Not Incentivized Yet Efficient: Working From Home in the Public Sector

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Abstract

This paper studies whether working from home (WFH) affects workers' performance in public sector jobs. Studying public sector initiatives allows us to establish baseline estimates on the impact of WFH net of incentives.

Exploiting novel administrative data and plausibly exogenous variation in work location, we find that WFH increases productivity by 12%. These productivity gains are primarily driven by reduced distractions. They are not explained by differences in quality, shift length, absenteeism, characteristics of reported cases, training, administrative duties, or task allocation. Importantly, productivity gains nearly double when tasks are assigned by the supervisor.

Keywords: working from home, productivity, public sector.

JEL: D23, J45, L23, M54.

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1 Introduction

Firms have been experimenting with new working from home (WFH) arrangements for a long time (Barrero et al., 2023; Mas and Pallais, 2020), and the pandemic accelerated this trend (Aksoy et al., 2022; Bloom et al., 2021). While part of this has been reversed, many workers still work from home multiple days per week, and firms and organizations worldwide are grappling with finding a new status quo.

A key question is whether WFH affects workers' performance (Emanuel and Harrington, 2024). WFH may benefit workers and make them more productive by saving commute time (Barrero et al., 2020), reducing the number of breaks and sick days (Bloom et al., 2015), increasing workers' satisfaction (Choudhury et al., 2024), allowing for more flexible hours (Bloom et al., 2022), and a better balance of career opportunities and care-taking responsibilities (Harrington and Kahn, 2023). On the other hand, WFH may also reduce supervisors' monitoring, prevent workers from having valuable professional interactions (Emanuel et al., 2023), as well as learning opportunities (Atkin et al., 2023).

As there is no consensus in the literature on the impact of WFH on workers' performance, organizations experiment along the full spectrum of solutions. Some push to go back to the office five days a week, while others are considering flexible work arrangements that allow workers to combine the benefits of WFH with those of in-person interactions.

In this paper, we study the performance impact of WFH in the public sector, where pecuniary incentives are typically not allowed, and workers have strong job security. This allows us to establish baseline estimates on the impact of WFH, net of the impact of incentives. We combine novel high-frequency administrative and survey data with a design that provides us with quasi-exogenous variation in work location. The design compares workers' performance under different work arrangements. To the best of our knowledge, this is the first paper to provide causal evidence of WFH on workers' productivity for public sector jobs.

We use the records of the Crime Recording and Resolution Unit (CRRU), a division of the Greater Manchester Police (GMP) tasked with recording case details in a computer system. The task consists primarily of recording the details of cases from emergency and non-emergency calls. Recording cases does not require team interactions. Following a deterministic work schedule, police staff alternate between working from home (WFH) and working from the office (WFO). The CRRU is an ideal setting to study the impact of WFH on workers' productivity: there is an objective and well-measured metric to evaluate workers' performance (i.e., the number of cases recorded per day), staff alternate working at the office and at home, and tasks are as good as randomly assigned (in certain periods).

In this paper, we exploit the plausibly random source of variation in work location introduced by the rotation schedule to compare the performance of the CRRU workers assigned to WFH vs. WFO. We corroborate the argument that the rotation schedule generates plausibly random variation in work location by showing that being assigned to WFH does not predict the demographic characteristics of the police staff on duty on a given day. To quantify the benefits of a human vs. machine, we exploit two competing set-ups, one where a computer randomly allocates cases and another where a human performs this task. In the former, staff record 12% more cases when WFH. In the latter, staff record 20% more.

These productivity gains do not come at the cost of people working less overall. Moreover, these gains are not driven by differences in absenteeism, the nature of the tasks, characteristics of reported crimes, quality, training, administrative duties, or shift length. We explore the mechanisms and find evidence that the productivity gains from WFH are primarily driven by reduced distractions when WFH relative to WFO, which makes the staff more efficient. However, WFH did not affect the likelihood that police staff start working earlier than their shift or work past the end of it. When the supervisor allocates cases, the mechanism at play is that supervisors have a good understanding of their staff's comparative advantages and use this information to assign tasks.

In addition, we observe worker-idiosyncratic performance variation (i.e., some workers are better than others). Our within-worker design allows us to estimate location-specific worker effects and *individual-level* treatment effects. We find that location-specific worker effects are highly correlated, challenging the widely held belief that certain individuals are particularly well-suited for WFH. While the individual-level treatment effects reveal substantial heterogeneity across workers, this variation is largely unexplained by observable worker characteristics.

Finally, we evaluate whether work arrangements that allow police staff to work (almost) exclusively from home generate additional productivity gains over hybrid work. To this end, we designed an experiment to compare the performance of workers who were experimentally assigned to WFH 70% of their time (status quo) to those assigned to WFH 95% of their time (treatment). Our results indicate that working almost exclusively from home does not offer additional productivity gains relative to the status quo. We do not find evidence that working entirely from home generates adverse effects over the course of our study.

We contribute to the literature in three fundamental ways. First, we provide the underpinning parameters to the WFH literature by estimating the effect of WFH net of incentives and based on a semi-routine task. Second, our within-worker design allows us to disentan-

gle the underlying workers' productivity under different working arrangements and estimate *individual-level* treatment effects. Third, we show that humans outperform machines in allocating tasks in our setting and that supervisors play an important role in harnessing the benefits of WFH.

The literature on WFH complements our study in several ways. Some recent papers use survey data to document the prevalence of WFH, the preferences and perceptions of both employees and employers on these novel working arrangements, and the savings that WFH generates (Aksoy et al., 2022; Barrero et al., 2020, 2023). Another set of studies focuses on the causal effects of WFH on workers' performance in the private sector. Working entirely from home lowers workers' productivity (Atkin et al., 2023; Emanuel and Harrington, 2024; Gibbs et al., 2023) and cognitive performance (Künn et al., 2022). There is no consensus on the productivity effects of hybrid work. In some settings, it generates substantial productivity gains (Angelici and Profeta, 2024; Bloom et al., 2015; Choudhury et al., 2021, 2024), while in others, the effects range from zero to negative (Bloom et al., 2024; Morikawa, 2023). Hybrid work has also been found to increase workers' job satisfaction, well-being, and work-life balance, and decrease employees' turnover (Angelici and Profeta, 2024; Bloom et al., 2015, 2022; Choudhury et al., 2024).

In many ways, our work also speaks to the literature on the role of middle-level managers and social determinants of workers' productivity. Previous studies show that managers affect their subordinates' performance by mentoring (Lazear et al., 2015), targeting effort (Bandiera et al., 2009), and assigning tasks based on the workers' comparative advantage (Adhvaryu et al., 2022). Face-to-face communication and peer pressure increase workers' productivity (Battiston et al., 2021, 2023; Emanuel et al., 2023; Kandel and Lazear, 1992; Mas and Moretti, 2009; Silver, 2021), while negative beliefs about co-workers' effort levels can lower it (Dutcher and Saral, 2022).

The rest of the paper is organized as follows. Sections 2 and 3 describe the background and the data. Section 4 illustrates the empirical strategy, and Section 5 reports the main results. Section 6 quantifies the impact of supervisors allocating tasks, Section 7 compares the productivity gains in hybrid regimes vs. working entirely from home, and Section 8 concludes.

2 The Crime Recording and Resolution Unit

The Crime Recording and Resolution Unit (CRRU) is a division of the Greater Manchester Police tasked with recording the details of the various crimes and incidents.

Nature and Allocation of Work. The job consists primarily of recording the details of cases stemming from all calls (incoming calls) and reports (outgoing calls) in their computer system. The police staff also triages cases, i.e., evaluates whether reported incidents fall under the preview of the CRRU. Triaging does not result in workers logging cases into the system. Recording cases is individual work and does not require team interactions. All staff is trained in all three workstreams (i.e., answering incoming calls, making outgoing calls, and triaging cases) and work all three of them regularly. Before 22 September 2023, supervisors assigned their workers to workstreams each day. From that day onward, the assignment is done by a computer algorithm. The algorithm uses the previous 12 months of data to predict the daily staffing needs of each workstream and assigns workers to workstreams based on their schedules. Importantly, the computer algorithm does not take into account workers' characteristics (e.g., gender, age, or seniority), their past performance, or their assigned work location. In other words, the assignment of workers to workstreams is unrelated to the workers' intrinsic ability and comparative advantages. Within each workstream, the assignment of crimes or incidents to workers is plausibly random as they are assigned on a first-in-first-out basis. Each incoming call is assigned randomly to the first available person. Similarly, reports are handled in the order they are received. In our main analysis, we only include the data starting from 22 September 2023 to ensure that the allocation of workers to tasks is plausibly exogenous. We corroborate this argument by providing evidence that the tasks are as good as randomly assigned to workers in Section 4.

The Rotation Schedule. Each staff member is assigned to one of five teams and one of two shift patterns. All staff work 4 to 5 days per week, Monday through Sunday, depending on the rotation schedule. The "day shift pattern" staff cover shifts between 07:00 and 21:00, while those on the "24/7 shift pattern" cover both day and night shifts. All teams follow a rotation schedule that determines their shifts (e.g., 08:00 to 18:00) and whether they work from home each day. Panel A of Table 1 reports the rotation schedule for staff assigned to the day shift pattern. In week 1 of the rotation schedule, they work entirely from home. They work from 08:00 to 18:00 on Mondays and Tuesdays and from 11:00 to 21:00 on Fridays, Saturdays, and Sundays. In week 2, staff work entirely from the office and cover the shifts between 07:00 and 17:00 on Thursdays and Fridays and 10:00 to 18:00 on Saturdays and Sundays. Weeks 3 to 5 work similarly. Every five weeks, the pattern repeats. All staff on the "day shift pattern" cycle through this 5-week pattern but are on different weeks in the schedule depending on their assigned team. At the beginning of time, team 1 started their schedule from week 1; team 2 started from week 2, and so on and so forth. Panel B reports the rotation schedule for workers assigned to the 24/7 shift pattern. The rotation works similarly, the only difference being that their rotation pattern repeats every 10 weeks. New

hires are mandated to WFO for the first six months. Because the rotation schedule does not apply during this period, we exclude from our sample all new hires for the first six months.

The rotation schedule has two important features. First, it does not allow workers to choose their hours and work location (office vs. home) on each day. Second, it is designed so that at any given time, some staff work from home, and others work from the office.

Supervisors. Each team has 6-7 supervisors who monitor their work, offer support and advice, and evaluate them regularly. Before 22 September 2023, supervisors also allocated workers to workstreams (and hence to tasks). We exclude all supervisors from our analysis.

