Work from Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals

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We study employee productivity before and during the working-from-home period of the COVID-19 pandemic, using personnel and analytics data from over 10,000 skilled professionals at an Indian technology company. Hours worked increased, output declined slightly, and productivity fell 8%–19%. We then analyze determinants of productivity changes. An important source is higher communication costs. Time spent on coordination activities and meetings increased, while uninterrupted work hours shrank considerably. Employees networked with fewer individuals and business units inside and outside the firm and had fewer one-to-one meetings with supervisors. The findings suggest key issues for firms in implementing remote work.

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I. 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. Even if only a fraction of this shift became permanent, it would have implications for urban design, infrastructure development, and reallocation of investment from inner cities to residential areas. It would also have significant implications for how businesses organize and manage their workforces. However, little is yet known about some of the more fundamental consequences of WFH, including its effects on employee productivity.

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. Some employees may find it easier to concentrate if they have a quiet space at home. On the other hand, collaboration, innovation, and interactions with clients may suffer. That WFH was not used for the majority of the workforce prior to the pandemic suggests that for many employers there was at least a perception that WFH productivity is lower compared to WFO productivity. Indeed, some firms question the sustainability of extensive WFH (*Wall Street Journal* 2020; *Financial Times* 2021b).

In this paper we provide a comprehensive analysis of the effect of WFH on employee productivity at HCL Technologies, a large information technology (IT) services company based in India. 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.

First, our sample is of a type not previously studied in the small WFH literature: high-skilled employees in cognitively demanding jobs involving collaboration and innovation. Previous studies either use survey self-reports or focus on low-skilled, individualistic, and narrow jobs. Our sample therefore sheds light on the potential for WFH among the large fraction of the workforce in previously unstudied professional occupations.[1]

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[1] The need for research on WFH for these types of professions is highlighted by the fact that the incidence of WFH is highest for these types of jobs. Professionals, managers, knowledge workers, those in clerical support or data processing, and those with higher education or income make more use of WFH (Bick, Blandin, and Mertens 2020; Brynjolfsson et al. 2020; Hensvik, Le Barbanchon, and Rathelot 2020; Gottlieb et al. 2021; Zimpelmann

Second, the firm provided unusually broad and high-quality data. Employee productivity for high-skilled jobs is notoriously hard to measure. The data include a quantitative measure of employee output, which the firm goes to significant lengths to calculate and uses to supervise and evaluate these high-skilled professionals. Employee time use was captured by monitoring applications on work devices, so we know total hours worked, start and end times, how much time was spent in various types of meetings and communications, and how much time the employee focused on work without interruptions. The high-quality performance measure and total work time provide a natural and relatively accurate measure of the employee's productivity. These outcome measures are some of the best that modern analytics and monitoring software can provide. The firm also provided information on the types of meetings and communications in which employees engaged, providing valuable insights into how employees spent their work time in WFH compared to WFO. Finally, we know employee experience, age, gender, whether there are children at home, and the employee's usual commute time.

Since we can link employee productivity, demographics, and detailed communication logs, our rich data set allows for in-depth analysis of the causes of employee productivity differences when working remotely, which has not been possible in other studies. Analyses of unskilled jobs find that WFH may improve productivity (Bloom et al. 2015; Emanuel and Harrington 2021), but it is an open question whether these effects extend to more complex jobs. Our analyses provide valuable insights into the types of work for which WFH may be especially challenging.

Our key findings are as follows. Employees significantly increased average hours worked during WFH. Much of this came from starting work earlier and ending it later in the day. At the same time, there was a slight decline in output as measured by the employer's primary performance measure. Combining these, we estimate that average employee output per hour of work declined by 8%–19%.

The effects on work time and productivity materialize immediately after the transition to WFH. In contrast, there is no change in our outcome measures at the start of the pandemic before WFH was implemented. Changes in work time and productivity also do not comove with the evolution of the pandemic, such as the rate of infections or easing of lockdown measures.[2] These show that WFH and not the pandemic best explain these changes.

et al. 2021). The industry and occupations analyzed here are among those predicted to most effectively switch to WFH (Adams-Prassl et al. 2020; Dingel and Neiman 2020).

[2] Further, as with many information technology firms, the company's business performance was strong throughout the pandemic, so employees did not have increased risk of job loss or decreased promotion prospects. There was a decline, not an increase, in sick days during WFH.

The increase in overall working hours and corresponding decrease in productivity are associated with substantial changes in working patterns during WFH. Employees spent more time participating in a larger number of shorter, larger group meetings, but less time in personal or small group meetings with their manager. They had less "focus time," that is, work time uninterrupted by meetings or calls. At the same time, they narrowed the scope of their networks, engaging in fewer contacts with colleagues and organizational units inside and outside the firm. All of these factors were significantly correlated with changes in employee productivity. These findings are evidence that coordination and communication are more difficult with remote work.

