WORKING PAPER · NO. 2021-56

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JULY 2021

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July 13, 2021

Abstract

We study productivity before and during the working from home [WFH] period of the Covid-19 pandemic, using personnel and analytics data from over 10,000 skilled professionals at a large Asian IT services company. Hours worked increased, including a rise of 18% outside normal business hours. Average output declined slightly, thus productivity fell 8-19%. We then analyze determinants of changes in productivity. Employees with children at home increased work hours more and had a larger decline in productivity than those without children. Women had a larger decline in productivity, while those with longer company tenure fared better. An important source of changes in WFH productivity is higher communication and coordination costs. Time spent on coordination activities and meetings increased, while uninterrupted work hours shrank considerably. Employees communicated with fewer individuals and business units, both inside and outside the firm. They also received less coaching and 1:1 meetings with supervisors. The findings suggest key issues for firms to address in implementing WFH policies.

Keywords: Collaboration, Coordination, Covid-19 Pandemic, Productivity, Remote Working, Telecommuting, Working From Home, Work Hours, Work Time

JEL Classification: D2, M5.

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*We are grateful to several employees of the company who spent a great deal of time helping us collect the data and understand the firm and context, during a difficult period of time. We thank the Tata Center for Development at the University of Chicago for funding that helped cover the cost of WPA licenses. We appreciate helpful comments from Sonia Bhalotra, Ron Burt, Matthew Clancy, Hans Peter Grüner, Emma Harrington, Kathryn Ierulli, Alan Kwan, Duk Gyoo Kim, Michael Lotus, Adam Ozimek, Tim Perri, Paul Smeets and Wim Van der Stede, and from seminar participants at the University of Mannheim and the University of Essex.

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1 Introduction

Working from Home [WFH] has been rising for years, as more occupations use computers and telecommunications, more people have reliable home Internet connections, and more families have both parents working full time. The Covid-19 pandemic accelerated this process by forcing a large fraction of the global workforce to switch to WFH at least temporarily. Compared to Working from the Office [WFO], WFH has the potential to reduce commute time, provide more flexible working hours, increase job satisfaction, and improve work-life balance. However, little is yet known about some of the more fundamental consequences of WFH, including its effects on productivity and which factors play a role in making WFH more or less productive than WFO (WSJ, 2020; Financial Times, 2021b).

In this paper we provide an analysis of the effects of WFH in a large Asian IT services company. The company abruptly switched all employees from WFO to WFH in March 2020, in response to the largely unanticipated pandemic shock. Our study has several novel and interesting features.

The industry and occupations analyzed here are among those predicted to be most amenable to WFH. The employees are highly-skilled professionals in an information technology company where a high degree of work has always been computer driven. At the same time they are some of the most difficult to analyze. The jobs involve significant cognitive work, collaboration on teams, working with clients, and innovation. Productivity is hard to measure for such professions. WFH for occupations with such characteristics has not previously been studied with non-survey data.

For a panel of over 10,000 employees and a period of 17 months including both WFO and WFH, we obtained unusually rich data data from the company's personnel records and workforce analytics systems. These include each employee's key output and work hours, which provide a natural measure of productivity. For a sub-sample, the firm provided data on how employees allocated time between work tasks. This includes meetings, collaboration and time focused on performing work without distractions. It also includes information on networking activities (contacts) with colleagues both inside and outside the firm. We also have employee experience, tenure, age, commute time (for WFO), gender, and the number of children at home.

These data provide a unique opportunity to obtain a measure of productivity for this complex type of work, and to investigate the determinants of productivity during WFH. We analyze how WFH productivity varied by employee characteristics, whether or not children were at home, and commute time. We also analyze how it varied with the nature of the work: the extent of collaboration, networking, supervision and coaching. Our analysis of the productivity differences between WFH and WHO provide valuable insights about the issues that are likely to be most important when designing future WFH schemes.

Our findings are presented in two parts. We first analyze how average work time, output, and productivity changed during WFH. With that foundation, we then analyze what drives those changes and which employees are more affected. We consider the role of both employee and job characteristics and study extensively changes in working patterns induced by WFH.

We find that employees significantly increased average hours worked during WFH. Much of this came outside of normal office hours. At the same time, there was a slight decline in output as measured by the employee's primary performance measure. Combining these, we estimate that productivity declined by 8-19%. These results are consistent with employees becoming less productive during WFH, and working longer hours to try to compensate.

Employees with children at home had a greater decline in productivity than those without, but even those without suffered productivity losses. Moreover, women were more negatively affected by WFH than men, but this gender difference was not due to the presence of children in the home. We conjecture that it might be due to other demands placed on women in the domestic setting while working from home.[1]

Employees with lower company tenure decreased output slightly during WFH, whereas output remained about the same for those with longer tenure. This is separate from age or experience effects. This suggests that employees who are more adapted to firm culture and processes are better able to perform in WFH, where there is no colleague at the next desk for quick help or advice.

WFH also affected working patterns in substantial ways. Employees spent more time participating in various types of meetings, but less time in personal meetings with their manager or receiving coaching. They engaged in fewer contacts with colleagues inside and outside of the firm. At the same time, they had less "focus time," i.e., uninterrupted time to perform tasks. All of these factors were significantly correlated with the productivity changes due to WFH. These were not temporary adjustments to a switch to WFH, but persisted over time. These findings suggest that increased coordination costs during WFH at least partially explain the drop in productivity.

A potential concern is that the pandemic affected estimates of productivity changes during WFH. However, several pieces of evidence suggest that this is not a major concern. First, the effects on work time and productivity begin immediately at the move to WFH, not gradually as the pandemic developed. Second, the decline in productivity is also observed among employees without children at home, though to a lesser degree, so the detrimental productivity effects are not solely driven by school closures. Third, changes in work time and productivity do not correlate with the evolution of the pandemic, such as the rate of infections or easing of lockdown measures. Fourth, there is a decline, not an increase, in sick days during WFH. Finally, as with many information technology firms, the company's economic performance was quite strong throughout the pandemic, so employees were not at more risk of job loss.

The evidence presented below provides important insights into how WFH may vary across different types of occupations and firms employing a blended WFH / WFO approach. Our analyses indicate that communication, coordination and collaboration are more costly in a virtual work setting. This is likely to present a significant challenge to WFH in occupations where such aspects are important, especially for less experienced employees. While WFH is likely to remain a feature of modern workplaces, some aspects of in-person interactions cannot easily be replicated virtually, including the quality of

[1] In the Western context it has often been reported that the burden of childcare and home-schooling disproportionately affected women during the pandemic (Financial Times, 2021a). In the country from which our data are drawn, extended families often live together, and middle and upper class families often have domestic staff. Having extended family and staff at home can provide help with childcare, but may place other demands on women at home whether or not children are present.

collaboration and coaching, and "productive accidents" that arise from spontaneously meeting people (including those with whom there is not yet a working relationship).

2 Literature

Our research contributes to a broad agenda in economics trying to understand determinants of individual productivity. A significant amount of work has focused on incentive pay (e.g., Lazear, 2000; Hamilton et al., 2003; Shearer, 2004; Babcock et al., 2015; Friebel et al., 2017; Aakvik et al., 2017; Dohmen and Falk, 2011). Some research looks at effects of other human resource practices, particularly those aimed at eliciting employee participation in continuous improvement, and on complementarities between these policies (Ichniowski et al., 1995; Ichniowski and Shaw, 2003; Bartel et al., 2007). There is limited research in other areas, such as ways to engage employees in innovation (Gibbs et al., 2017). Some literature studies the effects of supervisors (Lazear et al., 2015) or peers (Bandiera et al., 2005; Arcidiacono et al., 2017; Song et al., 2018). Presumably peer effects would be weaker during WFH as there is no face-to-face interaction and probably less overall interaction. Supervisor effects might be stronger, if managers vary significantly in their ability to lead and coordinate virtual teams.

A growing literature analyzes working from home policies. At the start of the pandemic, a few papers predicted the likelihood that a job would shift from WFO to WFH, typically using descriptions of occupations in classifications such as O*NET (e.g., Dingel and Neiman, 2020; Adams-Prassl et al., 2020). The industry and occupations analyzed here are among those predicted most likely to effectively switch to WFH.

Several surveys document incidence of WFH, and perceptions of its effects (Bick et al., 2020; Brynjolfsson et al., 2020; Von Gaudecker et al., 2020; Gottlieb et al., 2021; Hensvik et al., 2020). Professionals, managers, knowledge workers, those in clerical support or data processing, and those with higher education or income make more use of WFH. In the UK Household Longitudinal Survey, employees who work from home state that they are about as productive as in the office (Etheridge et al., 2020). Those who perceive declines also experience lower levels of well-being from WFH. Bellmann and Hübler (2020) find that working remotely has no long-run effect on work-life balance, and that a switch to WFH increases job satisfaction only temporarily. Barrero et al. (2020) estimate that WFH reduced total commuting time among US workers by more than 60 million hours per work day at the height of the pandemic, and that about 35% of this time saved was reallocated to work. We do not find that commute time predicts increases in WFH work hours.

Barrero et al. (2021) provide evidence from waves of a large panel of US employees working from home. Respondents report benefits from lower commute time, more flexible work hours, and increased productivity. Employers have made investments in technology, revised practices, and moved up the learning curve with respect to WFH. They suggest that use of WFH will remain four times more prevalent than before the pandemic.

DeFilippis et al. (2020) use communication and email meta-data. Their estimate that WFH employees work 0.8 more hours per day is between estimates from our two time measures. They also find that employees attend more meetings, with more attendees. Teevan et al. (2020) present similar evidence for Microsoft employees. Kwan (2021) analyzes reading of Internet content by employees in a very large sample of firms in ten countries. He uses IP addresses to identify when employees WFH, and creates proxies for employee interactions and need for coordination. These proxies are negatively associated with a shift to WFH.

Survey data on productivity might be biased if employees enjoy WFH and hope to retain the practice, conflate output with productivity, or refer to individual performance without full consideration of collaboration with others. Only a few papers have studied WFH using employee data. Bloom et al. (2015) analyzed call-center employees at a Chinese firm. Output rose for those assigned to WFH, partly because they worked more hours, and partly because productivity increased. Employee satisfaction increased, and attrition declined. Emanuel and Harrington (2021) studied call-center workers at a large US company, including those who abruptly moved to WFH in response to Covid-19. Productivity rose in the switch to remote work. However, average productivity was lower for remote workers than office workers. They conclude that remote work has an adverse selection effect, and more productive workers prefer to be at the office.

WFH may be relatively effective for call-center workers, who work independently and follow scripts. Künn et al. (2020) analyze an occupation with extremely high cognitive demands but no collaboration: professional chess players. They had lower quality performance when playing online during Covid-19, compared to in-person tournaments. Of course, the highly unusual occupation makes it difficult to generalize from their findings.

A policy that goes beyond WFH is Working from Anywhere [WFA], in which an employee is allowed to choose where they live and work. This might provide additional benefits in quality of life, managing a dual-career couple, or real estate prices. Choudhury et al. (2019) study a natural experiment in which examiners at the US Patent and Trademark Office were allowed to work from anywhere. Productivity rose by 4.4%, with no decline in the quality of work. However, they note that these jobs do not require significant collaboration and coordination.

