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

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Abstract

When performance incentives are weak, working from home (WFH) can entail significant risks, such as reduced effort or shirking. This paper estimates the individual-level treatment effects of WFH on worker productivity in public sector jobs. Exploiting novel administrative data and exogenous variation in work location, we find that WFH instead *increases* productivity by 12% on average, with considerable heterogeneity across workers. These gains are primarily driven by reduced distractions and are not explained by changes in work quality, hours worked, absenteeism, characteristics of reported cases, training, administrative duties, or task allocation. When tasks are assigned by a supervisor, productivity gains nearly double.

Keywords: working from home, productivity, public sector.

JEL: D23, J45, L23, M54.

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1 Introduction

Firms have long experimented with working from home (WFH) arrangements (Barrero et al., 2023; Mas and Pallais, 2020), a trend accelerated by the COVID-19 pandemic (Aksoy et al., 2022; Bloom et al., 2021). While some of this shift has since been reversed, many workers continue to work from home several days a week, and organizations around the world are still grappling with how to define a new status quo.

A central question is how WFH affects worker performance (Emanuel and Harrington, 2024). On one hand, WFH can boost productivity by saving commute time (Barrero et al., 2020), reducing breaks and sick days (Bloom et al., 2015), increasing worker 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 reduce monitoring and limit valuable professional interactions (Emanuel et al., 2023) and learning opportunities (Atkin et al., 2023).

The potential costs of WFH—such as reduced effort or shirking—are likely to be more pronounced in public sector organizations, where the incentives for workers to perform are weaker. Nevertheless, little is known about the productivity effects of WFH in the public sector because of the challenges associated with directly measuring worker productivity.

In this paper, we study the performance impact of WFH in the public sector, leveraging 1) novel high-frequency administrative and survey data, and 2) quasi-exogenous variation in work location. 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. Police staff work from home under a hybrid 70% WFH regime alternating deterministically between WFH and WFO. We exploit the plausibly exogenous variation in work location introduced by the rotation schedule to compare the performance of the CRRU workers assigned to WFH vs. WFO. Three factors make the CRRU is an ideal setting to study the impact of WFH on workers' productivity: first, there is an objective and well-measured metric to evaluate workers' performance (i.e., the number of cases recorded per day); second, workers switch exogenously between WFH and WFO; and, third, tasks are as good as randomly assigned by a computer algorithm during our primary analysis period. We corroborate the argument that the rotation schedule generates plausibly exogenous variation in work location by showing that being assigned to WFH does not predict either the demographic characteristics of the police staff on duty or the case characteristics. We find that WFH increases workers' productivity by 12% on average.

Our detailed data enables us to explore the mechanisms driving WFH's productivity increases. We find evidence that the productivity gains from WFH are primarily driven by reduced distractions when WFH, which makes the staff more efficient. We show that the productivity gains are not explained by changes in hours worked, absenteeism, characteristics of reported crimes, work quality, training, administrative duties, or task allocation. While our main analysis focuses on the productivity effects of WFH on days when staff are working (i.e., the intensive margin), we also examine whether WFH influences absenteeism (i.e., the extensive margin). We find that workers are 3.6 percentage points less likely to be absent on days they are assigned to WFH. This is consistent with workers' reports that WFH enables them to continue working when feeling mildly unwell or when managing chronic health conditions.

In addition, our within-worker design allows us to estimate 1) *individual* worker productivity when assigned to WFH and WFO, and 2) *individual-level* treatment effects. We establish five novel findings. First, we uncover substantial variation in workers' performance (i.e., some workers are consistently more productive than others). Second, individuals who are productive in the office also tend to be productive at home. Third, the productivity gains from WFH are very heterogeneous across workers. However, this variation is only partially explained by observable worker characteristics. Fourth, the productivity gains from WFH are larger for workers with lower productivity when WFO. Finally, we assess selection into remote jobs by comparing workers hired before the shift to hybrid operations with those hired afterward. We find no evidence of selection based on either absolute or comparative advantage.

We supplement our main analysis with two complementary exercises. First, we compare our main estimates to corresponding estimates from a pre-period in which tasks were assigned by supervisors rather than randomly. Highlighting the important role played by managers in harnessing the benefits of WFH, we find that WFH increases productivity by 20% in this setting—nearly twice the effect observed in our main analysis. We show that supervisors possess valuable knowledge about which tasks are better suited for remote work and effectively use this information when making assignments.

Finally, our main analysis compares worker productivity under a hybrid arrangement in which staff WFH approximately 70% of the time to when they WFO. However, the productivity effects of WFH may vary with the intensity of remote work. To assess this, we conducted a randomized experiment comparing the status quo hybrid regime to a treatment condition in which staff WFH approximately 95% of the time. We find no evidence of additional productivity gains from increasing the share of remote work, nor do we observe any

adverse effects.

We contribute to the literature in three fundamental ways. First, we estimate the effect of WFH in a context where incentives to perform are inherently weak–namely, workers enjoy strong job security, are not subject to pay-for-performance schemes, and have limited opportunities for career advancement.[1] This is important because in settings with muted incentives, the potential costs of WFH—such as reduced effort or shirking—are likely to be higher than in private-sector environments, where workers can be directly or indirectly motivated through performance-based pay, promotion prospects, or the threat of dismissal. Second, our within-worker design allows us to isolate workers' productivity under different working arrangements and to estimate *individual*-level treatment effects. This enables us to move beyond Intention-to-Treat (ITT) estimates and characterize the full distribution of impacts. The substantial heterogeneity we document may help reconcile the mixed findings in the existing literature on remote work and performance: variation in estimated effects may stem not only from institutional or contextual differences, but also from *who* is working from home. Third, we find that supervisors outperform algorithmic task allocation and play a key role in harnessing the benefits of WFH—an aspect that, to our knowledge, has not been previously explored in the context of remote work arrangements.

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). Studies on the causal effects of WFH on workers' performance almost exclusively focus on the private sector. Working entirely from home mostly lowers workers' productivity (Aksoy et al., 2025; 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; Linos, 2018; Morikawa, 2023). Hybrid work has also been found to increase workers' job satisfaction, well-being, and work-life balance, decrease employees turnover, and change how coworkers communicate with each other (Angelici and Profeta, 2024; Bloom et al., 2015, 2022; Choudhury et al., 2024, 2025).

[1] Our work adds to the limited evidence on remote work arrangements in public sector organizations, which thus far has focused exclusively on the U.S. Patent Office (Linos, 2018; Choudhury et al., 2021). Our finding of a positive effect of WFH contrasts with Linos (2018), who documents negative impacts of remote work. Unlike Choudhury et al. (2021), who examine "work-from-anywhere" arrangements relative to a WFH regime, we assess the productivity impact of WFH relative to WFO.

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 responsible for recording the details of various crimes and incidents. Initially established in early 2020 as a fully in-person operation, the CRRU implemented remote work in response to the COVID-19 pandemic.

Nature and Allocation of Work. The primary responsibility of the job is to record the details of cases stemming from all calls (both incoming and outgoing) into the computer system. Typically, workers speak on the phone with the victim or informant and, upon concluding the conversation, enter the case details into the system. Workers are solely tasked with recording information; they are not involved in investigating the cases. Recording cases is individual work and does not require team interactions. In addition to recording, staff members also triage cases, i.e., they evaluate whether reported incidents fall under the purview of the CRRU. Triaging does not result in a case being logged into the system and represents approximately 7% of the workload. Occasionally, workers may be assigned to train new hires or to perform administrative duties, although these instances are rare, as documented in Section 5.3. All staff are trained in all three workstreams (i.e., answering incoming calls, making outgoing calls, and triaging cases) and work all three of them regularly. Shifts are staffed to balance two priorities: minimizing worker idle time and ensuring timely case recording. Typically, there is a steady queue of incoming calls and follow-up calls to complete, making it uncommon for workers to sit idle for extended periods while waiting

for calls. Consistent with this, 25% of cases are recorded immediately upon reporting, 50% within 40 minutes, and 75% within five hours. Before 22 September 2023, supervisors assigned their workers to workstreams each day. From that day onward, the assignment has been 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. All staff work 3 to 5 days per week, Monday through Sunday, following a rotation schedule that determines their shifts. The rotation schedule has two important features. First, it does not allow workers to choose their hours and work location (office vs. home). Second, it is designed so that at any given time, some staff work from home, and others work from the office.

Each staff member belongs to one of five teams and follows either a "day shift pattern" (covering shifts between 07:00 and 21:00) or a "24/7 shift pattern" (covering both day and night shifts). Table 1 summarizes the rotation schedule by shift pattern: Panel A for the day shift pattern and Panel B for the 24/7 shift pattern.

