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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, the COVID-19 pandemic forced governments in many countries to ask employees to work from home (WFH) where possible. Using representative data from the UK, we show that increases in WFH frequency are associated with a higher self-perceived productivity per hour and an increase in weekly working hours among the employed. The WFH-productivity relationship is stronger for employees residing in regions worse affected by the pandemic and those who previously commuted longer distances, while it is weaker for mothers with childcare responsibilities. Also, we find that employees with higher autonomy over job tasks and work hours and those with childcare responsibilities worked longer hours when working from home. With prospects that WFH possibility may remain permanently open for some employees, we discuss our results' labor market policy implications.

**Keywords:** Working from home, productivity, working hours, COVID-19 pandemic

**JEL Codes:** J22, J24

**Compliance with Ethical Standards:** This article does not contain any studies with human participants or animals performed by any of the authors.

**Conflict of Interest:** The authors declare that they have no conflict of interest.

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# 1 Introduction

Nowadays, many firms allow their employees the possibility to work from home (WFH). Although WFH has become a reality for some, until recently, many employers were not entirely convinced. Suspicions about employees misuse of freedom over assigned work resulting in an increased risk of shirking from home were generally cited reasons. 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. WFH became of great importance (Bonacini et al., 2021b), and in Western countries, about half of the employees worked exclusively from home (Felstead & Reuschke, 2020). This ‘forced innovation’ of WFH comes close to a “natural experiment”, allowing social scientists to analyze the effects of switching from the office to WFH on employees’ performance. Given that WFH is expected to remain in practice even after the pandemic ends (Barrero et al., 2020), a comprehensive assessment of employees’ WFH performance gains policy relevance.

In theory, WFH—which increases employees’ authority over working time, pace, and workplace—can be thought of as a principal-agent problem as the worker (agent) has fewer incentives to maximize the firm’s value than the owner (principal) (Aghion & Tirole, 1997; Bloom & Van Reenen, 2011). It follows that workers may exploit this increased authority, resulting in increased shirking, hindering teamwork, and lowering performance. In contrast, increased work authority may induce intrinsic motivation (Deci & Ryan, 2000; Blau, 2017; Delfgaauw & Dur, 2008), a pertinent determinant of employees’ productivity (Becchetti et al., 2013). The empirical research on the topic finds that increasing workers’ authority enhances their performance (Eaton, 2003; Lyness et al., 2012; Kelliher & Anderson, 2010; Beckmann et al., 2017; Bloom et al., 2015; Rupietta & Beckmann, 2018). However, research also suggests that the effect is not uniform and may depend on job characteristics. For instance, Dutcher (2012) finds that changing the working environment negatively affects the productivity of employees performing predominantly dull tasks, whereas the productivity of those performing creative tasks is positively affected.

While the recent research shows that WFH frequency increased among the employed in response to the workplace restrictions imposed during the 2020 COVID-19 pandemic (Brynjolfsson et al.,

2020; Bonacini et al., 2021b; Dingel & Neiman, 2020; Felstead & Reuschke, 2020; Schröder et al., 2020; Kunze et al., 2020), we empirically investigate the relationship between employees’ WFH frequency and their work performance. Using the novel Understanding Society COVID-19 survey data from the UK, we show that increases in WFH frequency are positively associated with employees’ performance, measured by changes in self-perceived productivity per hour and weekly working hours. The pandemic severity, measured by regional incidence of COVID-19 deaths, self-reported risk of contracting the virus, and government restrictions, strengthens the WFH-productivity association, whereas it weakens the association between WFH and weekly working hours. Moreover, the positive WFH-productivity relationship becomes stronger for employees who previously commuted longer distances to work, while the relationship between WFH and working hours is strengthened by employees’ increased work autonomy. Our results also indicate that the association between WFH and work performance is distinct for parents and non-parents in the sample. For parents, we find that increased childcare responsibilities in the aftermath of school closures reduced their WFH productivity and increased weekly working hours. Finally, we investigate the employees’ willingness to continue WFH in the future (*desired WFH frequency*) and find that it is positively associated with their current WFH frequency increases and work performance changes.

Separate from earlier research investigating how voluntarily taken WFH affects employees’ performance (Bloom et al., 2015; Rupietta & Beckmann, 2018), we establish the existence of a modest positive effect of WFH on employee performance even when WFH is ‘forced’ by the government, a scenario where positive reciprocity does not play a role. Second, our use of a dedicated and large control group of employees for the empirical analysis – those who observe no change in their WFH behavior because of the pandemic, including employees who never took WFH before and during the pandemic – captures general effects of the pandemic on labor market outcomes that are unrelated to WFH’s impact and sets the paper apart from emerging literature on the topic (Etheridge et al., 2020; Lee & Tipoe, 2020; Feng & Savani, 2020; Kunze et al., 2020). Furthermore, to seize the pandemic’s differential impact on the WFH-employee performance relationship, we also employ two additional datasets: administrative data on the pandemic severity (i.e., number of deaths) (Graeber et al., 2020) and government restrictions indexes (Bargain & Aminjonov, 2020), especially school closures.

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), our findings are important for policymakers aiming to expand flexible WFH arrangements. In addition to shedding a positive light on employees’ WFH performance, our findings indicate that employees’ increased familiarity with WFH and increases in WFH productivity are associated with their willingness to perform more WFH in the future. Our findings also call attention to mitigating policies aimed at curing the adverse differential experience of WFH. While the pandemic’s worsening had no adverse effect on employees’ WFH performance, our findings suggest that necessary support for WFH takers, such as childcare facilities, should also be considered.

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

## 2 Background

### 2.1 COVID-19 pandemic and government restrictions in the UK

In mid-March of 2020, Europe overtook China as the active center of the COVID-19 pandemic, with many European countries reporting increased infections and deaths. Figure 1 shows how the pandemic evolved in the UK.<sup>1</sup> In response to the worsening pandemic, Britain called for social distance measures to slow the virus’ spread following other European countries. As announced on 23 March by the British prime minister Boris Johnson, the measures included wide-ranging restrictions on freedom of movement, enforceable in law, under a stay-at-home order (BBC News, 2020). Figure 2 shows the daily variation in government-imposed COVID-19 restrictions in the UK, presented separately for four constituent countries, i.e., England, Scotland, Northern Ireland and Wales, respectively.<sup>2,3</sup> In subfigure (a), we plot the evolution of the government stringency index, a

<sup>1</sup>Information on the number of cases and deaths during the COVID-19 pandemic is provided by the UK Government at <https://coronavirus.data.gov.uk/>.

<sup>2</sup>The data are extracted from Coronavirus government tracker. More information can be found at <https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker>.

<sup>3</sup>These restrictions also had economic costs for the country, and the estimates suggest that they reduced the UK GDP by 20.4% in the second quarter of 2020 (Office for National Statistics, 2020).

composite measure based on different restriction indicators that includes school closures, workplace closures, and travel bans. The index is scaled from 0 (no restrictions) to 100 (strictest restriction). The figure confirms the observation that the country imposed stringent restrictions ( $\approx 80$ ) in the middle of March. The general stringency remained high in the following months with some regional variation. In subfigures (b) and (c), we show the evolution of the two indexes indicating government-imposed workplace and school closures, respectively. The index on workplace closures captures the following four restriction levels: 0 (no restrictions), 1 (recommend closing or work from home), 2 (require closing or WFH for some sectors or categories of workers), and 3 (require closing or WFH for all-but-essential workplaces). The figure shows that the highest workplace restrictions (level 3) were imposed starting in late March until May, and level 2 subsequently remained. Similar to the workplace restrictions index, restrictions on school closures also have four levels: 0 (no restrictions), 1 (recommend closing schools or keeping schools open with alterations resulting in significant differences compared to non-COVID-19 operations), 2 (require closing only at some levels or categories), and 3 (require closing all levels). Subfigure (c) shows that all schools were closed from mid-March to the end of May. We exploit this information in the empirical analysis.

