How Does Working from Home during COVID-19 Affect What Managers Do? Evidence from Time-Use Studies

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Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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We assess how the sudden and widespread shift to working from home during the pandemic impacted how managers allocate time throughout their working day. We analyze the results from an online time-use survey with data on 1,192 knowledge workers (out of which 973 are managers) in two waves, a pre-pandemic wave collected in August/2019 (615 participants, out of which 506 are managers) and a post-pandemic wave collected in August/2020 (577 participants, out of which 464 are managers). Our findings indicate that the forced transition to WFH created by the COVID pandemic was associated with a drastic reduction in commuting time for managers, but also an increase in time spent in work rather than on personal activities. This included reallocating time gained from commuting into more time spent in meetings, possibly to recoup some of the extemporaneous interactions that typically happen in the office. This change is particularly pronounced for managers employed in larger organizations. We use the results from the time-use studies to discuss implications for the development of new technologies.

Keywords: time-use; working-from-home; COVID; managers; knowledge workers

1. Introduction

The advent of the COVID-19 pandemic has forced millions of workers to suddenly shift their activity out of their offices and into their homes: 5-15% of Americans worked from home before the pandemic, whereas 50% of the Americans who were employed pre-COVID reported working from home at April/2020 (Brynjolfsson et al., 2020). While the effects of this sudden and exogenous shift on workers' behavior, as well as their productivity and wellbeing, are still largely unknown, organizations have already started to consider extending "working from home" (WFH) arrangements beyond the pandemic (J. Kelly, 2020).

In this research we explore the effects of the forced WFH arrangement during the COVID-19 pandemic on managers. We assess how the sudden and widespread shift to working from home during the pandemic impacted how managers allocate time throughout their working day, and how the type and length of work activities they engage in.

Managers are a particular type of "knowledge workers"—i.e. workers who typically focus on problem-solving and related cognitive tasks (Autor & Dorn, 2013). Unlike other knowledge workers whose tasks depend more on allocating one's individual efforts and skills to conduct solo-tasks, such as writing reports or coding, the job of managers requires primarily coordinative tasks, including the supervision, evaluation, and deployment of the work of others (Drucker, 2012). We focus our study on managers for two main reasons. First, broadly, managerial work is a central enabler that allows organizations to expand and thrive in distinct markets (Chandler, 1990), and the importance of managerial occupations in the U.S. economy has grown significantly over past decades (Autor & Dorn, 2009, 2013). However, we do not yet have a detailed understanding of how a forced transition to WFH affects managers' daily activities and the structure of their work. The need to understand these effects is made even more salient by the fact that the forced transition out of the office initiated by the pandemic will likely result in a more permanent shift towards WFH arrangements (Barrero, Bloom, & Davis, 2021). Second, more specifically, WFH presents a challenge for team-work and social activities (Lowy, 2020; Neeley, 2021), and managers are very likely to engage precisely in activities that rely on team-work and social interactions (Deming, 2017). Since coordination is such a central activity of what managers do and what organizations require, it is important to understand the extent to which a transition to WFH arrangements during the COVID-19 pandemic has affected this occupation. One method to characterize how managerial work has changed in a context of a sudden transition to WFH is to examine changes in where managers allocate their most valuable and scarce resource: their time (Mintzberg, 1990).

Our study examines the effects of the sudden shift to WFH on three specific aspects of managerial work: how managers allocate their time across different activities (e.g. the relative importance of activities performed alone vs. those that require communication and coordination with others); whether the incidence and length of different activities (e.g., meetings) changed; and whether the changes in time allocation and activity structure varied according to the type of organization employing the manager. We use this evidence to inform and inspire the discussion of two questions related to the development of human-computer interaction (HCI) technology. In particular: 1) can HCI technology reduce (or even eliminate) the possible additional burden that managers experience due to the shift to working from home? And 2) can HCI technology help take advantage of opportunities for improving managerial productivity and wellbeing that are made possible by this shift?

To pursue our research objectives, we analyze the results from an online time-use survey which collected data on 1,192 knowledge workers in two waves. The first wave was pre-pandemic, in August/2019 (615 participants). The second wave was conducted during the pandemic, but post the initial months where organizations were initially adjusting their activities, in August/2020 (577 participants). Participants included both managers and non-managers. In this study, we focus on the subsample of 973 managerial workers (509 in the pre-pandemic and 464 post-pandemic waves). Importantly, both waves of respondents commuted to work before the COVID-19 pandemic, which allows us to analyze the effects of the sudden shift out of the office for a subset of workers that experienced a sudden change in the primary location of work. Both surveys employed the Daily Reconstruction Method (Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004) , i.e. participants were asked to recall the most representative working day from the previous week, and then fill in a time-use diary reporting on the main activities they engaged in during that day (type of activity, start time, and end time). Both waves focused on U.S. full-time employees in knowledge-intensive occupations. Beyond time-use information, we also collected data on workers' socio-economic characteristics, including whether the participant had managerial responsibilities, which allows us to focus our analysis on managers.

Our findings indicate that the forced transition to WFH created by the COVID pandemic was associated with a drastic reduction in commuting time. Managers did not reallocate the "extra" time to personal activities, rather reallocating the time gained from commuting towards more time spent in meetings. These results suggest an attempt to to recoup some of the extemporaneous interactions that typically happen in the office. Furthermore, managers employed by larger organizations—i.e. managers whose typical interactions are likely to be more complex and include a broader number and variety of people—were disproportionately affected by WFH arrangements during the COVID pandemic. We find that this group ended up spending more time in work-related meetings, and less time in personal activities, relative to managers employed by small/medium-sized organizations.

We start from these findings to explore implications for technology development in two areas. First, our data points to an increase in the need for managers to communicate and interact virtually, and we expect that technology can help improve future team communication. Second, our data suggest that there might be new interruptions for managers to contend with when WFH. We expect that technology can help them navigate transitions between different tasks.

In the following sections we describe the empirical method of our time-use study and our findings in detail. We conclude with a discussion of how these results inform the development of new technologies aimed at supporting knowledge workers and in particular managers in the future. We begin with a review of related work.

2. Related work

2.1. Managerial Time Use

Time use has been a topic of interest in socio-economic sciences for decades (Becker, 1965; Heckman, 2015). The increasing availability of data on time allocation choices in the household (Kostyniuk & Kitamura, 1982), and more broadly across other personal and work activities, has led to a breadth in empirical research on the topic (Aguiar, Hurst, & Karabarbounis, 2013; Kitamura, Yamamoto, & Fujii, 1996) and to a broader understanding of the implications of different time-related behaviors and the sources of differences in time allocation across individuals (Gershuny & Fisher, 2013; Kahneman et al., 2004; Krueger, Kahneman, Schkade, Schwarz, & Stone, 2009).

Understanding differences and implications of different time use patterns is especially relevant for knowledge workers. The term "knowledge worker" was coined by Peter Drucker, who is considered one of the founders of modern management (Webster Jr, 2009), and refers to a wide range of occupations that are primarily focused on problem-solving—such as scientists, engineers, but also managers and salespeople. In particular, in Drucker’s view, managers are a particular type of knowledge worker that must pay close attention to their time, which he saw as the critical (and scarcest) input in their activity, but one that was also often misallocated (Drucker, 2012).

Managerial occupations involve a wide range of coordinative tasks, including the supervision, evaluation, and deployment of the work of others. Mintzberg (1973) was the first to empirically explore the nature of managerial time use with an in-depth ethnographic study of a small and selected sample of managers. Ever since Mintzberg's groundbreaking work on how managers allocate their time across different activities, a host of researchers have used ethnographic and qualitative observations to replicate and extend Mintzberg's characterization of managerial time use as divided between interpersonal tasks, decision-making, and information processing (Kurke & Aldrich, 1983; Martinko & Gardner, 1990), while also accounting for other the context of work, such as in small businesses (O'Gorman, Bourke, & Murray, 2005) or in the public sector (Lau, Newman, & Broedling, 1980).

In more recent work researchers expanded Mintzberg's work beyond qualitative evidence, using quantitative time-use data to explore the behavior of top managers from large organizations. These studies found that even within top managers, there are substantial differences in time allocation across CEOs and that such differences are correlated with differences in firm performance. For instance, in family firms, professional CEOs work longer hours than family CEOs, and this difference accounts for some of the performance gaps between the two types of governance structures (Bandiera, Lemos, Prat, & Sadun, 2018). CEOs also vary in the extent to which they allocate their time between coordinative and operational activities (Bandiera, Prat, Hansen, & Sadun, 2020). This paper builds on these earlier papers by providing detailed time use data on a large sample of middle managers, and by comparing time allocation patterns pre- and post-COVID pandemic.