None of these studies were able to analyze potential mechanisms underlying differences in productivity between WFH and WFO. This study is, to our knowledge, the first that is able to provide evidence on this question.

3 Data and Empirical Strategy

The setting for this study is one of the world's largest IT services companies, with over 150,000 employees who work with clients across the globe. While it employs workers in many countries, the group studied here are employed at its corporate campuses in the home country, a rapidly developing Asian nation. The company provides a wide range of technology consulting and outsourcing services. That includes outsourced product and process improvement and R&D to develop new products and services.

The workforce is highly skilled and educated. Virtually all have at least a bachelor's degree, often in a technology field such as computer engineering or electronics. Most work at the company's large, modern corporate campuses in several cities of its home country. These campuses look and feel very similar to what one sees at Microsoft, Apple or Amazon.

We were provided with anonymized employee data of various kinds, and executives spent considerable time explaining practices and business conditions. All authors have visited company headquarters.

A brief description of how the employees in our sample are evaluated is helpful. The company has a semi-annual planning process that culminates in goals for each organizational level from the CEO down. Ultimately the process leads to goals for each team, based on business unit objectives and expectations about customer requests during the next 6 months. The team supervisor then sets goals for each employee.[2] Analytics systems (described below) are used to track progress against the plan throughout the organization. Each manager is provided with reports for his or her unit. For example, the CEO reviews the corporate-wide report at least once per month. Such a "data-driven" approach is common in technology firms (Brynjolfsson and McAfee, 2012).

Company executives told us that this process was not changed during the sample period. Most customers are also information technology firms. That sector tended to perform well during the pandemic. This firm and its clients largely continued expected business activities. All of this means goals were not changed. Company financial statements reveal that total workforce size and revenue both rose by more than 5% in 2020 compared to 2019, and profit margins rose even more. That is noteworthy, since it also means that employees had no larger concerns about job loss.

These plans and goals form the basis of supervision. Informally, managers monitor employee work time and performance across key applications and tasks, in order to better supervise and coach them. This is supported by the analytics platforms described below. Formally, each employee is measured by performance against the semi-annual goal on a key performance metric, which we will refer to as "Output." He or she also receives quarterly supervisor feedback, and bi-annual subjective performance ratings.

A notable advantage of this study is that the performance measure is relatively rigorous and objective. The supervisor devises the key metric to reflect the most important aspect of the job, and this is tracked with the analytics systems. For example, for a software engineer it might be the number of code segments completed. Importantly, such a measure does not merely reflect quantity (which would lead to obvious multitask incentive problems). Rather it is Output *conditional* on adequate performance on other dimensions of the task, such as quality or customer satisfaction. For example, code segments will not be counted as complete until they meet company and customer standards for errors, speed, and functionality. Moreover, since the measure is output-based, it reflects various employee inputs, including time, effort, skill development, client interactions, drawing upon colleagues for advice, etc.

The employees in our sample do not receive incentive pay tied directly to this or any other measure. Compensation is comprised of salary, an annual merit bonus based on overall performance, and

[2] If an employee is reassigned, or a project is completed and the team begins a new one, this process is refreshed for affected employees before the next cycle begins.

Table 1: Summary statistics for outcome variables

	Mean	SD	1st Quartile	3rd Quartile	N
WFO (pre March 2020)					
Input	5.08	2.03	3.78	6.35	47387
Output	100.82	9.00	100.00	100.00	47387
Productivity	1.36	2.99	0.75	1.27	47387
WFH (post March 2020)					
Input	7.04	2.75	5.38	8.90	22862
Output	100.30	8.80	100.00	100.00	22862
Productivity	1.11	2.41	0.52	0.88	22862

occasional small rewards for activities such as suggestion of valuable new ideas. That the performance measure is tied to the company's business plan suggests employees are motivated to try to meet their goals, and our evidence confirms this. However, motivation is broader than this, due to supervisor monitoring, feedback, subjective evaluation, merit pay, and the potential to earn a promotion (as is true at most companies).

3.1 Main outcome variables

The company uses two systems, Sapience Analytics and IDMS ("Internal Data Management System"), to track employee activity and performance. Our three key outcome variables, Input, Output, and Productivity, derive from these. Managers use analytics reports based on these data to support decisions, goal-setting, monitoring, and performance evaluation. Because of its corporate-wide significance, the company has devoted substantial effort to making sure that the data are meaningful and reliable.

We obtained data for all employees from the R&D part of the firm who are managed via these systems. Data cover April 2019 through August 2020, resulting in a panel dataset with 10,384 unique employees observed over 17 months. The company moved abruptly to WFH in March 2020 as Covid-19 became serious in that country.

Sapience Analytics software is installed on the employee's computer. Sapience records the time that an employee is working, by tracking applications or websites used, and whether the employee is active (i.e., using the keyboard or mouse). If an employee procrastinates on a social media platform, and this is not part of the job, that would not be recorded as work time. If a program from a predefined list of relevant tools (programming, collaboration, document production, communication, etc.) is active, that is recorded as work time. It includes meetings entered in the Outlook calendar, which is used throughout the company, even if these are face-to-face (off the computer). Sapience therefore records *effective* work hours. If an employee sits at his or her desk for 8 hours a day, Sapience might only record 5 hours, because breaks or surfing the web are not effective work time. Employees are aware that the software is used in this way.

Based on these data, we calculate the outcome variable Input, equal to average working hours per working day that month. That is, we take the total time worked that month and divide it by the number of working days (taking into account weekends and local holidays). In section 3.3 below, we describe additional input measures that generate similar qualitative results; our findings are robust to details of the definition of hours worked.

IDMS is a proprietary system by which the company tracks employee performance, including the primary performance measure. That measure is normalized to make different jobs and roles comparable.[3] For example, key measures might be the number of code segments, code reviews, or reports delivered per month. In each case, these are divided by the monthly goal, multiplied by 100. It is possible to complete more tasks than are assigned, so the outcome variable Output can take values in $\mathbb{R}_0^+$, but is typically between 0 and 100. By far the most common value is 100, meaning that employees continue working longer hours until they meet their target, but we also see employees falling short of their targets or even exceeding them.

Finally, our outcome variable Productivity is calculated by dividing Output by Input. Differences in productivity will often be a consequence of differences in Input needed to reach the goal, but they can also come from employees falling short of or exceeding targets. Table 1 displays summary statistics before and during WFH. The number of observations under the two regimes differs, because we have more pre-WFH months.

3.2 Employee/HR variables

We obtained information on employee characteristics, collected as of March 20, 2020 (roughly the date on which WFH was implemented). Summary statistics are in Table 2. For some employees some variables are missing. One reason is that HR data are deleted if an employee leaves the company or transfers to a branch in a different country.

We have Age, company Tenure, and industry Experience (collected at hiring and updated to the current date), all measured in years. For each we generate median splits, HighAge, HighTenure and HighExperience. Mean age is quite young, which is not unusual in the IT sector. Mean tenure is low at about 4 years, as is expected since employee turnover is high in the IT sector. Male is a dummy variable representing male employees. As in tech companies around the world, men are a significant majority.

The variable NumChildren is the number of children up to age 21 who are covered under the company's employee health insurance plan. The company believes that the vast majority of employees who have dependent children insure them via the company, because of its relatively generous health insurance coverage. However, some might instead be insured through a partner's employer. Hence, a zero means that there are either no children at home, or there are but they have not been declared. A positive number is the actual number of children at home. The dummy Children equals one if and only if NumChildren is positive.

[3]Our analysis does not rely on this normalization, as our fixed effects regressions compare the same employee before and during WFH.

Table 2: Summary statistics for employee variables

	Mean	SD	1st Quartile	3rd Quartile	N
Age (in years)	31.91	5.95	27.10	36.03	7969
HighAge	0.50	0.50	0.00	1.00	7969
Tenure (in years)	4.21	3.90	1.11	5.11	7969
HighTenure	0.52	0.50	0.00	1.00	7969
Experience (in years)	8.10	5.22	4.04	11.10	7969
HighExperience	0.50	0.50	0.00	1.00	7969
Male	0.76	0.43	1.00	1.00	7969
NumChildren	0.52	0.73	0.00	1.00	8934
Children	0.39	0.49	0.00	1.00	8934
CommuteTime	0.65	0.33	0.38	0.85	4323
Rating	2.66	0.88	2.00	3.00	5354

CommuteTime is an estimate of the time in hours needed to get from the home address to the office (during WFO), one-way. The company calculated this based on home and office addresses, using the Google Maps API to incorporate factors such as traffic and not merely distance. Thus, it is an estimate of the usual time taken, assuming that the employee commutes by car.[4] Address data are often incomplete, so there are more missing values than for other variables. We discarded extreme values (larger than 2 hours). According to the company these are cases where commute time is unreliable; for example, an employee actually worked at a client office closer to home, not the company office where his or her team is located.

Rating is the supervisor's subjective evaluation of the employee on an integer scale of 1 to 5, where 1 is the best rating. We have the most recent rating from May/June 2020. The outcome measures discussed above are predictive of performance ratings: mean input and mean productivity in months prior to the rating significantly improve that rating (see Table A.1 in the Appendix). Figure B.1 in the Appendix plots kernel density estimates of subjective ratings for different levels of Output. Ratings generally rise with Output, but start to decrease once Output substantially exceeds the target. A possible interpretation is that such an employee gave too much emphasis to meeting the goal, and the supervisor gives a lower subjective rating to balance multitask incentives. Another is that the goal was too easy to achieve. Overall, this indicates that the outcome measures introduced above are meaningful.

3.3 Workplace Analytics Data

Microsoft Workplace Analytics [WPA] is a tool that many companies use to track and analyze various aspects of their workforces. For example, it can be used to study collaboration or professional networking activity by using data on emails, calendar appointments, amount of time spent in meetings, etc. WPA data have been used in several organizational studies (Brynjolfsson and McAfee, 2012; Hoffmann et al., 2012; Levenson, 2018).

[4]Some employees use public transport, but we have no data about mode of travel.

The company has been considering adoption of this tool. For the purposes of this study they purchased 914 licenses to apply to a subset of employees in our full sample. Appendix Table A.2 compares those in the WPA sample to those not in the WPA sample. The WPA group are slightly younger, have lower tenure and are less productive, but are overall quite similar on average.

