Centre for Economic Performance

Discussion Paper

ISSN 2042-2695

No. 2036
September 2024

Not incentivized yet efficient: Working from home in the public sector

Alessandra Fenizia
Tom Kirchmaier

THE LONDON SCHOOL OF ECONOMICS AND POLITICAL SCIENCE

Economic and Social Research Council

Abstract
This paper studies whether working from home (WFH) affects workers' performance in public sector jobs. Studying public sector initiatives allows us to establish baseline estimates on the impact of WFH net of incentives. Exploiting novel administrative data and plausibly exogenous variation in work location, we find that WFH increases productivity by 12%. These productivity gains are primarily driven by reduced distractions. They are not explained by differences in quality, shift length, or task allocation. The productivity gains more than double when tasks are assigned by the supervisor.

Keywords: working from home, productivity, public sector
JEL: D23; J45; L23; M54

This paper was produced as part of the Centre's Community Wellbeing Programme. The Centre for Economic Performance is financed by the Economic and Social Research Council.

We thank Ricky Wong for excellent research assistance. Also, many thanks to ACC Chris Sykes and many others at Greater Manchester Police for supporting us wholeheartedly in this project, and to Ian Wiggett to provide most helpful comments (as a former ACC at GMP). All errors are our own.

Alesandra Fenizia, The George Washington University and NBER. Tom Kirchmaier, Centre for Economic Performance, London School of Economics

Published by
Centre for Economic Performance
London School of Economic and Political Science
Houghton Street
London WC2A 2AE

1 Introduction

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

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

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

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

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

In this paper, we exploit the plausibly random source of variation in work location introduced by the rotation schedule to compare the performance of the CRRU workers assigned to WFH vs. WFO. We corroborate the argument that the rotation schedule generates plausibly random variation in work location by showing that being assigned to WFH does not predict the demographic characteristics of the police staff on duty on a given day. To quantify the benefits of a human vs. machine, we exploit two competing set-ups, one where a computer randomly allocates cases and another where a human performs this task. In the former, staff record an additional half case per day – a 12% increase in productivity – when WFH. In the latter, staff record an additional 1.5 cases per day, albeit from a different baseline.

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

In addition, we observe worker-idiosyncratic performance variation (i.e., some workers are better than others). Our within-worker design allows us to estimate location-specific worker effects and – as expected – establish that they are highly correlated. This also challenges the widely held belief that some people are particularly suited to WFH. Interestingly, observable worker characteristics explain little of this heterogeneity.

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

We contribute to the literature in three fundamental ways. First, we provide the underpinning parameters to the WFH literature by estimating the effect of WFH net of incentives and based on a semi-routine task. Second, we show that humans outperform machines in allocating tasks in our setting. Third, our within-worker design allows us to disentangle the underlying workers' productivity under different working arrangements.

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

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

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

2 The Crime Recording and Resolution Unit

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

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

The Rotation Schedule. Each staff member is assigned to one of five teams and one of two shift patterns. All staff work 4 to 5 days per week, Monday through Sunday, depending on the rotation schedule. The staff on the "day shift pattern" cover shifts between 07:00 and 21:00, while those on the "24/7 shift pattern" cover both day and night shifts. All teams follow a rotation schedule that determines their shifts (e.g., 08:00 to 18:00) and whether they work from home each day. Panel A of Table 1 reports the rotation schedule for staff assigned to the day shift pattern. In week 1 of the rotation schedule, they work entirely from home. They work from 08:00 to 18:00 on Mondays and Tuesdays and from 11:00 to 21:00 on Fridays, Saturdays, and Sundays. In week 2, staff work entirely from the office and cover the shifts between 07:00 and 17:00 on Thursdays and Fridays, 10:00 to 18:00 on Saturdays and Sundays. Weeks 3 to 5 work similarly. Every five weeks, the pattern repeats. All staff on the "day shift pattern" cycle through this 5-week pattern but are on different weeks in the schedule depending on their assigned team. At the beginning of time, team 1 started their schedule from week 1; team 2 started from week 2, and so on and so forth. Panel B reports the rotation schedule for workers assigned to the 24/7 shift pattern. The rotation works similarly, with the only difference being that their rotation pattern repeats every 10 weeks. New hires are mandated to WFO for the first six months, which is much longer than the expected training period, and hence the rotation schedule does not apply.

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

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

Measures of Performance. We measure workers' productivity as the number of cases they record per day. This measure captures the volume of crimes or incidents they handle every day but does not (currently) capture the quality of their work. We proxy for quality using the average time spent on each case and interpret consistently lower average times per case as an indication of a rushed job.

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 as well as the length of the queue when the workers are on duty. Police staff face the same incentives whether they work from the office or from home.

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

3 Data

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

Daily Records. We use the records of the CRRU from 1 November 2022 to 31 August 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.

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

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 additional RCT experiment was rolled out. Lastly, the experiment period (period 3) ranges from 22 January 2024 to 31 August 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% of them are female and 52% of them are below age 34 (column 1). Very few police staff are older than 65, reflecting the typical retirement age of public sector workers. Police staff are roughly equally split across the 5 teams, and 60% 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 57 staff on duty; 73% of them are assigned to WFH, and approximately 67% of them actually do (column 1). Staff jointly record roughly 349 cases per day and spend 4,976 minutes recording them. The average member of staff records about 6 cases per day and takes about 17 minutes each. This amounts to an average of 91 minutes spent actively recording cases per day. These statistics are fairly constant over time, with two notable exceptions: First, the average time spent recording a case was 22.4 minutes in period 1 and decreased to approximately 11-15 minutes per case in periods 2 and 3. This decline was partly driven by staff becoming increasingly familiar with the new computer platform initially introduced in September 2022. Second, the average number of full-time staff was 50 in the pre-period, increased to about 74 in the analysis period, and was 57 workers in the experiment period. The increase in the number of staff between periods 1 and 2 is driven by more and more workers being phased in on the computer system, as well as new hires. The average number of staff decreases between periods 2 and 3 because not all staff volunteered to be part of the experiment (refer to Section 6.1 for details).

The most common type of offense recorded at the CCRU is violence against the person (44.9%), closely followed by theft (32.7%). The remaining offences 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 typically not 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 daily average number of claims processed by staff assigned to WFH (orange circles) and those assigned to WFO (blue triangles). The former is consistently higher than the latter. Panel B depicts the difference between the two. These mean daily differences are positive and essentially stable over time. Next, we describe the empirical strategy and we explain how we use the variation illustrated in Figure 1 in our regression analysis.