Measures of Performance. We measure workers' productivity by the number of cases they record per day, reflecting the volume of crimes they handle daily. Additionally, we track the total amount of time staff spend actively recording crimes in the computer system. This measure excludes time spent gathering relevant information, speaking on the phone with victims or informants, or triaging cases. Using data on time and volume, we construct a measure of speed: the average time spent per case.

To assess the quality of staff work, we rely on internal audits routinely performed by supervisors. Supervisors are required to audit at least two randomly selected cases per worker each month. These audits are comprehensive, with supervisors scoring each case on various dimensions, such as the staff's use of soft skills and appropriate telephone manners, the quality of their questioning, and whether all necessary forms were added, along with correctly setting qualifiers and flags.

Incentives. As it is common in the public sector, staff are paid a fixed monthly amount, and their compensation is not tied to their performance. Supervisors routinely evaluate their workers on the basis of objective metrics such as the number of cases logged in the system, the length of the queue when the workers are on duty, and the quality of their work. Police staff face the same incentives whether working from the office or home.

Setting. The CRRU is an ideal setting to study the impact of working from home on workers' productivity: there is an objective and well-measured metric to evaluate workers' performance (i.e., the number of cases recorded per day), staff alternate working at the office or home deterministically, and tasks are as good as randomly assigned (starting 22 September 2023).

3 Data

This section describes the data we use in the empirical analysis. The data consists of three main elements: the daily records, the workers' personnel files that allow us to link police staff to their schedules, and a brief survey.

Daily Records. We use the records of the CRRU from 1 November 2022 to 31 October 2024. The data contains daily information on the reports filed by each worker, the time at which each report was filed, the nature of the incident or crime, and how long it took to record it. These records also contain information on when the case was reported. The data also includes information on work quality derived from internal audits conducted by supervisors on their subordinates between 1 February 2023 and 31 August 2024.

Personnel Files. We complement the data with the personnel files of the CRRU staff from 1 November 2022 to 31 October 2024. These files contain information on the workers' demographic characteristics and their team assignment. They also contain daily information on shift and location (i.e., work from home vs. office) based on the rotation schedule, their actual shift and location, and medical leave.

Survey. We conducted a brief anonymous survey in October 2024 to elicit the workers' perceived benefits and drawbacks of WFH. We elicit these through open-ended questions.

Descriptive Statistics and Stylized Facts. Table 2 reports the descriptive statistics. Column 1 pools all periods, while columns 2-4 focus on the three separate time windows we study. The pre-period (period 1) ranges from 1 November 2022 to 21 September 2023 and relates to the time in which the allocation of workers to tasks was not random. The analysis period (period 2) ranges from 22 September 2023 to 21 January 2024. It relates to the period when the allocation of staff to tasks was as good as random and before the experiment was rolled out. Lastly, the experiment period (period 3) ranges from 22 January 2024 to 31 October 2024 and includes the months during which staff were experimentally assigned to WFH. Panel A reports staff characteristics. Our sample includes the 220 full-time workers who are on the rotation schedule. 62.7% are female, and 52% are below age 34 (column 1). Very few police staff are older than 65, reflecting the typical retirement age of public sector workers. Police staff are roughly equally split across the 5 teams, and 60.5% of them work on the "day shift pattern." The composition of the CRRU staff remains (almost) constant over time.

Panel B reports the summary statistics for the CRRU. On a typical day, there are 56 staff on duty; 73.5% of them are assigned to WFH, and approximately 68% of them actually

do (column 1). Collectively, staff record roughly 350 cases per day, spending 5,040 minutes actively recording them. On average, each staff member records about six cases daily, spending approximately 17 minutes per case. This translates to an average of 93 minutes per day actively spent recording cases. While this figure may seem low, it is important to note that our measure only captures the time spent entering case details into the computer system. It does not include the time spent gathering relevant information, speaking on the phone with victims or informants, or triaging cases.

These statistics are relatively stable over time, with two notable exceptions. First, the average time spent recording a case was 22.4 minutes in Period 1 but decreased to approximately 12–15 minutes per case in Periods 2 and 3. This decline reflects staff becoming increasingly familiar with the new computer system introduced in September 2022. Second, the average number of full-time staff increased from 50 in the pre-period to about 74 during the analysis period before stabilizing at 56 workers in the experiment period. The increase between Periods 1 and 2 was driven by the gradual phasing in of workers onto the computer system as well as new hires. The subsequent decline in staff numbers between Periods 2 and 3 occurred because not all staff volunteered to participate in the experiment (see Section 7.1 for details).

The most common type of offense recorded at the CCRU is violence against the person (45%), closely followed by theft (32.2%). The remaining offenses involve criminal damage or arson (9.7%), public order (4.6%), possession of weapons (0.3%), and other miscellaneous cases (7.8%). The composition of cases is stable over time.

4 Empirical Strategy

The main challenge when comparing workers' performance at home vs. at the office is that workers often have a say in when to work from home. For example, workers may choose to work from home on days when they expect to have a light (heavy) workload or when they have some caretaking responsibilities (e.g., looking after sick children). Therefore, comparing workers' performance at home vs. at the office does not typically isolate the causal impact of work location.

We overcome this challenge by exploiting the plausibly random source of variation in work location introduced by the rotation schedule and compare the workers' productivity when *assigned* to WFH vs. WFO. We begin our empirical analysis by comparing the average productivity of police staff under these two work arrangements. Panel A of Figure 1 reports the logarithm of the daily average number of claims processed by staff assigned to WFH (orange circles) and those assigned to WFO (blue triangles). The former is consistently

higher than the latter. Panel B depicts the difference between the two. These mean daily differences are positive and essentially stable over time. Next, we describe the empirical strategy and we explain how we use the variation illustrated in Figure 1 in our regression analysis.

We estimate the following reduced-form model:

$$y_{it} = \alpha + \beta \text{Assigned to WFH}_{it} + \mu_i + \phi_t + u_{it}, \tag{1}$$

where y_{it} represents the outcome of worker i on day t and "Assigned to WFH_{it}" is a dummy variable that takes value 1 when worker i is assigned to WFH based on the rotation schedule. We include worker μ_i and day ϕ_t fixed effects to control for time-invariant heterogeneity in worker productivity and seasonality in case recording. We cluster the standard errors at the worker level.[1] β is the main coefficient of interest and represents the average difference in the outcome of interest when workers are assigned to WFH relative to when they are assigned to WFO. Workers follow their assignment closely, but not perfectly. Therefore, β reflects the Intent-To-Treat (ITT).

To estimate the effect of WFH on workers' performance, we use an instrumental variable strategy where we instrument *actual* work location (WFH_{it}) with *assigned* work location (Assigned to WFH_{it}). Our estimating equation becomes:

$$y_{it} = \alpha + \beta^{2sls} \text{WFH}_{it} + \mu_i + \phi_t + u_{it}, \tag{2}$$

where WFH_{it} is a dummy variable that takes value 1 when worker i works from home, and all the other variables are defined as above. We estimate model (2) via Two-Stage Least Squares (2SLS) and cluster the standard errors at the worker level.

Next, we discuss the validity of the design and show that the assigned work location is unrelated to both worker and case characteristics.

No Selection on Worker Characteristics. The rotation schedule forces all staff to alternate WFH and WFO deterministically. Hence, we expect all workers to be equally likely to be assigned to WFH. We evaluate this argument by regressing workers' characteristics and a covariate index on a constant and the WFH assignment dummy. Panel A of Table 3 reports the results. Column 1 shows the control mean, and columns 2-4 report the esti-

[1] We also show that our results are robust to clustering the standard errors at the team level (see Table A.1 for details).

mated coefficient, standard error, and p-value associated with the WFH assignment dummy. Reassuringly, the magnitudes of all coefficients are very small economically, and none of the coefficients are statistically significant. We corroborate the argument that more productive workers are not more (or less) likely to be assigned to WFH in Section 5, where we show that our main results are unaffected by controlling for worker fixed effects. Overall, we find no evidence that assigned work location is correlated with a worker's observable characteristics and intrinsic productivity.

No Differences in Case Characteristics. Cases are allocated randomly to workers by a computer after 22 September 2023. We evaluate this by showing that assigned work location does not predict case characteristics. Panel B of Table 3 reports the estimates obtained regressing the characteristics of the first and last case of the day on a constant, the WFH assignment dummy, and worker and day fixed effects. The point estimates are small and not statistically significant, suggesting that the staff works on similar cases when assigned to WFH or WFO. We also examine whether case characteristics jointly predict assigned work location by regressing 'Assigned to WFH' on case characteristics and worker and day fixed effects and testing whether the coefficients associated with case characteristics are jointly statistically significant. Appendix Figure A.1 reports the results and shows that none of the coefficients is statistically significant and that the p-value on the joint test is 0.869.

5 Does WFH Increase Workers' Productivity?

5.1 Main Results

Productivty. Table 4 reports our main results. Column 1 shows the estimates obtained by regressing the outcome of interest on the WFH assignment dummy. Columns 2 and 3 add day and worker fixed effects, respectively. Column 3 corresponds to model (1) above and is our preferred specification. We exclude the data before 22 September 2024 from this analysis because – before that date – tasks are not randomly assigned to workers. Table A.1 reports the estimated coefficients and standard errors obtained by clustering the standard errors at the team level. Our results survive clustering.

Panel A shows that when the workers are assigned to WFH, they record – depending on the specification – between 9% to 10% more cases per day. This amounts to approximately an additional half-case per day. These estimates reflect 'standard labor productivity' and are likely to underestimate the true productivity gains as they do not incorporate the commuting time that WFH saves (Barrero et al., 2023).

Input. Panels B and C report the impact of WFH assignment on the total time workers spend recording cases and the average time spent on each case. When the workers are assigned to WFH, they do not spend more time working but are, on average, faster. The fact that WFH does not affect the total amount of time the staff spends working is important, as one potential downside of WFH is that reduced monitoring may allow workers to shirk.

Alternative Specifications. In all three panels, including day and worker fixed effects has little impact on the point estimates, suggesting that the idiosyncratic daily shocks and differences in workers' underlying productivity are uncorrelated with the WFH assignment. As discussed in Section 4, this lends credibility to our empirical strategy and corroborates the argument that more productive staff are not more (or less) likely to be assigned to WFH. The increase in the R-squared between columns 2 and 4 is larger than the one between columns 1 and 2. This suggests that there is a substantial heterogeneity in workers' productivity and foreshadows the heterogeneity analysis discussed below.