Using Google Mobility data, in Figure 3, we plot the 7-day average of changes in workplace and residence place mobility during the pandemic compared to the baseline period in the UK.<sup>4</sup> It is clear that the country observed a considerable reduction in employees' mobility at the workplace, and the mobility at the place of residence increased consequently. This observation is in line with the early estimates by Felstead & Reuschke (2020), who find an eight-fold increase in those reporting to working exclusively from home (from 5.7% in January/February to 43.1% in April, remaining high in June (36.5%)). By the summer of 2020, however, the workplace restrictions were marginally relaxed and workplace mobility gradually improved (*see* figures 2b and 3). The formal empirical evidence also suggests that the incidence of COVID-19 cases in the region and consequential workplace restrictions predict WFH (Brynjolfsson et al., 2020; Bonacini et al., 2021b; Dingel & Neiman, 2020; Felstead & Reuschke, 2020; Schröder et al., 2020; Kunze et al., 2020).

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<sup>4</sup>Data are extracted from Google Mobility at <https://www.google.com/covid19/mobility/>. A baseline-day value is the value for that day of the week, which is the median value from the 5-week period of 3. January to 6. February 2020. We calculated the last-7-day average ourselves. A negative value represents a decrease in mobility, and a positive value means an increase in mobility.

## 2.2 Working from home and employee performance

Given the increased prevalence of WFH in recent years, emerging economics literature investigates whether switching to WFH affects employees' performance. For instance, using a randomized controlled trial with call center workers in China, Bloom et al. (2015) show that employees switching to WFH observe an increase in their performance by 13%, of which 9% was due to productivity change per shift, such as quieter and more convenient working environment, and 4% was due to longer minutes per day, such as fewer breaks and sick days. The literature investigating the employees' performance during the COVID-19 pandemic reports supporting evidence. For instance, a study similar to this paper uses data from the UK and finds that employees working more from home indeed reported higher WFH productivity (Etheridge et al., 2020). Similarly, using data on 700 telecommuting employees in Germany, Kunze et al. (2020) find that WFH increases perceived productivity and commitment during the pandemic and that the vast majority of employees wish to continue to work flexibly, at least to some extent. However, the authors also find trends of excessive workloads after switching to WFH resulting in exhaustion. Studies also show contradicting results on whether the pandemic increased or lowered WFH working hours (Lee & Tipoe, 2020; The Economist, 2020).

The existing research proposes several theoretical arguments to ascribe a positive view of WFH. We argue that the employers' decision to allow WFH possibility to their employees is synonymous with increasing their freedom and control on job tasks, pace, and place. It then follows that the theoretical expectation of the WFH's impact can be described as a principal-agent problem, where workers (agent) make decisions on behalf of the employer (principal).<sup>5</sup> In contrast, this newly found authority may motivate workers to act in their own best interests, and then become more motivated and committed to their employers, increasing intrinsic motivation and reciprocal behavior (Deci & Ryan, 2000; Blau, 2017; Delfgaauw & Dur, 2008). Allowing workers the WFH possibility signals a principal's prosocial attitude, leading to higher motivation of the agent (Ellingsen & Johannesson, 2008). If intrinsic incentives are strong, it might dominate the possible loss in extrinsic motivation and lead to extra effort (Beckmann et al., 2017). Building on existing literature, we construct theoretical expectations of WFH's on employees' performance. In particular, we refer to Bloom

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<sup>5</sup>For more details on the problem, see Falk & Kosfeld (2006)

et al. (2015) to further shed more light on our expected results.

First, a relatively more quiet work environment increases productivity at home, while in contrast, lower access to supervisor support and teamwork is expected to lower performance at home. Besides, the job’s WFH feasibility and availability of amenities at home (separate workroom, appropriate electronics, etc.) are also essential for employees to continue working from home without skimping on work performance. As per Dingel & Neiman (2020), in Western countries, about one-third of jobs can be performed entirely at home, and that WFH feasibility is notably higher for high paid jobs in high-income economies. Additionally, many individual-level characteristics are also important correlates of WFH possibility. For instance, research finds that male, older, and high-paid employees report higher WFH possibility (Adams-Prassl et al., 2020; Bonacini et al., 2021b).<sup>6</sup> These arguments highlight that the WFH’s impact on productivity may depend on the type of work and the level of interaction needed at work. The research finds that the productive impact of WFH is not uniform and depends on the job’s WFH feasibility and the respondents’ previous experience of WFH. Etheridge et al. (2020) employ British data and find that the self-perceived WFH productivity increased for workers in industries that are more suitable for home office and declined among those in low-paying jobs. Dutcher (2012) shows that WFH’s productive effect predominantly exists among workers performing creative tasks (with higher WFH feasibility), whereas WFH is counter-productive for workers dealing with dull tasks. The results of Felstead & Reuschke (2020) for the UK indicate that employees who worked at home relatively infrequently reported a downward shift in their productivity, whereas employees who did all their paid work at home reported that they got more done per hour than they did before the lockdown.

Second, time saved in commuting as well as multiple coffee breaks should allow employees to devote more time to work, denoted by increased working hours.<sup>7</sup> While time saved makes shirking and taking breaks more attractive, which employees can spend watching TV and/or playing video games, breaks at home might be less enjoyable as social interactions are also lower. Beyond leisure, other sources of time spent are also worth considering, such as increased childcare responsibilities in

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<sup>6</sup>Etheridge et al. (2020) find that, despite remaining constant during the pandemic, average WFH productivity declined for women. Cui et al. (2020) find that ten weeks after the lockdown in the United States, although the total research productivity (measured by published research preprints) increased by 35 percent, female academics’ productivity dropped by 13.2 percent relative to that of male academics.

<sup>7</sup>Rubin et al. (2020) show that workplace restrictions and forced WFH saved commuting time, which lead to increased satisfaction among employees, especially among those who commuted by car.

the aftermath of forced closure of schools and childcare during the COVID-19 lockdown. As shown in Panel (c) of Figure 2, all schools were closed from mid-March to the end of May. The resulting increase in childcare responsibility might have affected parents’ work performance compared to those without children. For the UK, for example, Andrew et al. (2020) formally show that parents’ time spent on childcare increased by 3.5 hours during the lockdown, while working time decreased by 3.5 hours, partly driven by large employment losses.<sup>8</sup> For the US, Zamarro & Prados (2021) show that mothers reduced working hours more and have an increased probability of transitioning out of employment.

Additionally, new evidence suggests that increased childcare responsibilities might be associated with an increased gender gap in WFH productivity within a household. Accordingly, the COVID-19 pandemic detrimentally affected mothers, as the closure of childcare facilities and schools, a “disruptive exogenous shock” to family life (Huebener et al., 2021), increased the need for private childcare (Alon et al., 2020). Although fathers nearly doubled the amount of time they spend with childcare, the pandemic increased the differences in work patterns between mothers and fathers, as mothers bear the brunt of childcare work. Gallen (2018) also finds that, while, in general, women were less productive than men, the “gender productivity gap” is mainly visible among parents due to mothers still being the primary childcare giver in Western countries. In contrast, for Germany, Kreyenfeld & Zinn (2020) do not find evidence of the gender gap in childcare as they show that fathers and mothers in Germany expanded their time spent on childcare to similar degrees.

### 3 Data and Methodology

#### 3.1 Data and variables

Our empirical investigation employs the high-quality data from Understanding Society, the UK household longitudinal study (University of Essex, Institute for Social and Economic Research, NatCen Social Research, Kantar Public, 2020). Initially starting in 2009 (wave 1), the survey records detailed information on approximately 40,000 British households annually. In response to

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<sup>8</sup>Using data from Germany, Arntz et al. (2019) also show that childless employees worked an extra hour per week of unpaid overtime after taking up WFH. For Italy, Bonacini et al. (2021a) find that the gender wage gap is more significant among females working in an occupation with a high level of WFH feasibility, potentially increasing the overall gender wage gap in the future.

the worsening COVID-19 pandemic in early 2020, in addition to the main survey data, respondents were asked since April 2020 to complete supplementary web-based surveys focused on capturing the impact of the COVID-19 pandemic on British life (University of Essex, Institute for Social and Economic Research, 2020). These special waves (referred to as COVID-19 waves) covered various questions on the welfare of individuals, families, and communities in the UK.<sup>9</sup> For our analysis, we use COVID-19 waves conducted in May, June, July, September, and November 2020.<sup>10</sup> Variables of individuals’ behavior during the pandemic and time-invariant variables, such as birth year and gender, are drawn from the COVID-19 survey data. Moreover, information absent in COVID-19 survey waves, such as individual’s occupation, industry, and region (rural/urban), is mainly sourced from wave 10 of the main survey data. Table 1 reports the summary statistics of the variables used.