Table 3: Summary statistics for WPA variables

	Mean	SD	1st Quartile	3rd Quartile	N
WFO (before March 15th 2020)					
Working Hours	44.71	5.16	43	46.46	6755
After Hours	9.64	9.55	2.33	14.04	6755
Focus Hours	34.49	9.02	30	41.25	6755
Collaboration Hours	10.20	9.24	3.55	13.75	6755
Meetings Manager	3.97	4.35	0.5	5	6755
Meetings 1:1	0.18	1.37	0	0.5	6755
Coaching Meets	0.13	1.03	0	0	6755
MS Teams Calls	0.36	1.63	0	0	6755
Internal NW	18.91	14.21	10	24	6755
External NW	2.58	3.61	0	3	6755
NW EXT	0.98	1.04	0	1	6755
NW ORG	0.05	0.22	0	1	6755
Emails	23.61	23.68	9	30	6755
WFH (after March 15th 2020)					
Working Hours	49.03	7.58	45.14	52.49	19220
After Hours	12.98	12.70	3.71	18.44	19220
Focus Hours	32.73	9.99	28	40	19220
Collaboration Hours	11.07	9.97	4.08	15	19220
Meetings Manager	5.48	6.57	1	7.33	19220
Meetings 1:1	0.11	1.07	0	0	19220
Coaching Meets	0.09	0.98	0	0	19220
MS Teams Calls	21.46	25.22	3	30	19220
Internal NW	23.44	19.89	11	30	19220
External NW	3.05	4.36	0	4	19220
NW EXT	0.91	0.89	0	1	19220
NW ORG	0.05	0.23	0	0	19220
Emails	25.26	29.89	8	30	19220

Note: "Working hours" are weekly hours worked. After hours are weekly hours worked outside regular work time. "Focus Hours" are hours with two or more hour blocks *not* spent in meetings, on calls or writing e-mails. "Collaboration Hours" are hours spent in meetings or MS Teams calls. "Meetings Manager" is the number of meetings involving the employee's manager. "Meetings 1:1" is the number of meetings between the employee and their manager. "Coaching Meets" is the number of meetings the employee attended with the manager and all of the manager's direct reports. "MS Teams Calls" is the number of calls the employee participated in. "Internal NW" is the number of people inside the company with whom employee had meaningful contact in the last 28 days. "External NW" is the same measure for people outside the company. "NW ORG" is the number of distinct company organizational units (outside his or her own) with which the employee had at least two meaningful interactions in the last four weeks. "NW EXT" is the same measure for domains outside the company. Emails is the weekly number of emails sent by the employee.

Table 3 summarizes variables obtained from WPA. WPA data were collected at the weekly level (in contract to Sapience data, collected at the monthly level). We have 10 weeks of data before WFH (starting January 1, 2020) and 24 weeks of data during WFH (ending September 6, 2020). The switch to WFH happened in the week starting March 16.

Variables fall into several categories. Working Hours measures overall time worked by the employee. It is best viewed as capturing time "at work" (at home or in the office), not every minute of which is necessarily spent working; e.g., it will count small breaks in between emails as work time. It can detect longer work hours due to additional email traffic, meetings in the calendar or online, and other activity involving Microsoft services. In contrast, Sapience Input captures time "effectively working," excluding breaks or non-work activities. Thus, Input is our preferred measure, as it is specifically designed to measure work time and has more technical access to employee activities than WPA.

During WFO, employees on average spent 44 Working Hours per week (Table 3), which is close to the contractual 40 hours per week, so Working Hours is close to the nominal work time. After Hours measures the number of weekly hours worked outside regular office hours. Despite different definitions and measurement, the Sapience variable Input and the (monthly mean of) Working Hours are significantly correlated ($\rho = 0.2715^{***}$).[5] The correlation between the variable After Hours and the Sapience variable Input is also positive and statistically significant ($\rho = 0.3127^{***}$). Working Hours and After Hours are mechanically related as the latter is part of the former.

A second group of variables (Focus Hours, Collaboration Hours, Meetings Manager, Meetings 1:1, Coaching Meets and MS Teams Calls) relate to meetings. Focus Hours is time that is uninterrupted by meetings, calls or emails. It is thus a measure of the amount of time the employee can concentrate on tasks. Collaboration Hours is the total time spent in various forms of meetings. The latter four variables measure time in meetings by structure and purpose. Meetings Manager is the number of meetings the employee attends that involve their manager, and Meetings 1:1 are personal meetings between the employee and manager. Coaching Meets is the number of meetings involving the employee, their manager and all of the manager's direct reports. MS Teams Calls is the number of calls using MS Teams (which allows for video meetings similar to Zoom or Skype).

Appendix Table A.3 shows (pre WFH) pairwise correlations between these meeting-related variables. As expected, all correlate negatively with Focus Hours, especially Collaboration Hours and Meetings Manager. All pairwise correlations are statistically significant at the 1% level. The different types of meetings are positively related among each other, but with smaller coefficients. These correlations are positive both across employees – some job roles involve more meetings than others – and across time – some periods involve more meetings of all types.

The third group of variables (Internal NW, External NW, NW EXT, NW ORG, Emails) relate to networking with colleagues and clients more explicitly. The first two measure the number of individuals (inside and outside of the company, respectively) with whom the employee had contact. The latter two measure the number of business units (e.g., teams) involved in those contacts. These measure the breadth of the employee's communications and networking contacts. Appendix Table A.4 shows

[5] The correlation is larger when aligning definitions by focusing on components of "Working Hours" measured by both tools. For example, WPA's measure of time spent writing emails correlates to Sapience Input with $\rho = 0.4099^{***}$. The correlation is still below 1 because it relates WPA's measure of only one activity with Sapience's measure of overall working time.

the (pre WFH) pairwise correlation between these networking-related variables. All correlations are positive and highly statistically significant, across employees as well as across time.

3.4 Empirical strategy

As a first step, in Section 4.1 we estimate the average WFH effect, using the data discussed in Sections 3.1 and 3.2. Our main specification exploits differences in outcomes for each employee, when working from home compared to working in the office during that month in the previous year, controlling for employee and customer team fixed effects. The unit of observation is the employee-month. Index the employee by i and the month by $t = 1, 2, \ldots, 17$. For outcome variable y_{it}, we estimate by OLS:

$$y_{it} = \alpha_i + \beta \mathrm{WFH}_t + \sum_j \gamma_j \mathrm{CustomerTeam}_{jit} + \sum_s \delta_s \mathrm{Month}_{st} + \varepsilon_{it}, \tag{1}$$

where α_i is the employee fixed effect, WFH is a dummy variable indicating months working from home, and $\mathrm{CustomerTeam}_{jit}$ is a dummy variable equal to one if and only if employee i in month t was part of team j. Month_{st} is a month (not month-year) dummy variable, so that $\mathrm{Month}_{1t} = 1$ if and only if t is January, $\mathrm{Month}_{2t} = 1$ if and only if t is February, etc. In addition, we report an alternative specification controlling for a linear rather than seasonal time trend:

$$y_{it} = \alpha_i + \beta \mathrm{WFH}_t + \sum_j \gamma_j \mathrm{CustomerTeam}_{jit} + \delta t + \varepsilon_{it}. \tag{2}$$

Once the average WFH effect is established, we analyze variation in this effect. Section 4.2 studies how effects vary with employee characteristics. We interact the WFH dummy in the previous specifications with additional explanatory variables $\mathrm{X}_{1i}, \mathrm{X}_{2i}, \ldots$. Because the X_{ji} variables are employee specific but time invariant, we do not separately control for them, as that is already achieved by the employee fixed effects.[6]

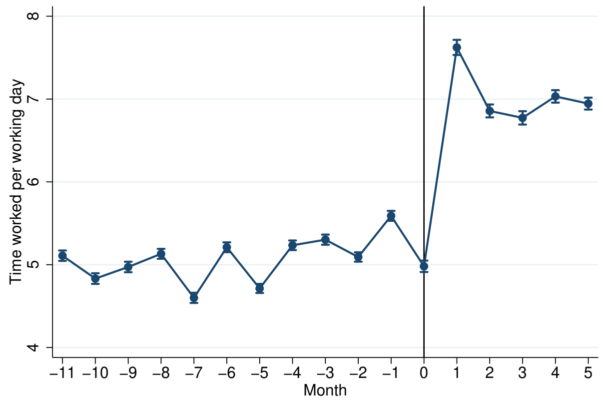
We exclude March 2020 ($t = 12$) from regressions because our main outcome variables are collected at the monthly level, and working from home started in mid-March 2020.[7] Thus, this month is neither purely WFO nor WFH. Moreover, it is likely that WFH increased in the days prior to the official WFH start, so the switch date was not clear-cut. An implication of excluding March 2020 is that teething problems and short-term adaption effects are not reflected in our estimate.[8]

Section 4.3 analyzes the effects of mechanisms such as time spent in communication, and focus time. For these we rely on the WPA data described above. Here our empirical strategy is identical to the one described in equation (2), except that we control for weekly instead of monthly time trends, as these data are available weekly. Hence, in these regressions $t = 1, ..., 34$ represents weeks. For all analyses we cluster standard errors at the employee level.

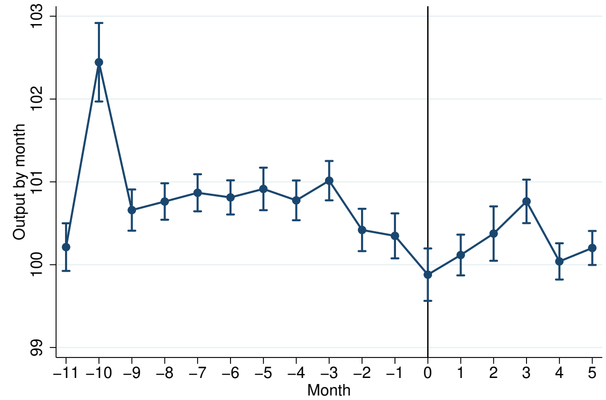
[6] While age, tenure, and experience are not time invariant, our sample window is only 17 months, so there is no meaningful variation during that window. Hence, to avoid collinearity issues, we use only employee fixed effects.

[7] This month is nevertheless plotted in the graphs.

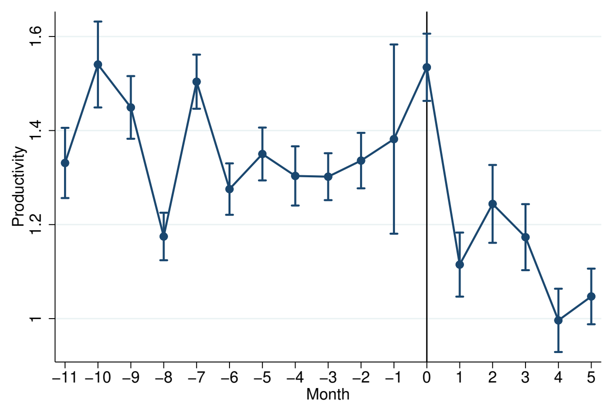
[8] For example, not every employee had suitable hardware at home to work with in the days after the switch. This was fixed quickly, but can explain some of the noticeable drops in work time and output in March 2020, see Figure 1a.



(a) Input: Time worked per working day



(b) Output: Tasks completed relative to target



(c) Productivity

Figure 1: Average outcomes by month. The vertical line (month 0) indicates the switch to working from home.

4 Results

4.1 Average WFH effect

Before proceeding to the regression analysis, Figure 1 plots the three main outcomes by month to get an intuitive idea about the WFH effect. This will also help us understand which of the econometric models (1) or (2) seems most appropriate for controlling for time trends.