Individual-Level Treatment Effects. WFH is likely not to suit everyone equally. We leverage our within-worker design to disentangle workers' underlying productivity when assigned to WFH and WFO and estimate *individual-level* treatment effects. We proceed in two steps. First, we estimate the worker's location-specific productivity by regressing the logarithm of the number of cases processed per day on day fixed effects and worker fixed effects interacted with WFH assignment:

$$\log \text{N Cases}_{it} = \beta_0 + \mu_i^{\text{Assigned WFH}} + \mu_i^{\text{Assigned WFO}} + \phi_t + u_{it}. \tag{3}$$

$\mu_i^{\text{Assigned WFH}}$ and $\mu_i^{\text{Assigned WFO}}$ represent the worker fixed effects interacted with assigned work location and ϕ_t represent the day fixed effects, respectively. The interacted worker effects estimate the underlying productivity of workers when assigned to the two work regimes. Second, we estimate the individual-level treatment effect as the difference between the estimated worker fixed effect when assigned to WFH and when assigned to WFO:

$$\widehat{\text{Treatment}} \text{ Effect}_i = \widehat{\mu_i}^{\text{Assigned WFH}} - \widehat{\mu_i}^{\text{Assigned WFO}}. \tag{4}$$

Figure 2a plots the estimated worker effects when assigned to WFH vs. WFO as well as the 45-degree line. If all workers were equally productive under these two working arrangements, all diamonds would align on the 45-degree line. Three patterns stand out. First, these two sets of fixed effects are highly correlated (correlation coefficient=0.77). In other words, workers who are highly productive at home are also highly productive at the office. Second,

there is tremendous heterogeneity in workers' productivity conditional on each working arrangement. Third, most workers are more productive when assigned to WFH than WFO (i.e., most diamonds are above the 45-degree line). Appendix Figure A.2 correlates workers' productivity with observable workers' characteristics and shows that, while the gains from WFH are heterogeneous across workers, no obvious group of workers is ill-suited for this work arrangement.

Figure 2b plots the distribution of the estimated treatment effects. While the ITT is positive (dashed vertical line), it masks a lot of heterogeneity. The individual-level treatment effects range from -0.48 to 0.89, with most values clustered between -0.03 and 0.22 (interquartile range). Observable worker characteristics explain only 6.1% of the variation in workers' treatment effects (Table A.2).

2SLS. To evaluate whether WFH affects workers' productivity, we estimate model (2) instrumenting actual WFH with WFH assignment. Column 1 of Table 5 reports the first stage results, while columns 2–4 report the 2SLS estimates.[2] Being assigned to WFH increases the probability of WFH by 73 percentage points (column 1). The WFH assignment is highly predictive of work location, and the first-stage F statistic is equal to 1,254.81, well above the threshold for weak instruments. WFH increases workers' productivity by 12.2% and does not impact the total time spent recording cases. The increase in productivity is primarily explained by the fact that workers are faster when they WFH.

5.2 Mechanisms

In this section, we explore some potential mechanisms underlying the productivity gains generated by WFH. We start by examining workers' perceived benefits and drawbacks of WFH, as reported in our survey. Building on these insights, we delve into specific factors such as reduced workplace distractions, changes in work patterns, and improvements in mental and physical health.

Exploring Worker Perceptions of WFH Benefits and Drawbacks. We begin exploring the mechanisms driving our estimated productivity gains from WFH by analyzing responses to two open-ended questions in which workers anonymously reported their perceived benefits and drawbacks of WFH. Figure 3 summarizes the results. Overall, workers express a strong preference for WFH, with 53.5% indicating that they experience no drawbacks. The three most commonly reported benefits are avoiding the commute (87.7%),

[2]Appendix Table A.3 reports the OLS estimates obtained by regressing the outcomes of interest on the WFH dummy, with and without fixed effects.

saving money (50%), and achieving a better work-life balance (42.1%).[3]

While these findings align with prior research, they do not reflect productivity-related factors and are unlikely to explain the productivity gains we observe. We delve into the productivity-related aspects in the next subsections.

Reduced Distractions. Anecdotally, the office atmosphere is convivial. Police staff often exchange pleasantries with their colleagues, take a break to chat over a cup of coffee ('brew'), or smoke a cigarette. While these interactions may be valuable, they may also distract workers and reduce their productivity. When staff work in the office, they are seated in a large open-plan room with side-by-side workstations (see Appendix Figure A.3 for a picture). The space is filled with background noise from colleagues making work calls and having casual conversations, resulting in a noisy and potentially distracting environment. It is not surprising that 35.1% of workers report fewer distractions as a key benefit of WFH, and 21.9% explicitly mention being more productive at home. In their open-ended responses, employees consistently highlight that the quieter environment at home enhances their concentration and productivity (see Appendix B for quotes). This is further supported by evidence showing that staff work faster at home (Panel C of Table 4) without any decline in the quality of their output (see the next section for a detailed discussion on quality). These benefits seem to be particularly valuable for workers with attention deficit disorder or learning disabilities. It's important to highlight that these answers are particularly insightful because workers volunteered them; we did not provide a predefined set of options in the survey.

Changes in Work Patterns. WFH may also affect when workers begin work or stop for the day. To this end, we construct four measures of working patterns: an indicator for whether staff log any cases before the beginning of their shift, an indicator for whether staff work past the end of their shift, a measure of how quickly they start working at the beginning of their shift (i.e., the number of minutes between the first case they log in and the beginning of their shift), and a measure of whether they keep on working until the very end of their shift (i.e., the number of minutes between the last case they log and the end of their shift). When the difference between the time of the first logged case and the beginning of the shift is positive (negative), this means that the worker logged their first case after (before) the beginning of their shift. Similarly, when the difference between the time of their last logged case and the end of the shift is positive (negative), this means that the staff worked (did not work) past the end of their shift. Table 6 reports the results. Being assigned to WFH does not make staff more likely to start working before the beginning of their shift or

[3]Many workers noted that WFH saves money on transportation and meals. Regarding work-life balance, respondents highlighted spending more time with family and completing household tasks during breaks.

work past the end of their shift (columns 1 and 2). However, it makes staff start their work day 23.4 minutes earlier and end it 3.5 minutes later (albeit the latter is not statistically significant). We stress that while workers start working earlier when assigned to WFH, this does not result in longer hours (Panel C in Table 4). The fact that staff begin their work day much more quickly when they are assigned to WFH is consistent with reduced distractions at home.

Less Stress. 19.3% of workers report better mental health and less stress when WFH (Panel A of Figure 3). While we cannot offer any direct evidence for this mechanism, our results are consistent with this explanation.

Absenteeism. Finally, 14% of workers report that working from home makes them less likely to call in sick when feeling unwell and helps them manage chronic health conditions (Panel A of Figure 3). If workers were less likely to be absent on days when assigned to WFH, differences in absenteeism may be a driver of our productivity gains. This is not the case because our main estimates are obtained on the sample of days when workers log at least one case. Nevertheless, we investigate whether working from home affects the likelihood that workers are absent. Appendix Table A.4 reports the estimated impact of being assigned to WFH on an indicator for whether the worker is absent (i.e., assigned to work based on the rotation schedule but does not log any case), an indicator for a medical absence, and an indicator for all other types of absences.[4] Being assigned to WFH *reduces* the probability that workers are absent by 3.6 pp. (column 1). In line with the survey evidence, one-third of this effect (0.012/0.036) is explained by medical absences (column 2). The remaining two-thirds (0.024/0.036) are attributable to non-medical absences. The reduction in non-medical absences is consistent with WFH allowing workers not to take leave when they need to provide unexpected care for children or other dependents, such as elderly parents. This interpretation is further supported by the survey finding that 12.2% (6.1%+6.1%) of workers mention the ability to care for dependents as one of the key benefits of WFH (Figure 3).

Accounting for differences in absenteeism, the estimated impact of being assigned to WFH on workers' productivity increases from 8.9% (column 3 of Table 4) to 12% (column 1 in Appendix Table A.5). The point estimate for time worked also increases in magnitude and becomes statistically significant. When we account for differences in absenteeism, being assigned to WFH increases the time spent recording crimes by 14.8% (column 2 in Appendix Table A.5). These results are in line with Bloom et al. (2015), who find that WFH reduces sick days.

[4]The reasons why a worker may not log any case in a given day include medical leave, other types of leave, secondments, triaging cases, training new hires, performing administrative duties, and being on vacation.

Summary. We conclude that we find evidence that WFH generates productivity gains in our setting thanks to the reduced distractions that WFH offers, which makes the staff more efficient. Our results are also consistent with better mental health and less stress when WFH. Importantly, our results are not explained by differences in absenteeism. One concern is that reduced interactions may generate short-term productivity gains but negatively impact workers' long-term productivity (Emanuel et al., 2023). The potential negative impact of reduced interactions is likely to be mitigated in our setting as the staff does not work entirely remotely and works from the office about a third of the time.

5.3 Alternative Explanations

In this Section, we show that our results are not driven by differences in task allocation, the characteristics of reported cases, work quality, training and administrative duties, or shift lengths.

Differences in Tasks. A potential concern is that workers perform different tasks when assigned to WFH and WFO and that these differences could confound our estimated productivity gains. This is unlikely to be a problem in our setting as the allocation of workers to tasks is performed by a computer algorithm that does not take into account assigned work location or workers' characteristics. We corroborate this argument by evaluating whether assigned location correlates with case characteristics. If staff worked on different tasks when assigned to WFH, this would translate into differences in case characteristics. Panel B of Table 3 shows no evidence that staff record different types of cases when assigned to WFH vs. WFO.

Differences in the Characteristics of Reported Cases. One may be concerned that the types of cases *reported* during shifts when workers are assigned to WFH differ from those reported when they are assigned to WFO and that the differences in the characteristics of reported cases confound our estimates. This is unlikely to be an issue in our setting because all staff draw cases from the same queues, and the rotation schedule ensures that at each point in time, there are workers assigned to both WFH and WFO. Nevertheless, we test whether our estimates are robust to controlling for the characteristics of cases *reported* during each shift. Appendix Table A.6 reports the results and shows that our estimates are unaffected by including these additional controls.

Differences in Quality. Another concern may be that the increase in workers' productivity associated with WFH may come at the cost of lower quality. To address this, we construct a measure of work quality based on internal audits routinely conducted by supervisors on their

subordinates. We then evaluate whether work quality differs when workers are assigned to WFH versus WFO. Table A.7 presents the results. Our findings indicate that work quality is unaffected by workers' assigned location, and these results remain robust to the inclusion of day and worker fixed effects. The productivity gains associated with WFH do not appear to come at the cost of lower quality. This conclusion aligns with anecdotal evidence from supervisors who regularly oversee and assess their subordinates' work.