### **Change in working from home frequency ( $\Delta WFH$ )**

The primary explanatory variable of interest is the change in the respondents’ frequency of working from home ( $\Delta WFH$ ). Individuals respond to the following survey question: “*During the last four weeks how often did you work at home?*”. Their answers can be 1 (*always*), 2 (*often*), 3 (*sometimes*) and 4 (*never*). A similarly defined question also records the respondents’ pre-COVID-19 WFH behavior by retrospectively asking them to report whether they took up WFH in January and February 2020 (baseline period). Using this information, we perform the following two steps to construct  $\Delta WFH$ . We first reverse individual responses so that larger values show higher frequency of WFH, i.e., 1 (*never*) to 4 (*always*). After that, we take the difference in WFH frequency between the current and baseline period to compute the change in WFH frequency, i.e.,  $\Delta WFH \approx WFH - WFH_{baseline}$ . The descriptive statistics presented in Table 1 show that UK respondents, on average, report more WFH during the pandemic than before.

### **Change in employee performance ( $\Delta PROD$ & $\Delta WH$ )**

We employ two outcome variables that measure employee performance. First, we consider the

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<sup>9</sup>More information on the COVID-19 data from Understanding Society can be found at <https://www.understandingsociety.ac.uk/documentation/COVID-19>.

<sup>10</sup>One of the important variables, self-reported likelihood of contracting COVID-19, was not asked in April. For the whole analysis, we omit observations interviewed in April to keep our estimation sample constant and to ease the comparison of results. Our main results broadly hold when this sample restriction is relaxed.

respondents’ self-reported change in productivity per hour ( $\Delta PROD$ ).<sup>11</sup> In COVID-19 waves 3 and 5, the 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 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*). We rescale the responses so that higher values indicate larger increases in work productivity. The newly generated variable  $\Delta PROD$  ranges from 1 - *much less done* to 5 - *much more done*. In Table 1, beyond overall sample means and standard deviations, columns (3)-(6) separately report information of individuals who reported an increase in WFH (columns (3)-(4)) and those who did not observe any change in their WFH frequency (columns (5)-(6)). From the statistics, we observe that, on average, respondents reported an increase in working productivity during the pandemic, compared to the baseline period (January and February 2020), and the increase is larger for individuals who reported more WFH, i.e.,  $\Delta WFH > 0$ .

Our second measure of work performance is the respondents’ change in weekly working hours ( $\Delta WH$ ). Generally construed as an input measure, working hours may also indicate worker’s performance as more time spent on work-related activities likely increases worker’s output (Bell & Freeman, 2001). In all five COVID-19 waves, respondents were asked to report weekly hours worked. In particular, the question asks, “*How many hours did you work, as an employee or self-employed, last week?*”. A similarly defined question recorded the respondents’ baseline weekly working hours, i.e., pre-COVID-19 behavior for January and February 2020. The question asks: “*During January and February 2020, how many hours did you usually work per week? Please include all jobs and self-employment activities*”. We construct our outcome variable  $\Delta WH$  by taking the difference in weekly working hours between the current and baseline period.<sup>12</sup> The statistics presented in Table 1 show that UK respondents, in general, report fewer working hours during the pandemic (column (1) and (2)), which is in line with evidence from other countries (see Schröder et al., 2020). However, the decrease in working hours is much smaller for individuals who observed an increase in WFH frequency (columns (3)-(4)) than those who did not observe any change in WFH frequency

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<sup>11</sup>In wave 3, only WFH takers were asked information on their  $\Delta PROD$ , whereas, in wave 5, all employed respondents were asked this question.

<sup>12</sup>We drop individuals who reported more than 60 hours either in the baseline period or in the current period, which is about 1% of the sample.

(columns 5-6).<sup>13</sup>

### Other covariates

The first set of control variables include the respondent’s demographic characteristics. We control for the respondents’ age, gender, couple status (whether living with a partner or not), urban/rural residence, and 12 dummy variables for the UK NUTS-1 regions. The second set of covariates are labor market characteristics that impact the respondents’ working performance and might be correlated with WFH frequency. These variables include nine occupation dummies, 21 industry dummies, and the logarithm of current monthly net labor income. Also, we consider a proxy for the pandemic’s severity by employing the average number of deaths per 100,000 population during the last seven days in the region as a control variable. Finally, we control for wave-fixed effects to capture the level difference in the frequency of WFH and employee performance across time. Summary statistics of these variables are also reported in Table 1.

### Sample restrictions

To study the association between the changes in the respondents’ WFH frequency and working performance, we restrict the sample to individuals aged 18-65 who reported to be paid employees or self-employed in January/February 2020 and during the pandemic. We drop individuals who reported a decrease in WFH frequency, as they might be a very special group and behave differently from others. For the outcome variable  $\Delta PROD$ , the sample size is smaller since the question was only asked in two waves. For the outcome  $\Delta WH$ , we only observe individuals whose current income was stable compared to the baseline income, because the number of actual working hours might change if the contractual working hours during the pandemic differed from the baseline. For this purpose, we drop individuals whose income changed by more than 10%.

### Supplementary information

As noted earlier, numerous individual-level variables may intervene in the WFH-work performance relationship. To test this, we also perform supplementary analysis using additional variables from

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<sup>13</sup>Time-difference in the phrasing of the questions recording our variables of interest is a data-related issue worth mentioning. The survey question recording WFH frequency asks respondents to report their WFH frequency for “the last four weeks”. In contrast, the survey question for productivity includes the phrasing “these days” or “the last week”. For the simplicity of our results’ interpretation, we assume that individuals’ behavior remains relatively constant during these two periods, i.e., the week or the month of the interview.

the Understanding Society survey and other sources. The supplementary analysis begins by considering the actual and perceived risk of the pandemic. Using the average COVID-19-related death rate during the last seven days, we generate a dummy variable equal to one if the death rate is above the sample median and zero otherwise. The survey also contains information on individuals’ perceptions of the likelihood of contracting the virus in the next month. Using this variable, we generate a dummy variable with the value of one if the individual self-reported likelihood of contracting COVID-19 is “*very likely*” or “*likely*”, and zero if “*unlikely*” or “*very unlikely*”. After that, we employ the pandemic-related government stringency index and use the sample median of the index to generate a dummy variable, which is one if the value is above the median and zero otherwise. After that, we analyze the differential impacts by job characteristics, including commuting distance and work autonomy. The information on commuting distance and work autonomy is derived from wave 10 of the main survey data. Commuting distance is a continuous variable, while the work autonomy is a dummy variable that takes the value of one if the individual reported a lot or some autonomy over job tasks or work hours, and zero if only a little or no autonomy is reported. Finally, we analyze heterogeneous effects by family characteristics. In doing so, we employ three variables indicating the respondents’ family structure and family life, i.e., the number of children, school closures, and childcare responsibility. Using the continuous variable indicating the number of children the respondent is responsible for, we generate a dummy variable of having children and a categorical variable taking the values of 0 (no children), 1 (1-2 children), and 2 (3 or more children). During the observation period, restrictions on school closures have three different stringency levels, i.e., one to three. We generate a dummy variable for school closures with this information, which takes the value of one if level two or three is required and zero otherwise. Finally, the variable indicating the level of childcare responsibility takes the following three values: 1 (individual’s partner is responsible for the child), 2 (if both partners are equally responsible), and 3 (if the respondent takes all the childcare responsibility).