2.2. Working from Home and the Nature of Work

Several studies within the economics and management literature have explored the implications of WFH arrangements within single organizations prior to the pandemic. A randomized controlled trial in a Chinese call-center found evidence of significant increases in worker productivity after workers could select into WFH arrangements (Bloom, Liang, Roberts, & Ying, 2015). While this study rigorously illustrates the possible benefits of WFH, it is hard to extrapolate its findings to less standardized and routinized occupations that are usually associated with knowledge workers. Choudhry, Foroughi, and Laron (2020), however, also found clear benefits in WFH in an experiment that allowed patent examiners from the United States Patent and Trademark Office to opt into WFH. Nonetheless, while both studies focus on worker productivity when working from home, both studies focus on workers that typically work independently. Therefore, the extent to which the benefits of WFH would extend to occupations characterized by a higher need for teamwork and coordination, and on managers in particular, is not yet known.

Moreover, while the above-mentioned studies focus on the productivity effects of WFH arrangements, research on how WFH arrangements change the nature of what workers do when work is not conducted in the office remains less studied. We also do not know the extent to which pre-pandemic studies could be extrapolated to understand the effect of a WFH in emergency contexts such as the ones forced by the pandemic (for example, school closures, business disruptions, etc.).

Recent research has started to tackle the question about how work changes when knowledge workers work from home. For instance, a study of 40 knowledge workers forced to work from home during COVID finds evidence of some productivity benefits of WFH, but also some concerns around longer-term effectiveness, creativity, and personal resilience (Birkinshaw, Cohen, & Stach, 2020). Evidence from a large sample of email and meetings metadata shows stark increases in virtual meetings and emails after government-enacted lockdowns during COVID (which effectively forced WFH on large samples of workers), presumably as a way to compensate for the loss of physical interactions (DeFilippis, Impink, Singell, Polzer, & Sadun, 2020). Work in the IT sector has also found that, when comparing pre-COVID working-in-the-office to post-COVID working-from-home, IT workers increased total hours worked and extended working hours (Gibbs, Menger, & Siemroth, 2021). However, the nature of work also changed, with workers spending more time on meetings, but less time on informal networking and coaching, suggesting a shift in the communication and coordination costs when working from home during the COVID pandemic. Such increase in coordination costs is at the core of this work.

This project contributes to the WFH literature in multiple ways. First, much of the research on WFH has typically focused on workers that conduct standardized tasks (Bloom et al., 2015; Harrington & Emanuel, 2020) or that are in highly specialized fields (Choudhury et al., 2020; Myers et al., 2020). We contribute to this literature by examining the impact of WHF arrangements on managers, a particular type of knowledge worker present across many industries. Second, the level of detail of the data collected on the time use of workers involved in WFH is also novel, in that it allows us to investigate variation in the time allocated to specific personal and work-related activities (e.g. work-related meetings, reading/writing reports, personal time) for a large sample of individuals and over time, rather than the overall time spent on "work activities". Third, the repeated cross-section nature of the data, which uses the same method to measure detailed daily time-allocation of workdays from a set of knowledge workers in mid-2019 and from a set of similar individuals in mid-2020, allows us to infer changes in personal versus work time allocation and in the composition of work activities before and during the COVID-19 pandemic and the forced transition to WFH. Importantly, these data does not rely on long-memory recall of how participants allocated their time prior to the COVID pandemic, thus providing a more accurate understanding of how the structure of the managerial workday changed with the sudden shift to remote work.

2.3. CSCW Research on Managerial Work in Remote Collaboration

Researchers in the fields of computer-supported collaborative work (CSCW) and human-computer interaction have investigated the factors and technologies in support of remote collaboration in the last three decades (Ens et al., 2019; Finholt & Sproull, 1990; Gutwin, Penner, & Schneider, 2004; Inkpen, Hegde, Czerwinski, & Zhang, 2010; Mark, Abrams, & Nassif, 2003; Nardi, 2005; O'Conaill, Whittaker, & Wilbur, 1993). In the seminal paper "Distance Matters", published in 2000, Olson & Olson examined the socio-technical conditions required for effective distance work within teams of knowledge workers (G. M. Olson & Olson, 2000). The paper provides a framework consisting of four key concepts critical for effective remote work: common ground, coupling of work, collaboration readiness, and collaboration technology readiness. The paper's main argument, which is often cited in the CSCW and HCI literature on remote work, is that even with emerging and future technology, distance still matters – "There will likely always be certain kinds of advantages to being together". In later extensions of their framework Olson & Olson added to the distance framework the concept of organizational management – the practices and activities which shape remote collaboration (J. S. Olson & Olson, 2014), highlighting that managing at a distance is very different from managing a collocated team or project.

In the 2014 article, “Does Distance Still Matter?”, Bjorn et al. (2014) revisited the distance framework’s factors through a comparative analysis of four ethnographic studies of global software development. Their findings indicate that managerial practices are critical to making the collaboration function well, highlighting that identifying managerial concerns is essential for CSCW research on distributed work. Bossen and Leimbach argue that project managers, who focus on a project’s team communication and coordination, often in distributed forms of working, share an interest with CSCW and HCI methods and aspirations for supporting cooperation and coordination through analogue and digital artefacts (Bossen & Leimbach, 2017). They highlight a need for research to advance the understanding of project management work and to support managers through the design of adequate computational tools.

The forced transition to WFH during COVID-19 introduces additional factors that impact managerial responsibilities for collaboration and coordination in remote teams such as social isolation of workers, and increased stress due to the pandemic. Yang et al. (2020) conducted a large-scale study on how WFH during COVID-19 affects collaboration in a sample of Microsoft US employees. Their findings indicate that the effect of WFH is moderated by individual remote collaboration experience prior to WFH, and that the medium for collaboration has shifted: instant messages were used more often, while scheduled meetings were used less. The findings also show more total collaboration hours, more meeting hours and fewer focus hours; however, the analysis suggests that the observed changes are mainly due to factors related to the COVID-19 pandemic, and that WFH under normal circumstances is likely to decrease collaboration and increase focus time. The authors conclude by stating that “a shift to WFH may be beneficial for those engaging in focused work that requires large blocks of free time but may be detrimental for those engaging in work that is highly collaborative in nature.” This claim further highlights a need to study the impact of COVID-19 WFH on managers - whose work responsibilities are more likely to rely on collaboration and social interactions (Deming, 2017)

The CSCW and HCI research discussed above indicates the importance of understanding and supporting the needs of managers in remote distributed collaboration. However, the distributed collaboration addressed in prior research is different in nature than the forced and rapid transition to WFH caused by the pandemic. Our study contributes to understanding the time-use of managers working-from-home during the COVID-19 pandemic, in particular our findings demonstrate that managing teams remotely during COVID-19 is different from managing teams in the workplace prior to the pandemic. Our findings are consistent with Olson and Olson’s (2014) claim that managing at a distance is very different from managing a collocated team or project, as well as with the Yang et al. (2020) study on how WFH during COVID-19 increased the time workers spent in collaboration in one organization. This highlights the need to develop technology to support managing remotely in general, and managing in response to rapid and forced changes in particular. We leverage the detailed account from the time use study to suggest specific areas of technology development that could better support managers and organizations while working remotely. For instance, the increase in time spent in interactions after the forced shift to remote work reinforces the importance of technologies which enhance both formal and informal remote interactions.

3. Time Use Study of Managers

This study addresses the following research questions:

RQ1: After the forced transition to WFH post the start of the COVID-19 pandemic how did managers re-allocate the time previously spent commuting towards personal or work-related tasks?

RQ2: How did the transition to WFH affect the structure of managers' workdays in terms of (a) workday span, as well as the (b) incidence and (c) length of engagements in different work tasks (e.g. activities performed alone vs. those that require communication and coordination with others)?

RQ3: Are the changes in time allocation and structure different across managers in organizations with more complex coordination activities?

We use our results to address the three research questions above, and provide implications for design for technologies that would support managers when working-from-home and/or managing distributed remote teams.

3.1. Materials and Methods

Recruitment and Participants

We designed a novel Time-Use survey to collect detailed time-use information on a large sample of U.S.-based knowledge workers. The data were collected across two waves: a first wave in August/2019 (pre-COVID) and a second wage in August/2020 (post-COVID). To ensure comparability across waves in both the pre- and post-COVID survey we recruited participants using the online paid marketplace platform Lucid, which partners with several companies to recruit individuals to answer online surveys.