Differences in Training and Administrative Duties. One potential concern is that when staff are assigned to WFO, they may be more likely to engage in training or perform administrative duties, which could confound our estimated productivity gains. However, there are two reasons why this is unlikely. First, while supervisors handle administrative duties, staff are only minimally involved in such tasks. Second, our sample excludes all new hires during their first six months, as this period is designated for mandatory training and requires them to work from the office. Table A.8 addresses this concern more directly showing that our main results are robust to excluding all days on which the staff is involved in administrative duties or training younger workers.

Differences in Shift Length. One concern is that if WFH shifts are longer on average, workers may work longer hours and, as a result, process more cases. If this were the case, then the differences in productivity would be attributable to differences in shift lengths rather than work location. Because our estimated productivity gains are not driven by staff working longer hours, it is unlikely that differences in shift lengths explain the bulk of our productivity gains. To address this concern more formally, we estimate the impact of WFH assignment controlling for assigned shift length. Importantly, we control for the *assigned* shift length and not the *actual* shift length, which is an outcome in and of itself and would be a "bad control" (Angrist and Pischke, 2009). Table A.9 shows that our results are robust to the inclusion of this additional control, albeit the estimated impact of WFH assignment on the number of cases recorded is marginally smaller.

6 Supervisors and the Assignment of Workers to Tasks

In the previous sections, we have abstracted from the role of supervisors. In this Section, we exploit the period in which supervisors assign workers tasks (pre-period) to evaluate whether supervisors can help harness the benefits of WFH.

Because workers follow the rotation schedule, we expect them to be equally likely to be assigned to WFH. As expected, WFH assignment does not predict workers' characteristics (Panel A of Appendix Table A.10). However, if supervisors assign tasks to workers based

on their work location, we would expect the case characteristics to be correlated with work location. Appendix Table A.10 shows that this is the case. This evidence corroborates the claim that supervisors assign tasks to workers in a non-random fashion in the pre-period.

Next, we estimate the impact of being assigned to WFH on workers' performance. Appendix Table A.11 reports the results. When assigned to WFH, workers' productivity increases by 15.6%, and the time they spend recording crimes also increases by 14.2%.

We estimate model (2) via 2SLS instrumenting WFH with WFH assignment to evaluate whether WFH affects workers' productivity. Appendix Table A.12 reports the results. WFH increases workers' productivity by 20.8%. When supervisors match workers to tasks, the gains from WFH are almost twice as large as those accrued when the computer makes the assignment (column 2 in Table 5). Moreover, WFH increases the time worked by 18.9% but does not impact the average time spent on each case.

While these estimates are unlikely to capture the causal impact of WFH, they are important as they suggest that supervisors know their subordinates' comparative advantages and use this information to assign tasks to workers. This results in larger productivity gains from WFH than those accrued when tasks are assigned randomly (column 2 in Table 5). A potential concern with this interpretation is that supervisors might reallocate tasks across workers based on their work location. Specifically, supervisors may assign simpler tasks to workers when they WFH and more challenging tasks when they WFO. This would increase the number of cases recorded when WFH and decrease it when WFO, yielding larger estimated productivity gains from WFH without impacting aggregate productivity.

Two pieces of evidence speak against this interpretation. First, if supervisors assigned easier tasks during WFH, workers would be expected to complete cases more quickly. However, the average time per case does not differ when workers are assigned to WFH vs. WFO. Second, while our design does not allow us to directly estimate the aggregate productivity effects of WFH, the aggregate productivity trends offer some suggestive evidence. Appendix Figure A.4 shows the average productivity by assigned work location before and after 22 September 2023—the date when task assignment shifted from supervisors to a computer algorithm. Aggregate productivity for both WFH and WFO decreases after this date, pushing against the interpretation that the productivity gains from supervisor-led task assignments are solely driven by reallocating tasks across workers based on their work location.

Overall, these findings are in line with recent papers that find that one of the mechanisms through which managers affect the performance of their organizations is precisely by better matching workers with tasks (Adhvaryu et al., 2022) and using resources more effectively

(Otero and Munoz, 2022). This result is also important as it suggests that supervisors are an extremely valuable lever organizations can use to harness the benefits of WFH.

7 Regime Comparison: Home vs. Hybrid

In this Section, we explore whether working (almost) exclusively from home generates additional productivity gains relative to hybrid work.

7.1 The Experiment

In addition to the above, we designed an experiment to evaluate the costs and benefits of hybrid regimes relative to working from home. We stratified workers by team and shift pattern and randomized the 138 police staff who volunteered to be part of the experiment into one treatment (N=69) and one control group (N=69).[5]

Workers assigned to the treatment group work from the office one day per month and work the remaining time from home. This amounts to a 5% WFO to 95% WFH split. Workers assigned to the control group follow the deterministic rotation schedule described in Section 2 and WFH approximately 70% of the time (status quo).

Of the 69 workers assigned to the treatment group, 16 decided they did not want to work exclusively from home and kept their previous schedules. We discuss how this form of non-compliance affects our estimates below.

If the staff who volunteered to be part of the experiment were a selected sample of the CRRU workers, this may affect the extent to which the estimates presented in Section 5 are directly comparable with those reported in Section 7.[6] We evaluate the selection of workers into the experiment in two ways. First, we compare the observable characteristics of the workers in the analysis sample with those in the experiment (columns 3 and 4 of Table 2). The gender, age, and team distribution of these two groups are very similar. Second, we estimate our baseline results by restricting the sample to the workers who are part of the experiment and compare these estimates with those obtained on the analysis sample. If these two sets of estimates were to differ substantially, this would be indicative of sample selection. Table A.13 reports the results. The point estimates are remarkably similar to our baseline estimates (column 3 of Table 4) and are not statistically different from them.

[5]Four staff dropped out of the experiment. Importantly, the reasons why they dropped out are unrelated to their treatment assignment (three of them became long-term sick, and one became a police officer). We exclude these workers from the regression analysis.

[6]Even if there were some sample selection, this would not affect the internal validity of our estimates.

We conclude that, while workers volunteer to be part of the experiment, we do not find much evidence of sample selection. Therefore, it is not unreasonable to directly compare the estimates presented in Section 5 with those in Section 7.

7.2 Empirical Strategy

Our empirical strategy entails a straightforward treatment to control comparison. We estimate the following model:

$$y_{it} = \delta_0 + \delta_1 T_i + \lambda_{\mathcal{S}(i)} + \tau_t + u_{it}, \tag{5}$$

where y_{it} is the outcome of interest for worker i at time t. T_i is a dummy variables that takes value 1 if worker i was assigned to the treatment group. τ_t and $\lambda_{\mathcal{S}(i)}$ represent the day and the team-by-shift pattern (strata) fixed effects, respectively.[7] We cluster standard errors at the worker level. The main parameter of interest is δ_1, which identifies the causal impact of working entirely from home (treatment) relative to a hybrid regime (status quo). Because of non compliance, δ_1 is an ITT.

To address the pattern of non-compliance described in the previous section, we estimate the following model via 2SLS where we instrument WFH with treatment assignment:

$$y_{it} = \delta_0 + \delta_1^{2SLS} WFH_{it} + \lambda_{T(i)} + \tau_t + u_{it}. \tag{6}$$

Balance on Observables. To test the validity of our design, we evaluate whether the treatment and the control group differ on observable characteristics at baseline. Table 7 reports the results. The treatment and control groups look alike at baseline both in terms of demographic characteristics and underlying productivity (estimated using worker-fixed effects).[8]

7.3 Experimental Results

Table 8 reports the estimated impact of WFH relative to a hybrid regime on staff's work location, number of cases recorded, total time spent recording cases, and average time per

[7] $\mathcal{S}(i)$ represents the team-by-shift stratum worker i is assigned to.

[8] We estimate baseline workers' productivity using the worker fixed effects obtained, regressing the number of cases recorded on worker and day fixed effects on the pre-experiment data. Four of the workers who were part of the experiment did not work full-time before the beginning of the experiment. Hence, we cannot compute their fixed effects (N=134).

case. Being assigned to work entirely from home increases the probability of WFH on any given day by 22.8 percentage points (pp) (column 1). This coefficient is large in magnitude and highly statistically significant.[9] Interestingly, working entirely from home does not affect the number of cases recorded or the time spent on them (columns 2–4). All coefficients are quantitatively small and not statistically significant.[10] Working entirely from home does not affect the probability that a worker is absent (Appendix Table A.15).

We conclude that while our experiment substantially increases WFH (first stage), working entirely from home does not offer additional productivity gains relative to a hybrid regime where workers work from home 70% of the time.

8 Summary and Conclusion

In this paper, we evaluate the productivity impact of WFH for public sector workers engaged in semi-routine tasks. We establish an average positive effect of 12% under random allocation, which nearly doubles once a human selects tasks that best suit a worker's comparative advantage.

We find that WFH increases workers' productivity and that this does not come at the cost of lower quality. Increasing the fraction of time spent WFH does not seem to offer additional productivity benefits or generate additional costs relative to a hybrid work environment.

Overall, these results paint a positive picture of working from home from a purely productivity perspective. This picture becomes considerably rosier when considering that working from home also saves workers commuting costs and time and allows organizations to save money by reducing the necessary office space.

An important caveat is that we study a setting where the nature of the work is individual, and workers benefit greatly from reduced distractions. The productivity gains we estimate may not translate to settings where the nature of the job is creative, and the production requires teamwork, constant interactions, and inputs from multiple workers (Gibbs et al., 2023).

[9] Under perfect compliance, our experiment shifts workers from WFH approximately 70% to 95% of the time. Hence, we would expect a coefficient of approximately 0.95-0.70=0.25. Given that our results of 22.8 pp is lower than the 25pp, it implies that we do not observe perfect compliance.

[10] For completeness, Appendix Table A.14 reports the 2SLS from model (6).