According to Figure 1a, Input, employees provide about 5-5.5 hours of daily input; i.e., time in which they are actively using their software or programming tools, or in meetings or communications. There is relatively little variation in average input pre-WFH, with a slight upward trend. Hence, a

Table 4: Average Working-From-Home effect

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Input	Input	Output	Output	Productivity	Productivity
WFH	2.117***	1.592***	-0.530***	-0.098	-0.256***	-0.138*
	(0.034)	(0.038)	(0.125)	(0.155)	(0.031)	(0.074)
Linear month trend		0.040***		-0.035**		-0.010
		(0.003)		(0.015)		(0.007)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No	Yes	No
R^2	0.24	0.22	0.02	0.02	0.01	0.01
Observations	70249	70249	70249	70249	70249	70249
Clusters	10312	10312	10312	10312	10312	10312

Note: Input is the time in hours per working day the employee worked in a month. Output is the employee's normalized output relative to target in a month. Productivity is output divided by time worked. The unit of observation is the employee-month. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

linear time trend as in model (2) might be more appropriate for this outcome measure. From the first month of WFH, there is a large and persistent jump in input by more than 1.5 hours per day.[9]

For Output, Figure 1b, there is a noticeable spike in May 2019, but no visible monotonic or linear trend otherwise, so a seasonal time correction might be more appropriate here. Moreover, average output appears to be roughly comparable to pre-WFH months, with the exception of a dip in March 2020 (this month is neither fully WFO nor WFH). This dip might be due to disruption caused by the transition from WFO to WFH.

Finally, for Productivity, Figure 1c, the graph is more volatile, which is not surprising for a ratio. There is no clear linear time trend pre-WFH, but some variation from month to month, so a seasonal correction might be more appropriate. Productivity drops visibly during WFH.

To quantify the WFH effect, and to control for employee and team time-invariant variables (via employee and team fixed effects), we now turn to the regression analyses. Informally, the estimates give us average differences in outcomes pre- and during WFH for the same employee, controlling for team effects (since employees sometimes switch teams) and time trends.

Table 4 reports WFH effect estimates based on OLS regressions for all three outcome variables, in each case with linear and seasonal time trend corrections. All estimates are in line with the visible effects in the raw data in Figure 1.[10]

According to the estimates, WFH increased the time worked per day by roughly 2.1 hours (based on a seasonal time trend) or by 1.6 hours (with a linear time trend). Both estimates are economically

[9] Note that a national statistical office, which does not have access to these effective work hours, would not pick up these changes in input at the intensive margin when using nominal work hours (which did not change during WFH) to compute productivity.

[10] Table A.5 in the appendix estimates the same regressions, but truncates the most extreme observations to account for outliers. The qualitative results of our preferred specifications remain the same.

very meaningful, and statistically significant at all conventional levels.[11] Since both Figure 1a and the regression indicate a linear time trend, we prefer column (2). The estimate of the WFH effect in column (1) is larger, because it does not take the pre-WFH time trend into account in the same way.

Columns (3) and (4) estimate that Output changed by -0.5 or -0.1 percentage points, depending on time controls (recall that fulfilling all monthly tasks implies an output of 100%). Both point estimates are slightly negative, but only the estimate with the seasonal time trend is significantly different from zero at all conventional levels. Hence, we conclude that WFH had no or only a small negative effect on Output. While the regression indicates a significantly negative linear time trend, due to the outlier in May 2019, we prefer specification (3) since a linear trend does not reflect the raw data very well.

Columns (5) and (6) estimate that Productivity decreased by 0.26 or 0.14 output percentage points per hour worked, depending on the time controls. Given an average WFO productivity of 1.36, these effects correspond to a 19% and a 10% drop in productivity. Both are economically significant: if employees worked a fixed 40 hours per week, this fall in productivity would imply a drop in output of 10.2 or 5.5 output percentage points in a week. In other words, if employees had not increased time worked during WFH, on average they would have completed only 90-95 of 100 assigned tasks. The WFH effect in specification (6) is significantly different from zero only at the 10% confidence level, whereas the effect in specification (5) is statistically significant at all conventional levels. We prefer specification (5), since both the plot and the linear time trend coefficient indicate that a linear trend is not as appropriate.[12]

In summary, this evidence indicates that employees worked longer but less productively, with output remaining about the same or dropping slightly. Thus, there appear to be two countervailing effects on output that roughly offset each other. Our interpretation of these patterns is that employees were less productive during WFH, but still aimed to reach the same output or goals, and hence work longer until the same output was reached. In the next sections, additional results will suggest that productivity decreased due to increased distractions and coordination costs.

A potential alternative explanation for the jump in work time during WFH might be that employees "gamed" the Input numbers. This is unlikely for several reasons. First, Sapience time measurement is sophisticated and designed to be resilient to manipulation attempts. Merely keeping the computer on for longer or watching videos instead of working does not increase Input. Rather, it would require having the relevant work software as the active window, and giving continuous mouse or keyboard input. Second, gaming time measurement in Sapience would not translate into increases in WPA's time measurement.[13] WPA time recording is from activity in MS Outlook, MS Teams etc., rather than programming tools or similar, and is not dependent on mouse / keyboard activity. Yet the WFH effect we see with this alternative time measurement is also positive, see section 4.3. Third, employees are not paid by the hour. To impress superiors, time is better spent generating output. Fourth, Sapience

[11] For comparison, the contractual working day (pre-WFH) is 9 hours at the company we study, which includes a 1 hour lunch break.

[12] We also estimated the productivity regression without time controls. The WFH estimate is -0.2 output percentage points per hour worked with a t-statistic of -6.8; i.e., a highly significant effect consistent with the other specifications.

[13] Unlike Sapience, employees were not aware of the use of WPA analytics. WPA licenses were purchased for the first time and for this study specifically. Very few people at the company knew about it and had access to these data.

was in use long before the switch to WFH, so this potential concern cannot explain the WFH effect well. Fifth, the additional WFH effects we find from WPA activity (section 4.3), such as more time spent on conference calls and fewer focus hours, cannot be explained by "gaming."

Another potential concern might be that the increase in Input is due to measurement error, as spontaneous (unscheduled) face-to-face meetings during WFO might not be counted as working time, while spontaneous online meetings during WFH are counted. This is not backed up by the data. We are able to reproduce the findings in this section using other measures of working time, available for a sub-sample of employees (Section 4.3). We also find adverse effects of WFH on direct measures of networking and training; in particular the number of some types of meetings decreases during WFH. Moreover, employees with children, and those working in roles where networking with people outside the company is more important, are more adversely affected by the switch to WFH. This is difficult to explain with unscheduled offline meetings, but is consistent with increased disruptions and coordination costs. Last, we observe when an employee starts and ends their working day. The length of the workday measured in this way increases from 7.64 hours to 9.17 hours during the WFH period. Taken together, these results suggest that spontaneous offline meetings explain at most a small part of our overall results.

If employees used their own devices to work from home, we would not track that activity (in either period). However, this company did not allow employees to do so, to insure integrity of confidential client information. Any employees who worked at home in both periods had to use a company-owned laptop computer and phone, both of which included the tracking software used to collect our variables, with one small exception. During the transition to WFH, a small percentage of employees who did not yet have a company-owned laptop computer were briefly allowed to use personal devices to perform some work. This lasted only until the company could provide them with laptops. In such cases Sapience would not track their work, so our Input variable has missing values. This affects a very small percentage of our data.

Another possible explanation for the increase in time worked is that pandemic lockdown measures closed restaurants, cinemas, etc., thereby reducing the value of leisure time. Under this explanation, however, we would expect Output to increase and Productivity to remain approximately constant, which is not what we observe. Appendix Figure B.5 shows that while we see a slight dip in working hours after every stage of lockdown easing, the effect is small and, more importantly, only temporary. We also do not find evidence that productivity or other outcomes co-vary with national or regional indicators of the severity of Covid, such as deaths or case rates.

Finally, we are able to measure the number of days the employee worked relative to the number of work days in a month. According to Table A.6 in the appendix, the number of sick days decreased significantly. This suggests that absences or sickness were not a driver of the decrease in productivity.

4.2 Who copes better with WFH? Heterogeneous WFH effects

We now explore what drives the WFH effect in more depth, and which subgroups are most affected by the shift to WFH. Table 5 displays estimates for all outcome variables, separately by whether

Table 5: Working-From-Home: Children at home and gender differences

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Input	Input	Output	Output	Productivity	Productivity
WFH	1.416***	1.599***	-0.528***	-1.176***	-0.206***	-0.361***
	(0.046)	(0.086)	(0.150)	(0.267)	(0.042)	(0.075)
WFH × Children	0.307***	0.091	0.061	0.673	-0.169***	-0.027
	(0.059)	(0.128)	(0.205)	(0.431)	(0.058)	(0.111)
WFH × Male		-0.211**		0.895***		0.149
		(0.094)		(0.300)		(0.093)
WFH × Male × Children		0.252*		-0.822*		-0.157
		(0.145)		(0.495)		(0.133)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Linear Month Trend	Yes	Yes	No	No	No	No
R^2	0.23	0.25	0.02	0.02	0.01	0.01
Observations	64392	58644	64392	58644	64392	58644
Clusters	8865	7911	8865	7911	8865	7911

Note: Input is the time in hours per working day that the employee worked in a month. Output is the employee's normalized output relative to target in a month. Productivity is output divided by time worked. The unit of observation is the employee-month. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

employees have children at home and by gender, using our preferred time control from the previous section. The number of observations is slightly reduced since the additional explanatory variables are missing for some employees. We converted the explanatory variables (except commute time) into dummy variables for easier interpretation.

In the country in which the company is located, all schools closed in March 2020 during the Covid-19 pandemic, so working from home was presumably an even greater challenge for some parents, as children needed to be supervised and perhaps taught. Hence, we investigate whether having children at home changed an employee's WFH effect. An important qualification is that under normal conditions, children would attend school and any adverse effects of WFH on productivity of parents might be lower.

Column (1) shows that employees who have at least one child at home (as measured by company health insurance coverage) increased work time more during WFH than did their counterparts without children. Possibly, this is due to the fact that employees with children get distracted more often during WFH and compensate by working longer hours. Employees with children at home work almost a third of an hour more per working day during WFH than those without children, who themselves still work 1.4 hours more during WFH. These effects are highly significant. Column (3) reveals no significant change in the WFH effect on output with children at home. However, column (5) shows that the increased working time implies a larger drop in productivity when there are children at home. Consequently, the patterns seen for the average employee are exacerbated for employees with children.

The even columns in Table 5 investigate whether there was a gender difference in how outcomes changed during WFH, conditional on whether there were children at home.

The WFH × Male interaction represents the difference in the WFH effect between male and female employees *without* children. Male employees without children increased working time by about 0.2 hours less per day than did female employees without children, a significant effect. They also suffered a smaller decline in output.

The WFH × Children interaction represents the difference in the WFH effect between female employees with and without children. Female employees with children did not significantly increase working time during WFH compared to female employees without children, nor did their output or productivity significantly differ.

Finally, the sum of WFH × Male and WFH × Male × Children is the difference in the WFH effect between male and female employees with children. This difference is roughly zero for all outcome measures, so there is no gender difference among employees with children at home.

Thus female employees are more adversely affected by WFH, but this is not due to child care responsibilities. The latter finding contrasts with much of the narrative in western countries, where childcare responsibilities are given as a main reason why women are more adversely affected by WFH (Financial Times, 2021a). We conjecture that this is due to greater expectations placed on women by parents and parents-in-law in the domestic setting.