In the day shift pattern (Panel A), staff follow a 5-week rotation cycle. For example, in Week 1, staff work entirely from home, with shifts from 08:00 to 18:00 on Mondays and Tuesdays, and from 11:00 to 21:00 on Fridays through Sundays. In Week 2, staff work entirely from the office, covering shifts from 07:00 to 17:00 on Thursdays and Fridays, and from 10:00 to 18:00 on Saturdays and Sundays. Weeks 3 to 5 follow a similar alternation, after which the cycle repeats. Teams are staggered within the rotation: Team 1 began with Week 1, Team 2 with Week 2, and so on. Panel B shows the rotation for the 24/7 shift pattern, which operates similarly but follows a 10-week cycle instead of a 5-week one.

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.

Supervisors. Each team has 6-7 supervisors who monitor their work, offer support and advice, and evaluate them regularly. The presence of multiple supervisors per team reflects the substantial administrative and monitoring responsibilities they shoulder. On any given day, the team requires at least one supervisor assigned to each workstream, others handling administrative tasks, and additional coverage to ensure redundancy. 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, which reflects the volume of crimes they handle. 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. While we cannot directly observe triaging or phone time, we argue that the number of cases recorded per day serves as a reliable proxy for productivity. Triaging accounts for only 7% of the workload, and any time spent on phone calls would ultimately be reflected in either the number or the quality of recorded 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. Career incentives are limited, as opportunities for advancement within the CRRU are minimal, and job security is strong–dismissal for poor performance is virtually unheard of. Importantly, police staff face the same incentive structure regardless of whether they are working from home or from the office.

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. In addition, we leverage data on work quality based on 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 assignments. They also contain daily information on assigned shift and location (i.e., work from home vs. office) based on the rotation schedule, their actual shift and location, and medical leave. In addition, the data contains information on worker assignments to specific workstreams between 1 November 2022 and 10 August 2023.

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. Moreover, we collected information on workers' household characteristics, including the number and ages of their children, as well as whether they have access to a dedicated workspace when working from home.

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. The average tenure is approximately 5 years, the staff are evenly distributed across the five 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.[2] 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 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.

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

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 estimated 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 are not affected.

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. We shrink the estimated fixed effects to account for sampling error (Morris, 1983). 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:

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

Panel A of Figure 2 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=0.78). 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.

Panel B of Figure 2 plots the distribution of the estimated treatment effects. While the ITT is positive (dashed vertical line), it masks a lot of heterogeneity (SD=0.14). The individual-level treatment effects range from -0.27 to 0.60, with the interquartile range spanning from –0.01 to 0.17. Notably, 22% of workers exhibit negative treatment effects. As shown in Table A.2, observable worker characteristics account for only 12% of the variation in these effects. This result is consistent with previous studies, which have shown that predicting workers' effectiveness based on observable characteristics is notoriously difficult (Canaan et al., 2022; Fenizia, 2022; Gordon et al., 2006; Jackson et al., 2014; Weidmann et al., 2024). To further explore this heterogeneity, we assess whether workers with lower office productivity (i.e., lower $\widehat{\mu}_i^{\text{Assigned WFO}}$) experience larger treatment effects by computing the (bias-corrected) covariance between individual-level treatment effects and estimated worker effects when assigned to the office.[3] The resulting covariance is negative (-0.01), suggesting that workers who are less productive in the office tend to benefit more from WFH.

Selection into Remote Jobs. Finally, we examine whether there is selection into remote jobs, either on the basis of absolute advantage (e.g., workers who select into remote jobs are intrinsically more productive) or comparative advantage (e.g., workers who are relatively

[3]The covariance between two estimated sets of fixed effects in linear models is known to be biased (Andrews et al., 2008). To address this, we use a leave-out approach: we correlate the estimated treatment effect in month t^* with the worker productivity when assigned to WFO, estimated excluding month t^*. We then average this covariance across months.

better at WFH than WFO). We begin by estimating individual worker productivity:

$$\log \text{N Cases}_{it} = \beta_0 + \mu_i + \phi_t + u_{it}, \tag{5}$$

where μ_i and ϕ_t represent worker and day fixed effects, respectively. The μ_i capture workers' intrinsic productivity, or absolute advantage. We shink the estimated worker effects to account for sampling error and normalize their mean to zero.

To assess selection, we compare the distribution of worker productivity ($\widehat{\mu}_i$) and treatment effects across two groups: those hired before early 2020–when the organization operated fully in person–and those hired after the shift to a hybrid model. Figure A.3 presents the results. In both panels, the distributions of worker productivity (Panel A) and treatment effects (Panel B) largely overlap, and the differences in means are not statistically significant ($p = 0.852$ and $p = 0.683$, respectively). We conclude that there is no evidence of selection into remote jobs based on either absolute or comparative advantage. This contrasts with prior studies that have found negative selection along both dimensions (Atkin et al., 2023; Emanuel and Harrington, 2024). One caveat to this conclusion is that our analysis is conditional on workers who were still employed as of 2023.

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.[4] Being assigned to WFH increases the probability of WFH by 73.4 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.

Our 2SLS estimates identify the effect of WFH for the compliers in our sample, i.e., the workers who WFH only because they are assigned to it via the rotation schedule, and who would not have chosen to do so otherwise (Imbens and Angrist, 1994). To contextualize these estimates, Table A.4 compares summary statistics for the workers in the analysis sample (column 1) and for the compliers (column 2). The two groups are remarkably similar, suggesting that compliers in our setting are not a particularly selected subgroup. This is perhaps unsurprising, given that compliers represent a large share–73.4%–of our sample (as shown in column 1 of Table 5).

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

5.2 Mechanisms

In this section, we explore some potential mechanisms underlying the productivity gains generated by WFH. We start by examining differences in assigned shift length and workers' perceived benefits and drawbacks of WFH. Building on these insights, we investigate specific factors that may contribute to higher productivity when working remotely–namely, reduced workplace distractions, the availability of a dedicated workspace at home, changes in work patterns, the absence of young children at home, improvements in mental and physical well-being, and differences in absenteeism.

Differences in Assigned Shift Length. If WFH shifts are, on average, longer than office shifts, part of the observed productivity increase may simply reflect longer working hours. To assess this, we estimate the effect of being assigned to WFH on shift length. Column 1 of Table A.5 shows that shifts in which workers are assigned to WFH are approximately 20 minutes longer (60×0.328). To ensure that our estimated productivity gains are not merely driven by longer shifts, we re-estimate model (1) controlling for shift length in columns 2–4. Crucially, we control for the *assigned* shift length and not the *actual* shift length–as the latter is an outcome variable and would constitute a "bad control" (Angrist and Pischke, 2009). After accounting for assigned shift length, the estimated productivity gains decrease from 8.9% (column 3 of Table 4) to 6.4% (column 2 of Table A.5), suggesting that roughly one-third of the effect is attributable to differences in assigned shift length.

Exploring Worker Perceptions of WFH Benefits and Drawbacks. To further understand the mechanisms behind the observed productivity gains, we analyze the 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% reporting no perceived drawbacks. The three most commonly cited benefits are avoiding the commute (87.7%), saving money (50%), and achieving a better work-life balance (42.1%).[5]

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

[5]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.

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.4 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 improve their concentration and productivity (see Appendix B for quotes). These insights align with the findings of Aksoy et al. (2025) and are supported by quantitative evidence: staff work faster at home (Panel C of Table 4) with no decline in the quality of their output (see next section for details). 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.

We next test more directly whether co-worker behavior in the office affects individual productivity. If background noise and distractions are key drivers of the WFH productivity gains, then productivity should decline with either (i) the number of co-workers present (due to increased noise) or (ii) the presence of particularly disruptive colleagues. While we cannot observe who is disruptive (e.g., talkative, loud, distracting, or prone to long breaks), these behaviors are likely reflected in lower office productivity. We therefore proxy disruptive co-workers as those in the bottom quartile of the $\widehat{\mu_i}^{\text{Assigned WFO}}$ distribution. To avoid common shocks that could mechanically induce a correlation between a worker's productivity and their peers' estimated productivity, we estimate $\widehat{\mu_i}^{\text{Assigned WFO}}$ excluding all observations from the calendar month in which the focal day occurs.

Exploiting the deterministic rotation schedule, we construct two variables: the number of co-workers assigned to the office on a given day, and the number of disruptive co-workers. We restrict the sample to days when workers are assigned to WFO and regress the log number of cases completed on either the total number of co-workers or the number of disruptive co-workers, controlling for worker and office fixed effects.

Panel A of Table A.6 reports the results. Column 1 indicates that the overall number of co-workers has a negative effect on productivity, albeit the coefficient is imprecisely estimated. Column 2 shows that being assigned to work alongside disruptive co-workers also significantly reduces productivity. Importantly, these results hold when controlling for both variables simultaneously (column 3): each additional co-worker reduces productivity by 3.6% (not statistically significant), while each additional disruptive co-worker reduces productivity by 6%.