We also uncover some interesting dimensions of heterogeneity. Employees with lower company tenure decreased output slightly more during WFH, whereas output remained about the same for those with longer tenure. This suggests that employees who are more adapted to firm culture and processes are better able to work remotely, where there is no colleague at the next desk for quick help or advice. As a separate effect, those with greater career experience increased hours worked during WFH more than those with lower experience, with no effect on productivity. This suggests that more senior employees, with greater managerial duties, spent more time coordinating during WFH.

Employees with children at home had a greater decline in productivity than those without, but even those without suffered significant productivity losses. 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.[3]

Our analysis and insights contribute to an emerging literature on how WFH affects work patterns, employee productivity, and well-being. Most of the early research in this area is based on survey data. Etheridge, Wang, and Tang (2020) find that employees who work from home state that they are about as productive as in the office and those who perceive declines experience lower levels of well-being from WFH. In Barrero, Bloom, and Davis (2021) employees report benefits from lower commute time, more flexible work hours, and increased productivity, but Bellmann and Hübler (2020) find that working remotely has no long-run effect on work-life balance, and increases job satisfaction only temporarily. Barrero, Bloom, and Davis (2020) estimate that WFH reduced self-reported US commuting

[3] In the Western context it has often been reported that the burden of child care and home schooling disproportionately affected women during the pandemic (*Financial Times* 2021a). In India, 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 child care, but may place other demands on women at home whether or not children are present.

time by more than 60 million hours per work day at the height of the pandemic. Further, employees report that about 35% of this time saved was reallocated to work. In our data, variation in estimated commute time does not predict the increase in WFH work hours that we observe.

Survey data may be biased if employees enjoy WFH and hope to retain the practice, conflate output with productivity, or refer to individual performance without consideration of effects on colleagues. A few WFH studies use employee performance data. Bloom et al. (2015) showed that both hours worked and productivity increased during WFH for call center employees at a Chinese firm. Emanuel and Harrington (2021) studied call center workers at a large US company, including some 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. This suggests that remote work has an adverse selection effect, with more productive workers preferring to be at the office. Choudhury, Foroughi, and Laron (2019) study examiners for the US Patent and Trademark Office who 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 (as with call center workers) do not require significant collaboration and coordination, and involve relatively simple tasks. Künn, Seel, and Zegners (2022) analyze an occupation with extremely high cognitive demands but no collaboration: professional chess players. The players showed worse performance when competing online during COVID-19, compared to in-person tournaments. To our knowledge, no research uses observational data to study WFH productivity for high-skilled work in which coordination is important. Our paper fills this gap.

Other recent studies document shifts in working patterns in high-skilled jobs, with findings that are very consistent with our evidence. DeFilippis et al. (2020) use communication and email metadata. Their estimate that WFH employees work 0.8 more hours per day is in line with our findings. They also find that employees attend more meetings, with more attendees (as do Teevan, Hecht, and Jaffe 2020 and Yang et al. 2022). Flassak et al. (2021) present survey data from a large international company. Under WFH, the firm used more standardization and planning, and employees spent more time in meetings. Kwan (2021) presents evidence that proxies for employee interactions and the need for coordination are negatively associated with a shift to WFH.

A broader agenda in economics studies determinants of employee productivity. Significant work has focused on incentive pay (e.g., Lazear 2000; Hamilton, Nickerson, and Owan 2003; Shearer 2004; Dohmen and Falk 2011; Babcock et al. 2015; Aakvik, Hansen, and Torsvik 2017; Friebel et al. 2017). Other research looked at effects of other human resource practices (Ichniowski, Shaw, and Prennushi 1995; Ichniowski and Shaw 2003; Bartel, Ichniowski, and Shaw 2007), ways to engage employees in innovation

(Gibbs, Neckermann, and Siemroth 2017), and the effects of supervisors (Lazear, Shaw, and Stanton 2015) or peers (Bandiera, Barankay, and Rasul 2005; Arcidiacono, Kinsler, and Price 2017; Song et al. 2018). Our research contributes to this agenda by analyzing productivity in a high-skilled, coordination-intensive profession, relating it to detailed measures of working patterns, and evaluating how it changes with WFH.

Our evidence yields important insights into how to implement hybrid WFH/WFO work. Communication, coordination, and collaboration are more difficult in a virtual context. This challenge must be addressed to implement significant WFH in occupations where such considerations are important, especially for less experienced employees. While WFH will remain a feature of modern workplaces, some aspects of in-person interactions cannot easily be replicated virtually, including the quality of collaboration and coaching, client engagement, and "productive accidents" that arise from spontaneously meeting people (including those with whom there is not yet a working relationship).

II. Data and Empirical Strategy

The setting for this study is HCL Technologies, 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 is employed at its corporate campuses in India. The company provides a wide range of technology consulting and outsourcing services for clients, including product and process improvement and R&D to develop new products and services. Additional details about the company are in Gibbs, Neckermann, and Siemroth (2017), which studies a field experiment by HCL on the use of incentives to motivate employee ideas.

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 Indian cities. These campuses look and feel very similar to what one sees at Microsoft, Apple, or Amazon. All authors have visited the company headquarters, and senior executives spent considerable time explaining practices and business conditions to us.