We estimate the following reduced-form model:

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

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

To estimate the effect of WFH on workers' performance, we use an instrumental variable strategy where we instrument *actual* work location (WFH$_{it}$) with *assigned* work location

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

(Assigned to WFH_{it}). Our estimating equation becomes:

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

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

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

No Selection on Worker Characteristics. The rotation schedule forces all staff to alternate WFH and WFO deterministically. Hence, we expect all workers to be equally likely to be assigned to WFH. We evaluate this argument by regressing workers' characteristics and a covariate index on a constant and the WFH assignment dummy. Panel A of Table 3 reports the results. Column 1 shows the control mean, and columns 2-4 report the 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 test whether case characteristics jointly predict assigned work location by regressing 'Assigned to WFH' on case characteristics and worker and day fixed effects and test 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 report the estimated coefficients and standard errors obtained by clustering the standard errors at the team level. Our results survive clustering.

Panel A shows that when the workers are assigned to WFH, they record – depending on the specification – between 0.46 and 0.52 additional cases per day. This amounts to a 9% to 10% increase in productivity (0.46/5.24 and 0.52/5.24). These estimates reflect 'standard labor productivity' and are likely to be an underestimate of 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, nor do they spend longer on each case. The fact that WFH does not affect the time workers spend on each case 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 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.

Heterogeneity. WFH is likely to not suit everyone equally. To explore the productivity gains associated with WFH we regress the number of cases processed per day on day fixed effects and worker fixed effects interacted with WFH assignment. The interacted worker effects estimate the underlying productivity of workers when assigned to the two work regimes. Figure 2 plots the estimated worker effects when assigned to WFH vs. WFH as well as the 45-degree line. If all workers were equally productive under these two working arrangements, all diamonds would align on the 45-degree line. Three patterns stand out. First, these two sets of fixed effects are highly correlated (correlation coefficient=0.77). In other words, workers who are highly productive at home are also highly productive at the office. Second, there is tremendous heterogeneity in workers' productivity conditional on each working arrangement. Third, most workers are more productive when assigned to WFH than WFO (i.e., most diamonds are above the 45-degree line). Appendix Figure A.2 correlates workers' productivity with observable workers' characteristics and shows that, while the gains from WFH are heterogeneous across workers, no obvious group of workers is ill-suited for this work arrangement. Overall, observable worker characteristics explain 3% to 9% of the variation in workers' productivity (Table A.2).

2SLS. To evaluate whether WFH affects workers' productivity, we estimate model (2) instrumenting actual WFH with WFH assignment. Column 1 of Table 5 reports the first stage results while columns 2–4 report the 2SLS estimates.[2] Being assigned to WFH increases the probability of WFH by 73 percentage points (column 1). The WFH assignment is highly predictive of work location and the first-stage F statistic is equal to 1,254.81, well above the threshold for weak instruments. WFH increases workers' productivity by 0.624 cases per day (a 12% increase in productivity) and does not impact the total time spent recording cases or the time spent on each of them.

5.2 Mechanisms

In this section, we test two potential mechanisms: reduced distractions when WFH and changes in work patterns.

Reduced Distractions. Anecdotally, the office atmosphere is convivial. Police staff often exchange pleasantries with their colleagues, take a break to chat over a cup of coffee ('brew'), or smoke a cigarette. While these interactions may be valuable, they may also distract workers and reduce their productivity. We evaluate whether reduced distractions when WFH are a driver of the estimated productivity gains by exploiting the fact that workers cover both day and night shifts. As fewer staff are on duty during night shifts than on day shifts, night shifts offer fewer distractions. If reduced distractions when WFH were to be an important driver of the productivity gains from WFH, we would expect workers to be more productive during the night and productivity gains from WFH to be higher during night than during day shifts. We test this claim by augmenting model (1) with an indicator for night shifts and the interaction between night shifts and assignment to WFH. Table 6 reports

[2] Appendix Table A.3 reports the OLS estimates obtained by regressing the outcomes of interest on the WFH dummy.

the results. Column 1 shows that workers are more productive during night shifts and that the productivity gains from WFH are larger at night, suggesting that reduced distractions are an important mechanism in our setting. While night shifts do not appear to have any appreciable effect on the total number of minutes worked (column 2), staff is marginally faster during night shifts when assigned to WFH (column 3).

Changes in Work Patterns. WFH may also affect when workers begin work, or stop for the day. To this end, we construct four measures of working patterns: an indicator for whether staff log any cases before the beginning of their shift, an indicator for whether staff work past the end of their shift, a measure of how quickly they start working at the beginning of their shift (i.e., the number of minutes between the first case they log in and the beginning of their shift), and a measure of whether they keep on working until the very end of their shift (i.e., the number of minutes between the last case they log and the end of their shift). When the difference between the time of the first logged case and the beginning of the shift is positive (negative), this means that the worker logged their first case after (before) the beginning of their shift. Similarly, when the difference between the time of their last logged case and the end of the shift is positive (negative), this means that the staff worked (did not work) past the end of their shift. Table 7 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). The fact that staff start their work day much more quickly when they are assigned to WFH is consistent with reduced distractions at home.

We conclude that we find evidence that WFH generates productivity gains in our setting thanks to the reduced distractions that WFH offers. One concern is that reduced interaction may generate some short-term productivity gains but have long-term negative impacts on workers' productivity (Emanuel et al., 2023). The potential negative impact of reduced interactions is likely to be mitigated in our setting as staff does not work entirely remotely and work from the office about a third of the time.

5.3 Alternative Explanations

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

Differences in Shift Length. One concern is that if WFH shifts are longer on average, workers may work longer hours and, as a result, process more cases. If this were the case, then the differences in productivity would be attributable to differences in shift lengths rather than work location. Because our estimated productivity gains are not driven by staff working longer hours, it is unlikely that differences in shift lengths explain the bulk of our productivity gains. To address this concern more formally we measure the length of the shifts the workers are assigned to (e.g., 08:00 to 18:00) and regress it on WFH assignment, controlling for day and worker fixed effects. Column 1 of Table Appendix A.4 shows that WFO shifts are 9 hours and 15 minutes long (control mean) and WFH shifts are, on average, 20 minutes longer (0.328×60). Columns 2–4 report the estimated impact of WFH assignment when controlling for assigned shift length. Importantly, we control for the *assigned* shift length and not the *actual* shift length, which is an outcome in and of itself and would be a "bad control" (Angrist and Pischke, 2009). Our results are robust to the inclusion of this additional control, albeit the estimated impact of WFH assignment on the number of cases recorded is marginally smaller.

