "sometimes" to "always". In contrast, only 2% of observations reported their WFH frequency to change from "often" to "often" and from "always" to "always".

We use "never–never" as the reference group, which is also the biggest group in the sample and can also capture the general association between the pandemic and labor market outcomes that are unrelated to WFH. The results are presented in Table A-6. In column (1), we observe the largest increase in hourly productivity for individuals switching their WFH frequency from "sometimes" to "always," followed by "sometimes" to "often" or from "never" to "always". Interestingly, individuals who often took WFH in the baseline period and kept this frequency also show a positive coefficient in some specifications. Although it is a small group of observations, it may suggest that individuals with an experience with WFH before the pandemic may profit even when the WFH frequency does not change much. The positive results for those with a continued level of WFH frequency during the pandemic could also be interpreted as indicative of positive peer-group effects. Those who had experienced WFH before the pandemic and did not observe changes in their WFH frequency during the pandemic, i.e., "sometimes-sometimes", "often-often", "always-always", witnessed productivity improvement. For these employees, as more of their work colleagues now worked from home, new collaborative forms of remote work became feasible, which were previously less possible. In most specifications, we find insignificant coefficients for "never-sometimes", i.e., those who never worked from home before the pandemic and were able to undertake WFH only partially during the pandemic. This indicates inexistent productivity gains for individuals with no prior experience of WFH and those who observed only smaller increases in WFH during the pandemic.

4.3. Robustness checks

The economic literature examines productivity changes across business cycles (see e.g. Senney and Dunn, 2019; Syverson, 2011) and concludes that fear of job loss (particularly during downturns) is a strong motivator that encourages more productivity, especially for at-will employees in high turnover occupations. Therefore, as a robustness check, we control local economic conditions and re-estimate the baseline model. We expect that a higher local unemployment rate in the workers' county of residence induces a fear of job loss. This fear can motivate workers to work harder, influencing their productivity and WFH decisions, biasing our baseline estimates. For the analysis, we consider the local unemployment rate at the NUTS-3 county level available for July 2020 to June 2021 (Office for National Statistics, 2022). Second, we identify occupations that are most at risk for termination (*"On a scale of 0–100% how likely do you think it is that you will lose your job in the next three months?"*).[21] In Table A-7 we can observe that the results remain unchanged when we control for insecure job characteristics. This identifies potential motivators for changes in worker productivity.

Earlier in Section 3.3.1, we observed that individual productivity changes relate positively to changes in mental well-being. The fact that the decline in well-being is lower for more productive workers is suggestive that they are better situated to handle the pandemic. Thus, produc-

[21] The variable is inserted for the next wave where it is missing.

tivity changes could be associated with several factors that need to be controlled for in order to isolate the effect of increased working from home on productivity. Therefore, we additionally include as control variables individuals' pre-COVID health status[22] and the amount of savings. Health status is positively correlated with the change in hourly productivity while the amount of savings is unrelated. Our baseline relationship between an increase in WFH frequency and productivity changes remains qualitatively unchanged (see Panels (A) and (B) of Table A-8). Moreover, instead of using the level of health status and savings, we also apply the change of these variables between the pre-COVID and COVID periods. Our results are also robust to the use of these variables (see Panels (C) and (D)).

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 WFH. While those with baseline WFH experience are likely to take up more WFH during the pandemic, Emanuel and Harrington (2021) highlight that better-performing employees preferred WFH to working more from the office in the pre-pandemic period. To account for the role of the baseline WFH experience, we include a set of dummy variables indicating the baseline WFH frequency to the regression model. Table A-9 presents the results, which provide further supporting evidence of the main findings.

In addition to the aforementioned variables, there might be other factors that are correlated with changes in WFH frequency and have an effect on hourly productivity. Therefore, our estimate may be biased due to omitted variables and could not be interpreted as a causal impact. Observing the coefficient movement by including further covariates to the regression model is a common approach to evaluate the robustness of the estimate to the omitted variable bias. To test the relevance of unobservables, we apply the strategy in Oster (2019) and show results in Table A-10. Our results suggest that the selection on unobservables does not appear to be of important relevance for the main finding.