The company has a semiannual 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.[4] Analytics systems (described below) are used to track progress against the plan throughout

[4] 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.

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.

That employee goal setting is embedded in a corporate-wide process and tied to each supervisor's own goals and evaluation is important. If managers lowered the goals of employees in their team, it would make fulfilling team goals harder, and is therefore not in their interest. Company executives confirmed that goals were not changed as a result of the pandemic or the switch to WFH. Indeed, most of the company's customers are also information technology firms, and that sector performed well during the pandemic. This firm and its clients largely continued expected business activities.

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 monthly goal on a key metric, which we will refer to as "Output." He or she also receives quarterly supervisor feedback and biannual subjective performance ratings.

A notable advantage of this study is that the performance measure is relatively rigorous and objective, despite the fact that the employees are high-skilled professionals for which performance is notoriously hard to measure.

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, the measure does not merely reflect quantity. It is Output conditional on adequate performance on other dimensions of the job, such as quality or client satisfaction. Code segments will not be counted as complete until they meet company and client 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, and so forth. Thus our measure is broader than might initially seem apparent, accounting for key intangible aspects of each employee's performance.

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

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. Promotion rates were higher in 2020 than in 2019. Thus employees did not experience any decline in formal or informal incentives during the sample period.

A. *Main Outcome Variables*

HCL 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. Such a "data-driven" approach is common in technology firms (Brynjolfsson and McAfee 2012).

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 data set with 10,384 unique employees observed over 17 months. The company moved abruptly to WFH in March 2020 as COVID-19 became serious in India.

Sapience Analytics software is installed on employee work devices. It 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. 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 II.C below, we describe other input measures that generate similar qualitative results; our findings are robust to details of the definition of hours worked.

IDMS is a proprietary system used to track employee performance, including the primary performance measure. That measure is normalized

TABLE 1
Summary Statistics for Outcome Variables

	Mean	Standard Deviation	1st Quartile	3rd Quartile	Observations
WFO (before March 2020):					
Input	5.08	2.03	3.78	6.35	47,387
Output	100.82	9.00	100.00	100.00	47,387
Productivity	1.36	2.99	.75	1.27	47,387
WFH (after March 2020):					
Input	7.04	2.75	5.38	8.90	22,862
Output	100.30	8.80	100.00	100.00	22,862
Productivity	1.11	2.41	.52	.88	22,862

to make different jobs and roles comparable.[5] For example, key measures might be the number of code segments, code reviews, or reports delivered per month (subject to quality and customer satisfaction standards). These are divided by the monthly goal, multiplied by 100, to scale as percentage achievement of the goal. As explained above, goals were not changed due to WFH.

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. The most common value is 100, meaning that employees continue working longer hours until they meet their targets, but we also see employees falling short of or exceeding their targets.

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.

B. 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 outside India.

Age, company tenure, and industry experience (collected at hiring and updated to the current date) are 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

[5] 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	Standard Deviation	1st Quartile	3rd Quartile	Observations
Age (years)	31.91	5.95	27.10	36.03	7,969
HighAge	.50	.50	.00	1.00	7,969
Tenure (years)	4.21	3.90	1.11	5.11	7,969
HighTenure	.52	.50	.00	1.00	7,969
Experience (years)	8.10	5.22	4.04	11.10	7,969
HighExperience	.50	.50	.00	1.00	7,969
Male	.76	.43	1.00	1.00	7,969
NumChildren	.52	.73	.00	1.00	8,934
Children	.39	.49	.00	1.00	8,934
CommuteTime	.65	.33	.38	.85	4,323
Rating	2.66	.88	2.00	3.00	5,354

is low at about 4 years, as is expected since employee turnover is high in the IT sector. 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. The dummy Children equals 1 if and only if NumChildren is positive.

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 application programming interface 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.[6] 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). Figure B.1 plots kernel density estimates of subjective ratings for different

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

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 is more evidence that the outcome measures introduced above are meaningful and reflected in subjective performance evaluations.

C. *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, and so forth. WPA data have been used in several organizational studies (Brynjolfsson and McAfee 2012; Hoffmann, Lesser, and Ringo 2012; Levenson 2018).

The company had 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. Table A.2 compares those in the WPA sample to those not in the WPA sample. Those in the WPA group are slightly younger, have lower tenure, and are less productive, but are overall quite similar.

Table 3 summarizes variables obtained from WPA. WPA data were collected at the weekly level (in contrast to Sapience data, which are 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; for example, 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 nonwork activities.