Differences in Tasks. Another 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 systematically different tasks when assigned to WFH then this would translate into differences in case characteristics. Panel B of Table 3 shows that there is no evidence that staff record different types of cases when assigned to WFH vs. WFO.

Differences in the Characteristics of Reported Cases. One may be concerned that the types of cases that are *reported* during shifts when workers are assigned to WFH may differ from those reported when they are assigned to WFO and that the differences in the characteristics of reported cases may confound our estimates. This is unlikely to be an issue in our setting because all staff draw cases from the same queues, and the rotation schedule ensures that at each point in time there are workers assigned to both WFH and WFO. Nevertheless, we test whether our estimates are robust to controlling for the characteristics of *reported* cases. Appendix Table A.5 reports the results and shows that our estimates are unaffected by including these additional controls.

Differences in Quality. Another concern may be that the increase in workers' productivity associated with WFH may come at the cost of lower quality. While we do not have any direct measure of quality, we can measure how long workers take to record each case. If the workers were to take substantially less time to record cases when assigned to WFH, this would be an indication of a rushed job. Panel C of Table 4 shows no difference in how much time workers spend on each case when assigned to WFH vs. WFO. The productivity gains associated with WFH do not seem to come at the cost of lower quality. This is also in line with the anecdotal evidence reported by the workers' supervisors who regularly oversee their work.

6 Regime Comparison: Home vs. Hybrid

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

6.1 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).[3]

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

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

If the staff who volunteered to be part of the experiment were a selected sample of the CRRU workers, this may affect the extent to which the estimates presented in Section 5 are directly comparable with those reported in Section 6.[4] 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 who are part of the experiment (columns 3 and 4 of Table 2). The gender, age, and team distribution of these two groups are very similar. Second, we estimate our baseline results 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.

[3] 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.

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

Table A.6 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, we feel comfortable to directly compare the estimates presented in Section 5 with those in Section 6.

6.2 Empirical Strategy

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

$$y_{it} = \delta_0 + \delta_1 T_i + \lambda_{\mathcal{S}(i)} + \tau_t + u_{it}, \tag{3}$$

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 $\lambda_{\mathcal{T}(i)}$ represent the day and the team-by-shift pattern (strata) fixed effects, respectively.[5] We cluster standard errors at the worker level. The main parameter of interest is δ_1, which identifies the causal impact of working entirely from home (treatment) relative to a hybrid regime (status quo). Because of non compliance, δ_1 is an ITT.

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

$$y_{it} = \delta_0 + \delta_1^{2SLS} WFH_{it} + \lambda_{T(i)} + \tau_t + u_{it}. \tag{4}$$

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 8 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).[6]

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

[6] 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).

6.3 Experimental Results

Table 9 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 20.7 percentage points (pp) (column 1). This coefficient is large in magnitude and highly statistically significant.[7] 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.[8]

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

7 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 Table A.8). However, if supervisors assign tasks to workers based on their work location, we would expect the case characteristics to be correlated with work location. Table A.8 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. Table A.9 reports the results. When supervisors match workers to tasks, the gains from WFH are more than twice as large as those accrued when the computer makes the assignment. When assigned to WFH, workers record an additional case per day and spend, on average, 17 additional minutes recording cases.

We estimate model (2) via 2SLS instrumenting WFH with WFH assignment to evaluate whether WFH affects workers' productivity. Table A.10 reports the results. WFH increases

[7] 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 20.7pp is lower than the 25pp, it implies that we do not observe perfect compliance.

[8] For completeness, Table A.7 reports the 2SLS from model (4).

workers' productivity by 1.5 cases per day ($\approx 28\%$) and the time worked by 22.8 minutes, but does not impact the average time spent on each case.

While these estimates are unlikely to capture the causal impact of WFH, they are important as they suggest that supervisors know their subordinates' comparative advantages and use this information to assign tasks to workers. This results in larger productivity gains from WFH than those accrued when tasks are assigned randomly (column 3 of Table 4). This finding is 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 that organizations can use to harness the benefits of WFH.

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 13% under random allocation, which more than doubles once a human selects tasks that best suit a worker's comparative advantage.

We find that WFH increases workers' productivity and that this does not come at the cost of lower quality. Increasing the fraction of time spent WFH does not seem to offer additional productivity benefits or generate additional costs relative an 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 taking into account the fact that working from home also saves workers commuting costs and time and allows organizations to save money by reducing the necessary office space.

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

References

Adhvaryu, A., Kala, N., and Nyshadham, A. (2022). Management and shocks to worker productivity. *Journal of Political Economy*, 130(1):1–47.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., and Zarate, P. (2022). Working from home around the world. Technical report, National Bureau of Economic Research.

Angelici, M. and Profeta, P. (2024). Smart working: work flexibility without constraints. *Management Science*, 70(3):1680–1705.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Atkin, D., Schoar, A., and Shinde, S. (2023). Working from home, worker sorting and development (no. w31515).

Bandiera, O., Barankay, I., and Rasul, I. (2009). Social connections and incentives in the workplace: Evidence from personnel data. *Econometrica*, 77(4):1047–1094.

Barrero, J. M., Bloom, N., and Davis, S. J. (2020). 60 million fewer commuting hours per day: How americans use time saved by working from home. *University of Chicago, Becker Friedman Institute for Economics Working Paper*, (2020-132).

Barrero, J. M., Bloom, N., and Davis, S. J. (2023). The evolution of work from home. *Journal of Economic Perspectives*, 37(4):23–49.

Battiston, D., Blanes i Vidal, J., and Kirchmaier, T. (2021). Face-to-face communication in organizations. *The Review of Economic Studies*, 88(2):574–609.

Battiston, D. E., Vidal, B. I., Kirchmaier, T., Szemeredi, K., et al. (2023). Peer pressure and manager pressure in organisations.

Bloom, N., Davis, S. J., and Zhestkova, Y. (2021). Covid-19 shifted patent applications toward technologies that support working from home. In *AEA Papers and Proceedings*, volume 111, pages 263–266. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Bloom, N., Han, R., and Liang, J. (2022). How hybrid working from home works out. Technical report, National Bureau of economic research.

Bloom, N., Liang, J., Roberts, J., and Ying, Z. J. (2015). Does working from home work? evidence from a chinese experiment. *The Quarterly journal of economics*, 130(1):165–218.