As a placebo test, we examine whether the number of co-workers and the number of disruptive co-workers affect productivity when the focal worker is assigned to WFH. If the main mechanism operates through in-person distractions, we would expect no effect when the worker is not physically co-located with colleagues. Panel B of Table A.6 confirms this intuition: neither variable significantly affects productivity when the focal worker is working remotely.

While some interactions with colleagues may indeed be valuable, the overall evidence suggests that co-workers tend to generate negative externalities in the office—supporting the argument that in-person distractions are an important driver of the productivity gains of WFH.

Dedicated Workspace. Ninety-six percent of workers report having a dedicated workspace when working remotely. This pattern suggests that having a dedicated workspace may be one of the mechanisms driving the positive treatment effects we estimate. It also aligns with prior research showing large productivity gains from WFH in contexts where workers have access to an independent workspace (Bloom et al., 2015).

Changes in Work Patterns. WFH may also influence when workers begin and end their workday. To explore this, we construct four measures of working patterns: (i) an indicator for whether staff log any cases before the start of their assigned shift, (ii) an indicator for whether they continue working past the end of their assigned shift, (iii) standardized start time, which captures how quickly workers begin logging cases after their shift begins, and (iv) standardized end time, which captures how close to the end of their shift they log their final case. For example, a standardized start time of 20 indicates that the worker logged their first case 20 minutes after their shift began; a standardized end time of –20 means their last case was recorded 20 minutes before their shift ended. 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 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 working hours overall (Panel C in Table 4), suggesting that they may take more frequent or longer breaks during the day. The fact that staff begin their work day much more quickly when they are assigned to WFH is consistent with reduced distractions at home.

No Young Children. Working productively from home can be particularly challenging for individuals with young children at home (Adams et al., 2025). However, this does not appear to be a major concern in our context. 60% of workers in our sample report not

having any children, and among those who do, the average age of their children is 17 (Figure A.5). Only 5% of workers have children under the age of five. These figures suggest that childcare-related distractions are unlikely to be a significant driver of the productivity effects observed in our setting.

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. This result aligns with recent survey evidence where workers report that WFH 2 to 3.6 days per week would improve their mental health (Barrero et al. 2021, May 2025 update).

Absenteeism. While our main analysis focuses on the productivity effects of WFH on days when staff are working (i.e., the intensive margin), we also examine whether WFH influences absenteeism (i.e., the extensive margin). 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). Appendix Table A.7 investigates this relationship more formally by estimating the effect of being assigned to WFH on three outcomes: (i) an indicator for overall absence–defined as being scheduled to work but not logging any case; (ii) an indicator for medical absences; and (iii) an indicator for all other types of absences.[6] 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.8). 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.8). These results are in line with Bloom et al. (2015), who find that WFH reduces

[6]The reasons why a worker may not log any case on a given day are varied and include medical leave, other types of leave, secondments, triaging cases, training new hires, performing administrative duties, and being on vacation. Most staff are entitled to around 28 vacation days per year, which–if fully used, as anecdotal evidence suggests–would account for approximately 13.9% of total workdays and therefore a sizable share of observed absences.

sick days.

Summary. We conclude that, while some of the observed productivity gains can be attributed to differences in assigned shift length, the majority of the effect appears to stem from the reduction in workplace distractions that WFH provides, enabling staff to work more efficiently. Our findings are also consistent with additional mechanisms, including the presence of a dedicated workspace at home, improved mental health, and reduced stress levels when working remotely. Importantly, the results are not driven by differences in absenteeism or the presence of young children at home. One potential concern is that reduced workplace interactions–while beneficial for short-term productivity–may have adverse long-term effects on performance or skill development (Emanuel et al., 2023). However, this risk is likely mitigated in our context, as staff do not work fully remotely but instead spend approximately one-third of their time working from the office.

5.3 Alternative Explanations

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

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 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. Each month, supervisors audit at least two randomly selected cases per worker and assess them across a wide range of dimensions, scoring each from zero (lowest) to two (highest). These dimensions cover both interpersonal and procedural aspects–for example, whether the worker demonstrated strong soft skills, maintained appropriate telephone manners, and used effective questioning techniques, as well as whether all relevant forms were submitted, qualifiers were set correctly, and the outcome code was accurately recorded.

We aggregate these scores into a summary measure of quality using the same weighted average employed by GMP in their internal evaluations. We then assess whether work quality differs when workers are assigned to WFH versus WFO. Appendix Table A.9 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. Thus, the productivity gains associated with WFH do not appear to come at the expense of quality. This conclusion is consistent with anecdotal evidence from supervisors who regularly monitor and assess their teams' work.

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. Nonetheless, we formally test the robustness of our results by controlling for the characteristics of reported cases. Panel A of Appendix Figure A.6 compares our baseline estimates (blue bars) with those obtained by including these additional controls (orange bars). The results remain virtually unchanged, confirming that differences in case characteristics do not drive our findings.

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. Panel B of Appendix Figure A.6 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.

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 possess valuable information about which tasks are more amenable to remote work and leverage this information in making assignments. This results in larger productivity gains from WFH than those accrued when tasks are assigned randomly (column 2 in Table 5). To support this interpretation, we examine how supervisors allocate workers across workstreams and how this affects the productivity gains of WFH. Table A.13 shows that supervisors are significantly more likely to assign workers to outgoing calls (and, to a lesser extent, triaging) when they are WFH, and to incoming calls when they are in the office. We further explore this mechanism by restricting the sample to days when workers are assigned to either incoming or outgoing calls. Table A.14 shows that the productivity gains from WFH are substantially higher for outgoing calls (column 2) than for incoming calls (column 1), providing suggestive evidence that supervisors actively match workers to tasks that are better suited to the WFH environment.

A potential concern is that, if supervisors 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.7 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 assigning easier tasks to workers when they WFH.

Alternative Explanations: A New Computer System. A potential concern is that our estimated productivity effects may be confounded by the rollout of a new computer system in September 2022. To mitigate this, we exclude the first two months following the system's introduction from our "pre-period" sample. Additionally, Appendix Figure A.8 demonstrates that our results remain robust when excluding up to six months after the system change.

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).[7]

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).

[7]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.

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.[8] 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, tenure, 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.15 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. 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:

$$y_{it} = \delta_0 + \delta_1 T_i + \lambda_{\mathcal{S}(i)} + \tau_t + u_{it}, \tag{6}$$

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.[9] 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:

[8] Even if there were some sample selection, this would not affect the internal validity of our estimates.
[9] $\mathcal{S}(i)$ represents the team-by-shift stratum worker i is assigned to.

$$y_{it} = \delta_0 + \delta_1^{2SLS} WFH_{it} + \lambda_{T(i)} + \tau_t + u_{it}. \quad (7)$$

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).[10]

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 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.[11] 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.[12] A potential concern is that initial enthusiasm about working fully remotely could fade over time, potentially leading to declining productivity due to increased isolation. To explore this, we estimate model (6) separately for each calendar month, using the log number of cases as the outcome. Appendix Figure A.9 shows that there is no evidence of a downward trend in the treatment effects over time, indicating that full-time remote work does not lead to a progressive decline in productivity. Finally, we find no effect of working entirely from home on the probability that a worker is absent (Appendix Table A.17).

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

[10] 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).

[11] 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.

[12] For completeness, Appendix Table A.16 reports the 2SLS from model (7).

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 supervisors select 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 tasks are complex or creative, and the production requires teamwork and frequent interactions (Gibbs et al., 2023).