Next, we investigate whether employees with more industry experience or company tenure were affected differently by WFH. One reason this could be the case is that they have greater institutional knowledge and social capital, and are less reliant on help from colleagues or find it relatively easier to obtain during WFH. To investigate the effects of age, company tenure, and industry experience (at the company or elsewhere), we generate dummy variables with a median split. Since these variables are highly correlated, we estimate their effect on the WFH estimate jointly in Table 6.[14]

Column (1) shows that work experience has the largest and only significant impact on the WFH effect for time worked. During WFH, experienced employees worked roughly a quarter hour more per day compared to less experienced employees, holding age and company tenure constant.[15] Our interpretation is that more experienced employees have more managerial duties. The increased costs of coordination (also see next section) during WFH are therefore borne by these experienced employees, who have to put in more time to coordinate their team. Additionally, it is likely that the lion's share of managing the WFH transition falls on experienced employees with more responsibility.[16]

[14]Appendix Figure B.3 illustrates individual employee productivity during WFH as a function of productivity before WFH. Two patterns emerge. First, most employees are more productive in WFO than WFH. Second, those who are more productive in WFO tend to also be more productive WFH. However, there is considerable heterogeneity.

[15]When estimating the regression with one interaction for age, tenure, and experience at a time (not displayed), all interactions show significantly positive point estimates due to their positive correlation. That is, older employees increased WFH work hours more compared to younger employees, but this is no longer true when holding tenure and experience constant, see Table 6.

[16]While more experienced employees might be more likely to have children at home, this experience effect is unrelated to having children. When adding the interaction with Children to regression (1) in Table 6 (not displayed), the interaction with HighExperience remains significantly positive.

Table 6: Working-From-Home: Age, experience, tenure, commute times

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Input	Input	Output	Output	Productivity	Productivity
WFH	1.361***	1.516***	-0.743***	-0.603*	-0.245***	-0.286***
	(0.058)	(0.095)	(0.194)	(0.334)	(0.048)	(0.083)
WFH × HighTenure	0.036		0.519**		0.003	
	(0.067)		(0.229)		(0.090)	
WFH × HighAge	0.057		0.097		-0.084	
	(0.092)		(0.366)		(0.073)	
WFH × HighExperience	0.270***		-0.138		-0.038	
	(0.094)		(0.390)		(0.084)	
WFH × CommuteTime		0.107		0.316		-0.030
		(0.122)		(0.405)		(0.093)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	No	No	Yes	Yes	Yes	Yes
Linear Month Trend	Yes	Yes	No	No	No	No
R^2	0.25	0.26	0.02	0.03	0.01	0.01
Observations	58644	31848	58644	31848	58644	31848
Clusters	7911	4295	7911	4295	7911	4295

Note: Input is the time in hours per working day that the employee worked in a month. Output is the employee's normalized output relative to target in a month. Productivity is output divided by time worked. The unit of observation is the employee-month. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

The change in Output during WFH is roughly 0.5 percentage points larger per hour for employees with longer company tenure, holding age and experience constant. Thus, while low tenure employees' Output falls, high tenure employees keep meeting their goals. The other characteristics do not show a significant effect. It appears that employees who had worked at the company for longer were able to adapt more effectively to the WFH-shock, and that this was more important than general industry experience. This finding suggests that greater firm-specific human capital in the form of familiarity with company procedures, or more fully-developed networks and working relationships with colleagues and clients, were helpful during WFH. Alternatively, those with greater experience or tenure might be in positions with more responsibility, and so responded more to the shift to WFH. For the last outcome measure, productivity, there is no significant difference in the WFH effect among these employee groups.

The even columns in Table 6 estimate the WFH effect by employee commute time (when working from the office). The WFH effect does not significantly differ by commute time for any outcome measure. Hence, the finding that WFH increased hours worked is not merely due to more available time. Rather, it supports the interpretation that productivity fell during WFH, and employees worked more to compensate.

Figure 2 shows the mean and 95% confidence intervals of the estimated effect of WFH on productivity separately for different customer teams. Those are teams of employees who work for the same

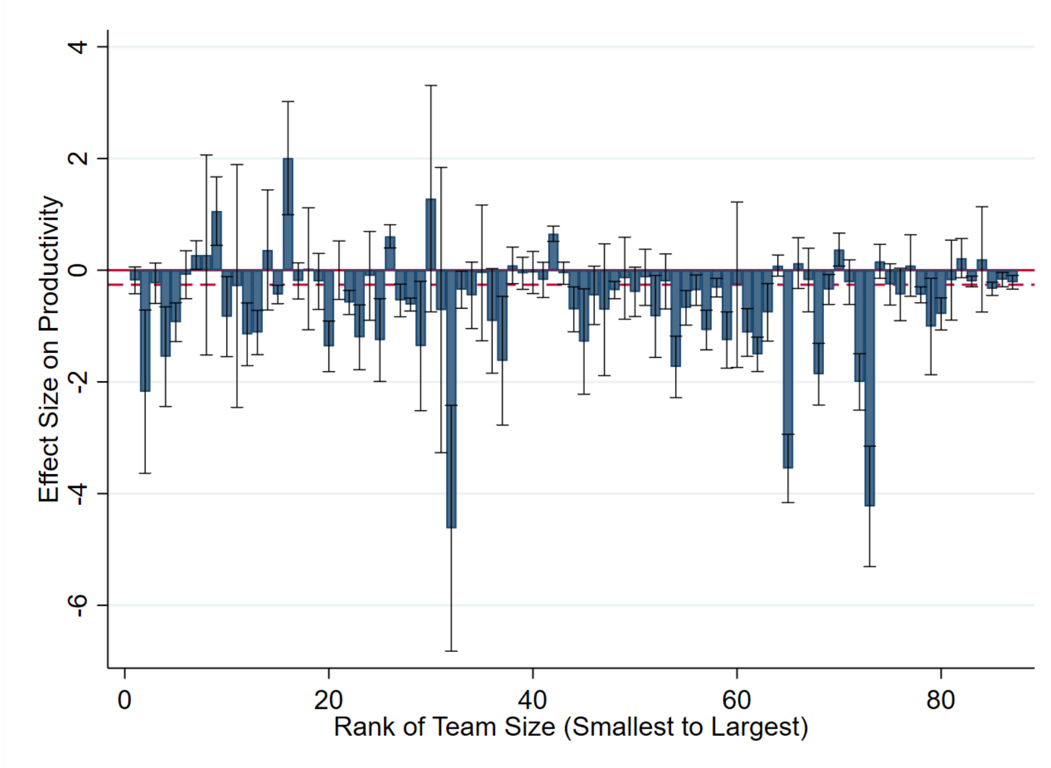


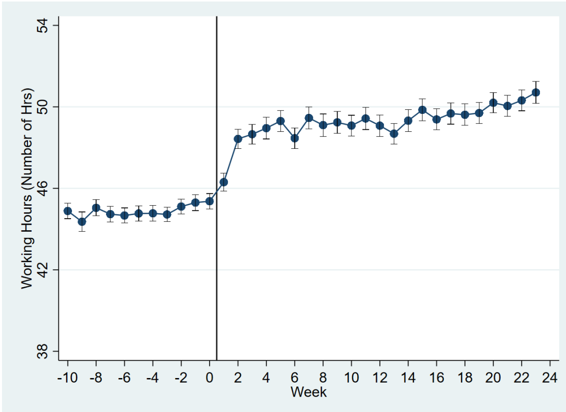
Figure 2: Heterogeneity of WFH Effect on Productivity Across Teams.

customer, but not necessarily on the same project. In the figure teams are sorted by size (number of team members) in increasing order from left to right. The effect is negative for almost all teams. This illustrates that the overall negative effect on productivity (illustrated by the dashed line in Figure 2) is not driven by a few customers or teams. Rather, WFH productivity declined broadly across the group studied.

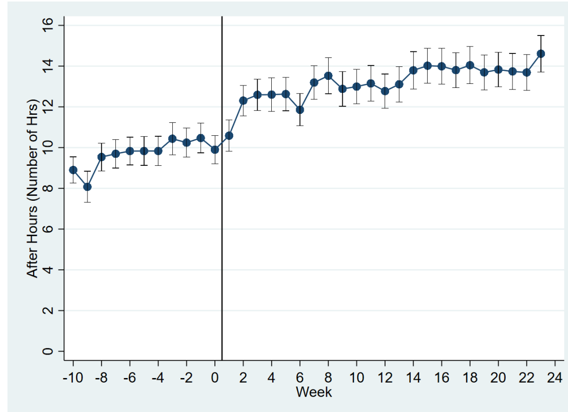
For 43 teams the negative effect is statistically significant. Five teams, by contrast, show a statistically significant positive effect on productivity. With the exception of one team, those are all teams in the bottom half of the size distribution. In smaller teams it might be easier to solve coordination problems during WFH. Still, even among the smaller teams, the effect on productivity is negative for the vast majority.

4.3 Mechanisms: What contributes to lower productivity?

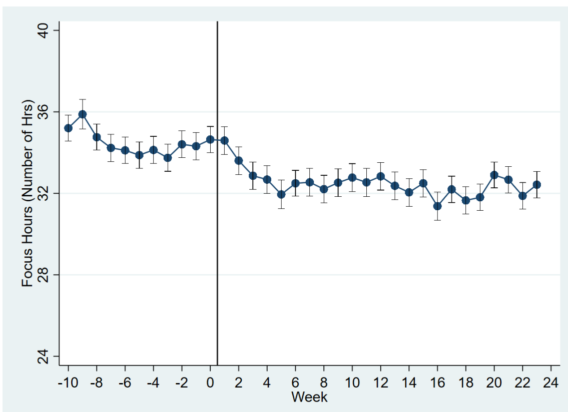
To better understand the mechanisms behind the decrease in productivity, we study the sub-sample of 914 employees for which WPA data were obtained (see Table A.2). Using these data we document three patterns: an overall increase in working time; a shift away from performing work tasks and towards spending time on meetings, calls, or answering e-mails; and reduced time networking with others or meeting 1:1 with one's manager.



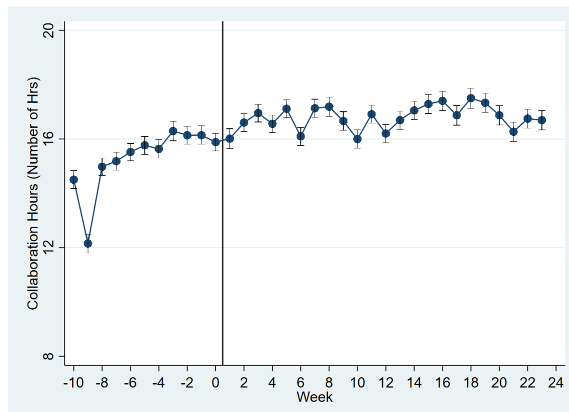
(a) Working Hours



(b) After Hours



(c) Focus Hours



(d) Collaboration Hours

Figure 3: Working patterns pre- and post WFH. Panel (a): mean weekly working hours. Panel (b): hours worked outside regular working hours. Panel (c): number of hours with two or more hour blocks *not* spent in meetings, on calls or writing e-mails. Panel (d): hours spent in meetings or in calls. Week= 0 is 9th-15th March 2020.