During WFO, employees spent on average 44 Working Hours per week (table 3), which is close to the contractual 40 hours per week. After Hours measures the number of weekly hours worked outside regular office hours. 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

TABLE 3
Summary Statistics for WPA Variables

	Mean	Standard Deviation	1st Quartile	3rd Quartile	Observations
WFO (before March 15, 2020):					
Working Hours	44.71	5.16	43	46.46	6,755
After Hours	9.64	9.55	2.33	14.04	6,755
Focus Hours	34.49	9.02	30	41.25	6,755
Collaboration Hours	10.20	9.24	3.55	13.75	6,755
Meetings Manager	3.97	4.35	.5	5	6,755
Meetings 1:1	.18	1.37	0	.5	6,755
Coaching Meets	.13	1.03	0	0	6,755
MS Teams Calls	.36	1.63	0	0	6,755
Internal NW	18.91	14.21	10	24	6,755
External NW	2.58	3.61	0	3	6,755
NW EXT	.98	1.04	0	1	6,755
NW ORG	.05	.22	0	1	6,755
Emails	23.61	23.68	9	30	6,755
WFH (after March 15, 2020):					
Working Hours	49.03	7.58	45.14	52.49	19,220
After Hours	12.98	12.70	3.71	18.44	19,220
Focus Hours	32.73	9.99	28	40	19,220
Collaboration Hours	11.07	9.97	4.08	15	19,220
Meetings Manager	5.48	6.57	1	7.33	19,220
Meetings 1:1	.11	1.07	0	0	19,220
Coaching Meets	.09	.98	0	0	19,220
MS Teams Calls	21.46	25.22	3	30	19,220
Internal NW	23.44	19.89	11	30	19,220
External NW	3.05	4.36	0	4	19,220
NW EXT	.91	.89	0	1	19,220
NW ORG	.05	.23	0	0	19,220
Emails	25.26	29.89	8	30	19,220

Note.—“Working Hours” are weekly hours worked. “After Hours” are weekly hours worked outside regular work time. “Focus Hours” are hours with 2 or more hour blocks not spent in meetings, on calls, or writing emails. “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 his or her 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 in which the employee participated. “Internal NW” is the number of people inside the company with whom the 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 4 weeks. “NW EXT” is the same measure for domains outside the company. “Emails” is the weekly number of emails sent by the employee.

to meetings. Focus Hours measures time blocks of 2 hours or more that are 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, his or her manager, and the manager's direct reports. MS Teams Calls is the number of calls using MS Teams (which hosts video meetings similar to Zoom or Skype).

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) relates to networking with colleagues and clients more explicitly. The first two measure the number of individuals (inside and outside the company, respectively) with whom the employee had contact. The next 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. The last is the number of emails sent by the employees that week. Table A.4 shows 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.

D. *Empirical Strategy*

As a first step, in section III.A we estimate the average WFH effect. Our main specification exploits differences in outcomes for each employee, when working from home compared to working in the office, 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 $t = 1, 2, \dots, 17$. For outcome variable y_{it}, we estimate by OLS:

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

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 1 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, and so forth. In addition, we report an alternative specification controlling for a linear rather than seasonal time trend:

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

Once the average WFH effect is established, we analyze variation in this effect. Section III.B studies how effects vary with employee characteristics. We interact the WFH dummy in the previous specifications with additional explanatory variables X_{1i}, X_{2i}, … . 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.[7]

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.[8] 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 adaptation effects are not reflected in our estimate.

Section III.C 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 $t = 1, \ldots, 34$ represents weeks. For all analyses we cluster standard errors at the employee level.

III. Results

A. *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 1*A*, Input, employees provide about 5–5.5 hours of daily input, that is, 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 before WFH, with a slight upward trend. Hence, a 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]

[7] 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.

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

[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.

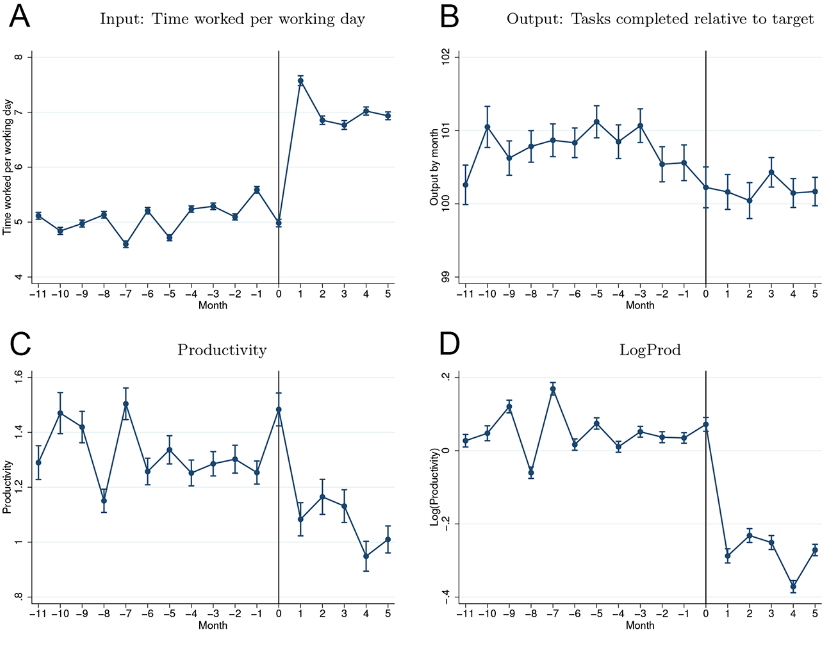

FIG. 1.—Average outcomes by month without outliers (bottom and top 0.1%). LogProd is the natural logarithm of Productivity. The vertical line (month 0) indicates the switch to working from home. The vertical bars represent 95% confidence intervals based on clustered standard errors. Month: −11 = April 2019; 0 = March 2020; 5 = August 2020.