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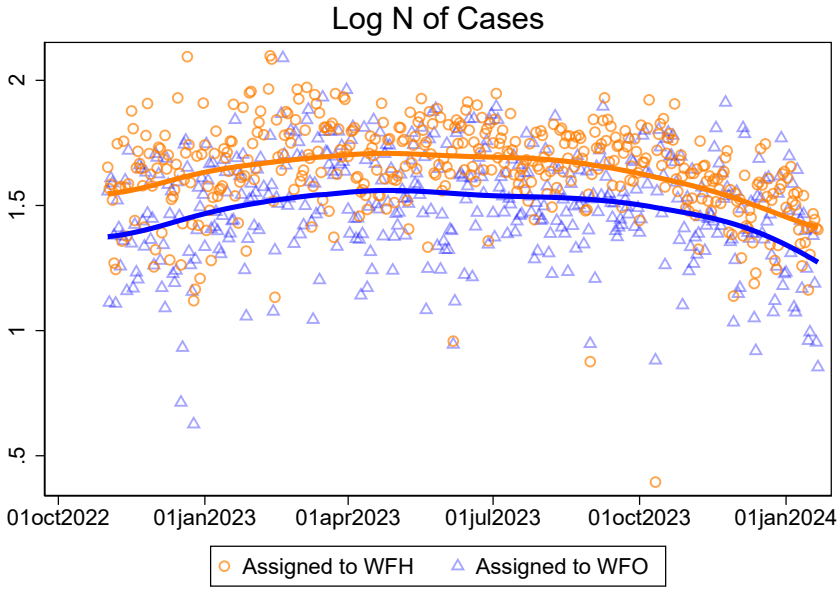
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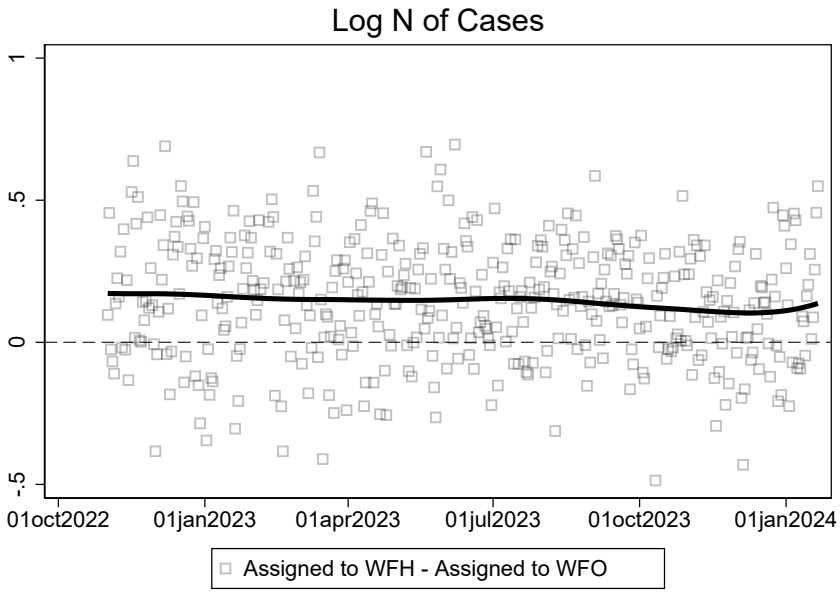
Weidmann, B., Vecci, J., Said, F., Deming, D. J., and Bhalotra, S. R. (2024). How do you find a good manager? Technical report, National Bureau of Economic Research.

9 Figures

Figure 1: Cases Recorded by Assigned Work Location



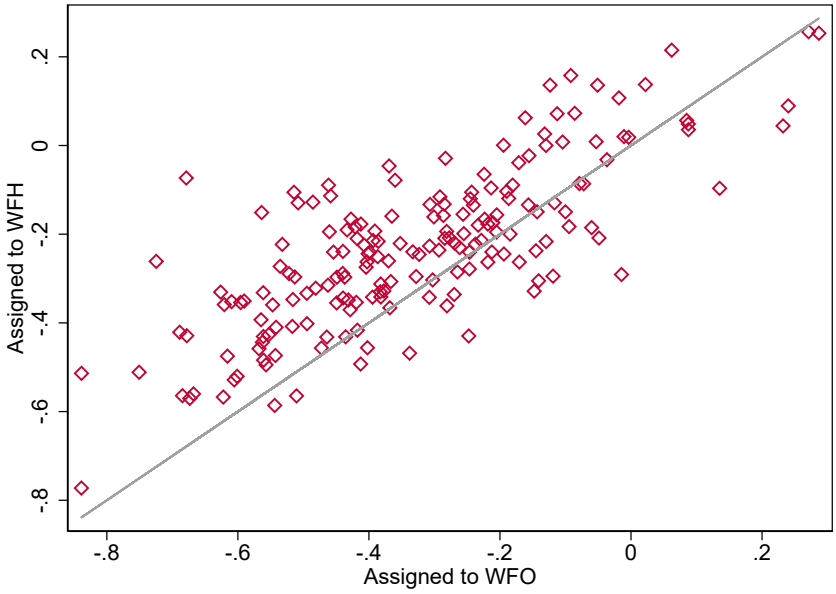
(a)



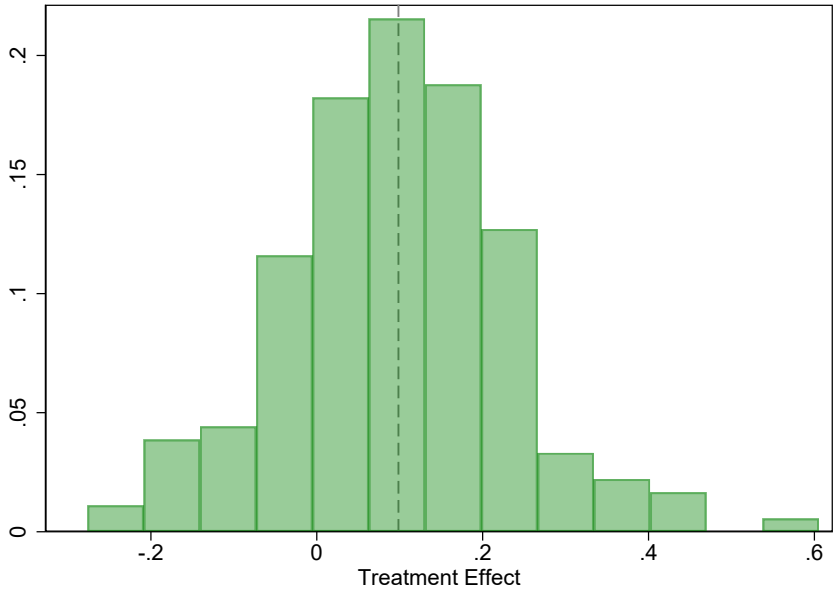
(b)

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



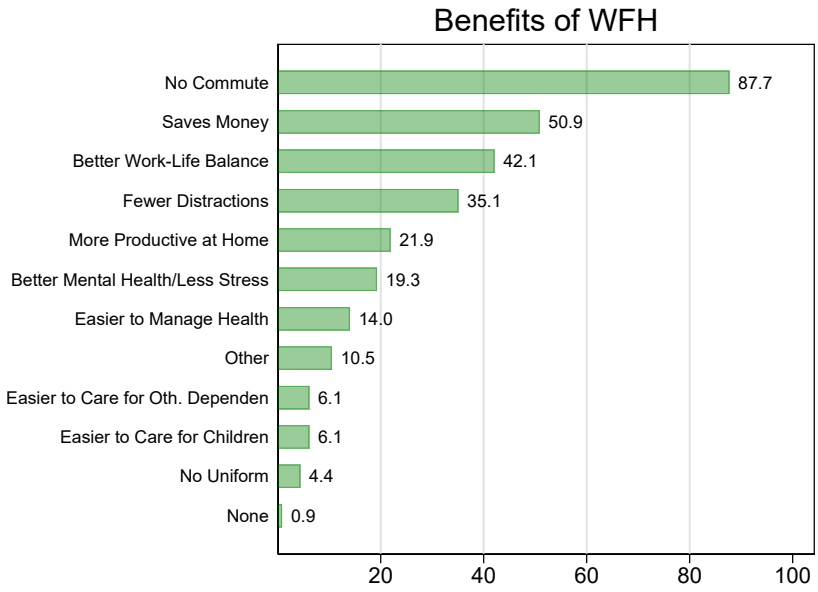
(a)



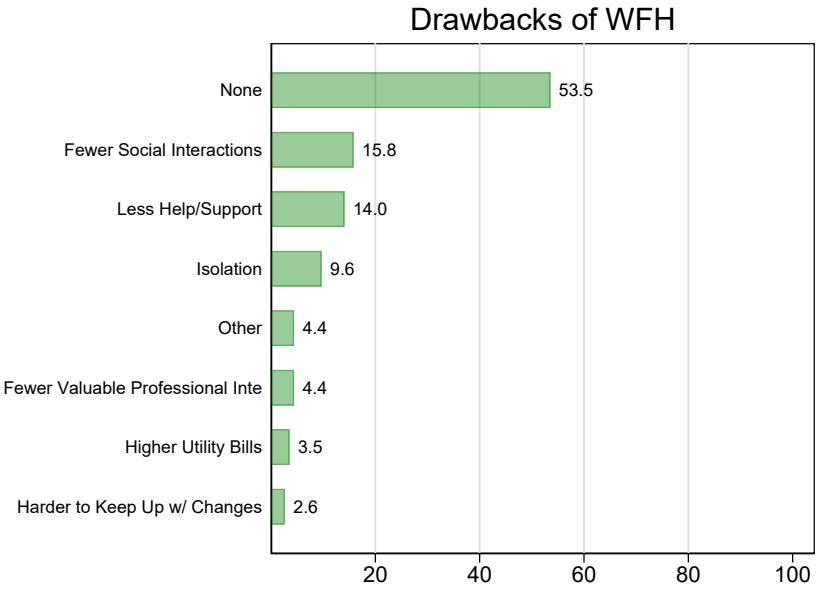
(b)

Notes: CRRU records (22 September 2023–21 January 2024). Panel A displays the estimated (shrunk) 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 (shrunk) 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
Tenure (years)	5.534	4.804	5.355	6.481
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
Tenure (years)	5.337	.156	.1629	.3395	8795
Covariate Index	1.519	.0014	.0016	.3591	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 and tenure. 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. * p<0.10, ** p<0.05, *** p<0.01.