Working Hours

Figure 3 illustrates the shift in working patterns after the start of WFH. In line with the evidence in Section 4.1, the WPA data show that overall hours worked increased, including those after regular office hours. Panels (c) and (d) show an interesting pattern. Employees spend more time in meetings or calls and have less "focus time" (i.e., time uninterrupted by meetings or calls to focus on completing tasks). The increased time spent in meetings, and its persistence after the initial WFH transition phase, suggest substantial and ongoing coordination costs with WFH, which negatively impact time available to work in a productive manner. The fact that employees have less time to work in a focused or uninterrupted manner could also explain why they have been found to multitask more during meetings (Cao et al., 2021).[17]

[17] Appendix Figure B.2 illustrates the technological shift post WFH, with a drastically increased number of hours spent on virtual meetings using MS Teams. Interestingly, the number of such meetings continues to increase almost

Table 7: Shift in Working Patterns due to WFH

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Working Hours		After Hours		Focus Hours		Collaboration Hours	
WFH	4.431***	2.743***	4.212***	1.822***	-2.665***	-1.417***	1.251***	0.704***
	(0.161)	(0.218)	(0.288)	(0.320)	(0.245)	(0.297)	(0.122)	(0.137)
Linear weekly trend		0.096***		0.137***		-0.071***		0.031***
		(0.009)		(0.0141)		(0.012)		(0.005)
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.703	0.709	0.743	0.747	0.717	0.719	0.745	0.746
Observations	25,893	25,893	25,893	25,893	25,893	25,893	25,893	25,893
Clusters	914	914	914	914	914	914	914	914

Note: Working hours are weekly hours worked. After hours are weekly hours worked outside regular work time. Focus Hours are hours with two or more hour blocks *not* spent in meetings, on calls or writing e-mails. Collaboration Hours are hours spent in meetings or in calls. The unit of observation is the employee-week. Standard errors are shown in brackets below the point estimates, and are clustered at the employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table 7 shows regressions estimating the WFH effect on these outcomes. Both overall working hours and working hours outside of regular office time increase during WFH. In fact, comparing the size of coefficients in columns (1) and (3) we see that the increase in overall working hours takes place almost entirely outside of normal working hours. The table also confirms the increase in time spent in meetings and on calls, with a corresponding decrease in uninterrupted work time (focus hours). In all cases, the WFH effect persists and remains highly statistically significant when we include a linear time trend. The estimated effect size is smaller in these cases but remains substantial. After controlling for time trends, employees work 2.7 hours more per week, out of which 1.8 are spent working outside regular office hours. However, they also spend 1.4 hours less working in a focused or uninterrupted manner. These shifts in working patterns could explain why productivity decreases under the WFH regime.[18]

We conjectured that some of the increase in working hours and decrease in productivity is due to increased costs of communication and coordination within teams. If this is the case then we should see that roles which are characterized by more interaction and networking *prior* to WFH are more affected by the switch to WFH. If we do a median split by how many internal networking contacts (variable Internal NW, see Table 3) an employee had prior to WFH, we see that working hours in specification (1) of Table 7 increase by 6.01*** hours for those with above median contacts and by 3.515*** hours for those with below median contacts. The difference is highly statistically significant (t-test $p < 0.0001$) suggesting that coordination costs are indeed an important factor behind the decline in productivity during WFH.

six months after the switch to WFH. Barrero et al. (2021) show evidence of the surge in technological innovations that support WFH during the pandemic.

[18] Additional analysis in Appendix A shows that for overall working hours the time trend is even stronger during WFH. In this case the pre-WFH trend is only about 60% of the overall trend. For the other outcomes the trend is mitigated after the initial shift in levels, in line with ceiling effects (Appendix Table A.7).

Table 8: Shift in Networking Patterns and types of meetings due to WFH

	(1) Internal NW	(2) External NW	(3) NW ORG	(4) NW EXT	(5) Meetings Manager	(6) Meetings 1:1	(7) Coaching Meets	(8) E-mails
WFH	-7.621***	-0.532***	-0.009	-0.150***	1.723***	-0.089*	-0.060*	4.282***
	(0.369)	(0.103)	(0.005)	(0.027)	(0.205)	(0.048)	(0.033)	(0.680)
Linear weekly trend	0.787***	0.078***	0.001***	0.008***	0.016**	0.002	0.002	-0.020
	(0.026)	(0.006)	(0.000)	(0.001)	(0.008)	(0.002)	(0.002)	(0.029)
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.801	0.758	0.665	0.624	0.757	0.320	0.386	0.766
Observations	25,893	25,893	25,893	25,893	25,893	25,893	25,893	25,893
Clusters	914	914	914	914	914	914	914	914

Note: "Internal NW" is the number of people inside the company with whom the employee had meaningful contact in the last 28 days. "External NW" the same measure for contacts outside the company. "NW ORG" is the number of distinct organizational units within the company with whom the employee had at least two meaningful interactions in the last four weeks. "NW EXT" is the same measure for domains outside the company. "Meetings Manager" is the number of meetings involving the manager. "Meetings 1:1" is the number of meetings between the employee and their manager. "Coaching Meets" is the number of meetings by the manager with all direct reports including the employee. "E-mails" is the number of emails sent. The unit of observation is the employee-week. Standard errors are shown in brackets below the point estimates, and are clustered at the employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Networking and Collaboration

We now focus on networking and collaboration patterns in more detail. Understanding changes in networking and collaboration can tell us something about the value of additional time spent in meetings. Shifts in networking patterns can also impact productivity in different ways, for example, by affecting the exchange of ideas and knowledge.

Table 8 shows how networking and collaboration patterns change with WFH. Columns (1) and (2) focus on the number of people inside and outside the company, respectively, with whom an employee had a meaningful contact (defined as an email, meeting, call, or at least 3 instant messages) during the last 28 days. There is a generally positive time trend, possibly reflecting the fact that networking is becoming more important at this company. However, there is a clear negative impact of WFH on the number of individuals with whom employees share meaningful interactions.[19]

Columns (3) and (4) contain results for similar measures, focused on the number of organizational units inside and outside the company at which an employee interacted with someone (column (4)). Here we also see a decline in contacts caused by WFH, despite a general upward trend, though in the case of internal organizational units the decline is not statistically significant.

Columns (5)-(7) focus on collaboration patterns. In line with our earlier analysis, we see that the number of meetings involving the manager increases. By contrast, the number of both 1:1 supervisor

[19] Appendix Table A.8 shows specifications where we allow the time trend to interact with WFH. By and large, there are no significant differences in trend pre- and post WFH. For internal networking the positive time trend is somewhat bigger during WFH suggesting some potential catch up, but for all other outcomes there is no significant (or even a negative) difference before and after the introduction of WFH.

Table 9: Productivity in the WPA sample

	(1)	(2)	(3)
	Sapience	WPA	
WFH	-0.149**	-0.056***	-0.049**
	(0.072)	(0.008)	(0.020)
Mean pre WFH	1.080	0.599	0.599
	(1.702)	(0.531)	(0.531)
Employee FE	Y	Y	Y
Team FE	Y	Y	Y
Linear Trend	N	N	Y
R-squared	0.356	0.783	0.784
Observations	4,359	4,359	4,359
Clusters	888	888	888

Note: Productivity is as in previous sections, Output divided by Sapience monthly work hours. Productivity WPA divides Output by the WPA Input measure "working hours" (aggregated to monthly level). The unit of observation is the employee-month. For 888 employees we have all three sources of information: Sapience, IDMS and WPA. Standard errors are shown in brackets below the point estimates and are clustered at the employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

meetings and coaching meetings decrease during WFH. Employees seem to receive less mentoring and coaching, even though these effects are only statistically significant at the 10% level. Moreover, in WFH managers are spending more time managing groups rather than individuals.

Last, column (8) shows that the number of emails sent increased substantially during WFH with about 4 more emails being sent on average. This corresponds to an about 17% increase over the baseline (see Table 3).

Overall, these patterns highlight a detrimental impact of WFH on networking. Employees have fewer contacts with different individuals and organizational units both inside and outside the company. They also have fewer 1:1 meetings with superiors, and receive less coaching. These lost opportunities to network may help explain why WFH lowers productivity. It is also likely that they slowed employee development, though that is beyond estimation with our data.

Productivity

Last, we study productivity in this sub-sample. We first ask whether the drop in productivity from our main sample can also be found in this smaller WPA sample of employees.

As we have additional variables for this smaller sample, we consider two measures of productivity: (i) the Sapience based measure used above, and (ii) where we replace the Sapience variable Input by WPA working hours to compute productivity. Because we only have two months of pre-WFH data, we do not include time trends for the monthly Sapience data here. Using the Sapience time measure, we estimate an approximately 15% drop in productivity after the introduction of WFH. With the WPA time measure, we find an approximately 10% drop in productivity, or 8% when controlling for a linear time trend. Both effects are highly statistically significant ($p < 0.040$, see Table 9). The drop in productivity from the full sample can thus be reproduced in this smaller sample, using different measures of hours worked. Appendix Figure B.4 plots the change in productivity after the introduction of WFH in this sample.

We next ask how these changes in work patterns are linked to productivity. This will help us understand whether the documented changes can explain the decrease in productivity. We would further like to know which variables are the most important predictors of productivity. For the remainder of the section we use the Sapience measure of productivity from Section 4.1.

To address these questions, we first estimate adaptive Lasso regressions (Zou, 2006) in which the dependent variable is productivity and prediction variables are dummies that identify weeks in which a variable is above average for a given employee. Lasso regressions select a set of variables that best explain variation in productivity by minimizing an estimate of the out-of-sample prediction error.[20] We use dummies identifying the weeks where a variable is above average for a given employee to focus on variation in productivity *within* employees.[21] We conduct this regression separately for WFO and WFH periods in order to see whether productivity determinants changed between the two environments. Table 10 presents these results. An X in the table indicates variables that the Lasso regression includes in the prediction model.

The variables selected include working hours, focus hours as well as most networking variables. Working After Hours and attending many meetings does not seem to contribute substantially to productivity, nor does spending time on MS Teams calls. The set of selected variables is quite consistent before and during WFH, with focus hours and the networking measures crucial indicators of productivity. Interestingly, overall working hours is selected before WFH but not afterwards.

To assess the economic significance of these associations, we compute the elasticity of productivity with respect to a 1 percentage point increase in the variables selected by Lasso. Table 10 shows the mean elasticities. Before WFH, the most important variables associated with productivity are working hours, focus hours and NW EXT. A 1 percentage point increase in overall working hours is associated with a 0.014 percentage point average increase in productivity. A 1 percentage point increase in focus hours is associated with a 0.033 percentage point average increase in productivity, and a 1 percentage point increase in network contacts outside the company is associated with a 0.01 percentage point average increase in productivity. These elasticities show that these variables are important correlates of productivity. During WFH, the most important variables are focus hours, and internal and external networking. As before, both internal and external networking are positively associated with productivity. Focus Hours are now more than twice as important in terms of their average marginal effect on productivity, with a 1 percentage point increase in focus hours associated with a 0.072 percentage point average increase in productivity. There seems to be a broadly stable

[20] Lasso models have a free parameter λ which is the weight on the penalty term. Adaptive Lasso performs multiple Lassos, where in each the λ is selected that minimizes an estimate of the out-of-sample prediction error. After each Lasso, variables with zero coefficients are removed and remaining variables are given a penalty weight designed to drive small coefficients to zero. Zou (2006) has shown that adaptive Lasso enjoys oracle properties; they perform as well as if the true underlying model were known ex ante.