Finally, as discussed in Section 3.5, we include individuals who show decreases in WFH frequency to the estimation sample, and the main findings hold (see Table A-11). Moreover, employees who previously worked in industries strongly affected by the pandemic, i.e., the service sector, may have more incentive to change jobs to find new employment opportunities than other employees. We re-estimate our baseline specifications by excluding the individuals who previously worked in service industries and switched to non-service industries during the pandemic.[23] Our results (not depicted) are robust to this change in the estimation sample, which suggests that we still find a positive correlation between hourly productivity and WFH frequency if more motivated employees are excluded.

4.4. School closures and childcare responsibilities

We expect the WFH-productivity relationship to differ across individuals' private childcare needs. We begin our investigation by considering the role of government-imposed school closures. During the lockdowns, schools were temporarily closed in most UK regions, especially during January/February 2021, affecting the observations recorded in January 2021 (*COVID-19 wave 7*). We expect the demand for childcare and homeschooling to increase in response to school closures, adversely affecting the WFH performance of those with children.

To study this, we first use the information denoting the level of restrictions on school closures in a nation. We generate a dummy variable, $SchClose$, that equals one for more restrictions (i.e., restriction levels 2 or 3 were imposed), and zero otherwise (see Appendix B for more information on school closures). Note that there is no variation in the variable $SchClose$ within a wave, and the dummy variable equals one only in January 2021, i.e., the lockdown wave. We include $SchClose$ and the interaction term between $WFH\ increase$ and $SchClose$ in the regression model. Table 3 shows the results for employees with children (columns (1)–(3)) and without children (columns (4)–(6)). We find that stronger school closure restrictions weaken the positive association between the increased WFH frequency and hourly productivity for employees with children. In terms of the gender difference, mothers' and fathers' hourly productivity at home were almost equally (negatively) affected by school closures, though the size of the coefficient is relatively larger for mothers (see columns (2) and (3)).[24] These results generally align with the findings in the existing literature showing that mothers' work performance was particularly affected during the pandemic (see Section 2.2.2). We also find a negative coefficient on the interaction term for females without children (see column (5)). Note that this estimate also captures the effect of the lockdown because the dummy variable for school closures is identical to the dummy variable for the lockdown wave. However, column (2) shows a much larger coefficient than column (5), which indicates that the negative effect of school closures is stronger for mothers than non-mothers, assuming that they are similarly affected by other restrictions during the lockdown. It would be helpful if we could differentiate the effect of school closures from other restrictions. However, other restrictions were also strictly implemented during the lockdown and it is challenging to make a differentiation. In order to partly solve this problem, we do one robustness check by controlling for the *stringency index* and its interaction term with $WFH\ increase$. However, the *stringency index* also takes school closures into consideration. The estimates depicted in Table A-12 suggest that only parents, especially mothers, suffer from school closures and their hourly productivity decreases significantly.

The second analysis investigates the heterogeneous WFH-productivity relationship associated with having children and the number of children, which strengthens our discussion on school closures. Panel (A) in Table A-13 employs a dummy variable indicating whether an employee has children under 16 in the household. The results report that having children weakens the WFH productivity gains reported earlier, but this is mainly driven by the lockdown wave. In January 2021, the negative effect is relatively larger for mothers than for fathers. In Panel (B), we use the number of children as a continuous variable and find a similar result pattern as in Panel (A). Our results suggest that having children at home may be disproportionately more stressful for employees with children than without children due to increased distractions at home.

In addition to observing the number of children, we also check whether the baseline relationship differs by the age of children and the time spent in childcare (results not depicted). We find that mothers with younger children report a larger reduction in WFH productivity during the lockdown months when working more from home, compared to mothers with older children. Moreover, mothers doing more childcare, compared to those doing less childcare, show a larger reduction in their productivity while working more from home only during the lockdown period, i.e., when schools were closed.