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. * p<0.10, ** p<0.05, *** p<0.01.

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	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. * p<0.10, ** p<0.05, *** p<0.01.

Table 6: The Effects of WFH Assignment on Work Patterns

	(1) Work Before Shift	(2) Work After Shift	(3) Standardized Start Time (minutes)	(4) Standardized End Time (minutes)
Assigned to WFH	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. * p<0.10, ** p<0.05, *** p<0.01.

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
Tenure (years)	6.063	-.6933	1.197	.5635	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 (6)). SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

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 (6). 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. * p<0.10, ** p<0.05, *** p<0.01.

Online Appendix

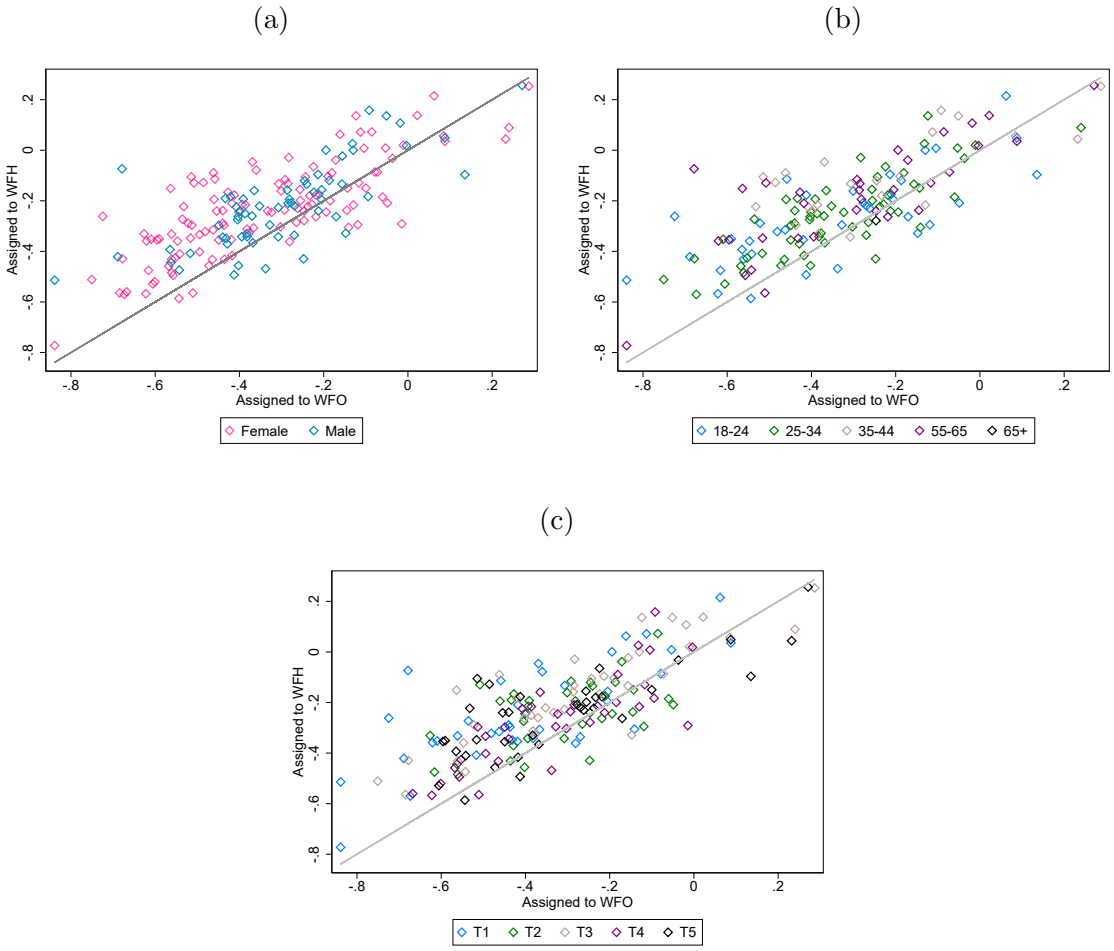
Appendix A Additional Figures and Tables

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.

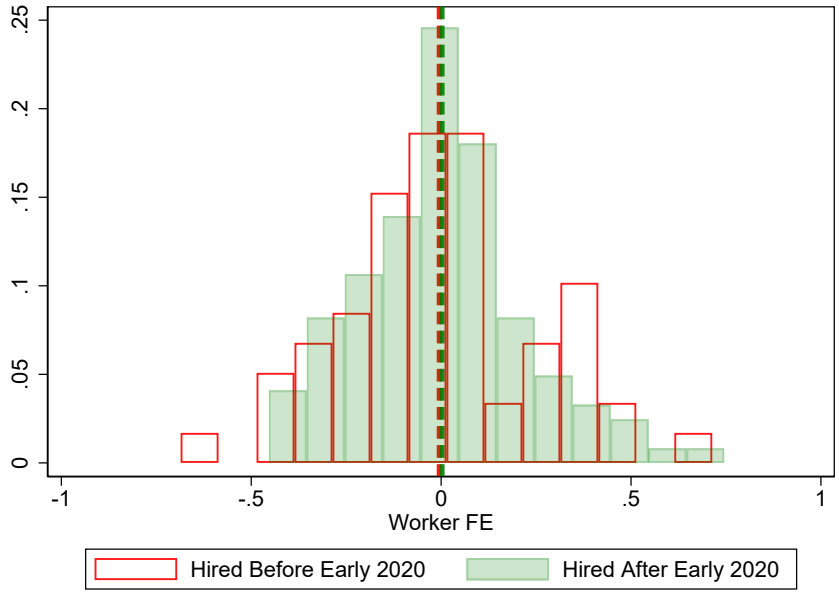
Figure A.2: Productivity Gains and Observable Characteristics



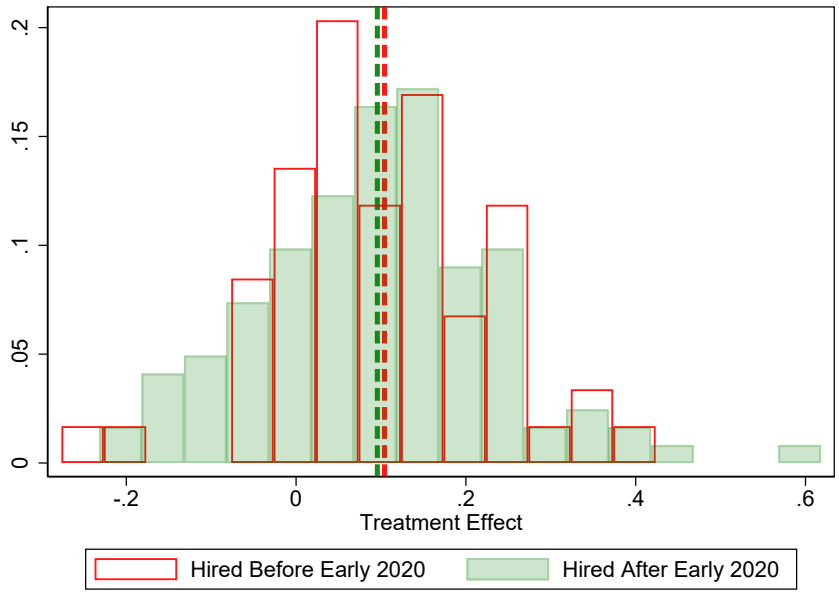
Notes: CRRU records (22 September 2023–21 January 2024). This figure displays the estimated (shrunk) worker fixed effects when assigned to WFH versus WFO, represented by diamonds, along with the 45-degree line for reference. The worker effects are estimated using model (3). Panels A–C explore heterogeneity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

Figure A.3: Selection into Remote Jobs

(a)



(b)