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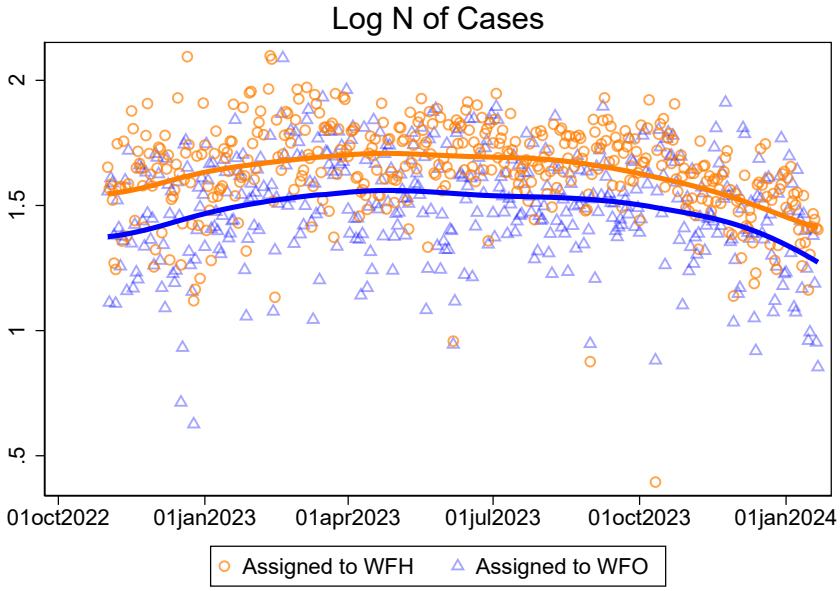
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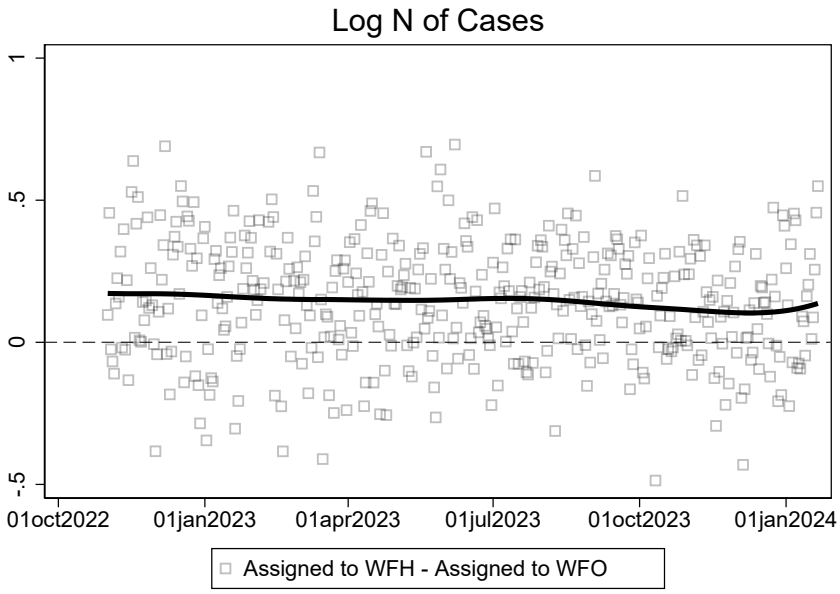
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9 Figures

Figure 1: Cases Recorded by Assigned Work Location



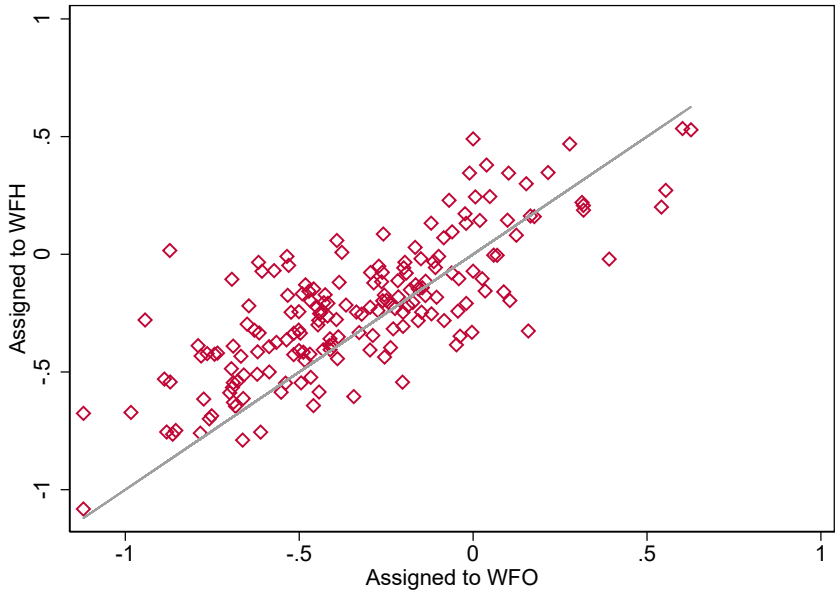
(a)



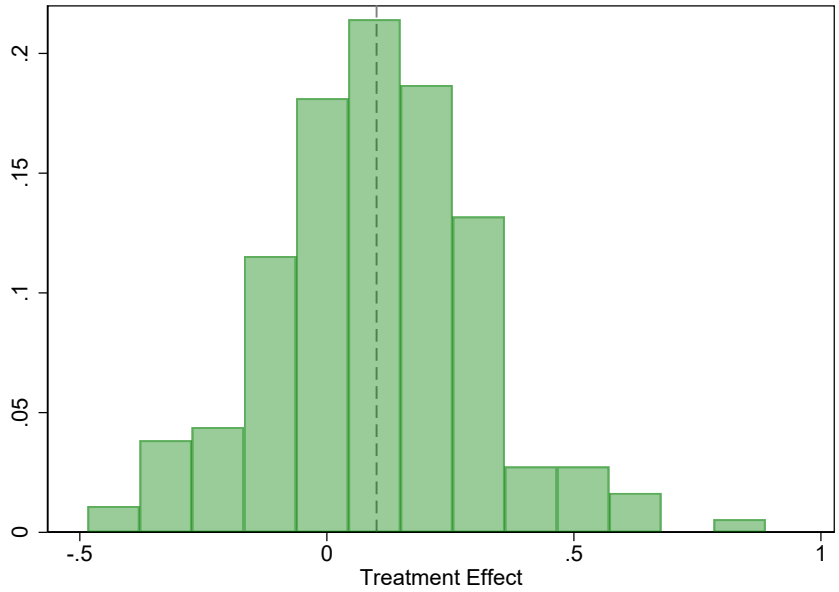
(b)

Notes: CRRU records (1 November 2022–21 January 2023). Panel A displays the logarithm of the average number of cases recorded per worker per day by staff assigned to WFH (orange circles) and WFO (blue triangles). The two thick lines represent the respective local linear smooths. Panel B illustrates the difference in the logarithm of the average number of cases recorded per day between workers assigned to WFH and WFO, with the thick black line indicating the local linear smooth.

Figure 2: Treatment Effect Heterogeneity



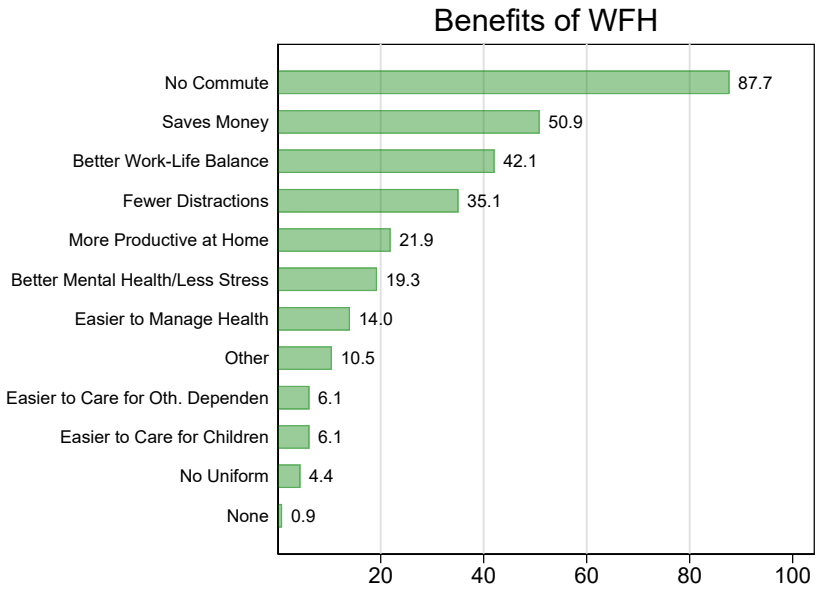
(a)



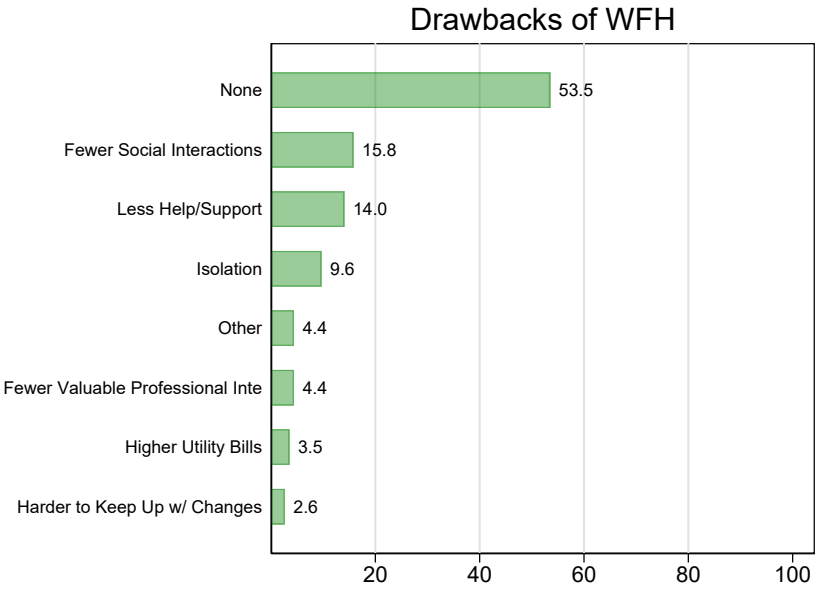
(b)

Notes: CRRU records (22 September 2023–21 January 2024). Panel A displays the estimated worker fixed effects when assigned to WFH versus WFO, represented by red diamonds, along with the 45-degree line for reference. The worker effects are estimated using model (3). Panel B presents the distribution of the estimated Intent-to-Treat (ITT) treatment effects, calculated as the difference between the worker fixed effects when assigned to WFH and WFO (equation (4)). The vertical dashed line represents the average of the ITTs.

Figure 3: Benefits and Drawbacks of WFH



(a)



(b)

Notes: Survey (October 2024). Panels A and B report the answers to two open-ended questions eliciting the workers' perceived benefits and costs of WFH, respectively. The questions were phrased as: "When thinking about working from home, what are the main benefits for you?" and "When thinking about working from home, what are the main drawbacks for you?". The categories are not mutually exclusive.