[22] For self-reported health status, we employ the question "*In general, would you say your health is 1 - excellent, 2 - very good, 3 - good, 4 - fair, 5 - poor*?" and recode the variable such that higher values correspond to better health.

[23] We apply the information about industries from *the main waves 9* and *10* as the pre-COVID industries and the information from the *COVID-19 waves* as the industries during the pandemic. We define four industries as service sectors: accommodation and food service activities; real estate activities; administrative and support service activities; and other service activities.

[24] Moreover, we do not observe any substantial gender difference in increases in WFH frequency of parents, i.e., 48% mothers vs. 56% fathers observed increases in WFH frequency. We also test whether school closures affect parents' weekly working hours (results available upon request). Our results suggest that school closures do not change the association between WFH frequency and working hours for parents. We interpret these findings as follows: the effects associated with school closures are primarily driven by their qualitative impact on parents' work performance, e.g., potentially through the reduced quality of WFH performance due to increased disturbances by children.

Table 3
School closures (OLS estimates).

	(1)	(2) With children	(3)	(4)	(5) Without children	(6)
	All	Female	Male	All	Female	Male
Dependent variable: $\Delta PRODC$						
WFH increase (0/1)	0.132***	0.166***	0.091	0.217***	0.235***	0.211***
	(0.044)	(0.053)	(0.069)	(0.031)	(0.042)	(0.045)
$SchClose$	0.245	0.427	0.019	-0.016	-0.066	0.062
	(0.245)	(0.456)	(0.223)	(0.158)	(0.158)	(0.222)
WFH increase (0/1) × $SchClose$	-0.224***	-0.281***	-0.206**	-0.072	-0.117**	-0.002
	(0.065)	(0.087)	(0.101)	(0.047)	(0.059)	(0.070)
Observations	3064	1720	1344	5345	3211	2134

Note: This table shows the heterogeneous associations between the increase in WFH frequency and the change in hourly productivity ($\Delta PRODC$) by school closures for employees with and without children (columns (1)–(3) and (4)–(6), respectively). We include a dummy variable for more restrictions on school closures and its interaction with $WFH\ increase$ in the model. Other control variables are the same as in the baseline specification. Standard errors (clustered at the individual-level) in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4.5. Heterogeneous results by job-related characteristics

As noted earlier, numerous variables may intervene in the WFH-performance relationship. Therefore, we perform heterogeneous analysis using additional information on job-related characteristics.

4.5.1. WFH feasibility

WFH may not be feasible for all employees, and forced WFH may adversely affect the work performance of those who find WFH infeasible. Moreover, since the constantly employed population may be of higher than average productivity and more established at their job than the recently unemployed, our results may be driven by employees that are better able to work from home. Using external measures of the WFH feasibility at the occupation level sourced from Adams-Prassl et al. (2022), we test whether the positive correlation between hourly productivity and WFH frequency varies with WFH feasibility.[25] To be precise, we apply the WFH feasibility scores of occupations as a continuous variable. Columns (1)–(3) in Table 4 show the results if the occupational WFH feasibility is accounted for and interacted with the dummy variable for increased WFH frequency, indicating that the WFH-productivity correlation becomes larger for female employees working in occupations with a higher WFH feasibility.[26] In other words, employees observe increased hourly productivity in response to increases in WFH frequency in occupations where work tasks are suitable to perform at home.

Moreover, applying the WFH feasibility scores from Adams-Prassl et al. (2022), we do a subgroup analysis. For the first subgroup, we only observe employees with occupations that are more feasible for WFH, i.e., the occupation WFH feasibility score bigger than 50 (the median of the estimation sample).[27] The other employees form the second subgroup, i.e., individuals whose occupations are less feasible for WFH. Subgroup analysis allows us to consider more homogeneous individuals, and individuals with unchanged and increased WFH frequency in each subgroup are now more comparable to each other. Results depicted in Table A-14 show that we do not find a significant relationship for both subgroups in the lockdown period. However, the positive association is mostly observed among employees who are more able to work from home in the non-lockdown period.