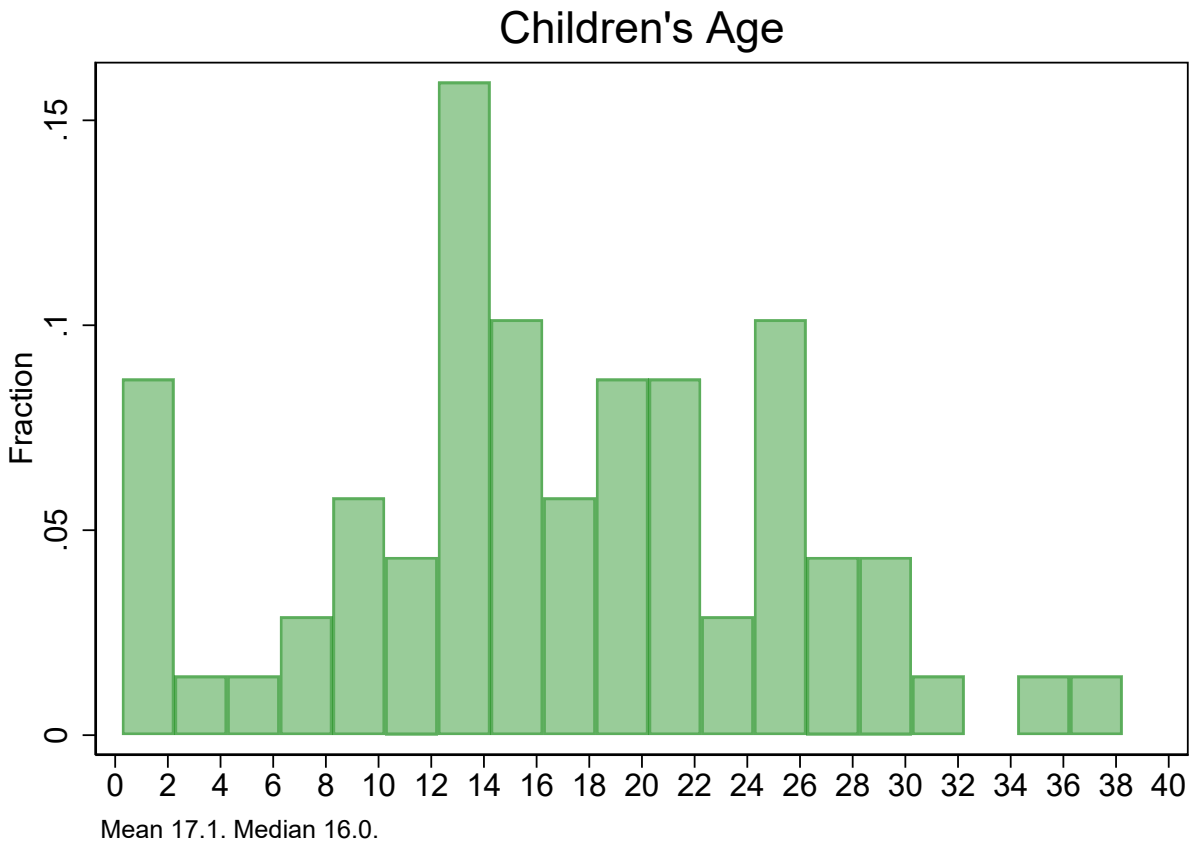
Notes: CRRU records (22 September 2023–21 January 2024). This figure examines whether workers sort into remote jobs based on either absolute or comparative advantage. Panel A displays the distribution of the estimated (shrunk) worker fixed effects, as defined in equation (5), by hiring date. The distribution for workers hired before early 2020 is shown in solid green bars, while that for workers hired after early 2020 is depicted with hollow red bars. The vertical dashed lines represent the mean worker fixed effect for each group. The difference in means is not statistically significant (p-value = 0.852). Panel B shows the distribution of the estimated (shrunk) Intent-to-Treat (ITT) treatment effects, as defined in equation (4), using the same legend as above. The vertical dashed lines indicate the average ITT for each group. Again, the difference in means is not statistically significant (p-value = 0.683).

Figure A.4: The Office



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

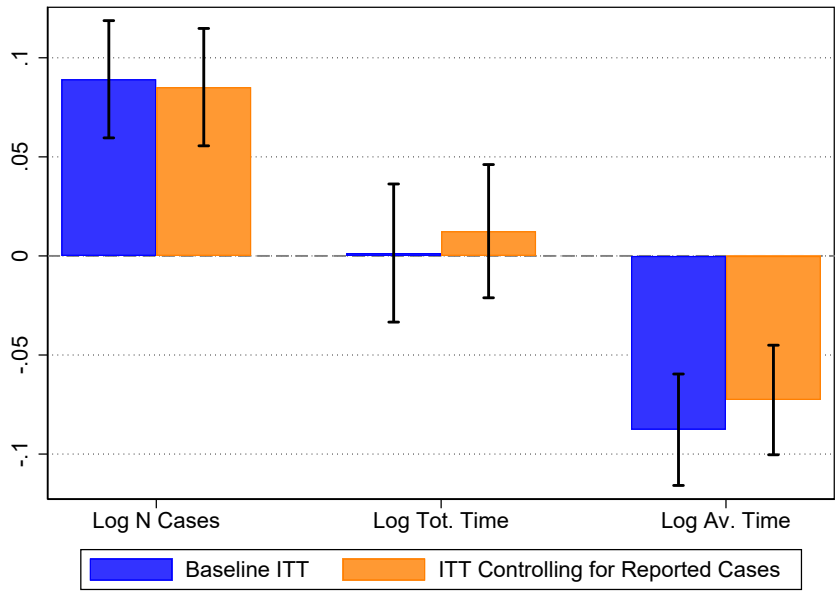
Figure A.5: Distribution of Children's Age



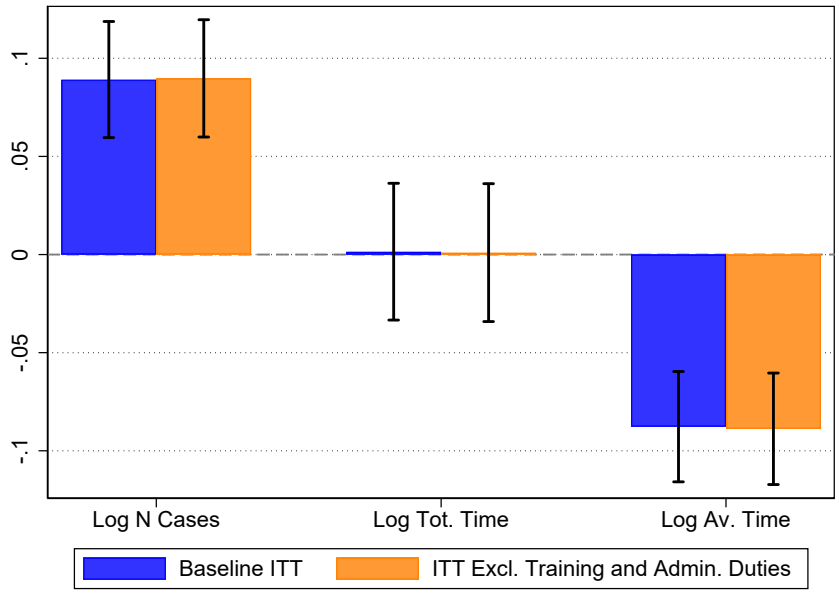
Notes: Survey (October 2024). This figure shows the distribution of children's ages, conditional on workers reporting that they have children.

Figure A.6: Robustness

(a)