[21] An alternative would be to force Lasso to select employee fixed effects. This is not possible for us as in the merged dataset containing both productivity and WPA variables we do not have enough observations pre-WFH for this approach.

Table 10: Variables selected by Lasso and Elasticity of Productivity with respect to selected variable.

	pre WFH		during WFH	
	Lasso	Elasticity	Lasso	Elasticity
Hours				
Working Hours	X	0.014***		
After Hours				
Meetings				
Focus Hours	X	0.033***	X	0.072***
Collaboration Hours				
Meetings Manager				
Meetings 1:1	X	0.002***		
Coaching 1:1			X	0.003
MS Teams Calls				
Networking				
Internal NW			X	0.040***
External NW	X	−0.000	X	0.029***
NW EXT	X	0.010**	X	0.011***
NW ORG	X	0.000	X	−0.001
Emails				
Emails			X	0.053***

Note: Adaptive Lasso linear regression results (X indicates a variable was selected) and mean elasticity of productivity with respect to an increase of 1 percentage point in the variables selected by Lasso. The left two columns show the results restricted to the period before WFH and the right columns the results restricted to the period during WFH. For all variables in the table Lasso regressions include a dummy identifying weeks in which the variable is above average for a given employee.

relationship between working patterns and productivity. The increased importance of focus hours during WFH might be explained by the fact that employees have less of it during WFH.

In summary, in this section we showed that WFH induced a significant shift in working patterns. Employees worked more, including outside regular office hours, but had less uninterrupted time to focus on task completion as they spent more time in meetings. They networked less and spent less time being evaluated, trained and coached. We further showed evidence that these reductions, especially in focus hours and networking, were detrimental to productivity.

5 Conclusion

In this paper we have presented the most detailed analysis of WFH productivity changes for knowledge workers. The paper makes a number of significant contributions. We study an occupation that is expected to be amenable to WFH, but involves significant cognitive, collaborative and innovation tasks. The data provide an unusually high quality measure of employee productivity for knowledge workers. The breadth of the data allow for the first thorough analysis of determinants of WFH productivity. We provide evidence on how WFH productivity varies with employee characteristics, presence of children at home, and WFO commute time. We also use detailed data on how employees spend their work time to study the effects of job characteristics on WFH productivity. These latter results are important, since they provide insights into how the effectiveness of WFH may vary, and key issues for firms to consider in deploying WFH.

In our sample, employees were able to maintain similar or just slightly lower levels of output during WFH. In order to do so, they worked longer hours. Despite this, employees had less focus time to perform tasks, and the net effect was a drop in productivity. It would be interesting to see if this change is sustainable, especially in light of evidence of the adverse effect of long work hours on employee well-being, and mental and physical health (Sparks et al., 1997; Sokejima and Kagamimori, 1998; Sparks et al., 2001).

It is likely that WFH also resulted in a decline in intangibles that are valuable to the employee and company. Working relationships, professional networks and corporate culture may have suffered. More subtly, when people work in the same location, they experience unplanned interactions. That can lead to new working relationships, and "productive accidents" that spur innovation. It is not easy to generate similar unplanned interactions on teleconferences. Finally, employees had fewer opportunities for coaching, and meeting directly with supervisors. This undoubtedly slowed their development of human capital.

We explored several possible explanations for the decline in productivity. Our main explanation is that some aspects of work are more difficult to perform in a virtual environment. We provide clear evidence that this is the case. More time was spent in meetings, and those tended to involve larger groups. Less time was spent in direct interactions with the supervisor or colleagues. Employees also narrowed their spheres of communication, interacting with fewer people and business units, both inside and outside the firm. Collectively these indicate that costs of communication, collaboration and coordination are higher when done virtually. Moreover, these factors are likely causes of changes in focus time, and in the decline in productivity.

Alternative explanations could be related to the stresses of the pandemic. However, the data show an immediate and persistent jump in work patterns and productivity at the shift to WFH, which is inconsistent with the gradual evolution of the pandemic. We found no evidence that employee work behavior varied with changes in lockdown restrictions. Employees actually had a decline in sick days. Finally, company economic performance was quite good during this period of time, stronger than the prior year, so fear of job loss was not an issue.

Another possible explanation is the presence of children at home, which was exacerbated by the closing of schools. Indeed, WFH productivity was lower for employees who had children at home, so this is a partial explanation. However, those without children at home also suffered a decline in productivity, with similar patterns for reduced focus time, increased time spent in large meetings, and decreased 1:1 communications and meetings.

Company executives were not surprised by the findings in this paper, which accord with their perceptions of the experience with WFH. As of early July 2021, they estimate that perhaps half of their employees had moved from their original locations, primarily to live with extended family (there were still significant pandemic-related restrictions). According to one senior executive, "bringing them back to our base locations will not be easy." The company expects to make significant use of WFH in the future, with perhaps 30-40% of employees in WFO on any given day. No doubt productivity will improve as the firm refines implementation of WFH and moves to a blended model with WFO. Moreover, employees enjoy greater flexibility and lower commute times.

The findings in this paper will be helpful well beyond this firm. We have presented evidence on some of the challenges of implementing WFH. In particular, WFH may be more difficult for employees who are less experienced, have lower tenure, and for jobs that involve significant collaboration and coordination. Firms will have to develop tools, training and policies to give greater emphasis to interpersonal interactions during WFO, improve effectiveness of virtual communication, and train supervisors and employees to schedule work time at home more efficiently.

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Online Appendix "Productivity, Collaboration & Networking During Work From Home: Evidence from IT Professionals"

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For Online Publication

Contents

A Additional Tables

Table A.1 presents OLS and ordered Logit regressions, explaining the performance rating with that employee's mean time worked, output, and productivity over the most recent 5 or 10 months. All regressions show that both time worked and productivity significantly improve an employee's performance rating (a lower score is better). The coefficient on mean output goes in that direction, but is not statistically significant, because the effect is not monotonic (see also Figure B.1 below). The time horizon of 5 or 10 months does not noticeably change coefficients. Hence, Sapience input and outcome measures are meaningful in explaining performance ratings, which the company uses for promotion decisions, among other things.

Table A.1: Do Sapience outcome measures predict performance evaluations?

	(1) OLS	(2) Ordered Logit	(3) OLS	(4) Ordered Logit
Dependent variable	Rating	Rating	Rating	Rating
MeanInput5	-0.097***	-0.219***		
	(0.007)	(0.015)		
MeanOutput5	-0.003	-0.006		
	(0.002)	(0.004)		
MeanProductivity5	-0.020***	-0.041***		
	(0.006)	(0.015)		
MeanInput10			-0.093***	-0.205***
			(0.007)	(0.016)
MeanOutput10			-0.002	-0.004
			(0.002)	(0.004)
MeanProductivity10			-0.023***	-0.047***
			(0.007)	(0.015)
Constant	3.498***		3.365***	
	(0.173)		(0.183)	
R^2	0.06		0.04	
Observations	4220	4220	4930	4930

Note: MeanInputX is the average of Input (hours worked) over the most recent X months prior to the performance rating. Similarly, MeanOutputX and MeanProductivityX are the averages of Output and Productivity, respectively, over the most recent X months prior to the performance rating. Rating takes integer values 1 to 5, with 1 being the best. Each observation is one employee. Heteroskedasticity-robust standard errors are shown in brackets below the point estimates. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table A.2 provides summary statistics for employees in the WPA sub-sample, compared with other employees for whom we do not have WPA data. Employees covered by WPA are somewhat younger and more junior in the company. They are also somewhat less productive. However, these differences are generally small.

Tables A.3 and A.4 show pairwise raw correlations among meeting variables and networking variables, respectively. As expected focus hours is negatively related to all meeting variables, while the meeting variables have positive correlation among themselves. Networking variables are positively related among each other, as expected.

Table A.2: Summary Characteristics of Non WPA and WPA sample.

	Non WPA	WPA	p-value
Age (yrs)	31.98	31.29	0.001
Male	0.76	0.78	0.191
Children	0.52	0.50	0.366
Tenure (yrs)	4.49	4.17	0.023
Productivity	1.66	1.49	0.034
N	9398	914	

Table A.3: Pairwise Correlation of Meeting-Related Variables.

	Focus Hours	Collab. Hours	Meetings Mgr	Meetings 1:1	Coaching Meets	Calls
Focus Hours	1					
Collab. Hours	−0.4710***	1				
Meetings Mgr	−0.4223***	0.4365***	1			
Meetings 1:1	−0.0857***	0.0327***	0.1871***	1		
Coaching Meets	−0.1115***	0.0814***	0.0261***	0.0059*	1	
MS Teams Calls	−0.0883***	0.1633***	0.0180***	−0.0121	0.0317***	1

Note: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table A.4: Pairwise Correlation of Networking-Related Variables.

	Internal NW	External NW	NW ORG	NW EXT	Emails
Internal NW	1				
External NW	0.5553***	1			
NW ORG	0.3060***	0.1770***	1		
NW EXT	0.4314***	0.7186***	0.1183***	1	
Emails	0.6385***	0.5342***	0.2316***	0.3854*	1

Note: ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table A.5 estimates the same average WFH effect as Table 4, except with the most extreme 1% of observations truncated to assess the impact of outliers. The comparison between the two tables shows that qualitative results are all the same, except that the WFH estimate in specification 4 turns statistically significant. However, as explained in the text, this is not our preferred specification, as the linear time trend does not represent the raw data well, and the effect in specification 3 remains not significantly different from zero.

Table A.6 estimates the average effect of WFH on the share of non-sick days. Based on both time controls, the effect is significantly positive, i.e., there were fewer sick days during WFH.

Table A.7 analyzes the same outcomes as Table 7 in the main text, but now also includes an interaction between the time trend and the WFH dummy. The table shows that in the case of working hours the increasing trend is even steeper after WFH. In all other cases the trend is mitigated during WFH.

Table A.5: Average Working-From-Home effect (top and bottom 1% of outcomes truncated)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	Input	Input	Output	Output	Productivity	Productivity
WFH	2.045***	1.547***	-0.384***	-0.388***	-0.300***	-0.226***
	(0.031)	(0.035)	(0.084)	(0.097)	(0.013)	(0.015)
Linear month trend		0.038***		0.000		-0.006***
		(0.003)		(0.010)		(0.002)
Employee FE	Yes	Yes	Yes	Yes	Yes	Yes
Team FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	No	Yes	No	Yes	No
R^2	0.24	0.23	0.01	0.01	0.06	0.06
Observations	68845	68845	68911	68911	68846	68846
Clusters	10217	10217	10258	10258	10217	10217

Note: Input is the time in hours per working day the employee worked in a month. Output is the employee's normalized output relative to target in a month. Productivity is output divided by time worked. The unit of observation is the employee-month. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. The top 1% and bottom 1% of outcomes are discarded before running the regression to deal with potential outliers. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table A.8 analyzes the same outcomes as Table 8 in the main text, but now also includes an interaction between the time trend and the WFH dummy. The table shows that in the case of Internal NW the increasing trend is even steeper after WFH. In all other cases the trend is mitigated during WFH or not statistically different from the WFO period.