4.5.2. Work autonomy

Additionally, we investigate whether the WFH-productivity association differs between employees with more or less autonomy over the pace of work and over work hours, variables borrowed from the *main wave 10*. For this analysis, we first generate a dummy variable, *autonomy over work pace*, 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 was reported. Second, we generate a dummy variable, *autonomy over work hours*, that takes the value of one if the individual had *little, some*, or *a lot* autonomy over work hours, and zero if *none*.[28] In the analysis we control for the newly constructed variables for the autonomy and their interaction terms with $WFH\ increase$ in the model. Our results, depicted in columns (4)–(9) of Table 4, broadly show that more autonomy over work pace or work hours strengthens the WFH-productivity association among female workers. Male employees always show a positive correlation between increased WFH frequency and changes in hourly productivity, but the association does not differ based on work autonomy. In our attempt to explain these results, we argue that employees with more work autonomy in the pre-pandemic period may need less coordination with their supervisors or colleagues while managing pandemic-era WFH restrictions and are quick to benefit from working from home. Work autonomy is more relevant for female employees because they usually perform the most childcare at home. Thus, women with more autonomy may benefit stronger when working from home, since they are better able to rearrange the time caring for their children.

4.5.3. Commuting

In addition to WFH feasibility and work autonomy, we now consider the respondents' pre-pandemic commuting behavior, i.e., their one-way commuting distance and commuting time to work. We obtain information on pre-pandemic commuting distance and commuting time from *main waves 9* to *11*. The data measure commuting distance in miles and commuting time in minutes. Those who commuted longer distances or spent more time commuting before the pandemic can now save commuting time due to workplace restrictions. The increased WFH frequency

[25] For this application, we first transfer our 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. (2022).

[26] Alternatively, we generate dummy variables for the quartiles of the WFH feasibility scores. Instead of the continuous variable, we include the dummy variables and their interactions with $WFH\ increase$ in the regression model. Results (not depicted) show that female employees in the fourth quartile have a significantly higher correlation between the increased WFH frequency and hourly productivity than the other females.

[27] These occupations include: Legislators and senior officials; corporate managers; managers of small enterprises; physical, mathematical and engineering science professionals; other professionals; physical and engineering science associate professionals; other associate professionals; office clerks; customer services clerks.

[28] The coding for *autonomy over work hours* differs from *autonomy over work pace* because only very few individuals state to have some or a lot autonomy over their work hours.

Table 4
WFH feasibility and work autonomy (OLS estimates).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Occ. WFH feasibility			Autonomy over work pace			Autonomy over work hours		
	All	Female	Male	All	Female	Male	All	Female	Male
Dependent variable: $\Delta PRODC$									
WFH increase (0/1)	-0.001	-0.025	0.061	0.095**	0.050	0.144**	0.074	0.031	0.148*
	(0.076)	(0.090)	(0.119)	(0.043)	(0.052)	(0.066)	(0.046)	(0.053)	(0.077)
WFH increase (0/1) × Occ. WFH feasibility	0.003**	0.004**	0.001						
	(0.002)	(0.002)	(0.002)						
Reference group: None/a little									
WFH increase (0/1) × Autonomy over work pace				0.056	0.137**	-0.027			
				(0.047)	(0.059)	(0.071)			
Reference group: None									
WFH increase (0/1) × Autonomy over work hours							0.078	0.166***	-0.050
							(0.050)	(0.060)	(0.080)
Observations	8409	4931	3478	8409	4931	3478	8409	4931	3478