### 3.2 Empirical strategy

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

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

where  $\Delta Y_{it}$  denotes the change in employee performance, i.e., hourly productivity ( $\Delta PROD$ ) and weekly working hours ( $\Delta WH$ ), of individual  $i$  interviewed in wave  $t$  between the baseline and current period.  $\Delta WFH_{it}$  represents the change in self-reported WFH frequency of individual  $i$  in the last four weeks. Both  $\Delta Y_{it}$  and  $\Delta WFH_{it}$  are standardized with a mean of zero and standard deviation of one.  $\mathbf{X}_{it}$  is a vector of individual characteristics in levels. These include age and its quadratic term, gender, living with a partner, living in the urban region, dummy variables for occupation and industry, the logarithm of income, the average COVID-19 death rate during the last seven days, and region fixed effects.  $\lambda_t$  represents wave fixed effects and  $\varepsilon_{it}$  is the error term.

Correlating outcomes and the frequency of WFH in first differences rather than in levels allows us to control for time-invariant (un-)observable factors that may be correlated with employee performance and WFH frequencies, such as WFH feasibility and individuals' personality. Those recording  $\Delta WFH = 0$ , e.g., the WFH non-takers, act as a reference group, controlling for the general impacts of the pandemic on employees' WFH performance that are not correlated with taking more WFH. The use of non-takers before and during the pandemic as a large control group differs from the strategy applied in the existing literature (Etheridge et al., 2020; Lee & Tipoe, 2020; Feng & Savani, 2020; Kunze et al., 2020). The results are estimated with the OLS estimation technique. The standard errors are clustered at the individual level. Individual cross-sectional weights are applied in all regressions.<sup>14</sup> In addition to the estimates for the entire sample, we show separate estimates for male and female subsamples.

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<sup>14</sup>To deliver credible population estimates, we employ cross-sectional weights released with each wave of the Understanding Society COVID-19 study. As noted in Crossley et al. (2021), these weights account for different selection probabilities of individuals.

## 4 Results

### 4.1 Main results

Before presenting our formal empirical evidence, in Figure 4, we plot the weighted average of the level changes in outcome variables against WFH frequency changes. The figure provides evidence of a positive relationship between the variables of interest. In other words, employees reporting increases in WFH frequency depict increases in work performance. Now, we investigate whether the positive association also holds when covariates are included. Table 2 presents the main results of our analysis. The table is divided into two panels, reporting the estimates separately for the changes in self-reported productivity ( $\Delta PROD$  in Panel (1)) and changes in weekly working hours ( $\Delta WH$  in Panel (2)). In column (1), we show the baseline results for the entire sample.<sup>15</sup> The results suggest that increases in WFH frequency are associated with increases in work productivity and working hours. In terms of magnitude, one standard deviation increase in WFH frequency is associated with a 0.144 standard deviation increase in work productivity and a 0.152 standard deviation increase in work hours, an increase equivalent of about 1.9 ( $= 0.152 \times 12.4113$ ) hours per week. Column (2) investigates whether the baseline relationship is non-linear. We do this by including a polynomial of the second-order in the model of the primary variable of interest, i.e.,  $\Delta WFH$ . The results find no evidence of non-linearity for productivity, but mild non-linearity for working hours. In columns (3)-(4), we estimate the results separately for female and male respondents. The coefficients are qualitatively the same for both subsamples. While the magnitude of the  $\Delta WFH$ - $\Delta PROD$  relationship is smaller for males than females, there are no gender differences in the association between  $\Delta WFH$ - $\Delta WH$ .

Now, we consider two variations of our baseline model to test the robustness of the baseline results. As Felstead & Reuschke (2020) note, WFH had already increased in recent years in the UK. According to the authors, the share of people reporting to work mainly at home gradually increased from 1.5% in 1981 to 4.7% in 2019. Evidently, a sizable portion of our sample observations reports having worked from home in the baseline period. That is, approximately 5% of observations “often” or “always” worked from home, and around 20% “sometimes” worked from home before

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<sup>15</sup>We also estimate the baseline specification by clustering standard errors at the district level and our main findings hold. The results are available from authors upon request.

the COVID-19 pandemic began. It is plausible that the impact of increasing WFH frequencies on employees' performance may differ depending on their previous experience and familiarity with WFH. Therefore, as a robustness check, we re-estimate the main results after controlling for the employees' baseline WFH behavior. The results depicted in Table A-1 in the online appendix show that the paper's main message suggesting a positive association between WFH and employee performance hold.

After that, we address the concern that employee performance changes may be distinct for different jumps in their WFH frequencies. In other words, performance measures may respond differently to an increase of WFH frequency from "never" to "sometimes" compared to from "sometimes" to "often". Therefore, as a second robustness check, we restrict the sample to those who never took WFH in the baseline period and re-estimate our results. Instead of a continuous variable  $\Delta WFH$ , we now employ a set of dummy variables indicating current WFH frequencies. For the categorical outcome variable  $\Delta PROD$ , we apply the ordered probit model. The results are shown in Table A-2. We observe that the size of the coefficient increases as the change in WFH frequencies becomes larger. Marginal effects (not depicted) provide similar evidence, i.e., the more WFH employees take, the larger the increases in their productivity. We still use the standardized change in working hours for the second outcome and estimate an OLS model. Again, results in Table A-2 show that more WFH frequencies are positively correlated with longer working time.

## 4.2 Heterogeneous effects

### 4.2.1 COVID-19 effects

In Table 3, we study whether the pandemic-related variables influence the baseline relationships of interest. Columns (1)-(3) consider the role played by the respondent's self-reported risk of contracting COVID-19 infection. The results suggest that the positive association between WFH and productivity becomes stronger for individuals who reported a higher likelihood of contracting the virus, though males mainly drive the association. In contrast, higher perceived COVID-19 risk weakens the positive relationship between WFH and working hours, and females mainly drive the impact.

Next, we investigate the role of the intensity of the COVID-19 pandemic, denoted by the dummy

variable indicating above-median COVID-19 related death rates in the last seven days in the region. The results are reported in columns (4)-(6). The results in Panel (1) suggest that the pandemic’s intensity strengthens the  $\Delta WFH$ - $\Delta PROD$  relationship. In contrast, the evidence presented in Panel (2) shows that respondents living in regions worse affected by the COVID-19 pandemic report smaller increases in working hours in response to increased WFH take-up. We also observe that the results hold uniformly among male and female respondents.

Finally, we consider the role of government restrictions in response to the worsening COVID-19 pandemic, measured by the dummy variable indicating the above-median stringency index. The results presented in columns (7)-(9) suggest that the increased intensity of restriction strengthens the  $\Delta WFH$ - $\Delta PROD$  relationship for females, but not for males. In contrast, we find that government restrictions’ stringency weakens the  $\Delta WFH$ - $\Delta WH$  association, especially for females.

#### 4.2.2 Job-related characteristics

Next, we focus on the respondents’ job-related characteristics. The results are reported in Table 4. First, columns (1)-(3) investigate whether employees’ saved commuting time intervenes in the relationship between WFH and employee performance. We find that employees who previously commuted longer distances to work reported a stronger association between WFH and their productivity, but the relationship with weekly working hours is not affected by this characteristic. Next, the results in columns (4)-(9) show how work autonomy affects the relationship. For doing this, we employ two types of autonomies, i.e., work autonomy over job tasks (columns (4)-(6)) and over work hours (columns (7)-(9)). With "no autonomy" individuals as the reference group, our results broadly show that the level of work autonomy an employee has does not play a role in the  $\Delta WFH$ - $\Delta PROD$  relationship, but it strengthens the  $\Delta WFH$ - $\Delta WH$  association.

#### 4.2.3 School closures and childcare responsibilities

In Table 5, we consider the role played by increased childcare responsibilities due to school closures imposed during the pandemic. The analysis begins by investigating the heterogeneous impact associated with having children. Columns (1)-(3) employ two dummy variables indicating that the respondent is responsible for one to two or more than two children between the ages of 0 and 16. The reference group consists of individuals without children. The results show that having

more children is detrimental for the  $\Delta WFH$ - $\Delta PROD$  among female respondents, especially those with more than two children, while males do not show such an effect. Also, we find that having three or more children weakens the  $\Delta WFH$ - $\Delta WH$  relationship among female respondents. As discussed in Section 2.2, these results are in line with previous literature showing that mothers' work performance is affected strongly by the pandemic.