Our team defined the sampling frame to reflect a set of average socioeconomic characteristics of full-time employed knowledge workers, as described in the US Census' 2018 Current Population Survey (CPS) (United States Census Bureau, 2018). Furthermore, a criteria was for at least 90% of the respondents to have reported that they commuted to work between 4 and 5 days per week prior to the COVID pandemic. In Appendix A1 we provide a detailed account of the sampling criteria and quotas that Lucid enforced when launching the survey for potential respondents.

Participation in the two waves was anonymous and each treatment wave involved an independent process to reach out to participants. As a result, participation across survey waves is not linked and we treat the information as representing separate samples of respondents. Since Lucid’s process to recruit participants involves reaching out to multiple panels of thousands of individuals, it is unlikely that a participant replied to both waves of the survey.

Table 1 reports the descriptive statistics of the screening variables, that is the variables used to define the sampling frame across both waves, and the corresponding values in the 2018 Current Population Survey (CPS) (United States Census Bureau, 2018). In Table 1 we report the composition of the whole sample of knowledge workers and the subsample of managers, which is the focus of this work. In total, 615 knowledge workers responded to the pre-COVID wave and 577 knowledge workers responded to the post-COVID wave. Columns [2] to [5] show that the pre- and post-COVID samples are similar across the socioeconomic characteristics used to define the sampling frame. Column [5] reports the p-value of a chi-squared test of equality of frequencies comparing the pre-COVID to the post-COVID sample. The screening variables are balanced across the overall sample of the study. Beyond the screening variables, pre- and post-COVID respondents had differences: post-COVID respondents were +1.4 years older (p-value<0.05), 8.3% more likely to live with children (p-value < 0.01), 9.1% less likely to live more than 12 miles away from work (p-value < 0.01), and 6.7% more likely to work in a large firm (p-value < 0.01). While these differences are small in magnitude, we nevertheless make sure to account for them with the inclusion of controls for socioeconomic characteristics, and characteristics associated to individuals' work arrangements in our analysis.

We define managers as participants who report supervising at least one other worker at work. Managers comprise 81.6% of our sample and we report the descriptive statistics of the screening variables for managers in columns [6]-[9]. The only statistical difference in the screening variables is on the education variable, with managers in the post-COVID sample being 9.28% more likely to have post-graduate education (p-value < 0.05).

INSERT TABLE 1

Data Collection

In both waves (pre- and during-COVID), participants responded to a time-use survey which asked for them to enter a detailed mapping of the activities they engaged in during the most representative working day of the previous week, as well as to answer to additional questions about their well-being, work, and socioeconomic characteristics. Both survey waves were hosted on Qualtrics.

Time Use Survey

We developed a time-use survey by adapting the well-known Daily Reconstruction Method (DRM) (Kahneman et al., 2004) to a distributed, on-line data collection method. In the DRM method, participants are asked to fill in a diary about the activities undertaken the previous day. This approach allows researchers to collect detailed information on the types of activities conducted by respondents.

The procedure to fill in the time-use diary was the same across the pre- and post-COVID waves. First, participants were instructed to report information about which of preceding five working days they believed to be the most typical working day they experienced, and to mark which day of the week it was.[1] We also asked participants what times they woke up and went to sleep. Then, we asked participants to fill in a time-use diary with information about activities they engaged in during that day. For each activity, participants had to select an activity title from a list of 22 activities as well as the start and end times for the activity. The time-use diary had three different sections, one for each part of the day (morning, afternoon, and evening) in which participants could report on 10 activities that had lasted at least 15 minutes or that they felt had been particularly important per part of the day, with a maximum of 30 activities per day.[2]

Figure 1 shows a screenshot from the morning section of the diary.

INSERT FIGURE 1

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[1] This instruction aimed to reduce noise - we wanted to filter out responses for cases participants had an unusual working day (e.g. a day where unanticipated and rare personal events got in the way of regular work-related activities).

[2] To help participants recollect the activities undertaken on that representative working day, we encouraged them to enter personal notes in a free text field in the survey: this field was optional, and we notified participants that the research team would delete this information as soon as the survey ended. Participants could also add free text subtitles to each activity.

Across the pre- and post-COVID waves, participants went through the same survey tool up to, and including, the stage where they filled out information in their time-use diary. In the pre-COVID wave we followed the time use questionnaire with additional questions to detail the commuting activities, while in the post-COVID survey we asked participants to provide additional details also about other work-related activities. In this paper we do not report on the data from these additional questions.

The DRM method is a widely used tool in time-use studies whose benefit comes from first asking the participants to recollect the day as a sequence of activities as if they were recovering a series of episodes within a specific day, beginning with when they awoke and ending when they went to bed (Kahneman et al, 2004). While recovering these episodes, participants are asked to describe these episodes by writing down what they felt and experienced. Evoking the context of the day is indented to reduce recall bias and elicit memories about each activity (Belli, 1998). As a result, although the DRM is similar to the procedure used in standard large-scale time-use surveys such as the American Time Use Survey (Horrigan & Herz, 2004), it has an added benefit of being more accurate than direct survey questions in which participants indicate, for instance, the share of time they spent on a pre-defined task while also activating respondents' memories about each activity (Diener & Tay, 2014; Kahneman & Krueger, 2006; Kahneman et al., 2004; OECD, 2013). Indeed, the reliability and validity of the DRM approach has been studied extensively, with results comparing it favorably to alternative techniques (Dockray et al., 2010; Kahneman et al., 2004; Krueger et al., 2009; Krueger & Schkade, 2008; Stone et al., 2006). Nonetheless, it is important to note that people might have an inaccurate memory and their responses might be less accurate when compared to data collected in a diary study, especially when asked to report about a single day during the COVID-19 pandemic. To mitigate this concern, we conducted a validation exercise with a sample of that suggested our approach was able to recover "stable" time allocation decisions even within the context of the COVID-19 pandemic.[3]

Data Analysis

We start with a comparison of the workday of managers in the pre- and post-COVID surveys in terms of the allocation of time across work, personal, and commuting activities. The main dependent variables are the total time reported on commuting, personal, and work-related activities, and the total time of the work span (time between the start of the first work-related activity and the end of the last work-related activity). Next, we examine pre- and post-COVID differences in a manager's probability of engaging in, number of, average length of, and total time spent in four types of work-related activities: 1) work-related email/social media activities (e.g. reading/replying emails, using social media for work-related purposes); (2) work-related interactive activities (e.g. meetings, phone calls, video-conferences); (3) work-related solo-cognitive activities (e.g. planning for a meeting, preparing a presentation, writing a report, programming); and (4) other work-related activities (e.g. work-related leisure as business meals, and "other" work-related activities). All measures of time allocation are reported in minutes and all variables are measured at the respondent-level.

To examine changes in the dependent variables above, we report results from multivariate ordinary least square regression models (OLS), unless otherwise stated. Each

[3] The validation exercise consisted of collecting longitudinal data for 203 knowledge workers – all outside the sample of respondents from the main analyses reported in this paper- about their time allocation on one day of their week over three consecutive weeks. We deployed the validation exercise in June/2020. That data suggested that working days were already substantially stable within-workers by June/2020 and reassured our team that the DRM is able to capture persistent differences in work behavior.

model estimates the conditional mean difference between each respective dependent variable at two points in time: before and after COVID. Time is modeled by a binary variable indicating whether the respondent is in the post-COVID sample. Since we collected the post-COVID data 5 to 6 months after the initial lockdowns, our results should be interpreted as descriptive evidence about how the working day of managers have changed from working-from-the-office pre-COVID to a scenario where managers are (forced into) working-from-home during the COVID-19 pandemic, but after organizations had time to adapt to the initial COVID-19 shock.

All models control for the following socioeconomic and work-related characteristics: age, gender, income, highest educational degree, marital status, whether the person lives with children, whether the person lives in a large city, whether the person lives less than 6 miles, between 6 and 12 miles, or more than 12 miles away from work, whether the person works in a firm with more than 249 employees, whether the person works in the service sector, and tenure in the firm. All estimates also add the following control variables to account for differences in how well respondents answered the time-use diary: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary. All estimated standard errors are White-Huber errors robust to heteroskedasticity and we report statistical significance using a two-tailed student-t test.

We used StataCorp's Stata software, version 16, to conduct all quantitative analyses.

3.2. Results

In this section we report the results using responses from the 973 managers in our sample (509 in the pre-COVID sample and 464 in the post-COVID sample). Data on the pre- and post-COVID samples are from participants independently recruited to answer the survey (i.e. our data are two samples of independent cross-sectional observations).