Note: This table shows the heterogeneous associations between the increase in WFH frequency and the change in hourly productivity ($\Delta PRODC$) by occupation WFH feasibility (columns (1)–(3)), autonomy over work pace (columns (4)–(6)), and autonomy over work hours (columns (7)–(9)). Data on the occupation-level WFH feasibility source from Adams-Prassl et al. (2022). Control variables are the same as in the baseline specification, except that we exclude the dummy variables for occupations in columns (1)–(3). Standard errors (clustered at the individual-level) in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5
Commuting distance and time (OLS estimates).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All waves & occupations			All waves & Occ. WFH feasibility ≥32			January 2021 & Occ. WFH feasibility ≥32		
	All	Female	Male	All	Female	Male	All	Female	Male
Dependent variable: $\Delta PRODC$									
Panel (A): Commuting distance									
Reference group: $Distance < 11$ *miles*									
WFH increase (0/1)	0.146***	0.164***	0.124***	0.140***	0.161***	0.116**	-0.014	0.037	-0.059
	(0.029)	(0.036)	(0.045)	(0.032)	(0.040)	(0.049)	(0.057)	(0.071)	(0.090)
WFH increase (0/1) × *Long dis.*	-0.026	-0.060	-0.002	-0.020	-0.041	0.006	0.150*	-0.035	0.264**
	(0.042)	(0.060)	(0.058)	(0.052)	(0.072)	(0.072)	(0.088)	(0.121)	(0.129)
Observations	8409	4931	3478	5732	3376	2356	1809	1055	754
Panel (B): Commuting time									
Reference group: $Time < 30$ *min*									
WFH increase (0/1)	0.102***	0.142***	0.061	0.112***	0.160***	0.051	-0.054	0.012	-0.145
	(0.032)	(0.038)	(0.050)	(0.035)	(0.044)	(0.056)	(0.060)	(0.074)	(0.098)
WFH increase (0/1) × *More time*	0.066	0.008	0.113*	0.038	-0.033	0.126*	0.194**	0.040	0.383***
	(0.042)	(0.055)	(0.062)	(0.049)	(0.064)	(0.072)	(0.083)	(0.108)	(0.121)
Observations	8409	4931	3478	5732	3376	2356	1809	1055	754

Note: This table shows the heterogeneous associations between the increase in WFH frequency and the change in hourly productivity ($\Delta PRODC$) by commuting distance (Panel (A)) and commuting time (Panel (B)). Columns (1)–(3) depict results for all waves and all occupations. Columns (4)–(6) present results for employees with high WFH feasibility over all waves while columns (7)–(9) only focus on individuals interviewed in January 2021 (*COVID-19 wave 7*). Data on the occupation-level WFH feasibility source from Adams-Prassl et al. (2022). Control variables are the same as in the baseline specification. Standard errors (clustered at the individual-level) in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

may help them avoid the stress of commuting long distances, improving their work performance.

In Panel (A) of Table 5, we consider commuting distance. We generate a dummy variable indicating a longer commuting distance, taking the value of 1 if the one-way commuting distance is longer than 11 miles and 0 otherwise. We consider commuting time in Panel (B) with the help of a dummy variable indicating longer than 30 min of commuting time. Following the previous estimation strategy, we include the dummy variable for longer commuting distance/time and its interaction term with $WFH\ increase$ in the model. Columns (1)–(3) show the results for all three waves. We only find a slight positive correlation for male employees concerning commuting time. We expect the heterogeneous effect to be more pronounced for employees who can work from home. Therefore, columns (4)–(6) show the results for all waves but only for employees with high WFH feasibility (occupational feasibility ≥ 32, about 70% of the whole sample). However, we find similar results as in columns (1)–(3). Since our previous results suggest that employees are differently affected in the lockdown wave, we check the heterogeneous effect in columns (7)–(9) for high WFH-feasible employees surveyed in January 2021.

In line with earlier discussions, we find that individuals, especially male employees, who previously spent more time commuting became more productive when taking up more WFH. Different gender composition of occupations may explain the commuting benefits for males absent for women, e.g., most childcare facilities are staffed by women, with many being in the owners' primary residence. Our data shows that male employees commute over 4 miles more to their job than women, which is consistent with Le Barbanchon et al. (2021), showing that women have a preference for shorter commutes compared to men. Commuting longer distances or time may be positively correlated with the infection risk. The reduced time may lead to less stress or worries with commutes and enable employees to concentrate better on tasks of the job, especially in the lockdown period. This, for example, is also in line with Barrero et al. (2021) who show that respondents in the US who report higher efficiency while working from home mention commute time savings (85.5 percent) and a quiet environment at home (64.9 percent) as the main reasons.