Next, in columns (4)-(9), we observe parent respondents alone and study whether increased childcare responsibilities due to school closures affected the baseline relationships. In columns (4)-(6), we investigate whether school closures themselves had an independent association with the baseline relationships. We once again find that school closures reduce the  $\Delta WFH$ - $\Delta PROD$  association only for mothers, but not for fathers. However, the  $\Delta WFH$ - $\Delta WH$  relationship is strengthened in the whole sample of parents, but the positive estimate loses significance in the subsample of mothers due to imprecise estimation with a small sample size. After that, we study the role played by childcare responsibilities. Similar to school closures, the results presented in columns (7)-(9) show evidence that childcare responsibility is particularly detrimental to females'  $\Delta WFH$ - $\Delta PROD$  relationship, but strengthens the  $\Delta WFH$ - $\Delta WH$  relationship in the whole sample.

### 4.3 Discussion

Beyond highlighting the productive impact of the forced WFH during the 2020 COVID-19 lockdowns, our analysis demands a thorough discussion of its many results. First, we put our baseline results in the perspective of the existing research. Our results suggested a positive association between the employees' WFH frequency and their productivity per hour, a finding consistent with other research on the topic (Etheridge et al., 2020). According to The Economist (2020), the increased WFH productivity cannot be explained away by employees' exaggerated self-reporting of their productivity. The article cites a survey by PricewaterhouseCoopers (PwC), which reported that 44% of American bosses think that their employees have become more productive during the pandemic, while only 28% of workers agreed. Our baseline result shows that employees switching to WFH reported increased weekly working hours, an indicator of their work effort, which is also broadly consistent with the existing literature. For instance, Rupietta & Beckmann (2018) also show that employees increase their work effort when they undertake WFH even in normal times. According to The Economist (2020), researchers at Atlassian, a developer of workplace software,

found that employees in industrialized countries were logged into the software on average 30 minutes longer during the lockdown than before. They also show that employees made better use of their increased work authority by working more in the evening. In contrast, Lee & Tipoe (2020) find that the employees working from home reduced work-related activities during the UK lockdown.

Second, while emphasizing the role of various individual characteristics as deciding factors in assessing the employees' WFH performance, on some occasions, we found "seemingly" contradictory results on two outcomes considered, productivity per hour and weekly working hours, which need more elaboration. For instance, we find that school closures induced increases in childcare responsibilities weakened the  $\Delta WFH$ - $\Delta PROD$  relationship, whereas they strengthened  $\Delta WFH$ - $\Delta WH$ . In our effort to explain these findings, we argue that having children at home during lockdown adversely affected parents' productivity per hour, which they compensated by working longer hours.<sup>16</sup> Also, we found that the severity of the COVID-19 pandemic strengthens the positive relationship between  $\Delta WFH$  and  $\Delta PROD$  but weakens the  $\Delta WFH$ - $\Delta WH$  association. In other words, we argue that residents in worse affected regions observed smaller increases in working hours as they spent more time coping with the limitations imposed on their routine movements (time spent in long queues for grocery shopping, etc.). Simultaneously, however, as the clarity on social distancing measures is likely to be higher and relatively durable in the regions worse affected by the pandemic, employees had enough time to become familiar with changed circumstances, manage routine better, and with so explain why hourly productivity increased.

Next, we employ additional variables from the survey to consider the role of the individuals' self-reported ability to concentrate in baseline relationships. Besides being a variable proxy for the individuals' personality, we argue that the individuals' ability to concentrate represents their feasibility to perform WFH uninterrupted, an essential determinant of their WFH performance. The results presented in Table A-3 show that individuals' ability to concentrate plays a significant role in the employees' WFH performance, strengthens  $\Delta WFH$ - $\Delta PROD$  association, and weakens the  $\Delta WFH$ - $\Delta WH$  relationship. In other words, the findings iterate our earlier findings that individuals who are better able to concentrate are more productive and work few hours when switching to WFH.

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<sup>16</sup>Our findings also hold when time spent on childcare is controlled for. Parents might sacrifice their leisure time to reimburse their disadvantages in labor market performance. Results are not depicted and can be available from authors upon request.

We end our analysis by discussing the future of WFH. As many expect WFH to “stick” (Dingel & Neiman, 2020), a formal analysis of employees’ willingness to continue WFH in the future (*desired WFH*) has not been conducted. The results presented in Table A-4 investigate whether employees’ current WFH frequency and work performance measures are associated with their desired WFH. The outcome variable indicates the respondents’ self-reported desired WFH frequency once social distancing measures are relaxed, and workplaces go back to normal. The results in columns (1)-(3) show that increased current WFH frequency is positively associated with individuals’ willingness to continue WFH in the future. Columns (4)-(6) reveal whether work performance measures have an independent association with the new outcome variable. We find evidence that improvement in employees’ productivity is associated with willingness to do more WFH in the future, but changes in working hours show no significant association. Finally, in columns (7)-(9), we analyze whether having children at home affects the desired WFH frequency. The results show that having more younger children at home is associated with taking more WFH in the future but only for women.

## 5 Conclusion

The 2020 COVID-19 pandemic affected lives all around the world. While responding to the pandemic, many countries imposed “lockdowns” and enforced workplace restrictions, which forced a vast number of employees to work from home, a great challenge for employers and employees alike. Using representative data from the UK, we showed that the increased frequency of working from home is associated with a higher self-perceived productivity per hour and an increase in weekly working hours. Employees residing in regions worse affected by the pandemic reported reduced weekly working hours, but observed increases in hourly productivity when working more from home. This positive relationship between WFH and working performance becomes stronger for employees who previously commuted longer distances to work and had a higher work autonomy. However, the positive association becomes weaker for mothers compared to non-mothers. For parents, school closures and childcare responsibility adversely affected their WFH productivity per hour and increased weekly working hours.

Although lockdown measures are temporary, the possibility of working from home may persist for many. While our results shed a positive light on the employees’ WFH performance, they also

highlight the need for mitigating policies to address the relative adverse effects on population subgroups' WFH productivity. The finding that increased childcare responsibilities due to forced school closures disproportionately affected mothers' WFH productivity needs policymakers' particular attention. It contributes to the emerging evidence that the pandemic adversely impacted women by highlighting the moderating role special childcare arrangements can perform in addressing the pandemics' gender-unequal effects. Finally, our analysis of employees' willingness to continue WFH in the future indicates that the employees' "forced" familiarity with WFH and relative productivity increases they observed during the lockdown have contributed to generate a positive view towards the future of WFH. The flexibility showed by employers and employees towards WFH arrangements in response to the COVID-19 pandemic, are symbolic for a future where the possibility of working from home is here to stay.