Time Diaries

Participants entered an average of 14.6 daily activities (SD = 7.6). Including time allocated to sleeping, participants reported an average of 1170.8 minutes (19.5 hours) of time spent on different activities (SD = 212.8 minutes); this translates to 81.3% of the day. Participants reported their activities for Mondays (38.1%), Tuesdays (24.9%), Wednesdays (17.2%), Thursdays (10.1%), and Fridays (9.8%). All models control for which day of the week was reported.

Re-allocating commuting time post-COVID (RQ1)

Figure 2 summarizes how managers allocated their time by every 15-minute time window in a pre-COVID vs. a post-COVID day. Each color represents one type of activity (work, personal, commuting, or unreported) and the area represents the share of participants that reported engaging in such activity at every 15-minute time window. Figure 2 illustrates three main differences in terms of the working day of managers post-COVID. First, as expected, commuting time (represented by the orange area) is compressed to almost zero throughout the day. Second, the compressed commuting time in the morning is replaced by personal activities (represented by the expansion of the green area between 6AM and 9AM). Third, managers' workday spans more hours: managers engage in more personal activities in the early afternoon (expansion of orange area between 12PM and 3PM) while working until later in the evening (red area expands between 6PM and 10PM). Because personal time expands in the early morning and in the early afternoon while work time expands until later in the evening, Figure 1 indicates that managers do not necessarily reallocate all their commuting towards personal or work activities. Rather, managers stretch their working day for longer hours, potentially interweaving it with personal and work-related tasks.

INSERT FIGURE 2

Table 2 provides further details on time use. The table reports the results of the multivariate ordinary least squares regressions estimating the pre- vs. post-COVID average difference in how managers allocated their daily time across different activities, while adjusting for differences in socioeconomic and work-related characteristics of participants (as detailed in the methods section, we assess statistical significance via a two-tailed t-test). Managers in our sample report a -27.2 minute decline in the time allocated to commuting events (p-value < 0.01) in the post-COVID sample, an increase in total time allocated to work-related activities (+18.2 minutes, p-value < 0.05), but no statistically significant increase in time allocated to personal activities (+8.9 minutes, p-value = 0.33). These results suggest that managers reallocated more of the commuting time they saved by working-from-home to work-related activities rather than personal activities.

The structure of the managerial working day pre- vs. post-COVID (RQ2)

Column [4] in Table 2 further shows that beyond the increase in total work-time, the structure of the workday of a manager changed post-COVID. The work-day span of managers (the difference between the start of the first work activity and the end of the last work activity) increased by +60.8 minutes (p-value < 0.01). This is aligned with the expansion of the blue area after 6PM in Figure 2 and implies that participants reallocated work activities previously concentrated in a 9AM-5PM work-day towards the evening.

INSERT TABLE 2

Table 3 shows results where we explore, in more detail, changes in the structure of work post-COVID. More specifically, we analyze changes associated to the incidence and length of 4 types of main work-related activities captured in the time-use diary:

1. Work-related email/social media (e.g. reading/replying to emails);
2. Interactive work-activities (e.g. phone calls, videoconferences, meetings)
3. Cognitive activities performed alone (solo) (e.g. analyzing a report, preparing for a meeting); or
4. Other work-related activities (e.g.: leisure with clients, business meals).

In Table 3, Panel A, we show that managers spend marginally more time on interactive activities (+12.0 minutes, p-value < 0.1), and less time in other work-related activities (-14.3 minutes, p-value < 0.05). Although the time spent on solo-cognitive activities is also higher (+13.1), the difference is not statistically significant with a p-value = 0.13. In Table 3, Panels B, C and D explore these changes in more detail, distinguishing between different types of work activities. Panel B shows that post-COVID, managers are +11.9p.p. more likely to engage in at least one interactive activity (p-value < 0.01). Panel C reports that post-COVID managers also reported an increase in the number of work-related activities (+1.5 activities, p-value < 0.01). The additional activities were spread across email/social media activities (+0.38 activity, p-value < 0.01), interactive activities (+0.38 activity, p-value < 0.01), and solo cognitive activities (+0.61 activity, p-value < 0.01). Finally, Panel D reports the difference in the average duration of engagement in work activities (overall and by type of activity) in the pre- and post-

COVID samples. The data show that the average duration of individual engagement in work activities decreased post-COVID: conditional on engaging in an activity, the average engagement in a work activity was -10.9 minutes shorter in the post-COVID sample (p-value < 0.01). Although all types of work-activities are, on average, shorter, activities that we identify as other work-related activities are the ones where these differences are statistically significant (-11.7 minutes, p-value < 0.01). Our results suggest that solo-cognitive work could also be, on average, shorter (-9.2 minutes), but the difference is only significant at p-value < 0.1.

INSERT TABLE 3

Are the experiences of managers at large firms different? (RQ3)

Taken together, these results show that the shift to WFH due to the COVID-19 pandemic resulted in a significant change in the composition of tasks undertaken by managers, with a reallocation of time spent commuting into work (rather than personal) activities. The shift also resulted in a different structure of the working day, with an increase in the span of the working day, and a greater incidence of shorter, more fragmented, and interactive tasks.

One possible interpretation of these results is that the sudden shift to WFH led managers to allocate more time to coordinative and interactive activities to compensate for the loss of a common physical space of interaction, such as the office. For example, meetings may have been used to replace "watercooler conversations" or informal interactions that typically take place in the office. To assess whether the shifts observed in the data are consistent with this interpretation, we examined a difference of differences: we examined whether changes in time allocation post-COVID are larger for managers employed by large firms relative to managers employed by small/medium-sized firms. The logic behind this comparison is that managers employed by larger firms are typically in charge of larger and more complex teams (Caliendo, Monte, & Rossi-Hansberg, 2015; Garicano & Rossi-Hansberg, 2015), and would therefore need to compensate more for the lost physical interactions that typically take place in the office.

In Figure 3, panel A, we show the difference in the change in time allocation pre and post-COVID for managers employed in large firms relative to managers employed by small/medium-sized firms. We look separately at the time allocated to commuting, personal, and work-related activities, as well as for the length of the work day (workspan). In panel B, we report the analogous estimates with the dependent variables being time allocated to the four different types work-related we captured in the time-use diary. Figure 3, panel A shows that the change in time allocation is driven by managers employed by large firms. The pre- vs. post-COVID changes in time allocation for managers from large firms are substantially different from changes experienced by managers in small/medium firms. The change in time allocated to personal activities was - 31.9 minutes (p-value < 0.1), the change in workday span was 62.6 minutes (p-value < 0.05), and the change in total work time was 28.2 minutes more (though this difference is only significant at p-value $= 0.11$). In other words, managers in large firms lost more of their personal time than managers in small/medium firms, they increased their work span more, and there are indications that they spent more time working. Furthermore, Figure 3 (panel B) shows that these differences are driven by interactive tasks (+33.9 minutes, p-value < 0.05). In the appendix (table A1), we also report analyses where we estimate the effects of WFH post-COVID separately for managers from large firms and for managers from small firms. The results confirm that managers from large firms indeed experienced most of the changes related to increase in work time, workspan and time spent on interactive tasks.

INSERT FIGURE 3

Are the changes different between managers and non-managers? (Robustness analysis)

As a robustness analysis, we also compared the changes in time allocation between managers and non-managers, again based on the idea that managers typically have greater coordination needs relative to non-managers. Figure 4 compares changes in time allocation between managers and non-managers employed by large firms. Figure 4 (panel A) shows that pre- vs. post-COVID changes in time allocation for managers from large firms are substantially different from changes experienced by non-managers from large firms: the change in total time allocated to work-activities was +55.7 minutes larger for managers when compared to non-managers (p-value < 0.01). The analogous effect for change in total length of the workday was also +94.2 minutes greater for managers (p-value < 0.01). Furthermore, the change in time dedicated to personal activities was -76.6 minutes lower for managers when compared to non-managers (p-value < 0.01). Figure 4 (panel B) shows that pre- vs. post-COVID changes in time allocated to different work-related tasks is substantially different across managers and non-managers from large firms. Changes in time allocation for managers are more substantial than that for non-managers across all work-related tasks, being more positive in terms of time allocated to email (+50.2 minutes, p-value < 0.01), marginally more positive in terms of time allocated to interactive activities (+31.2 minutes, p-value < 0.1) and to solo-cognitive work (+49.1

minutes, p-value < 0.1), and less positive in terms of time dedicated to other work-related activities (- 74.8 minutes, p-value < 0.01).