For Output, figure 1*B*, there is no visible monotonic or linear trend, so a seasonal time correction might be more appropriate here. Moreover, average output appears to be slightly lower during WFH.

For Productivity, figure 1*C*, the graph is more volatile, which is not surprising for a ratio. There is no clear linear time trend before WFH, but some variation from month to month, so a seasonal correction might be more appropriate. Productivity drops visibly during WFH. Finally, figure 1*D* plots the log of Productivity, which drops considerably after the start of 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 before 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, plus the natural logarithm of Productivity, in

TABLE 4
Average WFH Effect

	Dependent Variable							
	Input		Output		Productivity		LogProd	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH	2.117***	1.592***	−.530***	−.098	−.256***	−.138	−.334***	−.288***
	(.034)	(.038)	(.125)	(.155)	(.031)	(.074)	(.008)	(.009)
Linear month trend		.040***		−.035*		−.010		−.004***
		(.003)		(.015)		(.007)		(.001)
Employee fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	Yes	No	Yes	No	Yes	No
R^2	.24	.22	.02	.02	.01	.01	.12	.11
Observations	70,249	70,249	70,249	70,249	70,249	70,249	70,239	70,239
Clusters	10,312	10,312	10,312	10,312	10,312	10,312	10,312	10,312

Note.—Input is the individual time in hours that the employee worked per working day in a month. Output is the normalized output of the employee relative to the target in a month. Productivity is output divided by time worked. LogProd is the natural logarithm of Productivity. The unit of observation is the employee-month. Standard errors are shown in parentheses below the point estimates and are clustered on employee level.
* Significant at the 5% level.
*** Significant at the 0.1% level.

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 very meaningful, and statistically significant at all conventional levels.[11] Since both figure 1*A* 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 show that both WFH effect estimates on Output are slightly negative, but only the estimate with the seasonal time trend is significantly different from zero. While the regression indicates a significantly negative linear time trend, we prefer specification 3, since a linear trend does not reflect the raw data in figure 1*B* very well. According to this specification, Output changed by −0.5 percentage points during WFH (recall that fulfilling all monthly tasks implies an output of 100%).

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

[11] For comparison, the contractual working day at HCL (before WFH) is 9 hours, which includes a 1 hour lunch break.

Hence, we conclude that WFH had no or only a small negative effect on Output.

Columns 5 and 6 show that both WFH effect estimates on Productivity are negative, but only the estimate with seasonal time trend is significantly different from zero. We prefer that specification, since both the plot and the linear time trend coefficient indicate that a linear trend is not as appropriate.[12] According to this specification, productivity decreased by 0.26 output percentage points per hour worked. Given an average WFO productivity of 1.36, this estimate corresponds to a 19% drop in output per hour worked. This is economically significant: if employees worked a fixed 40 hours per week, this would imply a drop in output of 10.2 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 of 100 assigned tasks.

Columns 7 and 8 explain the log of Productivity, which strongly increases the fit of the regression. The WFH effect is negative and significantly different from zero at all significance levels, irrespective of time controls.

In summary, this evidence indicates that employees worked longer but less productively, with output remaining about the same or dropping slightly. 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 worked 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, and so forth, 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 III.C. Third, employees are not paid

[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.

by the hour. To impress superiors, time is better spent generating output. Fourth, Sapience was in use long before the switch to WFH, so this potential concern cannot explain the WFH effect well. Fifth, the additional WFH effects that we find from WPA activity (sec. III.C), 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 subsample of employees (sec. III.C). 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 in which 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 off-line meetings, but is consistent with increased disruptions and communication costs. Last, we observe when an employee starts and ends his or her 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 findings suggest that spontaneous off-line 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, HCL 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, and so forth, 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. Figure B.2 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 covary 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, the number of sick days decreased significantly. This suggests that absences or sickness were not a driver of the decrease in productivity.

B. 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 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.

TABLE 5
WFH: Children at Home and Gender Differences

	Dependent Variable					
	Input		Output		Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
WFH	1.416***	1.599***	−.528***	−1.176***	−.206***	−.361***
	(.046)	(.086)	(.150)	(.267)	(.042)	(.075)
WFH × Children	.307***	.091	.061	.673	−.169**	−.027
	(.059)	(.128)	(.205)	(.431)	(.058)	(.111)
WFH × Male		−.211*		.895**		.149
		(.094)		(.300)		(.093)
WFH × Male × Children		.252		−.822		−.157
		(.145)		(.495)		(.133)
Employee fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes	Yes
Linear month trend	Yes	Yes	No	No	No	No
R^2	.23	.25	.02	.02	.01	.01
Observations	64,392	58,644	64,392	58,644	64,392	58,644
Clusters	8,865	7,911	8,865	7,911	8,865	7,911

Note.—Input is the individual time in hours that the employee worked per working day in a month. Output is the normalized output of the employee relative to the target in a month. Productivity is output divided by time worked. The unit of observation is the employee-month. Standard errors are shown in parentheses below the point estimates and are clustered on employee level.