Choudhury, P., Foroughi, C., and Larson, B. (2021). Work-from-anywhere: The productivity effects of geographic flexibility. *Strategic Management Journal*, 42(4):655–683.

Choudhury, P., Khanna, T., Makridis, C. A., and Schirmann, K. (2024). Is Hybrid Work the Best of Both Worlds? Evidence from a Field Experiment. *The Review of Economics and Statistics*, pages 1–24.

Dutcher, G. and Saral, K. (2022). Remote work and team productivity.

Emanuel, N. and Harrington, E. (2024). Selection, treatment, and the market for remote work. Technical report.

Emanuel, N., Harrington, E., and Pallais, A. (2023). The power of proximity to coworkers: training for tomorrow or productivity today? Technical report, National Bureau of Economic Research.

Gibbs, M., Mengel, F., and Siemroth, C. (2023). Work from home and productivity: Evidence from personnel and analytics data on information technology professionals. *Journal of Political Economy Microeconomics*, 1(1):7–41.

Harrington, E. and Kahn, M. E. (2023). Has the rise of work-from-home reduced the motherhood penalty in the labor market.

Kandel, E. and Lazear, E. P. (1992). Peer pressure and partnerships. *Journal of political Economy*, 100(4):801–817.

Künn, S., Seel, C., and Zegners, D. (2022). Cognitive performance in remote work: Evidence from professional chess. *The Economic Journal*, 132(643):1218–1232.

Lazear, E. P., Shaw, K. L., and Stanton, C. T. (2015). The value of bosses. *Journal of Labor Economics*, 33(4):823–861.

Mas, A. and Moretti, E. (2009). Peers at work. *American Economic Review*, 99(1):112–145.

Mas, A. and Pallais, A. (2020). Alternative work arrangements. *Annual Review of Economics*, 12(1):631–658.

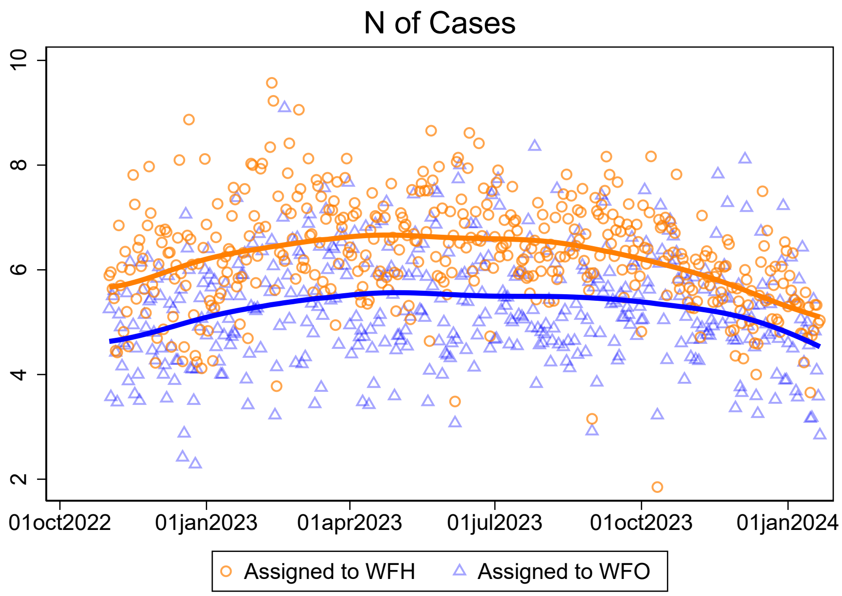
Morikawa, M. (2023). Productivity dynamics of remote work during the covid-19 pandemic. *Industrial Relations: A Journal of Economy and Society*, 62(3):317–331.

Otero, C. and Munoz, P. (2022). Managers and public hospital performance. *University of California, Berkeley*.

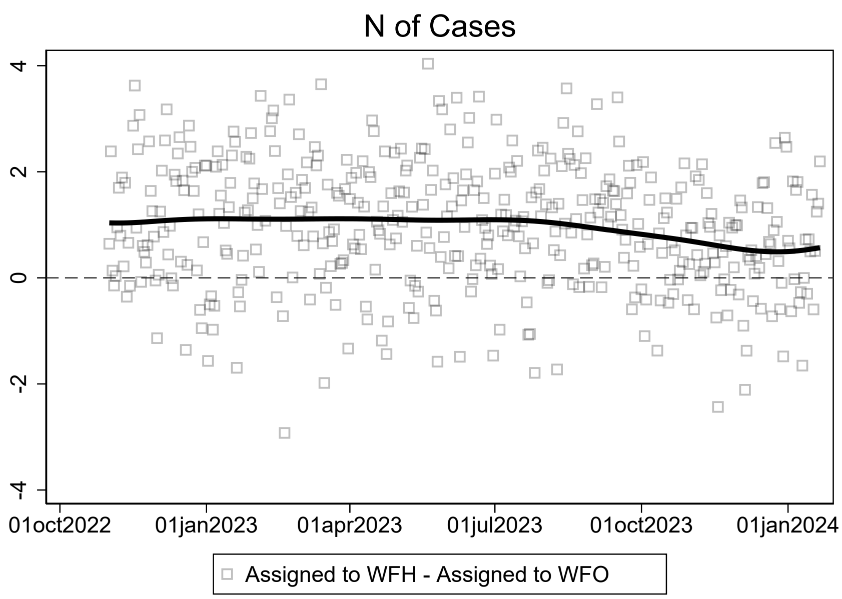
Silver, D. (2021). Haste or waste? peer pressure and productivity in the emergency department. *The Review of Economic Studies*, 88(3):1385–1417.