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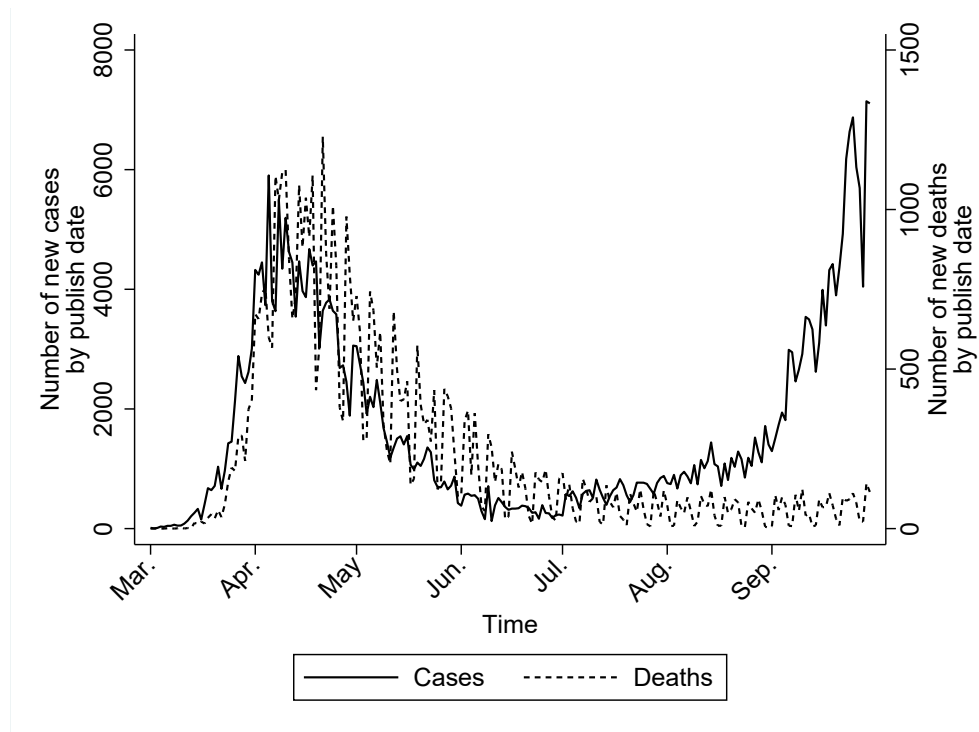
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## Figures and Tables

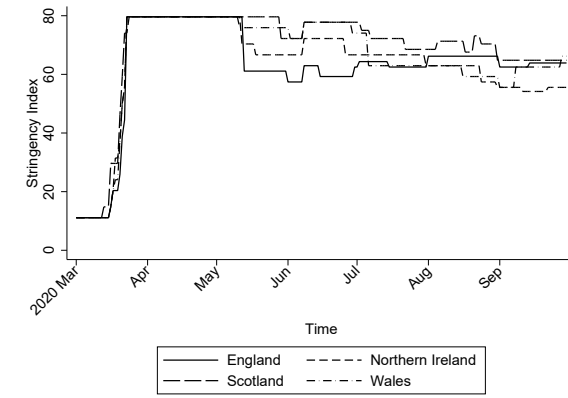
Figure 1: Number of COVID-19 cases and deaths by publish date in the UK



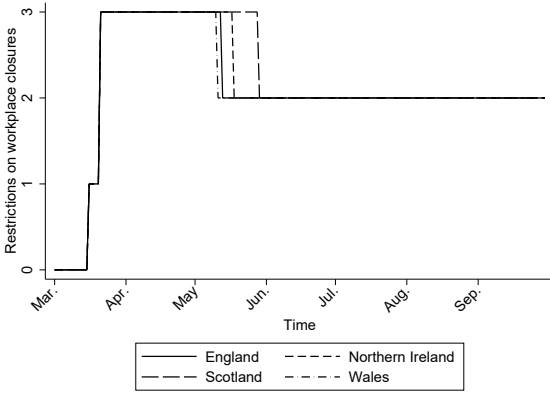
Data source: The official UK Government website for data and insights on Coronavirus (COVID-19).

Notes: This figure shows the number of new cases and deaths by publish date from March to September 2020 in the UK.

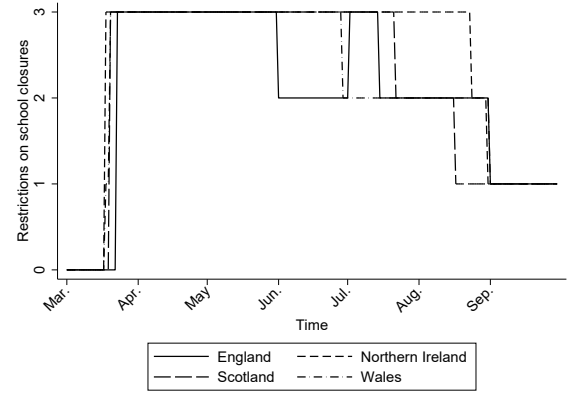
Figure 2: **Government restrictions during the COVID-19 pandemic in the UK**



(a) Government stringency index



(b) Restrictions on workplace closures

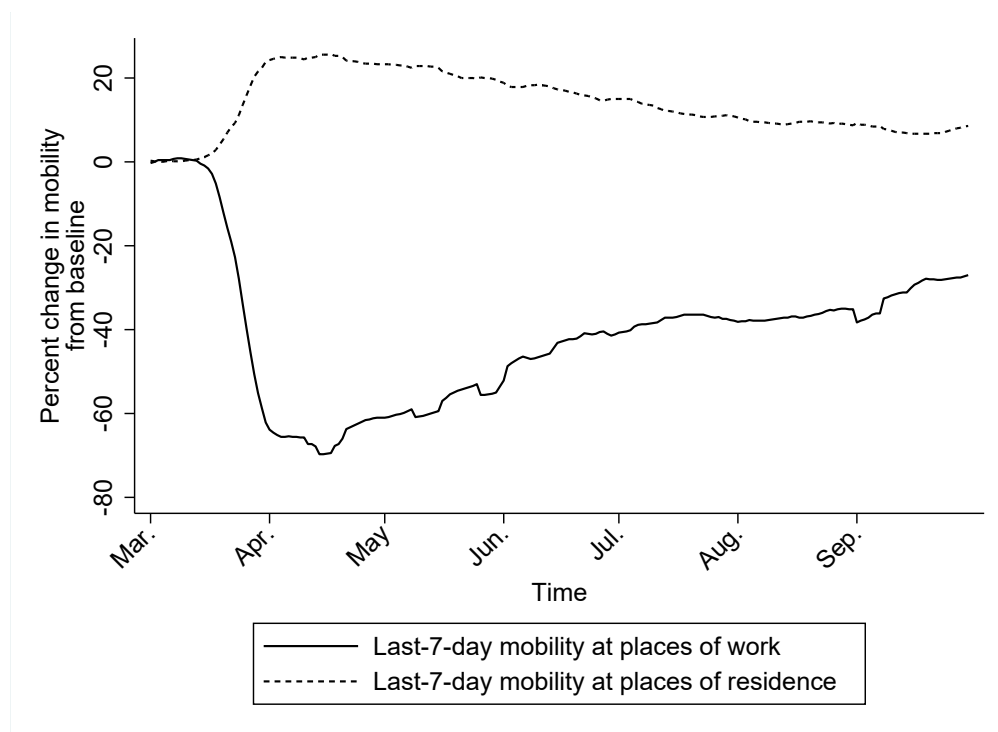


(c) Restrictions on school closures

Data source: Coronavirus government response tracker.

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

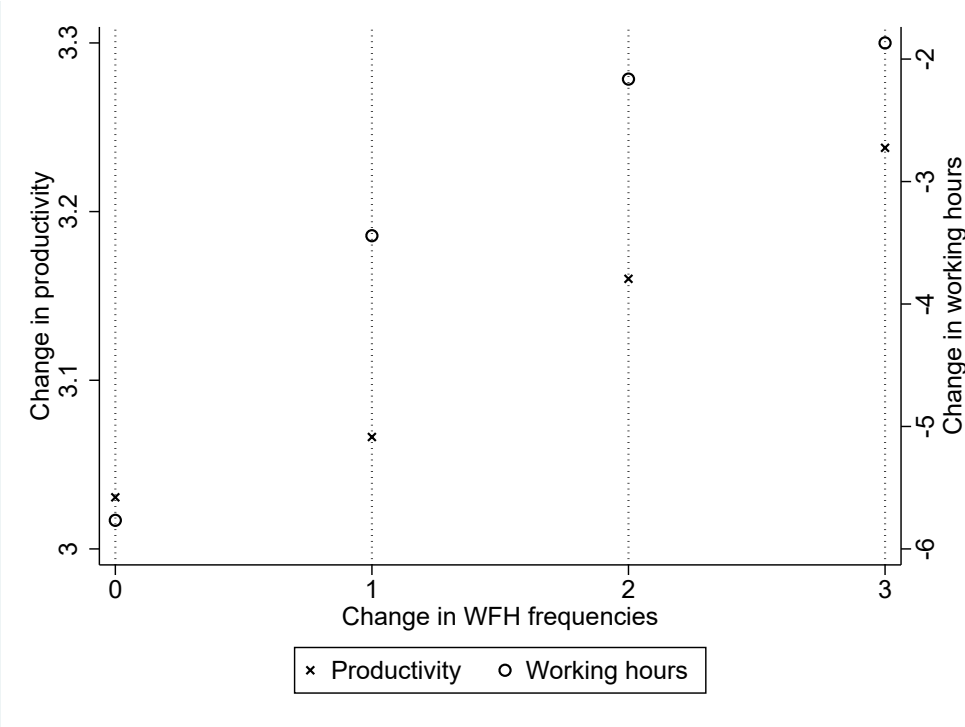
Figure 3: Last-7-day average mobility change at workplace and residence place in the UK



Data source: COVID-19 community mobility reports, own calculation.