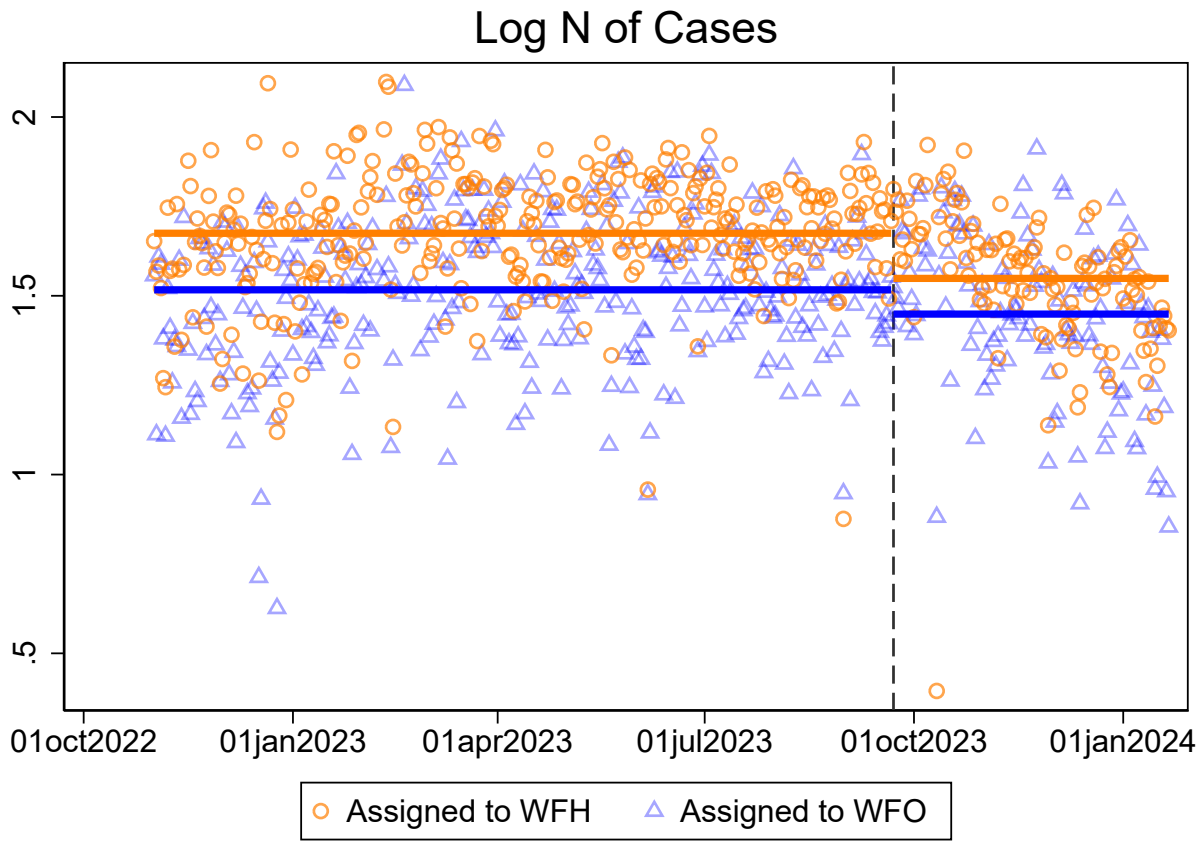


(b)



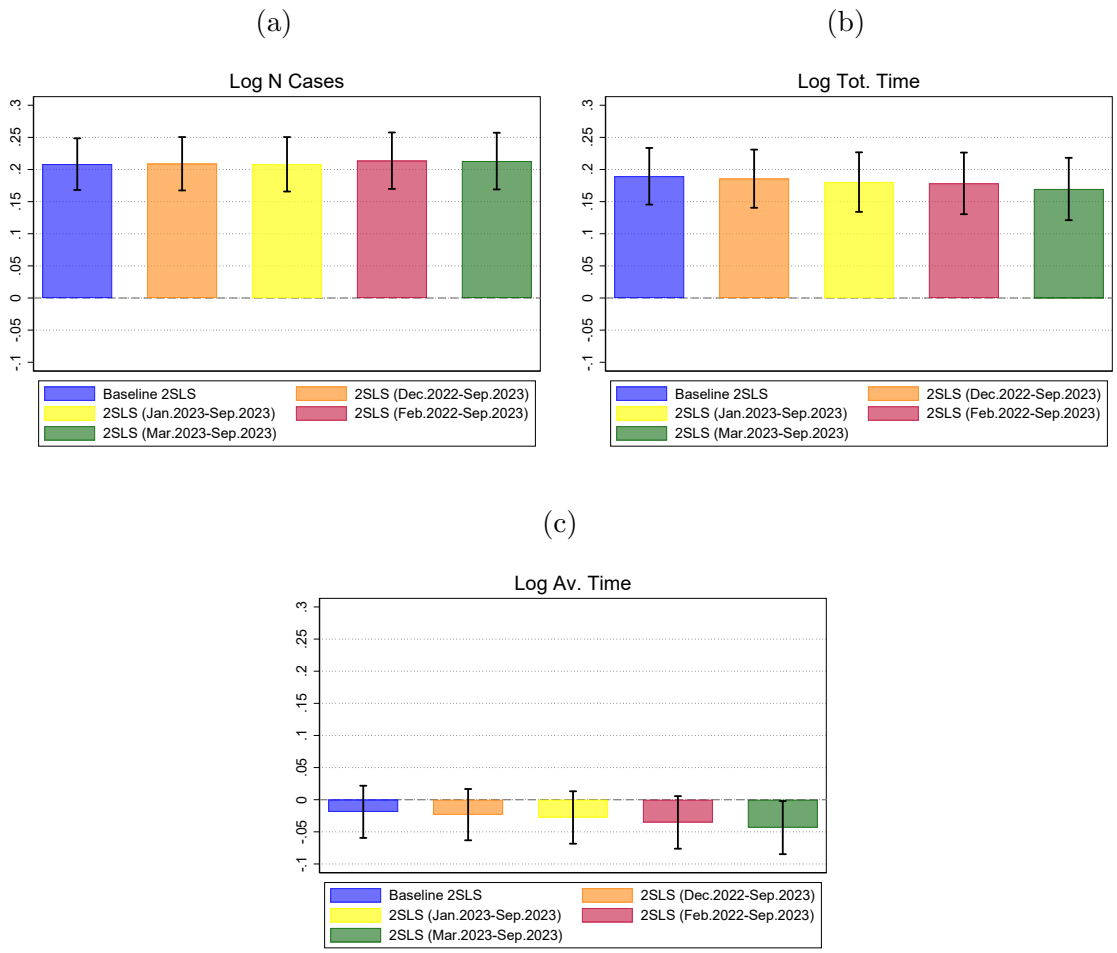
Notes: CRRU records (22 September 2023–21 January 2024). This figure presents the estimated coefficients β from model (1), along with 95% confidence intervals. The baseline Intent-to-Treat (ITT) estimates—identical to Column 3 of Table 4—are shown as blue bars in all panels for reference. Panel A compares the baseline estimates to those obtained when controlling for the characteristics of the reported cases. Panel B compares the baseline estimates to those obtained after excluding days in which workers were engaged in training or administrative duties. Standard errors are clustered at the worker level in all panels.

Figure A.7: Aggregate Trends in Cases Recorded by Assigned Work Location



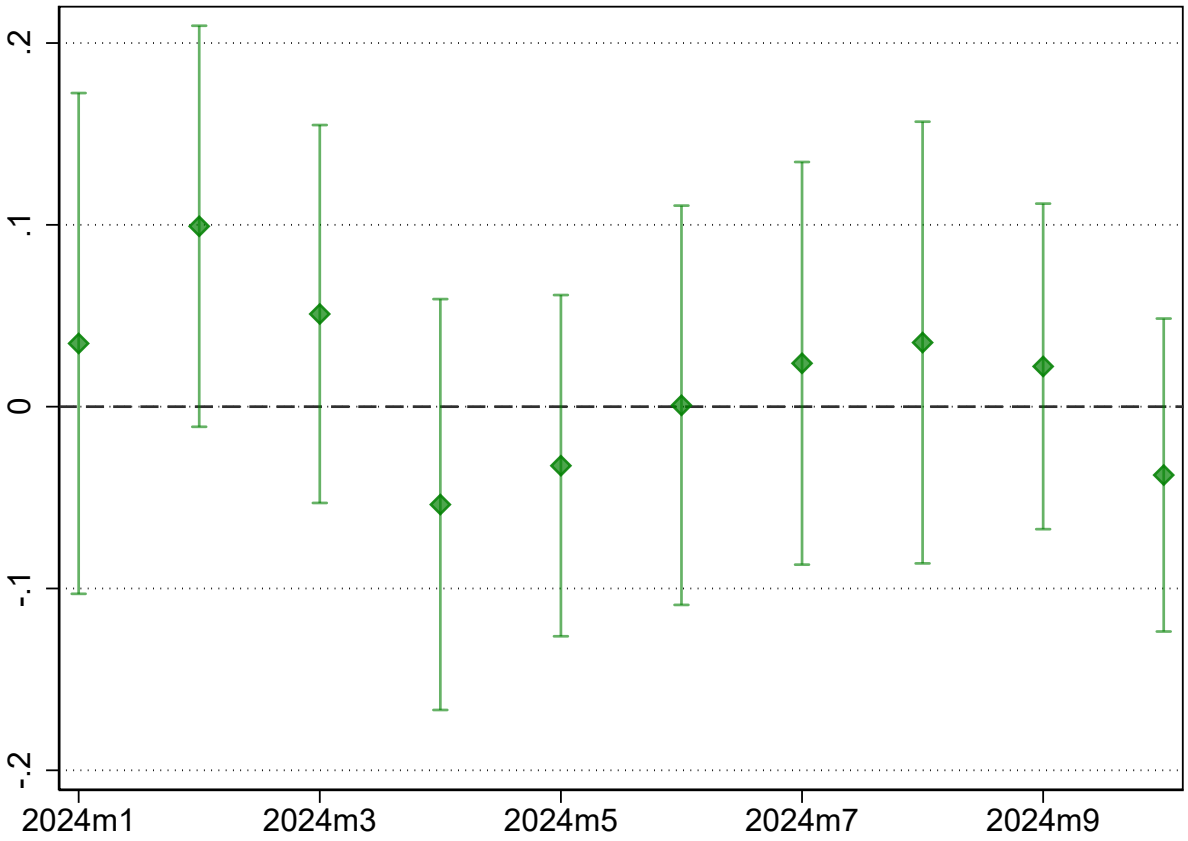
Notes: CRRU records (22 September 2023–21 January 2024). This figure illustrates aggregate productivity trends before and after 22 September 2023 – the date when task assignment shifted from supervisors to a computer algorithm. This Figure shows the logarithm of the average number of cases recorded per 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.