9 Figures

Figure 1: Cases Recorded by WFH vs. WFO Assignment



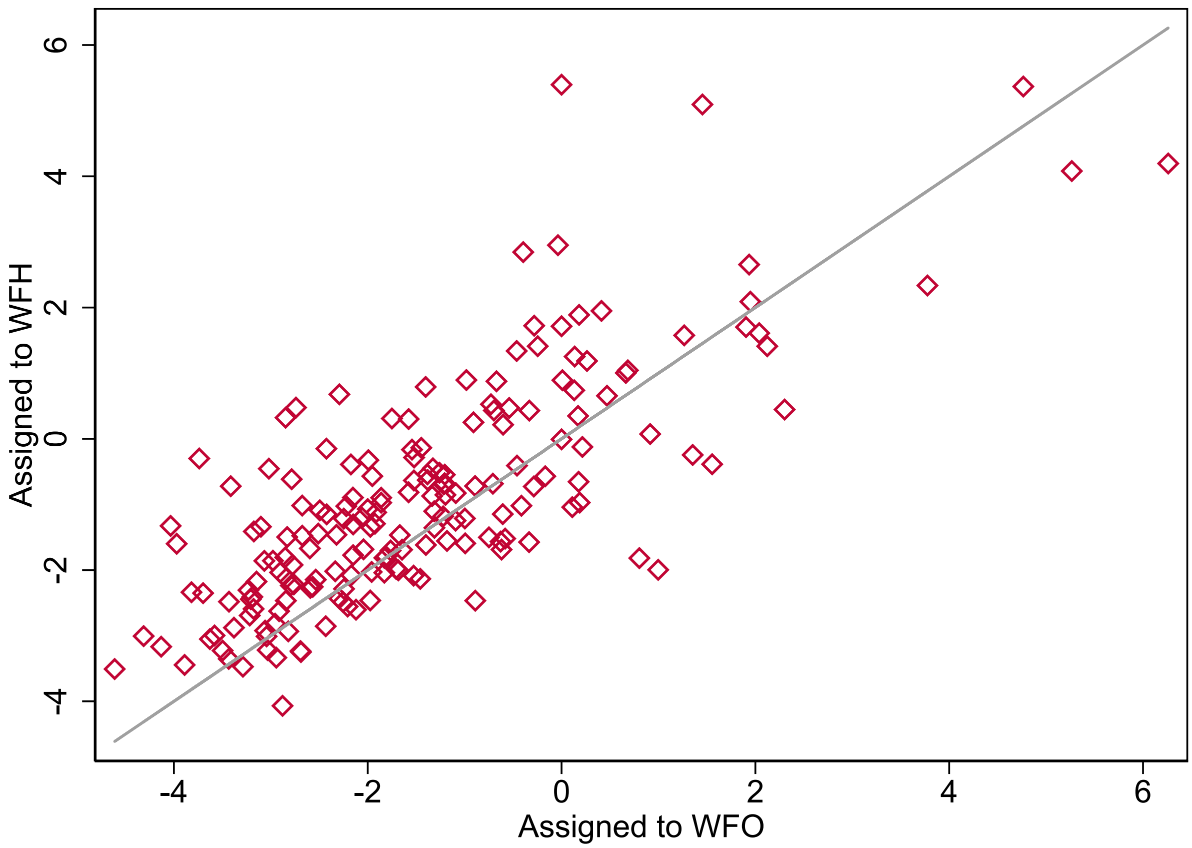
(a)



(b)

Notes: Internal CRRU records (November 1, 2022–January 21, 2023). Panel A reports the average number of cases recorded per worker per day for the staff assigned to WFH (orange circles) and those assigned to WFO (blue triangle). The two thick lines represent the two corresponding local linear smooth. Panel B reports the difference between the average number of cases per day for workers assigned to WFH and WFO. The thick black line is the local linear smooth.

Figure 2: Heterogeneity in Productivity Gains from WFH



Notes: Internal CRRU records (September 22, 2023–January 21, 2024). This figure plots the worker fixed effects when they are assigned to WFH vs. WFO (red diamonds) and the 45-degree line.

10 Tables

Table 1: Rotation Schedule

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

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

Table 2: Characteristics of the CRRU

	(1) All Periods	(2) Period 1: Pre-Period	(3) Period 2: Analysis	(4) Period 3: Experiment
Panel A: Workers				
Female	0.627	0.632	0.661	0.679
Age 18-24	0.205	0.201	0.201	0.187
Age 25-34	0.314	0.304	0.307	0.276
Age 35-44	0.127	0.132	0.122	0.142
Age 45-54	0.164	0.167	0.175	0.187
Age 55-65	0.182	0.186	0.190	0.209
Age 65 and over	0.009	0.010	0.005	0
Team 1	0.195	0.206	0.206	0.231
Team 2	0.214	0.211	0.201	0.164
Team 3	0.200	0.186	0.201	0.201
Team 4	0.186	0.191	0.190	0.201
Team 5	0.205	0.206	0.201	0.201
Day Shift	0.605	0.588	0.608	0.612
N	220	204	189	134
Panel B: CRRU				
N Officers	56.759	50.053	73.908	57.202
Assigned to WFH (rotation)	0.727	0.675	0.678	0.826
WFH	0.669	0.625	0.631	0.752
N Cases Recorded	349.012	308.094	412.672	373.574
Tot. Time (Min)	4974.081	5932.327	5192.672	3486.669
N Cases Recorded per Officer	6.176	6.119	5.589	6.570
Tot. Time per Officer (Min)	91.210	120.751	70.566	59.967
Av. Time per Crime (Min)	17.130	22.430	14.862	10.759
Share Violence Against the Person	0.449	0.425	0.461	0.477
Share Public Order	0.046	0.045	0.038	0.052
Share Criminal Damage or Arson	0.097	0.094	0.101	0.100
Share Theft	0.327	0.346	0.331	0.296
Share Possession of Weapons	0.003	0.002	0.002	0.004
Share Misc. Offences	0.078	0.087	0.067	0.070
N	661	319	119	223

Notes: Internal CRRU records (1 November 2022–31 August 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 August 2024 (period 3) in column 4.

Table 3: Balance on Observables

	(1) Mean	(2) Coeff.	(3) SE	(4) P-value	(5) N
Panel A: Worker Characteristics					
Female	.64	-.005	.0093	.5901	8795
Age 18-24	.205	-.0015	.0075	.8405	8795
Age 25-34	.334	-.0134	.0084	.1108	8795
Age 35-44	.118	.0085	.0053	.11	8795
Age 45-54	.168	.0062	.0083	.4576	8795
Age 55-65	.173	-.0002	.0085	.9849	8795
Age missing	.001	.0004	.0004	.321	8795
Covariate Index	5.578	.0087	.0085	.3098	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: Internal 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 number of cases on the workers' demographic characteristics. Column 1 reports the control mean. Columns 2 and 3 report the estimated coefficients and standard errors, respectively. These statistics are obtained in Panel A by regressing the row variable on a constant and the WFH assignment. The regressions in Panel B also include worker and day-fixed effects. Column 4 reports the p-value and column 5 the number of observations. SE clustered at the worker level.