INSERT FIGURE 4

4. Discussion

Our findings show that during COVID, managers reallocated commuting time to work-related time, but not to personal time (RQ1). We also found that the workdays of managers were more fragmented during COVID, with an increase in the number of activities, with shorter activity durations, and with activities that were more dispersed across the day, resulting in a longer workday (RQ2). We found that managers were more likely to engage in interactive activities, and that additional work activities include email/social media activities (RQ2). Our findings further show that the effects of WFH arrangements during COVID-19 were heterogeneous across firms. The change in time allocation that we observed in our sample of managers was driven by one group: managers employed by large firms. This group spent significantly less time on personal activities, and a longer workday when compared with managers of small/medium size firms. Furthermore, we found that these differences were driven by a significant increase in interactive tasks (e.g. meetings) (RQ3).

Taken together, these results provide suggestive evidence that the forced and unexpected transition to WHF created the necessity for managers to work harder (and longer) to make up for the loss of coordination activities that would typically take place as unplanned and extemporaneous interactions in the office. This interpretation is also aligned with: (1) the emergence of company-sponsored interactive “informal” activities (e.g. virtual watercoolers, mentoring events) that seek to facilitate informal conversations between managers and employees working remotely (Bojinov, Choudhury, & Lane, 2021), and (2) the thought that managers had to boost their digital communication with team members to assure not only coordination of work-related activities, but also to check-in on how their team members are handling a world where office needs and personal needs intertwine (Hill, 2020; Neeley, 2020). Our results extend existing work—and in particular Yang et al. (2020) — by showing changes in time allocation for a broad set of managers employed by firms that may be less technology-enabled than Microsoft, which was the focus of their exploration. The time-diary data method we used provides a broader picture of the full working day of knowledge workers and is more suitable to address our research questions on the reallocation of commuting time across different activities, including personal activities and potential off-network interactions (e.g. interactions outside instant communication tools). Reassuringly, our findings are consistent with those found by Yang et al. among Microsoft's employees—the increase in overall time allocated to interactive activities, a reduction in average activity length, and fewer uninterrupted work hours found among managers.

4.1. Implications for Design

Based on the interpretation of our findings and on the detailed account from the time use study, we suggest areas for organizations to further consider the use of technology to better support WFH arrangements, including for hybrid arrangements and more generally for distributed teams that are spread across multiple time zones. This question is important given the broad expectation that WFH will remain popular (Neeley, 2021), perhaps as part of a hybrid workplace (Freier, 2021; H. Kelly & Lerman, 2021). In this section we draw inspiration from our data to discuss two areas where technology can play a role in supporting managers.

Technology for improving time allocation in support of work and wellbeing

Our interpretation that managers allocate more time to interactive activities for the purpose of coordinating teams is in alignment with the findings of Olson and Olson's (G. M. Olson & Olson, 2000) that remote work requires "management overhead." Given the results on increased need for interactive activities, our study indicates that managers might be well-served by technological support for improved communications with their teams. For example, technology may help improve the efficiency of virtual interactions, reduce the time workers need to spend on synchronous communication, and reallocate time towards work tasks or personal tasks. As we discussed in the Related Work section, this problem is neither new, nor simple, but the current (and likely future) emphasis on WFH and hybrid work gives us new impetus to focus on it. Note that for WFH to be broadly available, the technologies will need to work for a broad cross-section of the workforce, and not just a select few. Consider the case of a pandemic when WFH is necessary for social distancing, or the case of a firm that makes a business decision to implement WFH. In these cases managers cannot simply "select the right people for the team" as suggested by Olson and Olson (2014), because everyone in the firm will be on some remote team.

One specific area where technology could help with time allocation when WFH is with coordination and organizational support tasks—for many such tasks, AI digital assistants might soon achieve a level of sophistication which is close to that of human assistants. Such digital assistants will be able to help workers increase their productivity, and possibly reduce email and short coordination meetings, by handling routine coordination tasks such as scheduling meetings, sharing access to resources, and locating needed information.

Our data also indicates that for some managers, WFH means interleaving work and personal life. We see this from the fact that for some managers the length of the workday (workspan) has increased compared to pre-COVID days, and this likely means that they switch between personal and work tasks at certain points during the day. This might indicate that, for these managers, work and personal life will collide, with the barriers between the two blurring. Technology can help managers and workers maintain barriers between work and personal life, which in turn can help shorten the span of their workday and possibly increase their wellbeing. The technological approach does not have to be complicated: Rudnicka et al. (2020) report on a number of simple approaches, including workers who use separate accounts for work and personal tasks.

It is important to note that, in the words of Ciolfi and Lockley (2018), flexibility with setting, blurring, and removing boundaries can be a resource in managing both work and personal priorities. It is possible that some managers take advantage of the flexibility of WFH and that this is the source of the longer workdays we observed after the start of the COVID pandemic. Technology could help with "sculpting boundaries" (Nippert-Eng, 2008), both in the form of planning tools, as well as in the form of AI assistants that can provide real-time suggestions and support. Planning tools could help managers see the big picture - how much time they are investing in different activities, and what they are able to accomplish. Real-time assistants could help them react, primarily when there is a need for flexibility with boundaries. These assistants could help list options for sculpting boundaries that workers could evaluate and implement. The assistants could also support managers' mental wellbeing as they look for ways to satisfy the competing demands of work and personal life.

Technology for improving the efficiency of work

One reason that managers spend additional time communicating might be that they have not found an adequate replacement for the formal and informal face-to-face meetings that were possible when working in a shared office. Managers can use video calling tools to have virtual face-to-face meetings. However, these tools make it difficult for conversants to observe each other's non-verbal cues, such as body posture, head and arm gestures, eye gaze (including eye contact), and non-verbal utterances (G. M. Olson & Olson, 2000; Otsuka, Sawada, & Yamato, 2007). Difficulties with identifying non-verbal cues can be additionally exacerbated by poor network connection. If technology can improve these issues this would help support effective communication. Emerging human-computer interaction styles such as augmented and virtual reality, as well as newly designed meeting spaces (Wakabayashi, 2021), hold promise for improving the quality of remote interactions among team members that might be distributed across different locations (some at home, some in the office), and could provide access to shared tools such as whiteboards, simulations, and shared social spaces (Ens et al., 2019).

The increase in communication and the shorter duration of work activities evidenced by our findings, might mean that managers are now more frequently interrupted by having to respond to a request, or having to send out timely messages to team members. In fact, interruptions, from those that pull knowledge workers to personal tasks during the workday, to work-related (and particularly communication-related) tasks, are one possible explanation for the reduction in the average length of engagement in work tasks. Interruptions can negatively affect performance—after all there is a cognitive cost to resuming an interrupted activity (Boehm-Davis & Remington, 2009; Janssen, Iqbal, Kun, & Donker, 2019). However, technology can help workers organize their tasks in a way that is resilient to interruptions. For example, researchers have been exploring how technology can help managers decompose large tasks into smaller ones, and how completing these so-called microtasks can allow workers to make consistent progress towards productivity goals (Hahn, Iqbal, & Teevan, 2019; Williams et al., 2019).

Furthermore, researchers have designed models of interleaving multiple tasks (Boehm-Davis & Remington, 2009; Janssen et al., 2019)— here interleaving refers to the idea that a worker who is engaged in a work task (such as communication), might be interrupted by another task (e.g. a personal task), and would then ultimately return to complete the interrupted work task. A model of interleaving points out that the shifts between the two tasks are often not instantaneous. Rather, a worker might complete these shifts in several steps, including steps such as casting a glance at the location of the interrupting task, glancing back at the work task, etc. It is also interesting to point out that some interruptions are non-negotiable: for example, a child crying or a pot of water starting to boil must be attended to immediately. Responding to other interruptions, such as a new email, can often be postponed. Thus, one place where technology can support managers is by helping to pace those interruptions where they have some flexibility in when to respond. This is what humans do in collaborative settings: they will attempt to interrupt an ongoing task at a natural breakpoint in that task (Kun, Shyrokov, & Heeman, 2013; F. Yang, Heeman, & Kun, 2011). Another place where technology can help is at the resumption of an ongoing work task. Here, the technology can support the worker with reminders of where in the task the worker left off, and with reminders of results of previous steps. Again, these are also behaviors that we observe in human-human collaborations (Kun et al., 2013; F. Yang et al., 2011).

Finally, it is important to note that interruptions can be beneficial, for example if the worker is losing focus or is becoming tired, and researchers are experimenting with systems that recommend breaks (Kaur et al., 2020).