Table A.6: WFH effect on (non-)sick days

	(1)	(2)
Dependent variable	NonSickDayShare	NonSickDayShare
WFH	0.069***	0.007**
	(0.003)	(0.004)
Linear month trend		0.005***
		(0.000)
Employee FE	Yes	Yes
Team FE	Yes	Yes
Month FE	Yes	No
R^2	0.08	0.05
Observations	70168	70168
Clusters	10247	10247

Note: NonSickDayShare is the share of days in a month where the employee worked at least two hours, based on the Sapience measurement, relative to the number of work days in that month. The unit of observation is the employee-month. Standard errors are shown in brackets below the point estimates, and are clustered on employee level. The top 1% and bottom 1% of outcomes are discarded before running the regression to deal with potential outliers. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table A.7: Shift in Working Patterns due to WFH with Change in Trend

	(1) Working Hours	(2) After Hours	(3) Focus Hours	(4) Collaboration Hours
WFH	2.919***	1.219***	-0.819***	0.560***
	(0.194)	(0.305)	(0.287)	(0.130)
Linear weekly trend	0.058***	0.270***	-0.203***	0.063***
	(0.012)	(0.029)	(0.028)	(0.011)
WFH× Time	0.041**	-0.142***	0.140***	-0.033***
	(0.016)	(0.033)	(0.031)	(0.013)
Employee FE	Y	Y	Y	Y
Team FE	Y	Y	Y	Y
R-squared	0.709	0.748	0.719	0.747
Observations	25,893	25,893	25,893	25,893
Clusters	914	914	914	914

Note: Working hours are weekly hours worked. After hours are weekly hours worked after regular work time. Focus Hours are hours with two or more hour blocks *not* spent in meetings, on calls or writing e-mails. Collaboration Hours are hours spent in meetings or in calls. The unit of observation is the employee-week. Standard errors are shown in brackets below the point estimates, and are clustered at the employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

Table A.8: Networking with Change in Trend

	(1) Internal NW	(2) External NW	(3) NW ORG	(4) NW EXT	(5) Meetings Manager	(6) Meetings 1:1	(7) Coaching Meets	(8) E-mails
WFH	-6.537***	-0.585***	-0.011**	-0.164***	1.165***	-0.094	-0.082*	1.285**
	(0.347)	(0.104)	(0.005)	(0.034)	(0.201)	(0.059)	(0.042)	(0.580)
Linear weekly trend	0.549***	0.089***	0.001**	0.011**	0.139***	0.003	0.007*	0.639***
	(0.040)	(0.011)	(0.000)	(0.004)	(0.020)	(0.005)	(0.004)	(0.073)
WFH $\times$ Time	0.254***	-0.012	-0.000	-0.003	-0.131***	-0.001	-0.005	-0.703***
	(0.043)	(0.013)	(0.000)	(0.004)	(0.023)	(0.005)	(0.004)	(0.081)
Employee FE	Y	Y	Y	Y	Y	Y	Y	Y
Team FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.801	0.758	0.665	0.624	0.758	0.320	0.386	0.768
Observations	25,893	25,893	25,893	25,893	25,893	25,893	25,893	25, 893
Clusters	914	914	914	914	914	914	914	914

Note: "Internal NW" is the number of people inside the company with who employee had meaningful contact in last 28 days. "External NW" the same measure for people outside the company. "NW ORG" is the number of distinct organizational units within the company that the employee had at least two meaningful interactions in the last four weeks. "NW EXT" the same measure for external domains outside the company. "Meetings Manager" is the number of meetings involving the manager. "Meetings 1:1" is the number of meetings between the employee and their manager. "Coaching Meets" is the number between the employee, the manager and all their direct reports. "E-mails" is the number of emails sent. The unit of observation is the employee-week. Standard errors are shown in brackets below the point estimates, and are clustered at the employee level. ***Significant at the 1% level; **significant at the 5% level; *significant at the 10% level.

B Additional Figures

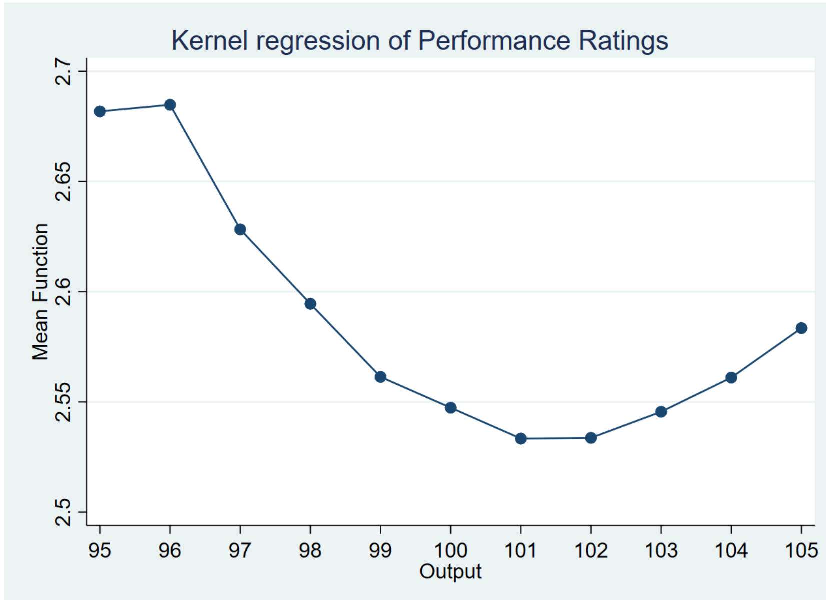
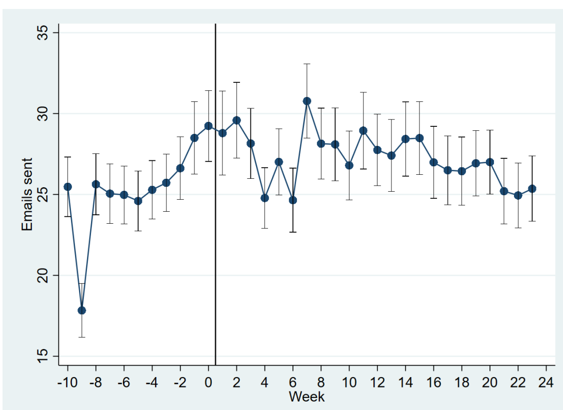
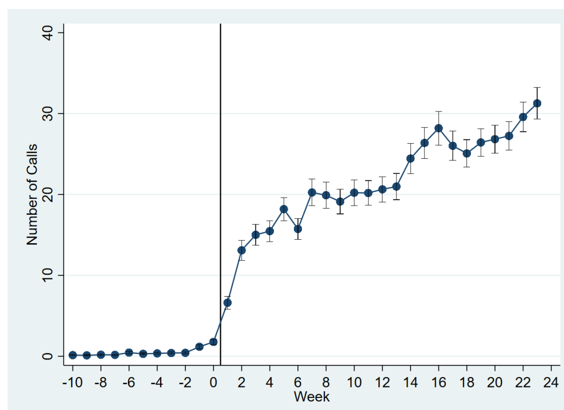


Figure B.1: Kernel density estimates of subjective **Ratings** for different levels of **Output**.



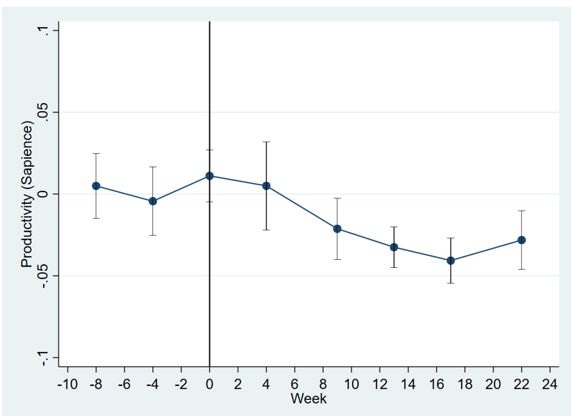
(a) Number of Emails



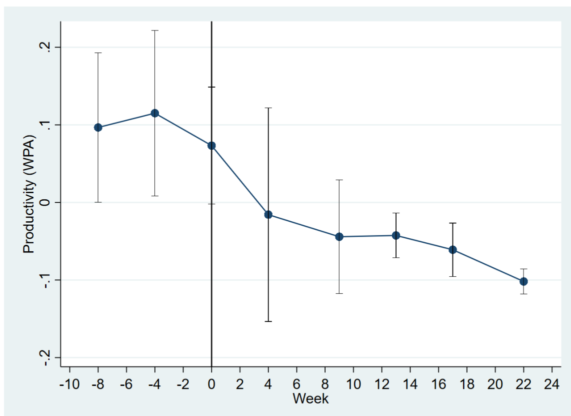
(b) Number of MS Teams Calls

Figure B.2: Technological shift pre- and post WFH. Panel (a): number of emails sent per week. Panel (b): weakly number of calls a person joined through MS Teams. Time= 0 is the week 9th-15th March 2020.

Figure B.3: Productivity during WFH depending on pre-WFH productivity. The solid line is the 45-degree line.



(a) Productivity Sapience



(b) Productivity WPA

Figure B.4: Productivity pre- and post WFH in the WPA sample. To make both measures comparable, we standardize them to mean 0 and standard deviation 1. Panel (a): standardized productivity using Sapience measure of Input. Panel(b): standardized productivity using the WPA variable working hours as input. Week= 0 is the week 9th-15th March 2020.

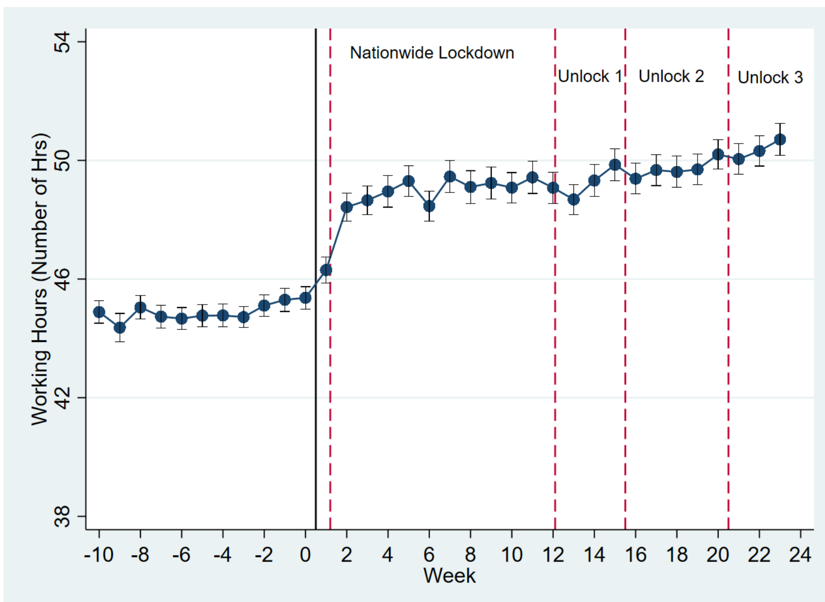


Figure B.5: Working Hours over time with different stages of lockdown and removal of lockdown restrictions. The leftmost dashed line indicates the time at which a national lockdown was imposed. The first stage of unlocking ("Unlock 1") allowed e.g. restaurants and shopping malls to reopen, the second stage ("Unlock 2") allowed limited travel and at the third stage ("Unlock 3") gyms for example reopened.