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

	(1)	(2)	(3)
Panel A: N of Cases			
Assigned to WFH (rotation)	0.514***	0.521***	0.458***
	(0.089)	(0.087)	(0.080)
N	8795	8795	8795
R-squared	0.004	0.051	0.252
Control Mean	5.235	5.235	5.235
Panel B: Tot. Time (minutes)			
Assigned to WFH (rotation)	-1.330	-0.855	-1.307
	(1.652)	(1.620)	(1.551)
N	8795	8795	8795
R-squared	0.000	0.051	0.230
Control Mean	71.162	71.162	71.162
Panel C: Av. Time (minutes)			
Assigned to WFH (rotation)	-0.952*	-0.699	-0.627
	(0.452)	(0.528)	(0.528)
N	8795	8795	8795
R-squared	0.000	0.045	0.114
Control Mean	15.23	15.23	15.23
Worker FE	No	No	Yes
Day FE	No	Yes	Yes

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

Table 5: The Effects of WFH on Workers' Productivity

	(1) WFH	(2) N Cases	(3) Tot. Time (minutes)	(4) Av. Time (minutes)
Assigned to WFH (rotation)	0.734***			
	(0.021)			
WFH		0.624***	-1.782	-0.855
		(0.106)	(2.103)	(0.715)
N	8795	8795	8795	8795
R-squared	0.646	0.002	0.000	0.000
Control Mean	.134	5.235	71.162	15.23
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	2SLS	2SLS	2SLS
F-stat	1254.81			

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

Table 6: Night Shifts

	(1) N Cases	(2) Tot. Time (minutes)	(3) Av. Time (minutes)
Assigned to WFH (rotation)	0.182	0.058	0.294
	(0.104)	(1.815)	(0.733)
Night Shift	0.647**	-1.289	-0.430
	(0.211)	(2.932)	(1.021)
Night Shift*Assigned to WFH (rotation)	1.131***	-5.502	-3.691***
	(0.221)	(3.392)	(0.987)
N	8795	8795	8795
R-squared	0.274	0.232	0.116
Control Mean	5.235	71.162	15.23
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: Internal CRRU records (22 September 2023–21 January 2024). This table reports the estimated coefficients obtained regressing the outcome of interest of a dummy variable for the assignment to WFH, a dummy for the night shift, an interaction between the two, and worker and day fixed effects. SE clustered at the worker level.

Table 7: Work Patterns

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

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

Table 8: Balance on Observables (Experiment)

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

Notes: Internal 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 (3)). SE clustered at the worker level.

Table 9: Regime Comparison: WFH vs. Hybrid

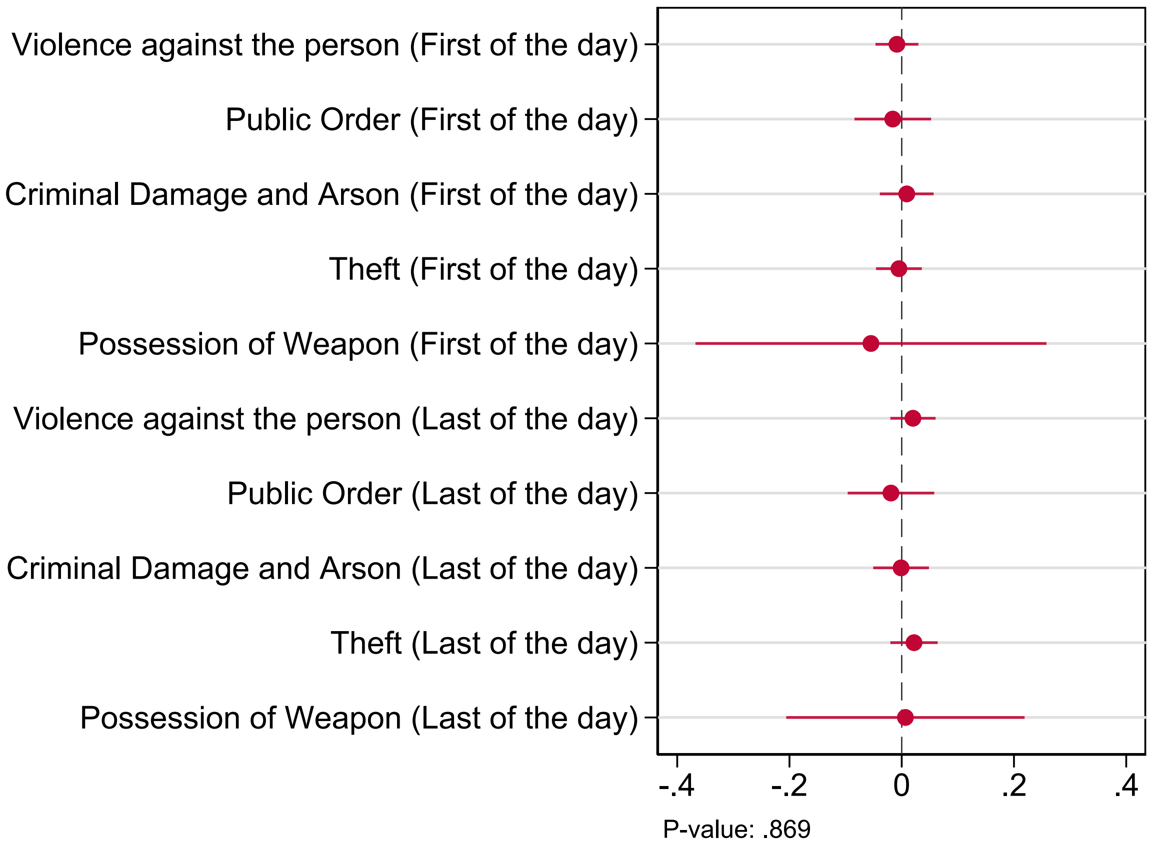
	(1) WFH	(2) N Cases	(3) Tot. Time (minutes)	(4) Av. Time (minutes)
Treated	0.207***	-0.011	3.618	0.450
	(0.032)	(0.285)	(3.916)	(0.708)
N	12937	12937	12937	12937
R-squared	0.062	0.000	0.002	0.001
Control Mean	.655	6.562	58.496	10.572
Strata FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	RF	RF	RF
F-stat	42.60			

Notes: Internal CRRU records (22 January 2024–31 August 2024). This table reports the estimated δ from model (3). Column 1 reports the first stage (FS) and the F-statistic for the null hypothesis that the coefficient associated with instrument is equal to zero. Columns 2-4 report the reduced form (RF). SE clustered at the worker level.