4.2. Limitations and Future Work

First, our study utilizes an adapted version of the Daily Reconstruction Method (DRM) survey, which asks participants to report on activities they conducted in a representative work day from the previous week. While the DRM method is widely used and is considered less burdensome than diary studies, we again highlight that people might have an inaccurate memory and their responses might be less accurate when compared to data collected in other time-use studies using, for instance, ethnographic methods to follow a small set of individuals over time. As reported previously, we tested the validity of our approach in recovering “stable” time allocation decisions. Furthermore, within the sample used in this study, total time reported in the time-use diary in the pre-COVID and in the post-COVID samples were comparable (1176 minutes reported in the average pre-COVID diary and 1164 minutes reported in the average post-COVID diary, p-value of t-test comparing means = 0.2). This reassured our team that the DRM is able to capture persistent differences in work behavior for the purposes of this study.

Second, our data does not allow us to disentangle the effects of the shift to WFH arrangements from those of the pandemic. To determine whether the changes observed in our data are due to WFH or to other unobserved factors associated with the COVID-19 crisis (e.g. family responsibilities, taking care of children, health considerations), we would need to have a “control” group of workers who used WFH arrangements prior to the pandemic. This is an important limitation, as shown in Yang et al. (2020), who use a large dataset measuring email and meeting usage by Microsoft workers in the early stages of the pandemic to examine how interactive and uninterrupted hours of work changed for workers that transitioned from working from the office pre-COVID to working from home post-COVID when compared to a control group of workers already worked from home even pre-COVID. Yang et al. (2020) show that, while there is a generalized increase in interactive activities post-COVID and generalized decrease in hours dedicated to focused work, these effects are attenuated for WFH "switchers" relative to those that were already working remotely. Extrapolating this result to our context, since our data is composed entirely of WFH switchers, this implies that the effects documented in our paper may be a lower bound relative to those that would be found in the larger population.

Third, though we use the same sample design criteria across waves, our data do not allow us to follow the same person over time. Effectively, we are comparing two cross sections of time usage from different points of time across similar types of knowledge workers—one collected in August/2019 and another in August/2020. We attenuate this concern by controlling for key demographic characteristics of the respondents, thus effectively comparing individuals with similar socio-economic characteristics. However, we readily acknowledge that the comparison is not perfect.

Fourth, and related, we are not able to measure the process of adaptation to a new WFH setting. Our data measures behavior several months before and after the sudden COVID-19 shock. Further studies should attempt to measure this journey of adaptation in detail (as, for example, Yang et al. do for the initial stages of the pandemic), to understand how firms and workers create new routines and adapt to a working-from-home reality.

Fifth, while we know many aspects of the work for our sample (such as their managerial status and firm size) there are other unobserved differences across individuals that we cannot fully account for. It is also important to mention that we focus on US workers, and the study should be deployed in other countries where cultural and structural factors might result in differences in managers' experiences and preferences.

Finally, our data both pre-COVID and post-COVID only covers workdays. We do not know how workers might have changed their practices during the weekend. It is possible that with WFH they now work more on weekends, and possibly there is heterogeneity between managers and non-managers. If this is the case, then our proposed work on sculpting barriers between work and personal life could be even more important to pursue. In future work we plan to explore how WFH affects work on weekends for knowledge workers.

5. Conclusion

In this work we explored two aspects related to the sudden and widespread shift to WFH due to the COVID-19 pandemic. First, it is important to understand the effect of this shift on the structure and intensity of different activities that managers engage in during WFH. Our results show that managers commute significantly less post-COVID, but that other effects of the pandemic are heterogeneous across managers in different sized firms (large vs. small).

Second, we are interested in relating our findings about structure and intensity of activities to technology—how could technological innovation support WFH, given the novel data? We argue that there are opportunities for technological innovation both in supporting workers as they structure their activities, and as they try to complete their activities efficiently. Furthermore, technology can help as workers strive to find work-life balance.

Our results also point to two main areas of future work. First, while we collected high-resolution data about time-use from a large sample of knowledge workers, there are other data sources that would shed light on a host of important questions that we could not address here. One example is that our data does not tell us about the content of worker communication—e.g. which messages between workers are simple coordination messages necessitated by poor communication channels, and which ones are helping workers add value to the shared effort of their firm? Shedding light on these questions would allow us to better identify the opportunities for technology to support WFH.

Third, the characteristics of WFH will be affected by the feedback loop we are helping to design—a loop that reacts to the demands of WFH with organizational and technological changes. How are these organizational and technological changes going to affect WFH? What will be the role of local and global factors, such as customs, social norms, and the developing health situation? And how will hybrid work arrangements, with some workers staying home and others working in the office, affect WFH? To answer these questions, we need to continue exploring WFH with the coordinated application of the tools of multiple disciplines.

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Table 1. Descriptive statistics (variables using when screening respondents): pre- and post-COVID samples of knowledge workers.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
		Full sample of knowledge workers				Subsample of managers			
Background characteristics	2018 US CPS	Pre-Covid Sample (N = 615)	Post-Covid Sample (N = 577)	Difference	p-value	Pre-Covid Sample (N = 509)	Post-Covid Sample (N = 464)	Difference	p-value
Gender					0.427				0.151
Female	*47.90%*	*49.27%*	*46.97%*	*-2.30%*		*46.17%*	*41.59%*	*-4.58%*	
Male	*52.10%*	*50.73%*	*53.03%*	*2.30%*		*53.83%*	*58.41%*	*4.58%*	
Education (highest degree)					0.469				0.013
Less than a college degree	*20.90%*	*13.66%*	*12.48%*	*-1.18%*		*13.75%*	*10.99%*	*-2.76%*	
College degree	*48.30%*	*49.43%*	*45.93%*	*-3.50%*		*48.33%*	*41.81%*	*-6.52%*	
Graduate School	*30.80%*	*36.91%*	*41.59%*	*4.68%*		*37.92%*	*47.20%*	*9.28%*	
Annual Salary (in USD)					0.131				0.265
$39,999 or lower	*5.90%*	-	-			-	-		
$40,000 to $60,000	*21.60%*	*19.84%*	*19.41%*	*-0.43%*		*17.29%*	*14.44%*	*-2.85%*	
$60,000 to $80,000	*31.10%*	*25.69%*	*20.28%*	*-5.41%*		*23.38%*	*20.04%*	*-3.34%*	
$80,000 to $100,000	*23.40%*	*19.19%*	*20.80%*	*1.61%*		*19.65%*	*21.77%*	*2.12%*	
$100,000 or higher	*18.10%*	*35.28%*	*39.51%*	*4.23%*		*39.69%*	*43.75%*	*4.06%*	
Lives in a large city (population of at least 500,000)	N/A	75.61%	73.83%	-1.78%	0.48	76.42%	76.72%	0.30%	0.912

Note: Our team does not report city size bins for the US Current Population Survey (CPS) because the variable corresponding to city size in the US CPS does not match the variable used by our research team.

Table 2. Change in daily time allocated by managers across activity types (pre vs. post-COVID surveys)

	[1]	[2]	[3]	[4]
	Time in commuting activities (minutes)	Time in personal activities (minutes)	Time in work-related activities (minutes)	Time in work span (minutes)
Post vs. Pre-COVID change	-27.2009***	8.9613	18.2396**	60.8869***
	[0.0000]	[0.3249]	[0.0391]	[0.0000]
Observations	973	973	973	973
Noise controls	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes
Work-related controls	Yes	Yes	Yes	Yes