In addition to hourly productivity, we also test whether employees increased their working efforts in response to the time saved on commuting.[29] We do not observe any significant relationship, indicating that the performance effects associated with time saved on commuting are primarily qualitative (less stress of commuting long distances) in nature and did not have any quantitative increases in employees' workload. The increased WFH frequency may help individuals avoid the stress of commuting long distances, improving their work performance, but not necessarily translating into increased working hours.

4.6. The future of WFH

Finally, we close our investigation by bringing attention to the future of WFH in the modern workplace. 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*. Individuals taking up more WFH during the pandemic and performing well, e.g., reporting higher hourly productivity, may be more willing to continue with WFH regularly. 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 less frequent than working at the office. Extended stays at home may increase boredom, worsening the individuals' mental health (Etheridge and Spantig, 2020). Declining 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 WFH experience during COVID-19 induced a desire to take up more WFH in the future (Kunze et al., 2020).

As many expect WFH to "stick" (Barrero et al., 2021; Dingel and Neiman, 2020), a formal analysis of employees' willingness to continue WFH in the future (*desired WFH*) is rare. Columns (1)–(3) in Table A-15 show that the increased WFH frequency during the pandemic is positively associated with individuals' willingness to continue WFH in the future. Columns (4)–(6) provide evidence that the self-reported improvement in employees' hourly productivity is positively associated with the willingness to take up WFH in the future while changes in working hours and wages show no significant associations.

5. Conclusion

The 2020 COVID-19 pandemic affected lives all around the world. Many countries imposed lockdowns and enforced workplace restrictions in response to the pandemic, forcing many employees to WFH, which presented a great challenge for employers and employees alike. Using representative data from the UK, we find that the increased frequency of working from home is positively associated with employees' self-reported hourly productivity. Notably, our analysis also shows that changes in WFH frequency are unrelated to the respondents' weekly working hours and weekly wages during the same period.

With respect to the heterogeneity in the WFH-productivity association, we discover that female employees working in occupations where WFH is more feasible and those with a higher autonomy over work pace and hours show more substantial WFH productivity than their counterparts. We demonstrate that male employees who commuted greater distances or spent more time going to the office showed higher WFH productivity. Finally, we find that the WFH-productivity association is weaker among parents living with school-age children, which we demonstrate to be caused by increased homeschooling needs due to pandemic-led school closures. These findings should draw the attention of policymakers.

As the world economy slowly recovers from the pandemic, many predict that the changes in working arrangements, such as increased use of technology and working from home, observed during this pandemic will stay. In this regard, the results presented in this paper shed a positive light on the alternative working arrangement of working from home. However, the positive association between productivity and WFH frequency might not fully apply in a post-COVID-19 time period. For example, the observed positive correlation between WFH frequency and productivity may be due to the fact that many colleagues also worked from home, which established new and efficient ways of remote work. However, it remains unclear whether individuals are similarly productive when most colleagues start to work on-site again after the pandemic. Furthermore, the positive correlation might stem from a possible selective sample of "better" employees, though our data do not confirm a severe selection problem. Thus, the observed association may not be generalized to all employees during normal times. Moreover, whether the positive productivity effects last in the long run needs careful consideration if gains from fewer commutes and breaks wear off while fewer face-to-face interactions become more disadvantageous after the pandemic. The positive peer effect of working from home might be solely applicable to individuals with high WFH feasibility.

In addition to highlighting the positive association between WFH and hourly productivity, we demonstrate that increased WFH frequency during the pandemic is associated with higher intentions to take up WFH in the future, which may establish WFH as an alternative to the conventional office setting. For future research, it may be pertinent to investigate whether the positive correlation between WFH frequency and employee performance still remains after the pandemic and whether employees benefit from taking up WFH for a relatively long period, e.g., a higher likelihood of promotion.

Data Availability

The authors do not have permission to share data.

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Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.labeco.2022.102295.

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[29] Results are available from the authors upon request.

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