Online Appendix

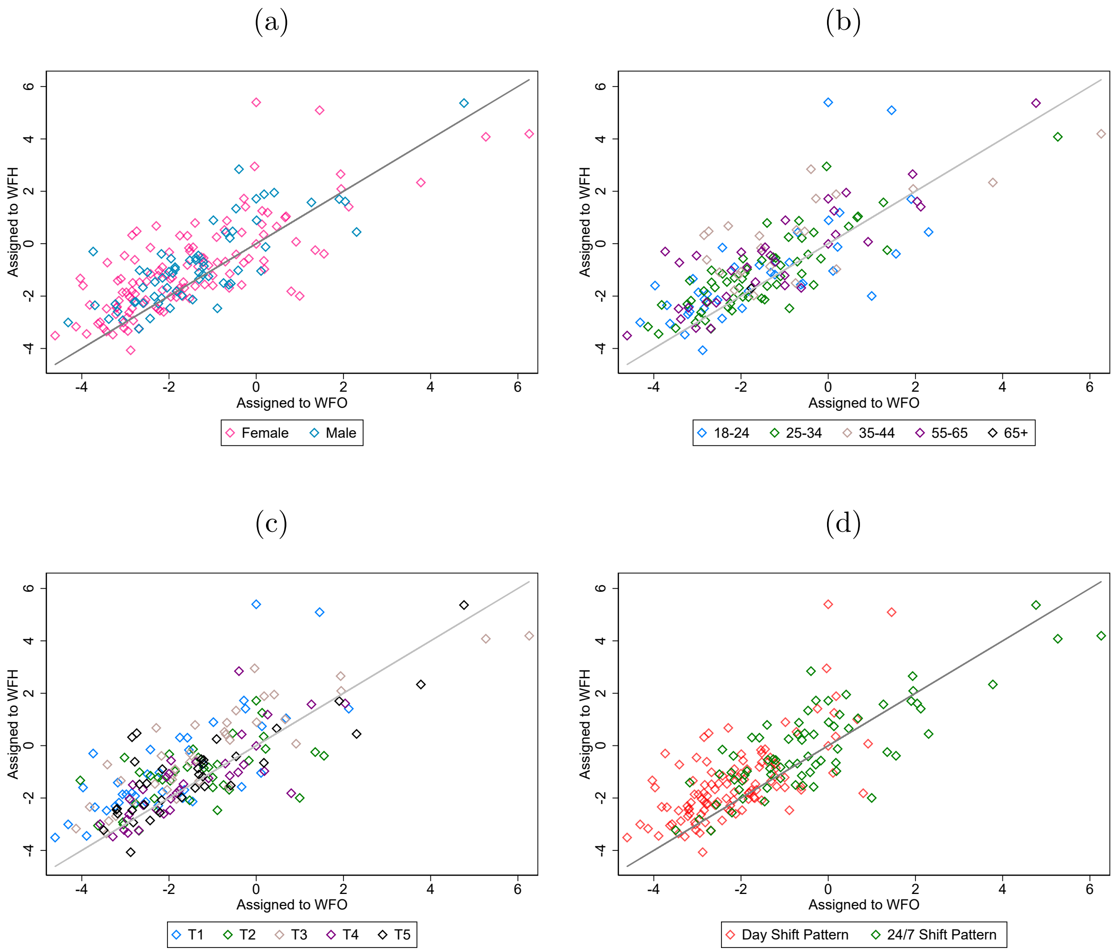
Appendix A Additional Figures and Tables

Figure A.1: Balance on Case Characteristics



Notes: Internal 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: Internal CRRU records (22 September 2023–21 January 2024). This figure plots the worker fixed effects when assigned to WFH vs. WFO and the 45-degree line. Panels A–D explore heterogeneity across gender, age, teams, and shift patterns, respectively.

Table A.1: Clustering

	(1) N Cases	(2) Tot. Time (minutes)	(3) Av. Time (minutes)
Panel A: Cluster at the Worker Level (Baseline Specification)			
Assigned to WFH (rotation)	0.458***	-1.307	-0.627
	(0.080)	(1.551)	(0.528)
Panel B: Cluster at the Team Level			
Assigned to WFH (rotation)	0.458**	-1.307	-0.627
	(0.074)	(1.258)	(0.538)
N	8795	8795	8795
R-squared	0.252	0.230	0.114
Control Mean	5.235	71.162	15.23
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

Notes: Internal 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. Panel B reports the estimates clustering the SE at the team level.

Table A.2: Worker FE and Observable Characteristics

	(1) WFH Worker FE	(2) WFO Worker FE
Female	-0.107	-0.161
	(0.260)	(0.258)
Age 18-24	0.571	0.155
	(0.369)	(0.304)
Age 25-34	0.489*	0.135
	(0.231)	(0.241)
Age 35-44	1.968***	0.991
	(0.357)	(0.503)
Age 45-54	0.325	-0.089
	(0.237)	(0.242)
Age 55-65	1.127***	0.455
	(0.323)	(0.345)
N	183	183
R-squared	0.090	0.034

Notes: Internal CRRU records (22 September 2023–21 January 2024). This table reports the estimated coefficients obtained by regressing the worker fixed effects on observable characteristics. The omitted age category is "older than 65 y.o.".

Table A.3: WFH and Workers' Productivity

	(1)	(2)	(3)
Panel A: N of Cases			
WFH	0.425**	0.434**	0.384***
	(0.137)	(0.138)	(0.099)
N	8795	8795	8795
R-squared	0.003	0.050	0.250
Control Mean	5.235	5.235	5.235
Panel B: Tot. Time (minutes)			
WFH	2.387	1.969	-1.288
	(1.960)	(1.949)	(1.517)
N	8795.000	8795.000	8795.000
R-squared	0.000	0.051	0.230
Control Mean	71.162	71.162	71.162
Panel C: Av. Time (minutes)			
WFH	-0.042	0.038	-0.563
	(0.527)	(0.593)	(0.578)
N	8795	8795	8795
R-squared	0.000	0.045	0.114
Control Mean	15.23	15.23	15.23
Worker FE	No	No	Yes
Day FE	No	Yes	Yes

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

Table A.4: Controlling for Assigned Shift Length

	(1) Shift Length (hours)	(2) N Cases	(3) Tot. Time (minutes)	(4) Av. Time (minutes)
Assigned to WFH (rotation)	0.328***	0.329***	-2.447	-0.514
	(0.025)	(0.082)	(1.609)	(0.586)
N	8795	8795	8795	8795
R-squared	0.249	0.257	0.232	0.114
Control Mean	9.27	5.235	71.162	15.23
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Assigned Shift Length		Yes	Yes	Yes