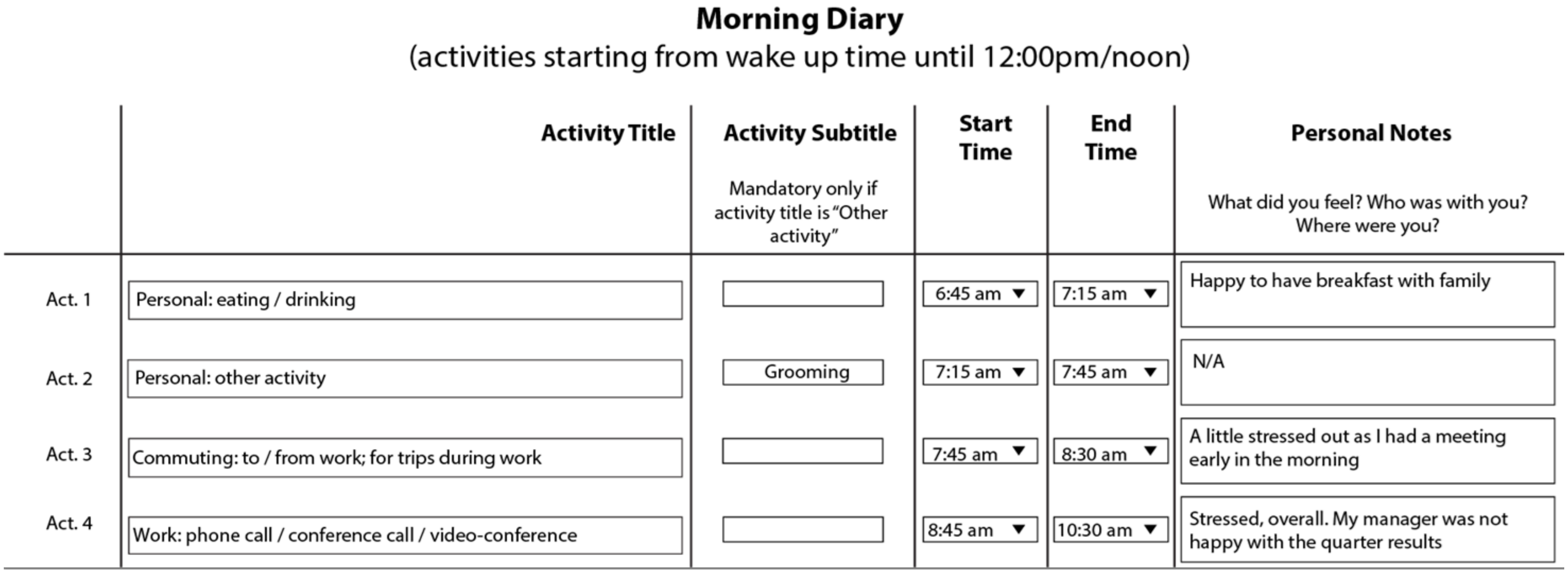
Notes: [1] *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1. All coefficients are estimates via ordinary least square regression models and all estimated standard errors are White-Huber errors robust to heteroskedasticity and we report the p-value of a two-tailed student-t test under brackets. [2] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] All columns report models that control for the following work-related variables: whether the person lives 6 miles or 12 miles away from work, whether the person works in a firm with more than 249 employees, whether the person works in the service sector, and tenure in the firm. [4] All columns report models that control for the following noise control variables: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary.

Table 3. Changes in managers' time allocated to, count of, and average duration of different types of work-related activities

	[1]	[2]	[3]	[4]	[5]
	All work	Work-related email/social media	Work-related interactive	Work-related solo-cognitive	Other work-related activity
	Panel A – Total duration of work-related activities of this type (in minutes)				
Post vs. Pre-COVID change	18.2396** [0.0391]	7.4135 [0.2244]	12.0126* [0.0772]	13.1328 [0.1335]	-14.3192** [0.0169]
Observations	*973*	*973*	*973*	*973*	*973*
	Panel B – Reported at least one work-related activity of this type				
Post vs. Pre-COVID change	- -	0.0389 [0.1089]	0.1199*** [0.0000]	0.0438* [0.0539]	-0.0578* [0.0891]
Observations	-	973	973	973	973
	Panel C – Count of work-related activities of this type				
Post vs. Pre-COVID change	1.5036*** [0.0000]	0.3798*** [0.0006]	0.3754*** [0.0001]	0.6123*** [0.0002]	0.0025 [0.9730]
Observations	*973*	*973*	*973*	*973*	*973*
	Panel D – Duration of average work-related activities of this type (in minutes)				
Post vs. Pre-COVID change	-10.9558*** [0.0019]	-4.3974 [0.2292]	-3.9424 [0.2874]	-9.2201* [0.0609]	-11.7353* [0.0602]
Observations	*971*	*840*	*751*	*846*	*473*
Noise controls	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes
Work-related controls	Yes	Yes	Yes	Yes	Yes

Notes: [1] *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1. All coefficients are estimates via ordinary least square regression models and all estimated standard errors are White-Huber errors robust to heteroskedasticity and we report the p-value of a two-tailed student-t test under brackets. [2] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] All columns report models that control for the following work-related variables: whether the person lives 6 miles or 12 miles away from work, whether the person works in a firm with more than 249 employees, whether the person works in the service sector, and tenure in the firm. [4] All columns report models that control for the following noise control variables: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary

Figure 1. Screenshot of the morning section of the time-use survey



Morning Diary

(activities starting from wake up time until 12:00pm/noon)

	Activity Title	Activity Subtitle Mandatory only if activity title is "Other activity"	Start Time	End Time	Personal Notes What did you feel? Who was with you? Where were you?
Act. 1	Personal: eating / drinking		6:45 am ▼	7:15 am ▼	Happy to have breakfast with family
Act. 2	Personal: other activity	Grooming	7:15 am ▼	7:45 am ▼	N/A
Act. 3	Commuting: to / from work; for trips during work		7:45 am ▼	8:30 am ▼	A little stressed out as I had a meeting early in the morning
Act. 4	Work: phone call / conference call / video-conference		8:45 am ▼	10:30 am ▼	Stressed, overall. My manager was not happy with the quarter results

Figure 2. Time-Use Map: share of respondents commuting, working, engaging in personal activities, or with unreported activities by time of day.

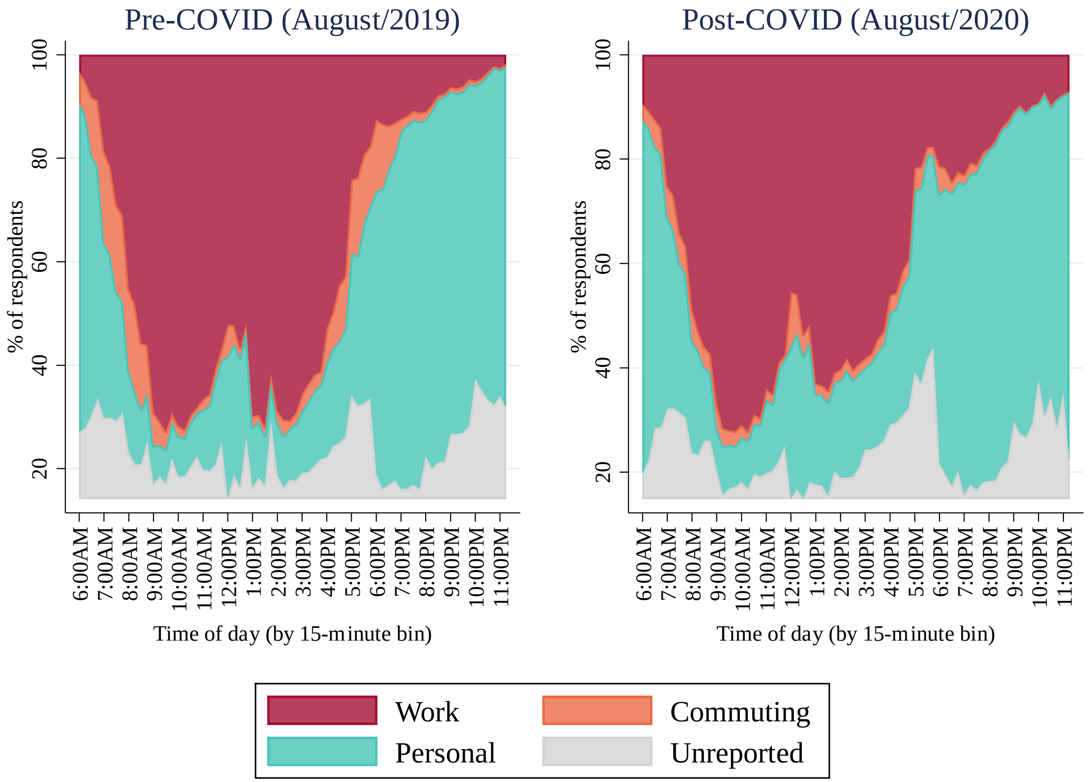
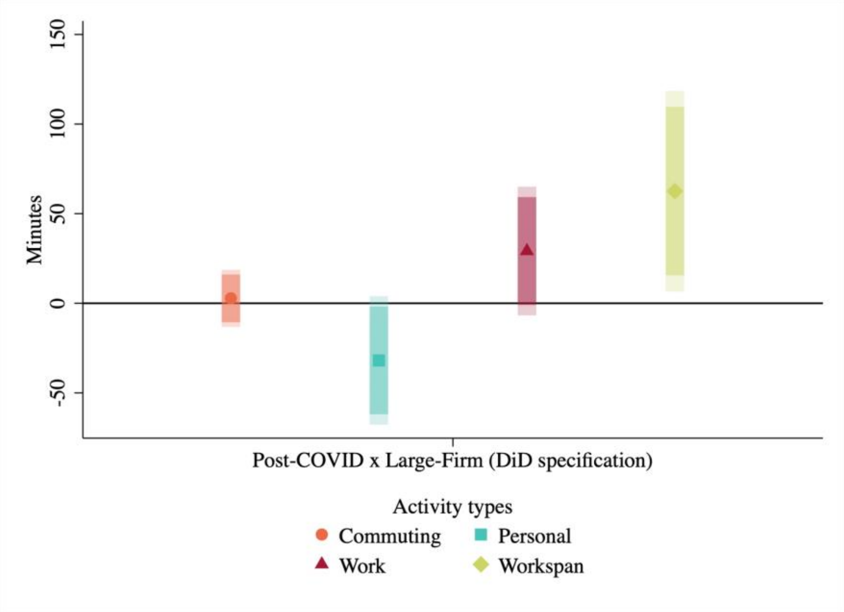
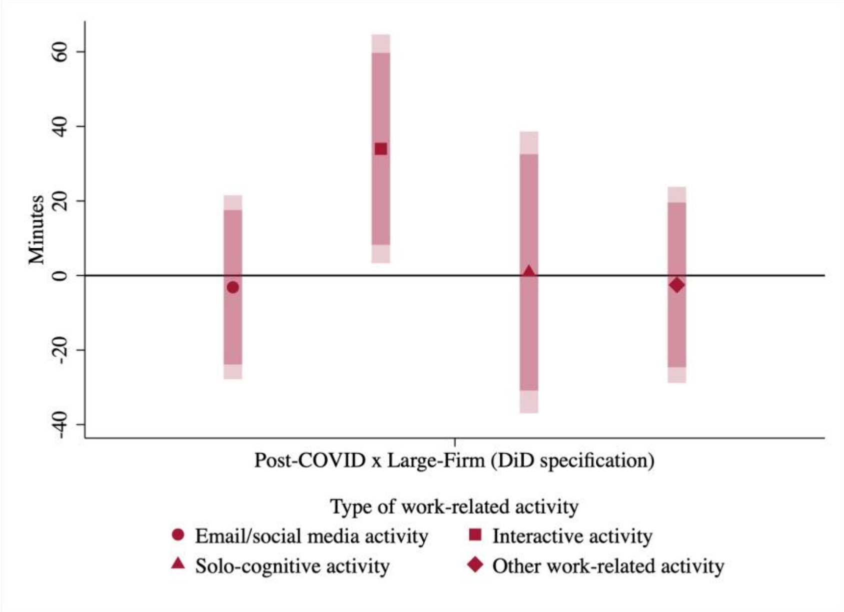