* Significant at the 5% level.

** Significant at the 1% level.

*** Significant at the 0.1% level.

In India, 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 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 at the 5% level. They also suffered a significantly 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 child care 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 Indian domestic setting.

TABLE 6
WFH: Age, Experience, Tenure, Commute Times

	Dependent Variable					
	Input		Output		Productivity	
	(1)	(2)	(3)	(4)	(5)	(6)
WFH	1.361***	1.516***	−.743***	−.603	−.245***	−.286***
	(.058)	(.095)	(.194)	(.334)	(.048)	(.083)
WFH × HighTenure	.036		.519*		.003	
	(.067)		(.229)		(.090)	
WFH × HighAge	.057		.097		−.084	
	(.092)		(.366)		(.073)	
WFH × HighExperience	.270**		−.138		−.038	
	(.094)		(.390)		(.084)	
WFH × CommuteTime		.107		.316		−.030
		(.122)		(.405)		(.093)
Employee fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	No	No	Yes	Yes	Yes	Yes
Linear month trend	Yes	Yes	No	No	No	No
R^2	.25	.26	.02	.03	.01	.01
Observations	58,644	31,848	58,644	31,848	58,644	31,848
Clusters	7,911	4,295	7,911	4,295	7,911	4,295

Note.—Input is the individual time in hours that the employee worked per working day in a month. Output is the normalized output of the employee relative to the target in a month. Productivity is output divided by time worked. The unit of observation is the employee-month. Standard errors are shown in parentheses below the point estimates and are clustered on employee level.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

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

[14] 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.

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]

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 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 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 fig. 2) is not driven by a few customers or teams. Rather, WFH productivity declined broadly across the group studied.

[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.

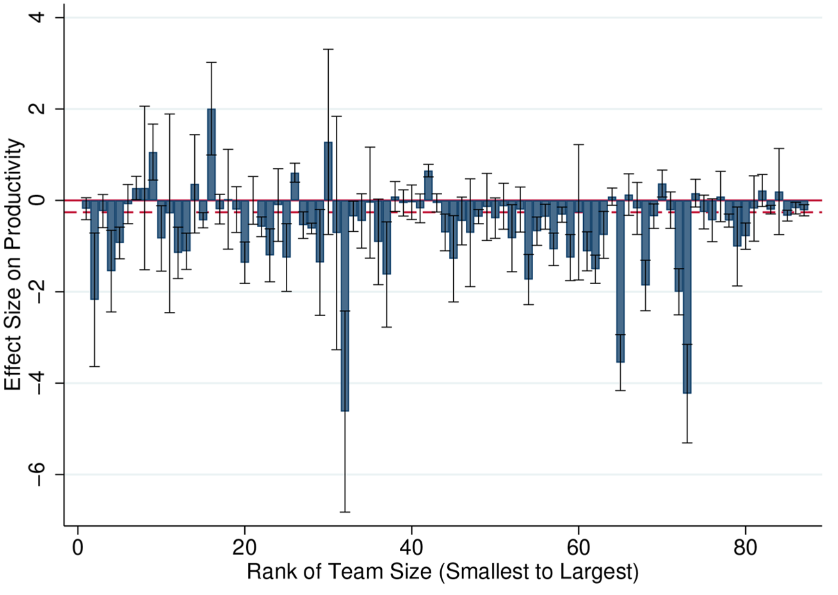

FIG. 2.—Heterogeneity of WFH effect on productivity across teams. The vertical bars represent 95% confidence intervals.

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.

C. Mechanisms: What Contributes to Lower Productivity?

To better understand the mechanisms behind the decrease in productivity, we study the subsample 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 toward spending time on meetings, calls, or answering emails; and reduced time networking with others or meeting one-to-one with one's manager.

1. Working Hours

Figure 3 illustrates the shift in working patterns after the start of WFH. In line with the evidence in section III.A, the WPA data show that overall