10 Tables

Table 1: Rotation Schedule

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Panel A: Day Shift Pattern							
Week 1	8am–6pm H	8am–6pm H	Rest Day	Rest Day	11am–9pm H	11am–9pm H	11am–9pm H
Week 2	Rest Day	Rest Day	Rest Day	7am–5pm O	7am–5pm O	10am–6pm O	10am–6pm O
Week 3	Rest Day	Rest Day	10am-7pm H	10am-7pm H	10am-7pm H	Rest Day	Rest Day
Week 4	11am-9pm H	11am-9pm H	11am-9pm H	11am-9pm H	Rest Day	Rest Day	Rest Day
Week 5	7am–5pm O	7am–5pm O	7am–5pm O	Rest Day	Rest Day	7am–4pm H	8am–4pm H
Panel B: 24/7 Shift Pattern							
Week 1	8am–6pm H	8am–6pm H	Rest Day	Rest Day	9pm-7am H	9pm-7am H	9pm-7am H
Week 2	Rest Day	Rest Day	Rest Day	4pm–00am O	5pm–2am O	5pm–2am O	4pm–00am O
Week 3	Rest Day	Rest Day	7am-4pm H	7am-5pm H	7am-5pm H	Rest Day	Rest Day
Week 4	6pm-3am H	6pm-3am H	6pm-4am H	6pm-4am H	Rest Day	Rest Day	Rest Day
Week 5	4pm–00am O	4pm–00am O	4pm–00am O	Rest Day	Rest Day	7am–5pm H	7am–4pm H
Week 6	7am–4pm H	7am–4pm H	Rest Day	Rest Day	9pm-7am H	9pm-7am H	7pm-3am H
Week 7	Rest Day	Rest Day	Rest Day	11am–9pm O	11am–9pm O	11am–9pm O	11am–9pm O
Week 8	Rest Day	Rest Day	8am-6pm H	8am-6pm H	8am-6pm H	Rest Day	Rest Day
Week 9	9pm-7am H	9pm-7am H	9pm-7am H	9pm-7am H	Rest Day	Rest Day	Rest Day
Week 10	11am–9pm O	11am–9pm O	11am–9pm O	Rest Day	Rest Day	8am–6pm H	8am–6pm H

Notes: This table reports the rotation schedule. Orange and blue index the shifts where the workers are assigned to work from home (H) and from the office (O), respectively.

Table 2: Characteristics of the CRRU

	(1) All Periods	(2) Period 1: Pre-Period	(3) Period 2: Analysis	(4) Period 3: Experiment
Panel A: Workers				
Female	0.627	0.632	0.661	0.679
Age 18-24	0.205	0.201	0.201	0.187
Age 25-34	0.314	0.304	0.307	0.276
Age 35-44	0.127	0.132	0.122	0.142
Age 45-54	0.164	0.167	0.175	0.187
Age 55-65	0.182	0.186	0.190	0.209
Age 65 and over	0.009	0.010	0.005	0
Team 1	0.195	0.206	0.206	0.231
Team 2	0.214	0.211	0.201	0.164
Team 3	0.200	0.186	0.201	0.201
Team 4	0.186	0.191	0.190	0.201
Team 5	0.205	0.206	0.201	0.201
Day Shift	0.605	0.588	0.608	0.612
N	220	204	189	134
Panel B: CRRU				
N Officers	56.255	50.053	73.908	55.824
Assigned to WFH	0.735	0.675	0.678	0.826
WFH	0.677	0.625	0.631	0.756
N Cases Recorded	349.697	308.094	412.672	370.039
Tot. Time (Min)	5039.988	5932.327	5192.672	3973.703
N Cases Recorded per Officer	6.249	6.119	5.589	6.671
Tot. Time per Officer (Min)	93.092	120.751	70.566	71.463
Av. Time per Crime (Min)	17.208	22.430	14.862	12.326
Share Violence Against the Person	0.450	0.425	0.461	0.475
Share Public Order	0.049	0.045	0.038	0.058
Share Criminal Damage or Arson	0.097	0.094	0.101	0.099
Share Theft	0.322	0.346	0.331	0.292
Share Possession of Weapons	0.003	0.002	0.002	0.005
Share Misc. Offences	0.078	0.087	0.067	0.072
Observations	722	319	119	284

Notes: CRRU records (1 November 2022–31 October 2024). This table reports the summary statistics for the CRRU. All statistics are computed across workers in Panel A and across day observations in Panel B. The statistics are computed over all periods in column 1, between 1 November 2022 and 21 September 2023 (period 1) in column 2, between 22 September 2023 and 21 January 2024 in column 3 (period 2), and finally between 22 January 2024 and 31 October 2024 (period 3) in column 4.

Table 3: Balance on Observables

	(1) Mean	(2) Coeff.	(3) SE	(4) P-value	(5) N
Panel A: Worker Characteristics					
Female	.64	-.005	.0093	.5901	8795
Age 18-24	.205	-.0015	.0075	.8405	8795
Age 25-34	.334	-.0134	.0084	.1108	8795
Age 35-44	.118	.0085	.0053	.11	8795
Age 45-54	.168	.0062	.0083	.4576	8795
Age 55-65	.173	-.0002	.0085	.9849	8795
Age missing	.001	.0004	.0004	.321	8795
Covariate Index	1.519	.0015	.0016	.3331	8795
Panel B: Case Characteristcs					
Violence against the person (First of the day)	.407	-.0064	.011	.564	8795
Public Order (First of the day)	.033	-.002	.004	.6175	8795
Criminal Damage and Arson (First of the day)	.101	.0061	.0068	.3676	8795
Theft (First of the day)	.393	.0016	.0118	.8952	8795
Possession of Weapon (First of the day)	.001	-.0003	.0009	.7675	8795
Misc. Offenses (First of the day)	.064	.0009	.0053	.859	8795
Violence against the person (Last of the day)	.41	.0068	.0116	.56	8795
Public Order (Last of the day)	.03	-.0045	.0041	.2753	8795
Criminal Damage and Arson (Last of the day)	.107	-.0074	.0069	.2835	8795
Theft (Last of the day)	.375	.0102	.0112	.3623	8795
Possession of Weapon (Last of the day)	.002	-.0001	.0011	.9207	8795
Misc. Offenses (Last of the day)	.075	-.005	.0059	.403	8795

Notes: CRRU records (22 September 2023–21 January 2024). Each line represents a different regression. The row variable indicates the dependent variable. The covariate index is constructed by regressing the log number of cases on the workers' demographic characteristics. Column 1 reports the control mean. Columns 2 and 3 report the estimated coefficients and standard errors, respectively. These statistics are obtained in Panel A by regressing the row variable on a constant and the WFH assignment. The regressions in Panel B also include worker and day-fixed effects. Column 4 reports the p-value and column 5 the number of observations. SE clustered at the worker level.

Table 4: The Effects of WFH Assignment on Workers' Productivity

	(1)	(2)	(3)
Panel A: Log N of Cases			
Assigned to WFH	0.098***	0.099***	0.089***
	(0.016)	(0.016)	(0.015)
N	8795	8795	8795
R-squared	0.005	0.068	0.235
Control Mean	1.454	1.454	1.454
Panel B: Log Tot. Time (minutes)			
Assigned to WFH	0.000	0.006	0.001
	(0.019)	(0.018)	(0.018)
N	8795	8795	8795
R-squared	0.000	0.077	0.270
Control Mean	3.977	3.977	3.977
Panel C: Log Av. Time (minutes)			
Assigned to WFH	-0.097***	-0.093***	-0.088***
	(0.015)	(0.015)	(0.014)
N	8795	8795	8795
R-squared	0.005	0.036	0.354
Control Mean	2.523	2.523	2.523
Worker FE	No	No	Yes
Day FE	No	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). Column 1 reports the estimated effect of regressing the outcome of interest on a constant and the WFH assignment. Column 2 controls for day fixed effects. Column 3 controls for worker and day fixed effects (model (1)). SE clustered at the worker level.

Table 5: The Effects of WFH on Workers' Productivity

	(1) WFH	(2) Log N Cases	(3) Log Tot. Time	(4) Log Av. Time
Assigned to WFH (rotation)	0.734***			
	(0.021)			
WFH		0.122***	0.002	-0.120***
		(0.020)	(0.024)	(0.019)
N	8795	8795	8795	8795
R-squared	0.646	0.002	-0.000	0.004
Control Mean	.134	1.454	3.977	2.523
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	2SLS	2SLS	2SLS
F-stat	1254.81			

Notes: CRRU records (22 September 2023–21 January 2024). Column 1 reports the first stage (FS) and the F-statistic for the null hypothesis that the coefficient associated with instrument is equal to zero. Columns 2-4 report the estimated β^{2SLS} from model (2). SE clustered at the worker level.

Table 6: Work Patterns

	(1) Work Before Shift	(2) Work After Shift	(3) Time First – Begin Shift (minutes)	(4) Time Last – End Shift (minutes)
Assigned to WFH (rotation)	0.002	-0.020*	-23.353***	3.538
	(0.015)	(0.012)	(6.374)	(6.192)
N	8795	8795	8795	8795
R-squared	0.287	0.206	0.210	0.226
Control Mean	.258	.12	72.904	-164.662
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1). SE clustered at the worker level.

Table 7: Balance on Observables (Experiment)

	(1) Mean	(2) Coeff.	(3) SE	(4) P-value	(5) N
Female	.71	-.0542	.0792	.4951	138
Age 18-24	.203	-.0462	.0657	.4833	138
Age 25-34	.29	-.0273	.0709	.7005	138
Age 35-44	.101	.0707	.059	.2328	138
Age 45-54	.174	.0294	.0652	.6528	138
Age 55-65	.232	-.0266	.0706	.7068	138
Worker FE	.403	-.0024	.0442	.9567	134

Notes: CRRU records (22 September 2023–21 January 2024). Each line represents a different regression. The row variable indicates the dependent variable. Column 1 reports the control mean. Columns 2 and 3 report the estimated coefficients and standard errors, respectively. These statistics are obtained by regressing the row variable on a constant, treatment assignment, strata and day fixed effects (model (5)). SE clustered at the worker level.