Notes: This figure shows the last-7-day average mobility change at workplace and residence place from March to September 2020 in the UK. This percentage change compares the mobility of people at work or at home for the report date to the baseline day.

Figure 4: WFH: Productivity Change and Change in Working Hours



Data source: Understanding Society 2020, own calculation.  
Notes: This figure shows the association between the change in WFH frequencies and the change in hourly productivity as well as weekly working hours.

Table 1: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)
	<b>All</b>		$\Delta WFH > 0$		$\Delta WFH = 0$	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
<b>Outcome variables</b>						
$\Delta PROD$	3.0995	0.9898	3.1542	1.0897	3.0306	0.8426
$\Delta WH \approx WH - WH_{baseline}$	-4.3306	12.4113	-2.4073	9.6345	-5.7662	13.9621
<b>Explanatory variables</b>						
$\Delta WFH \approx WFH - WFH_{baseline}$	0.8824	1.1391	2.0644	0.7716	0	0
Age	45.3848	12.6766	44.1681	12.3802	46.2930	12.8196
Female	0.5076	0.5000	0.5499	0.4976	0.4761	0.4995
Live with a partner	0.6461	0.4782	0.6695	0.4704	0.6286	0.4832
Urban	0.7718	0.4197	0.7943	0.4042	0.7550	0.4301
Log income	7.2567	0.7540	7.5918	0.5830	7.0066	0.7699
COVID-19 deaths in last 7 days/100,000	0.1542	0.3062	0.1409	0.2890	0.1641	0.3181
<b>Supplementary analysis</b>						
High risk of contracting the virus (0/1): $HiCov$	0.0972	0.2962	0.0637	0.2442	0.1222	0.3275
High death rates (0/1): $HiDeath$	0.4893	0.4999	0.4677	0.4990	0.5054	0.5000
High government restrictions (0/1): $HiRestr$	0.4516	0.4977	0.4128	0.4924	0.4806	0.4997
Commuting distance (miles): $ComDis$	10.6734	15.9604	12.9483	18.4739	8.9753	13.5436
Work autonomy over job tasks (categories 1-4)	2.9539	0.9873	3.1002	0.9171	2.8447	1.0232
Work autonomy over work hours (categories 1-4)	2.3753	1.1541	2.7303	1.0893	2.1103	1.1298
No children (0/1)	0.8541	0.3530	0.8426	0.3642	0.8627	0.3442
1 or 2 children (0/1)	0.1267	0.3326	0.1418	0.3488	0.1154	0.3196
$\geq 3$ children (0/1)	0.0192	0.1371	0.0156	0.1240	0.0218	0.1461
School closures (0/1): $SchClose$	0.6274	0.4835	0.6751	0.4684	0.5918	0.4915
Childcare responsibility (categories 1-3)	1.9800	0.7017	2.0970	0.6782	1.8798	0.7064

**Note:** This table shows the weighted summary statistics of the estimation sample and statistics on  $\Delta PROD$  are from the productivity sample. Statistics on all the other variables are from the effort sample. Columns (1)-(2) show statistics for the whole sample of 9,165 observations, columns (3)-(4) for 4,473 observations who reported increased WFH frequency, and columns (5)-(6) for 4,692 observations who did not report any increase in WFH frequency.

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

	(1)	(2)	(3)	(4)
	All sample		Gender-specific	
	Baseline	Non-linear	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>				
$\Delta WFH$	0.144*** (0.028)	0.149*** (0.030)	0.182*** (0.039)	0.095** (0.038)
$\Delta WFH^2$		-0.012 (0.030)		
Observations	5,416	5,416	3,094	2,322
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>				
$\Delta WFH$	0.152*** (0.021)	0.185*** (0.030)	0.168*** (0.029)	0.132*** (0.031)
$\Delta WFH^2$		-0.049** (0.024)		
Observations	9,165	9,165	5,370	3,795

**Note:** This table shows results of the impact of the change in WFH on the change in productivity (outcome 1) and working hours (outcome 2). Control variables include age, age<sup>2</sup>, female, living with a partner, living in the urban area, the logarithm of income, occupation dummies, industry dummies, and the average COVID-19 death rate in the last 7 days. Region and wave fixed effects are controlled for. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 3: **Heterogeneous effects I (COVID-19 effects)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Contracting the virus			Death rates			Government restrictions		
	All	Female	Male	All	Female	Male	All	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>									
$\Delta WFH$	0.131*** (0.027)	0.173*** (0.038)	0.081** (0.038)	0.080** (0.036)	0.113** (0.051)	0.043 (0.050)	0.108*** (0.039)	0.100* (0.052)	0.099* (0.059)
$\Delta WFH \times HiCov$	0.152** (0.076)	0.109 (0.097)	0.189* (0.109)						
$\Delta WFH \times HiDeath$				0.117*** (0.043)	0.124** (0.063)	0.100* (0.056)			
$\Delta WFH \times HiRestr$							0.053 (0.045)	0.119* (0.064)	-0.007 (0.063)
Observations	5,416	3,094	2,322	5,416	3,094	2,322	5,416	3,094	2,322
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>									
$\Delta WFH$	0.164*** (0.022)	0.185*** (0.031)	0.140*** (0.031)	0.212*** (0.029)	0.223*** (0.041)	0.191*** (0.040)	0.188*** (0.029)	0.212*** (0.041)	0.159*** (0.040)
$\Delta WFH \times HiCov$	-0.122** (0.050)	-0.164*** (0.057)	-0.088 (0.090)						
$\Delta WFH \times HiDeath$				-0.130*** (0.031)	-0.122*** (0.039)	-0.128*** (0.047)			
$\Delta WFH \times HiRestr$							-0.083** (0.033)	-0.103** (0.040)	-0.065 (0.049)
Observations	9,165	5,370	3,795	9,165	5,370	3,795	9,165	5,370	3,795

**Note:** This table shows results of the differential impacts of the change in WFH on the change in employee performance by characteristics of the COVID-19 pandemic. Control variables are the same as in the baseline specification. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 4: **Heterogeneous effects II (Job-related characteristics)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Commuting distance			Autonomy over job tasks			Autonomy over work hours		
	All	Female	Male	All	Female	Male	All	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>									
$\Delta WFH$	0.113*** (0.030)	0.158*** (0.044)	0.059 (0.041)	0.173** (0.072)	0.181** (0.086)	0.260*** (0.099)	0.096** (0.046)	0.123** (0.058)	0.065 (0.072)
$\Delta WFH \times ComDis$	0.003** (0.001)	0.003 (0.002)	0.003* (0.002)						
Reference category: <i>None</i>									
$\Delta WFH \times A \text{ little}$				0.017 (0.082)	0.116 (0.097)	-0.213* (0.117)	0.069 (0.057)	0.088 (0.070)	0.046 (0.094)
$\Delta WFH \times Some$				-0.046 (0.076)	-0.023 (0.094)	-0.167 (0.104)	0.033 (0.060)	0.034 (0.084)	0.027 (0.086)
$\Delta WFH \times A \text{ lot}$				-0.038 (0.078)	-0.026 (0.098)	-0.165 (0.105)	0.065 (0.057)	0.100 (0.077)	0.028 (0.085)
Observations	5,416	3,094	2,322	5,416	3,094	2,322	5,416	3,094	2,322
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>									
$\Delta WFH$	0.150*** (0.025)	0.156*** (0.036)	0.143*** (0.037)	0.087* (0.046)	0.084 (0.056)	0.095 (0.075)	0.058* (0.034)	0.088** (0.039)	-0.010 (0.057)
$\Delta WFH \times ComDis$	0.000 (0.001)	0.001 (0.002)	-0.001 (0.002)						
Reference category: <i>None</i>									
$\Delta WFH \times A \text{ little}$				0.088 (0.056)	0.122* (0.073)	0.026 (0.085)	0.126*** (0.046)	0.103* (0.056)	0.204*** (0.078)
$\Delta WFH \times Some$				0.050 (0.051)	0.102* (0.062)	-0.006 (0.083)	0.126** (0.049)	0.127* (0.069)	0.151** (0.075)
$\Delta WFH \times A \text{ lot}$				0.084 (0.052)	0.062 (0.064)	0.087 (0.083)	0.110** (0.046)	0.094* (0.056)	0.160** (0.071)
Observations	9,165	5,370	3,795	9,165	5,370	3,795	9,165	5,370	3,795