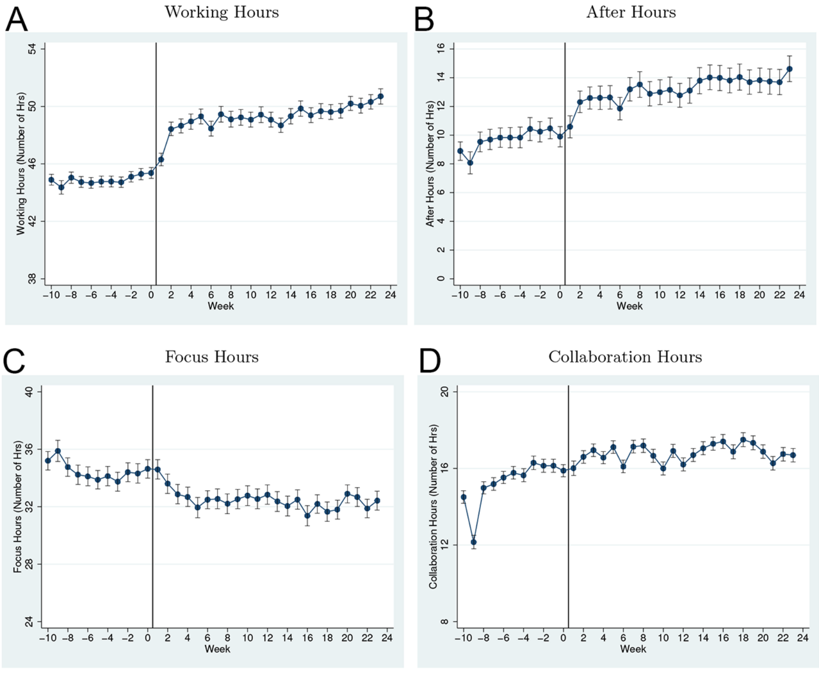

FIG. 3.—Working patterns before and after WFH. *A*, Mean weekly working hours. *B*, Hours worked outside regular working hours. *C*, Number of hours with 2 or more hour blocks not spent in meetings, on calls, or writing emails. *D*, Hours spent in meetings or in calls. Week = 0 is 9–15 March 2020.

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" (as described above, this measures the amount of work time that was not interrupted by various types of meetings or communications). 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).

The technological shift is illustrated in Figure B.4. In particular there is a drastic increase in the number of hours spent on virtual meetings using MS Teams. Interestingly, the number of such meetings continues rising almost 6 months after the switch to WFH. The increase in number of meetings is clearly much larger than the increase in total time spent in meetings. Therefore, employees are interrupted more frequently by having to attend more meetings of shorter duration.

TABLE 7
Shift in Working Patterns Due to WFH

	Working Hours		After Hours		Focus Hours		Collaboration Hours	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH	4.431***	2.743***	4.212***	1.822***	−2.665***	−1.417***	1.251***	.704***
	(.161)	(.218)	(.288)	(.320)	(.245)	(.297)	(.122)	(.137)
Linear weekly trend		.096***		.137***		−.071***		.031***
		(.009)		(.014)		(.012)		(.005)
Employee fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.703	.709	.743	.747	.717	.719	.745	.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 2 or more hour blocks not spent in meetings, on calls, or writing emails. "Collaboration Hours" are hours spent in meetings or in calls. The unit of observation is the employee-week. Standard errors are shown in parentheses below the point estimates and are clustered at the employee level.
*** Significant at the 0.1% level.

Table 7 shows regressions estimating the WFH effect on these outcomes. Both overall working hours and working hours outside 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 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. Since working hours are the sum of focus hours, collaboration hours, and "unfocused hours" (i.e., hours working but getting interrupted), the table also shows that WFH replaced focus hours by many more unfocused work hours. These shifts in working patterns could explain why productivity decreases under the WFH regime.[17]

We conjectured that some of the increase in working hours and decrease in productivity is due to increased costs of communication and

[17] Additional analysis in app. 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 (table A.7).

coordination within teams. If this is the case, then roles that are characterized by more interaction and networking prior to WFH are more affected by the switch to WFH. If we median split by how many internal networking contacts (variable Internal NW; see table 3) an employee had prior to WFH, 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 (both results are significant at the 0.1% level). 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.

2. 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 knowledge and ideas.

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 three 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.[18]

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 (col. 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, the number of meetings involving the manager increases. By contrast, the number of both one-to-one supervisor meetings and coaching meetings decrease during WFH. Employees seem to receive less mentoring and coaching, even though these effects are only statistically

[18] Table A.8 shows specifications in which we allow the time trend to interact with WFH. By and large, there are no significant differences in trend before and after 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 8

Shift in Networking Patterns and Types of Meetings Due to WFH

	Internal NW (1)	External NW (2)	NW ORG (3)	NW EXT (4)	Meetings Manager (5)	Meetings 1:1 (6)	Coaching Meets (7)	Emails (8)
WFH	−7.621***	−.532***	−.009	−.150***	1.723***	−.089	−.060	4.282***
	(.369)	(.103)	(.005)	(.027)	(.205)	(.048)	(.033)	(.680)
Linear weekly trend	.787***	.078***	.001**	.008***	.016*	.002	.002	−.020
	(.026)	(.006)	(.000)	(.001)	(.008)	(.002)	(.002)	(.029)
Employee fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Team fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.801	.758	.665	.624	.757	.320	.386	.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” is 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 4 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 his or her manager. “Coaching Meets” is the number of meetings by the manager with all direct reports including the employee. “Emails” is the number of emails sent. The unit of observation is the employee-week. Standard errors are shown in parentheses below the point estimates and are clustered at the employee level.

* Significant at the 5% level.

** Significant at the 1% level.

*** Significant at the 0.1% level.

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 four more emails being sent on average. This corresponds to a 17% increase over the baseline (see table 3).