Table 8: Regime Comparison: WFH vs. Hybrid

	(1) WFH	(2) Log N Cases	(3) Log Tot. Time	(4) Log Av. Time
Treated	0.228***	0.013	0.031	0.019
	(0.031)	(0.041)	(0.056)	(0.055)
N	15888	15888	15888	15888
R-squared	0.077	0.000	0.000	0.000
Control Mean	.657	1.701	4.015	2.314
Strata FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	RF	RF	RF
F-stat	54.15			

Notes: CRRU records (22 January 2024–31 October 2024). This table reports the estimated δ from model (5). Column 1 reports the first stage (FS) and the F-statistic for the null hypothesis that the coefficient associated with instrument is equal to zero. Columns 2-4 report the reduced form (RF). SE clustered at the worker level.

Online Appendix

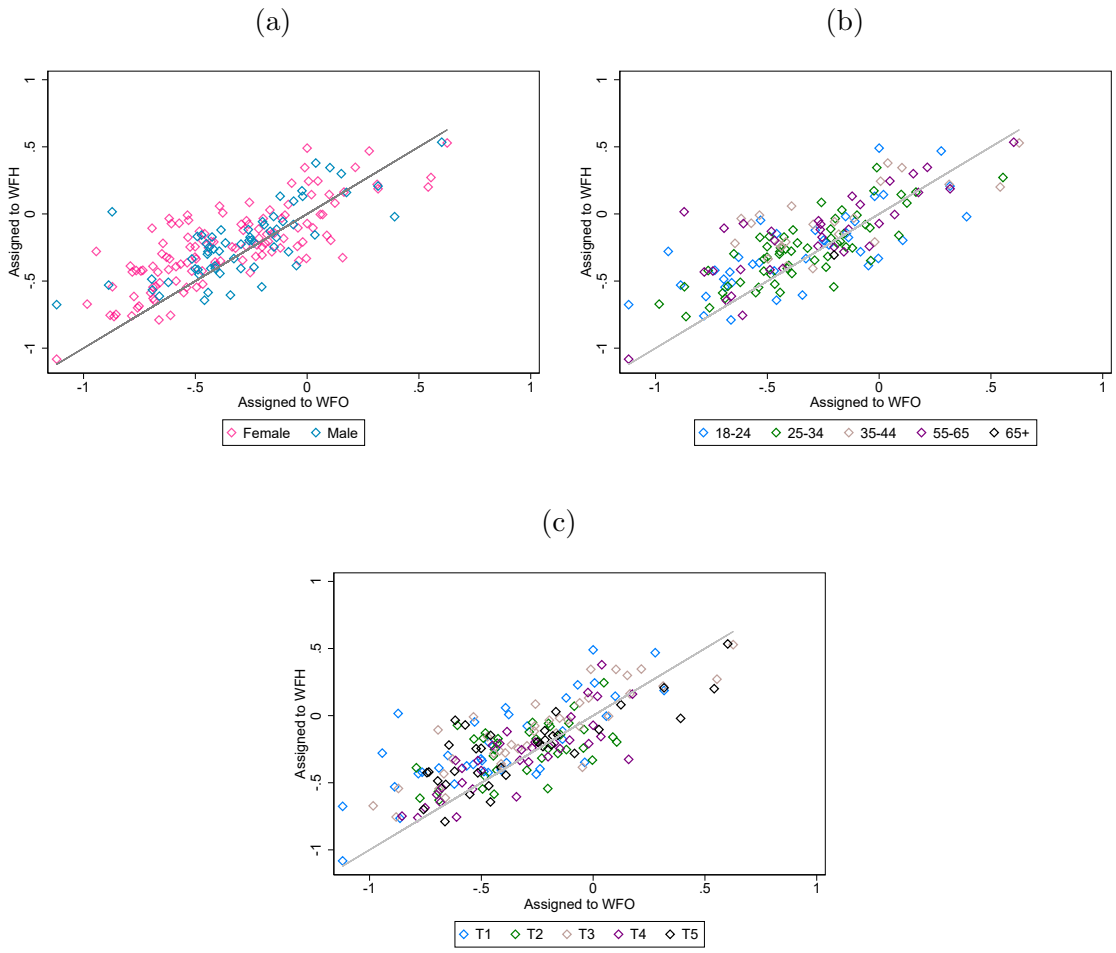
Appendix A Additional Figures and Tables

Figure A.1: Balance on Case Characteristics



Notes: CRRU records (22 September 2023–21 January 2024). This figure reports the estimated coefficients and the corresponding 95% confidence intervals obtained regressing 'Assignment to WFH' on the case characteristics for the first and last case of the day for each worker (displayed on the vertical axis) as well as the worker and day fixed effects. The number of observations is 8,795. The figure also reports the p-value for the null hypothesis that the coefficients associated with case characteristics are jointly zero.

Figure A.2: Productivity Gains and Observable Characteristics



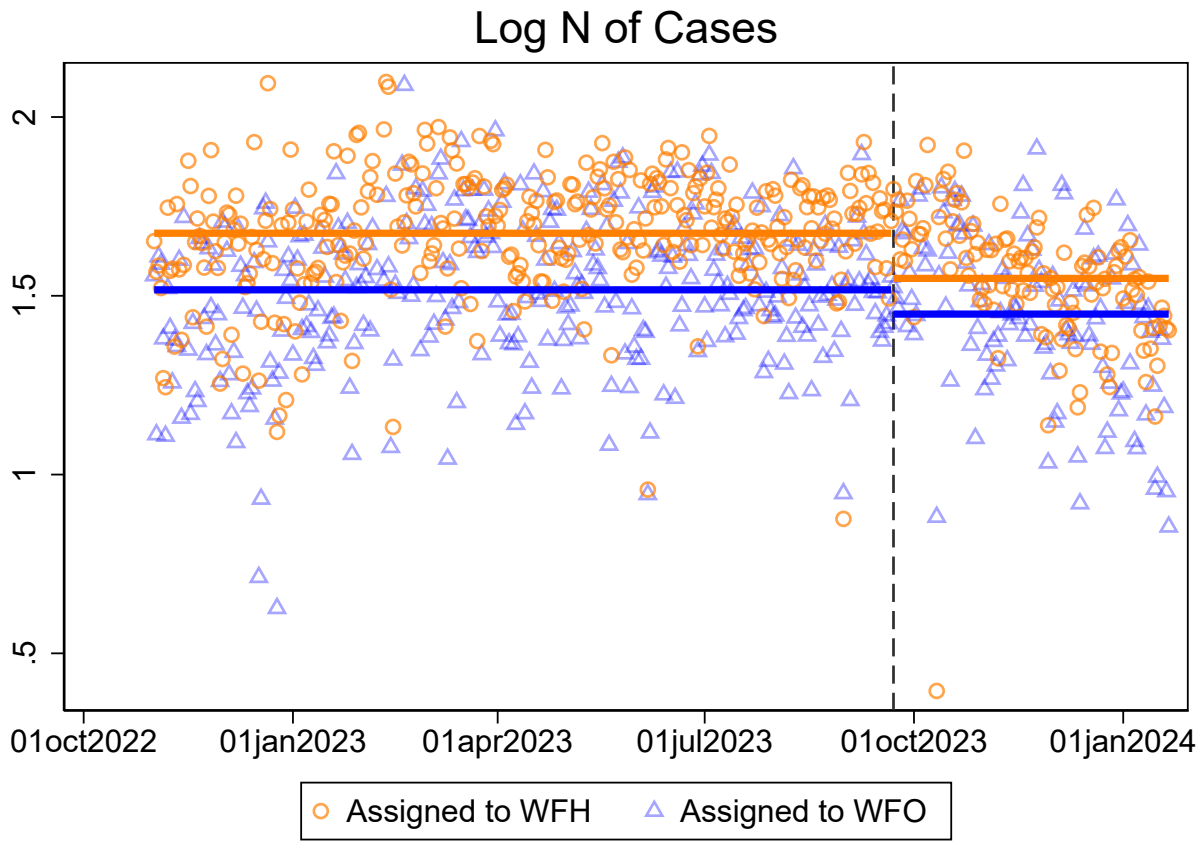
Notes: CRRU records (22 September 2023–21 January 2024). This figure displays the estimated worker fixed effects when assigned to WFH versus WFO, represented by diamonds, along with the 45-degree line for reference. The worker effects are estimated using model (3). Panels A–C explore heterogeneity across gender, age, and teams, respectively.

Figure A.3: The Office



Notes: This image illustrates the work environment and the open-floor office layout.

Figure A.4: Aggregate Trends in Cases Recorded by Assigned Work Location



Notes: CRRU records (22 September 2023–21 January 2024). This figure illustrates aggregate productivity trends before and after 22 September 2023 – the date when task assignment shifted from supervisors to a computer algorithm. This Figure shows the logarithm of the average number of cases recorded per worker per day by staff assigned to WFH (represented by orange circles) and WFO (represented by blue triangles). The two thick lines depict the corresponding average productivity levels for WFH and WFO assignments before and after 22 September 2023.

Table A.1: Clustering

	(1) Log Cases	(2) Log Tot. Time	(3) Log Av. Time
Panel A: Clustered SE at the Worker Level			
Assigned to WFH	0.089***	0.001	-0.088***
	(0.015)	(0.018)	(0.014)
Panel B: Clustered SE at the Team Level			
Assigned to WFH	0.089***	0.001	-0.088***
	(0.013)	(0.012)	(0.012)
N	8795	8795	8795
R-squared	0.235	0.270	0.354
Control Mean	1.454	3.977	2.523
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1). Panel A reports our baseline estimates where we cluster the SE at the worker level (baseline specification). Panel B reports the estimates clustering the SE at the team level.

Table A.2: Estimated Treatment Effects and Observable Characteristics

	(1) Treatment Effect
Female	0.163*
	(0.078)
Aged 25 to 34	0.076
	(0.071)
Aged 35 to 44	0.159*
	(0.081)
Aged 45 to 54	0.094
	(0.073)
Aged 55 to 64	0.153
	(0.098)
Aged 65 or more	-0.260***
	(0.051)
Aged 25 to 34 × Female	-0.156
	(0.092)
Aged 35 to 44 × Female	-0.134
	(0.120)
Aged 45 to 54 × Female	-0.157
	(0.101)
Aged 55 to 64 × Female	-0.180
	(0.120)
Aged 65 or more × Female	0.000
	(.)
N	182
R-squared	0.061

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated coefficients obtained by regressing the estimated treatment effects on observable characteristics. The omitted age category is "Aged 18 to 24".