**Note:** This table shows results of the differential impacts of the change in WFH on the change in employee performance by characteristics of the work. Control variables are the same as in the baseline specification. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 5: **Heterogeneous effects III (School closures and childcare)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline sample			With children					
	Childcare responsibility			School closures			Childcare responsibility		
	All	Female	Male	All	Female	Male	All	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>									
$\Delta WFH$	0.154*** (0.031)	0.211*** (0.043)	0.086** (0.040)	0.144*** (0.047)	0.240*** (0.062)	0.088 (0.069)	0.056 (0.086)	0.740*** (0.240)	-0.056 (0.095)
Reference category: <i>No children</i>									
$\Delta WFH \times 1 \text{ or } 2 \text{ children}$	-0.031 (0.044)	-0.096* (0.055)	0.032 (0.066)						
$\Delta WFH \times \geq 3 \text{ children}$	-0.086 (0.117)	-0.285* (0.163)	0.012 (0.155)						
$\Delta WFH \times SchClose$				-0.043 (0.073)	-0.154* (0.089)	0.057 (0.114)			
Reference category: <i>Partner is responsible</i>									
$\Delta WFH \times Both \text{ equally}$							0.111 (0.094)	-0.511** (0.243)	0.207* (0.108)
$\Delta WFH \times My \text{ responsibility}$							0.017 (0.099)	-0.595** (0.240)	0.311 (0.245)
Observations	5,416	3,094	2,322	1,676	900	776	1,676	900	776
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>									
$\Delta WFH$	0.156*** (0.022)	0.170*** (0.031)	0.139*** (0.034)	0.044 (0.042)	0.082* (0.048)	0.053 (0.066)	-0.023 (0.064)	0.135 (0.112)	-0.014 (0.072)
Reference category: <i>No children</i>									
$\Delta WFH \times 1 \text{ or } 2 \text{ children}$	-0.047 (0.035)	-0.008 (0.044)	-0.084 (0.052)						
$\Delta WFH \times \geq 3 \text{ children}$	0.115 (0.180)	-0.274* (0.147)	0.219 (0.191)						
$\Delta WFH \times SchClose$				0.096* (0.054)	0.064 (0.067)	0.089 (0.069)			
Reference category: <i>Partner is responsible</i>									
$\Delta WFH \times Both \text{ equally}$							0.162** (0.074)	-0.038 (0.122)	0.190** (0.082)
$\Delta WFH \times My \text{ responsibility}$							0.160* (0.088)	0.025 (0.118)	0.334 (0.548)
Observations	9,165	5,370	3,795	1,346	711	635	1,346	711	635

**Note:** This table shows results of the differential impacts of the change in WFH on the change in employee performance by characteristics of the work. Control variables are the same as in the baseline specification. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

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

Sumit Deole, Max Deter, Yue Huang

**Supplementary material**

## Appendix: Tables Cited in the Main Text

Table A-1: **Robustness check I**  
(After controlling for baseline WFH behavior)

	(1)	(2)	(3)
	All	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>			
$\Delta WFH$	0.172*** (0.028)	0.201*** (0.040)	0.133*** (0.038)
Observations	5,416	3,094	2,322
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>			
$\Delta WFH$	0.134*** (0.018)	0.146*** (0.025)	0.117*** (0.028)
Observations	9,165	5,370	3,795

**Note:** This table shows results of baseline regressions by additionally controlling for baseline WFH levels. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A-2: **Robustness check II**  
(Sample restriction: WFH non-takers before the pandemic)

	(1)	(2)	(3)
	All	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>			
Reference category: <i>None WFH</i>			
<i>Sometimes</i>	0.218** (0.089)	0.209* (0.111)	0.251* (0.136)
<i>Often</i>	0.268** (0.120)	0.395** (0.158)	0.123 (0.189)
<i>Always</i>	0.601*** (0.099)	0.647*** (0.129)	0.474*** (0.153)
Observations	3,525	2,113	1,412
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>			
Reference category: <i>None WFH</i>			
<i>Sometimes</i>	1.860** (0.807)	1.606* (0.903)	1.512 (1.462)
<i>Often</i>	2.578*** (0.813)	1.925* (1.020)	3.151** (1.459)
<i>Always</i>	5.136*** (0.686)	5.757*** (0.897)	4.187*** (1.106)
Observations	6,862	4,121	2,741

**Note:** This table shows results for individuals who never worked from home before the pandemic. We apply ordered probit estimation in Panel (1) and show coefficients of the main independent variable. Marginal effects can be obtained from authors upon request. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A-3: Heterogeneous effects by concentration

	(1)	(2)	(3)
	All	Female	Male
<b>Outcome 1: Changes in self-perceived hourly productivity (<math>\Delta PROD</math>)</b>			
$\Delta WFH$	0.002 (0.047)	0.058 (0.058)	-0.068 (0.076)
$concentration$	0.507*** (0.052)	0.547*** (0.056)	0.460*** (0.089)
$\Delta WFH \times concentration$	0.191*** (0.050)	0.168*** (0.058)	0.215*** (0.082)
Observations	5,352	3,056	2,296
<b>Outcome 2: Changes in weekly working hours (<math>\Delta WH</math>)</b>			
$\Delta WFH$	0.261*** (0.038)	0.265*** (0.046)	0.254*** (0.064)
$concentration$	0.135*** (0.044)	0.120** (0.054)	0.151** (0.072)
$\Delta WFH \times concentration$	-0.135*** (0.040)	-0.119** (0.047)	-0.153** (0.066)
Observations	9,109	5,334	3,775

**Note:** This table shows results of the differential impacts of the change in WFH on the change in employee performance by concentration changes during the pandemic. *concentration* takes value of one if the individual's concentration remains the same as or better than usual, and zero otherwise. Control variables are the same as in the baseline specification. Robust standard errors (clustered at the individual-level) in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table A-4: Desired WFH frequency in the future

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	All	Female	Male	All	Female	Male	All	Female	Male
<b>Outcome: Desired WFH frequency in the future (<math>FutWFH</math>)</b>									
$\Delta WFH$	0.121*** (0.025)	0.141*** (0.035)	0.066** (0.033)	0.099*** (0.025)	0.113*** (0.035)	0.054* (0.032)	0.099*** (0.025)	0.113*** (0.035)	0.053* (0.032)
$\Delta PROD$				0.233*** (0.020)	0.240*** (0.026)	0.219*** (0.031)	0.233*** (0.021)	0.247*** (0.026)	0.218*** (0.031)
$\Delta WH$				-0.010 (0.024)	0.013 (0.025)	-0.043 (0.039)	-0.011 (0.024)	0.009 (0.025)	-0.041 (0.039)
$\# of children$							0.009 (0.027)	0.083** (0.035)	-0.028 (0.038)
Observations	3,715	2,096	1,619	3,715	2,096	1,619	3,715	2,096	1,619

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