



International Journal of Advanced Research in Education and Technology (IJARETY)

Volume 11, Issue 6, November-December 2024

Impact Factor: 7.394



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



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

Kalidas Kailas Sabale, Dr. Rajendra Jarad, Dr. Dhananjay Bhavsar, Dr. Mahendra Yadav,
Dr. Praveen Suryavanshi, Prof. Nilambari Moholkar

Department of MBA, Dr. D.Y. Patil Institute of Technology, Pimpri, Pune, India

ABSTRACT: In this paper we provide a comprehensive analysis of the effect of WFH on employee productivity at EXL Services, a large information technology (IT) & services Based company based in India. With headquarters' Noida. In 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. 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.

I. INTRODUCTION

We study employee productivity before and during the working-from home period of the COVID-19 pandemic, using personnel and analytics data from over 5,000 skilled professionals at an Indian technology company. Hours worked increased, output declined slightly, and productivity fell 8%–19%. We then analyse 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.

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. 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%.

II. DATA AND EMPIRICAL STRATEGY

The setting for this study is EXL Services, one of the world's largest IT services & Service Based companies, with over 100,000 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. The workforce is highly skilled and educated. Virtually all have at least a bachelor's degree. Most work at the company's large, modern corporate campuses in several Indian cities.

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.⁴ Analytics



systems 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. 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.

Main Outcome Variables

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 (into taking 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

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. is low at about 4 years, as is expected since employee turnover is high in the IT sector.

The variable Num Children 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 Num Children is positive.

III. 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 (20.149 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 (20.056 from baseline 0.599), or an 8% drop (20.049 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.

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. 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.

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.

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.

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 allows 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. To do so, they worked longer hours.²¹ For this reason, productivity, measured by output per hour worked, fell by 8%–19%.

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.

The findings in this paper will be helpful well beyond this firm. We have presented evidence on some of the challenges of implementing WFH. 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.

REFERENCES

1. Aakvik, A., F. Hansen, and G. Torsvik. 2017. "Productivity Dynamics, Performance Feedback and Group Incentives in a Sales Organization." *Labour Econ.* 46:110– 17.
2. Adams-Prassl, A., T. Boneva, M. Golin, and C. Rauh. 2020. "Work Tasks That Can Be Done from Home: Evidence on Variation within and across Occupations and Industries." CEPR Discussion Paper no. DP14901, Centre Econ. Policy Res., London.
3. Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals." Harvard Dataverse. <https://doi.org/10.7910/DVN/K30VNE>.
4. Productivity Effects of Geographic Flexibility." *Strategic Management J.* 42:655–83. DeFilippis, E., S. M. Impink, M. Singell, J. Polzer, and R. Sadun. 2020. "Collaborating during Coronavirus: The Impact of COVID-19 on the Nature of Work." Working Paper no. 27612 (August), NBER, Cambridge, MA



International Journal of Advanced Research in Education and Technology

ISSN: 2394-2975

Impact Factor: 7.394