Overall, these patterns highlight a detrimental impact of WFH on networking. Employees attend more meetings, which tended to involve larger groups, but have shorter duration. This reduces their focus time. Furthermore, they communicate with fewer individuals and organizational units inside and outside the company. They have fewer one-to-one meetings with superiors, and receive less coaching. The next section shows that these observations help explain why WFH lowered productivity.

3. Productivity

Last, we study productivity in this subsample. 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 2 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 14% drop in productivity (−0.149 against a WFO mean of 1.08) after the introduction of WFH. With the WPA time measure, we find an approximately 9% drop in productivity (−0.056 from baseline 0.599), or an 8% drop (−0.049 from baseline 0.599) when controlling for a linear time trend. All of these drops are statistically significant at least at the 5% level (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. Figure B.5 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 III.A.

To address these questions, we first estimate adaptive LASSO (least absolute shrinkage and selection operator) 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

TABLE 9
PRODUCTIVITY IN THE WPA SAMPLE

	SAPIENCE	WPA	
	(1)	(2)	(3)
WFH	−.149*	−.056**	−.049*
	(.072)	(.008)	(.020)
Mean before WFH	1.080	.599	.599
	(1.702)	(.531)	(.531)
Employee fixed effects	Yes	Yes	Yes
Team fixed effects	Yes	Yes	Yes
Linear trend	No	No	Yes
R^2	.356	.783	.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 parentheses below the point estimates and are clustered at the employee level.
* Significant at the 5% level.
** Significant at the 1% level.

variation in productivity by minimizing an estimate of the out-of-sample prediction error.[19] We use dummies identifying the weeks in which a variable is above average for a given employee to focus on variation in productivity within employees.[20] 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. We indicate in the table variables that the LASSO regression includes in the prediction model.

The variables selected by the LASSO include Working Hours, Focus Hours, and 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 being crucial indicators of productivity. Interestingly, overall working hours is selected before WFH but not afterward.

[19] LASSO models have a free parameter λ that 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 the remaining variables are given a penalty weight designed to drive small coefficients to zero. Zou (2006) has shown that adaptive LASSO enjoys oracle properties: it performs as well as if the true underlying model were known ex ante.

[20] An alternative would be to force LASSO to select employee fixed effects. That is not possible here as in the merged data set containing both productivity and WPA variables we do not have enough pre-WFH observations.

TABLE 10
Variables Selected by LASSO and Elasticity of Productivity with Respect to Selected Variable

	Before WFH		During WFH	
	LASSO (1)	Elasticity (2)	LASSO (3)	Elasticity (4)
Hours:				
Working Hours	Yes	.014***		
After Hours				
Meetings:				
Focus Hours	Yes	.033***	Yes	.072***
Collaboration Hours				
Meetings Manager				
Meetings 1:1	Yes	.002***		
Coaching 1:1			Yes	.003
MS Teams Calls				
Networking:				
Internal NW			Yes	.040***
External NW	Yes	−.000	Yes	.029***
NW EXT	Yes	.010*	Yes	.011**
NW ORG	Yes	.000	Yes	−.001
Emails			Yes	.053***

Note.—Adaptive LASSO linear regression results (“yes” 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. Columns 1 and 2 show the results restricted to the period before WFH, and cols. 3 and 4 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.
* Significant at the 5% level.
** Significant at the 1% level.
*** Significant at the 0.1% level.

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

IV. Conclusion

In this paper we have presented the most detailed analysis of WFH productivity changes for knowledge workers available to date. 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 across different types of jobs, and thus 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.[21] For this reason, productivity, measured by output per hour worked, fell by 8%–19%.

Our main explanation for the decline in productivity is that some aspects of work are more difficult to perform in a virtual environment. We provide clear evidence that this is the case. Employees spent more total time attending more meetings of shorter duration. This reduced their focus time. Those meetings tended to involve larger groups. Less time was spent in direct interactions with the supervisor or close colleagues. Employees also narrowed their spheres of communication, interacting

[21] It would be interesting to see whether 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, Fragher, and Cooper 2001).

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.

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 in India. Employees actually had a decline in sick days. Finally, company economic performance was quite good during this period of time, and promotion rates rose, so career concerns were not an issue.

Another possible explanation is the presence of children at home, 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 large decline in productivity, with similar patterns for reduced focus time, increased time spent in large meetings, and decreased one-to-one communications and meetings.

It is likely that WFH also resulted in a decline in intangibles that are valuable to the employee and the 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 for meeting directly with supervisors. This undoubtedly slowed their development of human capital.

HCL executives were not surprised by the findings in this paper, which accord with their perceptions of the experience with WFH. As of mid-2021, they estimated 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 will enjoy greater flexibility and lower commute times, which compensates to some extent for lower productivity.

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 communication, 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.

Data Availability

Code replicating the tables and figures in this article can be found in Gibbs, Mengel, and Siemroth (2022) in the Harvard Dataverse, https://doi.org/10.7910/DVN/K30VNE. The replication package contains a copy of the programs (Stata do-file) used to create the final results and a read-me file with further information.

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