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

Table A.5: Controlling for Characteristics of Reported Cases

	(1) N Cases	(2) Tot. Time (minutes)	(3) Av. Time (minutes)
Assigned to WFH (rotation)	0.420***	-0.764	-0.448
	(0.083)	(1.601)	(0.538)
N	8795	8795	8795
R-squared	0.270	0.233	0.115
Control Mean	5.235	71.162	15.23
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Types of Reported Cases	Yes	Yes	Yes

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

Table A.6: The Effects of WFH Assignment on Workers' Productivity (Workers in the Experiment)

	(1) N Cases	(2) Tot. Time (minutes)	(3) Av. Time (minutes)
Assigned to WFH	0.567***	0.681	-0.198
	(0.093)	(1.644)	(0.746)
N	6341	6341	6341
R-squared	0.273	0.235	0.119
Control Mean	5.268	71.309	15.233
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Types of Reported Cases	Yes	Yes	Yes

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

Table A.7: The Effects of WFH on Workers' Productivity using the Experimental Variation

	(1) WFH	(2) N Cases	(3) Tot. Time (minutes)	(4) Av. Time (minutes)
Treated	0.207***			
	(0.032)			
WFH		-0.054	17.436	2.170
		(1.373)	(19.656)	(3.474)
N	12937	12937	12937	12937
Control Mean	.655	6.562	58.496	10.572
Strata FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	2SLS	2SLS	2SLS
F-stat	42.60			

Notes: Internal CRRU records (22 January 2024–31 August 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 (4). SE clustered at the worker level.

Table A.8: Balance on Observables (Pre-Period)

	(1) Mean	(2) Coeff.	(3) SE	(4) P-value	(5) N
Panel A: Worker Characteristics					
Female	.632	-.0085	.0092	.3588	15967
Age 18-24	.165	-.0066	.0051	.1953	15967
Age 25-34	.27	.0025	.0077	.7424	15967
Age 35-44	.139	.0076	.0059	.1976	15967
Age 45-54	.171	-.0034	.0096	.7233	15967
Age 55-65	.206	.0005	.0069	.9427	15967
Age missing	.049	-.0006	.0041	.8756	15967
Covariate Index	6.152	.0056	.0101	.5799	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: Internal 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 number of cases on the workers' demographic characteristics. Column 1 reports the control mean. Columns 2 and 3 report the estimated coefficients and standard errors, respectively. These statistics are obtained in Panel A by regressing the row variable on a constant and the WFH assignment. The regressions in Panel B also include worker and day fixed effects. Column 4 reports the p-value and column 5 the number of observations. SE clustered at the worker level.

Table A.9: The Effects of WFH Assignment of Worker' Productivity (Pre-Period)

	(1) N Cases	(2) Tot. Time (minutes)	(3) Av. Time (minutes)
Assigned to WFH	1.131***	17.130***	-0.101
	(0.114)	(2.369)	(0.454)
N	15967	15967	15967
R-squared	0.285	0.243	0.244
Control Mean	5.404	106.987	22.074
Worker FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes

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

Table A.10: The Effects of WFH on Workers' Productivity (Pre-Period)

	(1) WFH	(2) N Cases	(3) Tot. Time (minutes)	(4) Av. Time (minutes)
Assigned to WFH (rotation)	0.751***			
	(0.020)			
WFH		1.506***	22.806***	-0.134
		(0.146)	(3.048)	(0.597)
N	15967	15967	15967	15967
R-squared	0.637	0.011	0.006	0.000
Control Mean	.119	5.404	106.987	22.074
Worker FE	Yes	Yes	Yes	Yes
Day FE	Yes	Yes	Yes	Yes
Method	FS	2SLS	2SLS	2SLS
F-stat	1459.68			

Notes: Internal 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.

CENTRE FOR ECONOMIC PERFORMANCE
Recent Discussion Papers

2035	Elodie Andrieu John Morrow	Can firm subsidies spread growth?
2034	Miquel-Àngel Garcia López Luz Yadira Gómez-Hernández Rosa Sanchis-Guarner	Highway traffic in Britain: The effect of road capacity changes
2033	Stephan Heblich Stephen J. Redding Yanos Zylberberg	The distributional consequences of trade: Evidence from the Grain Invasion
2032	Brian Bell Philip Johnson	Immigrant downgrading: New evidence from UK panel data
2031	Ying Chen Paul Cheshire Xiangqing Wang You-Sin Wang	Valuing consumption services as technology transforms accessibility: Evidence from Beijing
2030	Johannes Boehm Thomas Chaney	Trade and the end of antiquity
2029	Jay Euijung Lee Martina Zanella	Learning about women's competence: The dynamic response of political parties to gender quotes in South Korea
2028	Christos Genakos Blair Yuan Lyu Mario Pagliero	Asymmetric pass-through and competition
2027	Fabrice Defever Alejandro Riaño Gonzalo Varela	Evaluating the impact of export finance support on firm-level export performance: Evidence from Pakistan
2026	Andrés Barrios-Fernández Christopher Neilson Seth Zimmerman	Elite universities and the intergenerational transmission of human and social capital

2025	Agnes Norris Keiller	Brexit and investment
2024	Lídia Farré Libertad González Claudia Hupkau Jenifer Ruiz-Valenzuela	Paternity leave and child development
2023	Gabriel M. Ahlfeldt Nikodem Szumilo Jagdish Tripathy	Housing-consumption channel of mortgage demand
2022	Agnes Norris Keiller Tim Obermeier Andreas Teichgraeber John Van Reenen	When trade drives markup divergence. An application to auto markets
2021	Amanda Dahlstrand Nestor Le Nestour Guy Michaels	Online versus in-person services: Effects on patients and providers
2020	Hanwei Huang Kalina Manova Oscar Perelló Frank Pisch	Firm heterogeneity and imperfect competition in global production networks
2019	Jan David Bakker Nikhil Datta	Avenging the tenants: Regulating the middle man's rents
2018	Agnes Norris Keiller Áureo de Paula John Van Reenen	Production function estimation using subjective expectations data
2017	Philippe Aghion Lint Barrage David Hémous Ernest Liu	Transition to green technology along the chain supply

The Centre for Economic Performance Publications Unit
Tel: +44 (0)20 7955 7673 Email info@cep.lse.ac.uk
Website: http://cep.lse.ac.uk Twitter: @CEP_LSE