Figure A.8: Robustness to the Introduction of the New Computer System



Notes: CRRU records (1 November 2022–21 September 2023). This figure displays the estimated β^{2SLS} from model (2). The blue bars report our baseline 2SLS estimates in the pre-period (22 September 2023–21 January 2024), corresponding to Columns 2 through 4 in Table A.12. The remaining bars show the estimates obtained by progressively excluding one additional month from the beginning of the sample. Each panel corresponds to a different outcome variable: Panel A reports results for Log Number of Cases, Panel B for Log Total Time Spent Working, and Panel C for Log Average Time Spent per Case. Standard errors are clustered at the worker level.

Figure A.9: Regime Comparison: WFH vs. Hybrid by Month



Notes: CRRU records (22 January 2024–31 October 2024).This figure presents the estimates of δ and their associated 95% confidence intervals from model (6), estimated separately for each calendar month. The outcome variable is the log number of cases. Standard errors are clustered at the worker level.

Table A.1: Clustering

	(1) Log Cases	(2) Log Tot. Time	(3) Log Av. Time
Panel A: Baseline Estimates			
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. * p<0.10, ** p<0.05, *** p<0.01.

Table A.2: Estimated Treatment Effects and Observable Characteristics

	(1) Treatment Effect
Female	0.030
	(0.084)
Aged 25 to 34	0.014
	(0.087)
Aged 35 to 44	0.154*
	(0.074)
Aged 45 to 54	-0.016
	(0.080)
Aged 55 to 64	0.123
	(0.110)
Aged 65 or more	-0.115*
	(0.044)
Aged 25 to 34 × Female	-0.011
	(0.104)
Aged 35 to 44 × Female	-0.111
	(0.105)
Aged 45 to 54 × Female	0.046
	(0.103)
Aged 55 to 64 × Female	-0.013
	(0.128)
Tenure (years)	-0.007
	(0.019)
Female × Tenure (years)	0.032
	(0.024)
Aged 25 to 34 × Tenure (years)	0.018
	(0.030)
Aged 35 to 44 × Tenure (years)	-0.002
	(0.020)
Aged 45 to 54 × Tenure (years)	0.014
	(0.020)
Aged 55 to 64 × Tenure (years)	0.001
	(0.020)
Aged 25 to 34 × Female × Tenure (years)	-0.041
	(0.035)
Aged 35 to 44 × Female × Tenure (years)	-0.018
	(0.026)
Aged 45 to 54 × Female × Tenure (years)	-0.040
	(0.025)
Aged 55 to 64 × Female × Tenure (years)	-0.031
	(0.025)
N	181
R-squared	0.120

Notes: CRRU records (22 September 2023–21 January 2024). This table reports the estimated coefficients obtained by regressing the estimated (shrunk) treatment effects on observable worker characteristics. The omitted age category is "Aged 18 to 24". * p<0.10, ** p<0.05, *** p<0.01.

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. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: Complier Analysis – Rotation Schedule

	(1) Period 2: Analysis	(2) Compliers
Female	.661	.645
Age 18-24	.201	.206
Age 25-34	.307	.305
Age 35-44	.122	.133
Age 45-54	.175	.183
Age 55-65	.19	.172
Age over 65	.005	-
Tenure (years)	5.355	5.417
Team 1	.206	.194
Team 2	.201	.181
Team 3	.201	.188
Team 4	.19	.216
Team 5	.201	.221
Day Shift	.608	.488
	189	

Notes: CRRU records (22 September 2023–21 January 2024). Column 1 reports the summary statistics for the CRRU in the analysis period for comparability (same as column 3 in Table 2. Column 2 reports the characteristics of the compilers for the natural experiment that leverages the variation in WFH assignment introduced by the rotation schedule.

Table A.5: The Effects of WFH Assignment Controlling for Assigned Shift Length

	(1) Assigned Shift Length (hours)	(2) Log N Cases	(3) Log Tot. Time	(4) Log Av. Time
Assigned to WFH	0.328***	0.064***	-0.018	-0.082***
	(0.025)	(0.015)	(0.018)	(0.014)
N	8795	8795	8795	8795
R-squared	0.249	0.241	0.273	0.354
Control Mean	9.27	1.454	3.977	2.523
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Assigned Shift Length	Yes	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). Column 1 reports the estimated β from model (1). Columns 2–4 report the estimated β from model (1) controlling for assigned shift length. SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.6: The Effects of Co-Workers on Workers' Productivity

	(1) Log(N Cases)	(2) Log(N Cases)	(3) Log(N Cases)
Panel A: Assigned to WFO Days			
N Co-workers Assigned to WFO	-0.025		-0.036
	(0.026)		(0.026)
N Disruptive Co-workers Assigned to WFO		-0.055*	-0.060**
		(0.030)	(0.030)
N	2826	2826	2826
R-squared	0.334	0.335	0.336
Control Mean	1.454	1.454	1.454
Panel B: Assigned to WFH Days (Placebo)			
N Co-workers Assigned to WFO	-0.006		-0.006
	(0.006)		(0.008)
N Disruptive Co-workers Assigned to WFO		-0.007	-0.002
		(0.009)	(0.011)
N	5969	5969	5969
R-squared	0.232	0.232	0.232
Control Mean	1.551	1.551	1.551
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (22 September 2023–21 January 2024). Panel A restricts the sample to the set of days in which the workers are assigned to WFO. Panel B restricts the sample to the set of days in which workers are assigned to WFH, which serves as a placebo. The dependent variable is the logarithm of the number of cases in all regressions. All regressions include an overall constant and worker and day fixed effects. SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.7: The Effects 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. * p<0.10, ** p<0.05, *** p<0.01.

Table A.8: The Effects 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 on which the worker is assigned to work according to the rotation schedule but does not log any cases. SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.9: The Effects of WFH Assignment on Work Quality

	(1) Quality Score	(2) Quality Score	(3) Quality Score
Assigned to WFH	-0.005	-0.003	-0.011
	(0.009)	(0.009)	(0.009)
N	1921	1921	1921
R-squared	0.000	0.125	0.411
Control Mean	1.357	1.357	1.357
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. * p<0.10, ** p<0.05, *** p<0.01.

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
Tenure (years)	5.994	.1336	.1848	.4705	15967
Covariate Index	1.63	.0014	.0014	.3056	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 and tenure. 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. * p<0.10, ** p<0.05, *** p<0.01.

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. * p<0.10, ** p<0.05, *** p<0.01.

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. * p<0.10, ** p<0.05, *** p<0.01.

Table A.13: The Effects of WFH Assignment on Workstream Allocation (Pre-Period)

	(1) Incoming Calls	(2) Outgoing Calls	(3) Triage
Assigned to WFH	-0.482***	0.459***	0.023***
	(0.018)	(0.017)	(0.006)
N	11578	11578	11578
R-squared	0.354	0.378	0.230
Control Mean	.773	.16	.068
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: CRRU records (1 November 2022–10 August 2023). This table reports the estimated β from model (1). SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.14: The Effects of WFH Assignment on Workers' Productivity by Workstream (Pre-Period)

	(1) Incoming Calls Sample	(2) Outgoing Calls Sample
	Log(N Cases)	Log(N Cases)
Assigned to WFH	0.047***	0.159***
	(0.016)	(0.024)
N	5209	5435
R-squared	0.373	0.418
Control Mean	1.539	1.474
Worker FE	Yes	Yes
Day FE	Yes	Yes

Notes: CRRU records (1 November 2022–10 August 2023). This table reports the estimated β from model (1). Panel A restricts the sample to days when workers are assigned to incoming calls. Panel B restricts the sample to days when workers are assigned to outgoing calls. SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.15: 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. * p<0.10, ** p<0.05, *** p<0.01.

Table A.16: 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 (7). SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.17: 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 (6). Columns 1-4 report the reduced form (RF). SE clustered at the worker level. * p<0.10, ** p<0.05, *** p<0.01.

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."