Table A.3: WFH and Workers' Productivity

	(1)	(2)	(3)
Panel A: Log N of Cases			
WFH	0.083***	0.080***	0.077***
	(0.023)	(0.023)	(0.018)
N	8795	8795	8795
R-squared	0.004	0.067	0.234
Control Mean	1.454	1.454	1.454
Panel B: Log Tot. Time (minutes)			
WFH	0.039	0.029	-0.006
	(0.025)	(0.025)	(0.020)
N	8795	8795	8795
R-squared	0.001	0.078	0.270
Control Mean	3.977	3.977	3.977
Panel C: Log Av. Time (minutes)			
WFH	-0.044*	-0.051**	-0.083***
	(0.024)	(0.024)	(0.016)
N	8795	8795	8795
R-squared	0.001	0.033	0.353
Control Mean	2.523	2.523	2.523
Worker FE	No	No	Yes
Day FE	No	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). Column 1 reports the estimated effect of regressing the outcome of interest on a constant and WFH. Column 2 controls for day fixed effects. Column 3 controls for worker and day fixed effects. SE clustered at the worker level.

Table A.4: The Effect of WFH Assignment on Absences

	(1) Absent	(2) Absent Medical	(3) Absent Non-Medical
Assigned to WFH	-0.036***	-0.012**	-0.024**
	(0.013)	(0.006)	(0.011)
N	12014	12014	12014
R-squared	0.196	0.111	0.196
Control Mean	.292	.051	.243
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1). SE clustered at the worker level.

Table A.5: The Effect of WFH Assignment on Workers' Productivity (Including Zeros)

	(1) Log (N Cases +1)	(2) Log (Tot. Time +1)
Assigned to WFH	0.120***	0.148***
	(0.025)	(0.053)
N	12014	12014
R-squared	0.208	0.196
Control Mean	1.203	2.833
Worker FE	Yes	Yes
Day FE	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1). The outcomes in this table are obtained by imputing zeros in the days in which the worker is assigned to working according to the rotation schedule but does not log any cases. SE clustered at the worker level.

Table A.6: Controlling for Characteristics of Reported Cases

	(1) Log N Cases	(2) Log Tot. Time	(3) Log Av. Time
Assigned to WFH	0.085***	0.012	-0.073***
	(0.015)	(0.017)	(0.014)
N	8795	8795	8795
R-squared	0.247	0.275	0.375
Control Mean	1.454	3.977	2.523
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Types of Reported Cases	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1) controlling the characteristics of cases reported during each shift. SE clustered at the worker level.

Table A.7: The Effects of WFH Assignment on Work Quality

	(1) Quality	(2) Quality	(3) Quality
Assigned to WFH	-0.030	-0.026	-0.035
	(0.020)	(0.023)	(0.024)
N	991	976	971
R-squared	0.002	0.001	0.003
Control Mean	.046	.045	.045
Worker FE	No	No	Yes
Day FE	No	Yes	Yes

Notes: CRRU records (1 February 2024–31 August 2024). Column 1 reports the estimated effect of regressing the outcome of interest on a constant and the WFH assign- ment. Column 2 controls for day fixed effects. Column 3 controls for worker and day fixed effects (model (1)). SE clustered at the worker level.

Table A.8: Excluding Training and Administrative Duties

	(1) Log N Cases	(2) Log Tot. Time	(3) Log Av. Time
Assigned to WFH	0.090***	0.001	-0.089***
	(0.015)	(0.018)	(0.014)
N	8716	8716	8716
R-squared	0.234	0.269	0.352
Control Mean	1.452	3.973	2.521
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1) excluding days in which the staff engages in training or administrative duties. SE clustered at the worker level.

Table A.9: Controlling for Assigned Shift Length

	(1) Log N Cases	(2) Log Tot. Time	(3) Log Av. Time
Assigned to WFH	0.064***	-0.018	-0.082***
	(0.015)	(0.018)	(0.014)
N	8795	8795	8795
R-squared	0.241	0.273	0.354
Control Mean	1.454	3.977	2.523
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Assigned Shift Length	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1) controlling for assigned shift length. SE clustered at the worker level.

Table A.10: Balance on Observables (Pre-Period)

	(1) Mean	(2) Coeff.	(3) SE	(4) P-value	(5) N
Panel A: Worker Characteristics					
Female	.632	-.0085	.0092	.3588	15967
Age 18-24	.165	-.0066	.0051	.1953	15967
Age 25-34	.27	.0025	.0077	.7424	15967
Age 35-44	.139	.0076	.0059	.1976	15967
Age 45-54	.171	-.0034	.0096	.7233	15967
Age 55-65	.206	.0005	.0069	.9427	15967
Age missing	.049	-.0006	.0041	.8756	15967
Covariate Index	1.63	.0013	.0013	.3489	15967
Panel B: Case Characteristcs					
Violence against the person (First of the day)	.246	.2094	.011	0	15967
Public Order (First of the day)	.034	.0053	.0036	.1458	15967
Criminal Damage and Arson (First of the day)	.133	-.0344	.0059	0	15967
Theft (First of the day)	.532	-.2165	.0113	0	15967
Possession of Weapon (First of the day)	.001	.0008	.0007	.2277	15967
Misc. Offenses (First of the day)	.054	.0354	.0044	0	15967
Violence against the person (Last of the day)	.291	.1362	.011	0	15967
Public Order (Last of the day)	.03	.0087	.0031	.0049	15967
Criminal Damage and Arson (Last of the day)	.11	-.0212	.005	0	15967
Theft (Last of the day)	.496	-.1476	.0118	0	15967
Possession of Weapon (Last of the day)	.001	.0021	.0005	.0001	15967
Misc. Offenses (Last of the day)	.073	.0218	.005	0	15967

Notes: CRRU records (1 November 2022–21 September 2023). Each line represents a different regression. The row variable indicates the dependent variable. The covariate index is constructed by regressing the log number of cases on the workers' demographic characteristics. Column 1 reports the control mean. Columns 2 and 3 report the estimated coefficients and standard errors, respectively. These statistics are obtained in Panel A by regressing the row variable on a constant and the WFH assignment. The regressions in Panel B also include worker and day fixed effects. Column 4 reports the p-value and column 5 the number of observations. SE clustered at the worker level.

Table A.11: The Effects of WFH Assignment on Worker' Productivity (Pre-Period)

	(1) Log N Cases	(2) Log Tot. Time	(3) Log Av. Time
Assigned to WFH	0.156***	0.142***	-0.014
	(0.016)	(0.017)	(0.016)
N	15967	15967	15967
R-squared	0.268	0.336	0.429
Control Mean	1.526	4.434	2.908
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (1 November 2022–21 September 2023). This table reports the estimated β from model (1). SE clustered at the worker level.

Table A.12: The Effects of WFH on Workers' Productivity (Pre-Period)

	(1) WFH	(2) Log N Cases	(3) Log Tot. Time	(4) Log Av. Time
Assigned to WFH	0.751***			
	(0.020)			
WFH		0.208***	0.189***	-0.019
		(0.021)	(0.022)	(0.021)
N	15967	15967	15967	15967
R-squared	0.637	0.008	0.005	0.000
Control Mean	.119	1.526	4.434	2.908
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	2SLS	2SLS	2SLS
F-stat	1459.68			

Notes: CRRU records (1 November 2022–21 September 2023). Column 1 reports the first stage (FS) and the F-statistic for the null hypothesis that the coefficient associated with instrument is equal to zero. Columns 2-4 report the estimated β^{2SLS} from model (2). SE clustered at the worker level.

Table A.13: The Effects of WFH Assignment on Workers' Productivity (Workers in the Experiment)

	(1) Log N Cases	(2) Log Tot. Time	(3) Log Av. Time
Assigned to WFH	0.115***	0.032	-0.084***
	(0.017)	(0.020)	(0.018)
N	6341	6341	6341
R-squared	0.242	0.272	0.360
Control Mean	1.454	3.977	2.522
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated β from model (1) restricting the sample to the workers who are part of the experiment. SE clustered at the worker level.

Table A.14: The Effects of WFH on Workers' Productivity using the Experimental Variation

	(1) WFH	(2) Log N Cases	(3) Log Tot. Time	(4) Log Av. Time
Treated	0.228***			
	(0.031)			
WFH		0.056	0.138	0.082
		(0.180)	(0.248)	(0.246)
N	15888	15888	15888	15888
Control Mean	.657	1.701	4.015	2.314
Strata FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	2SLS	2SLS	2SLS
F-stat	54.15			

Notes: CRRU records (22 January 2024–31 October 2024). Column 1 reports the first stage (FS) and the F-statistic for the null hypothesis that the coefficient associated with instrument is equal to zero. Columns 2-4 report the estimated δ^{2SLS} from model (6). SE clustered at the worker level.

Table A.15: Absences: WFH vs. Hybrid

	(1) Absent	(2) Absent Medical	(3) Absent Non-Medical
Treated	0.003	-0.011	0.014
	(0.017)	(0.011)	(0.014)
N	21125	21125	21125
R-squared	0.000	0.001	0.000
Control Mean	.246	.047	.2
Strata FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Method	RF	RF	RF

Notes: CRRU records (22 January 2024–31 October 2024). This table reports the estimated δ from model (5). Columns 1-4 report the reduced form (RF). SE clustered at the worker level.

Appendix B Survey Quotes

In this Appendix, we report selected quotes from the survey.

Quotes on reduced distractions and higher productivity at home. This section presents selected quotes in response to the question: "When thinking about working from home, what are the main benefits for you?" These quotes highlight that a key advantage of working from home is the reduction of distractions, which makes the staff more productive. Emphasis added.

> "I find I *concentrate better* when WFH making me more productive, I have *less distractions at home* rather than the office which at times can be a loud environment, making it personally difficult to work."
>
> "Having a *quiet* and comfortable space to work and *concentrate* in."
>
> "I feel I provide a *better service* from home with *less distractions from colleagues*."
>
> "I am more *productive* working from home, as do *not get distracted* and can *retain information* better."
>
> "I personally feel that my *concentration* improves without the *background noise* of the office."
>
> "I am more *productive* whilst working at home due to *less distractions*."
>
> "I *work better* from home my *concentration* is much better to that in the office."
>
> "I personally am more *productive* from home with *no distractions*."
>
> "Better *focus* on work due to *less distractions*."
>
> "[I] feel more *productive* [when WFH] as no chatter in office causing *distractions*"
>
> "This [the benefit is] due to how I am *more productive* whilst working at home due to *less distractions*."
>
> "I am *more productive* when left to my own devices."
>
> "[The] main reason [is that] I can *work more efficient[ly]*, *less noise* and quieter environment."
>
> "More *productive* due to *no distractions*."
>
> "I personally feel that my *concentration* improves without the background *noise* of the office."

"I also *perform better* whilst WFH , in the office I feel *distracted* by colleagues and the general office atmosphere."