Figure 3 – Difference in changes in time use across managers of large firms versus managers of small or medium-sized firms (Pre- vs. Post-COVID)

3.1 – Daily time allocated to different activities



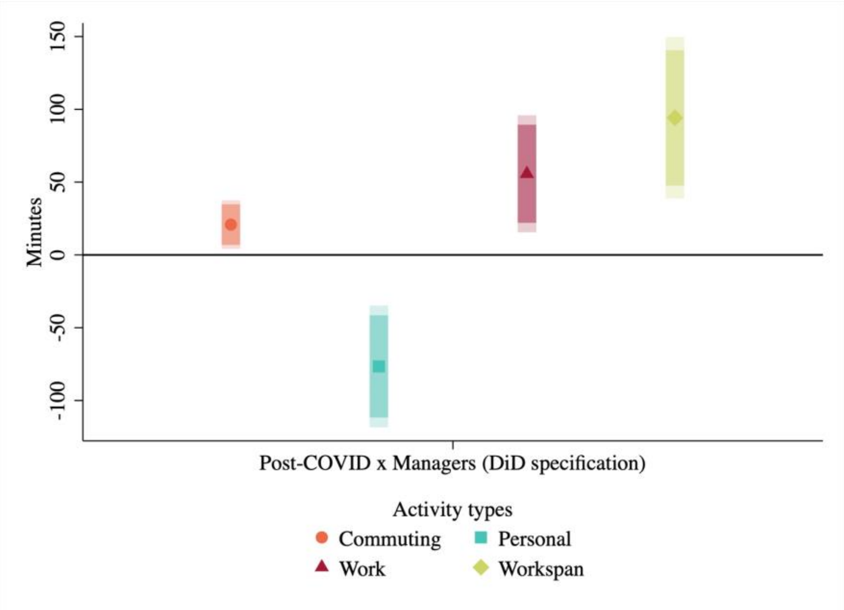
3.2 – Time allocated to different work tasks



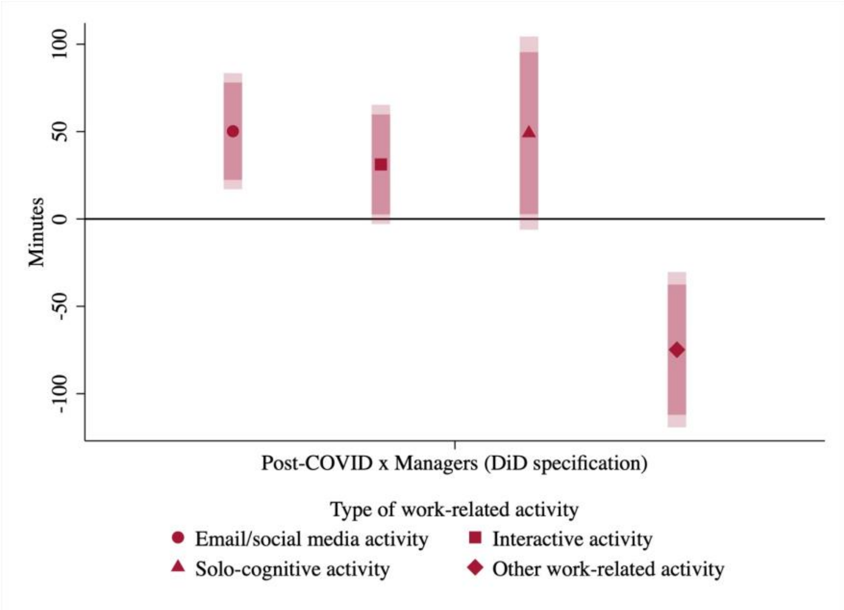
Notes: [1] Each coefficient in this figure originates from a separate differences-in-differences regression model, with the dependent variable being indicated in the legend. The plots correspond to point-estimated of the differences-in-differences coefficient (interaction between a post-COVID and a Large-Firm binary variables) and the bars represents 95% and 90% confidence intervals (darker and lighter bars). All standard errors are white-Huber errors robust to heteroskedasticity. [2] All models control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] All models control for the following work-related variables: whether the person lives 6 miles or 12 miles away from work, whether the person works in a firm with more than 249 employees (large firm), whether the person works in the service sector, and tenure in the firm. [4] All models control for the following noise control variables: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary. [5] All columns control for a post-COVID dummy. [6] The sample used in all estimates reported in this figure is that of all managers in our pre- and post-COVID surveys.

Figure 4 – Difference in changes in time use across managers of large firms versus non-managers of large firms (Pre- vs. Post-COVID)

4.1 – Daily time allocated to different activities



4.2 – Time allocated to different work tasks



Notes: [1] Each coefficient in this figure originates from a separate differences-in-differences regression model, with the dependent variable being indicated in the legend. The plots correspond to point-estimated of the differences-in-differences coefficient (interaction between a post-COVID and a Manager binary variables) and the bars represents 95% and 90% confidence intervals (darker and lighter bars). All standard errors are white-Huber errors robust to heteroskedasticity. [2] All models control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] All models control for the following work-related variables: whether the person is a manager, whether the person lives 6 miles or 12 miles away from work, whether the person works in the service sector, and tenure in the firm. [4] All models control for the following noise control variables: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary. [5] All columns control for a post-COVID dummy. [6] The sample used in all estimates reported in this figure is that of all knowledge workers (managers and non-managers) that worked in large firms in our pre- and post-COVID surveys.

Appendix

A1 – Recruiting Knowledge Workers via Lucid

Lucid received $13.00 per complete response and the research team does not control how much of this value is transferred towards survey participants, which could receive either direct financial compensation or indirect compensation (e.g. “fidelity” points similar to credit card points that are redeemable by products) by the companies that partner with Lucid. In both the 2019 and 2020 waves of our survey, potential participants were screened for the same criteria:

1) employed in a full-time job at the time of response (+35 hours/week);

2) earning an annual salary income of at least $40,000 US dollars (which corresponds to approximately the 6th percentile of the income distribution of knowledge workers in the US);

3) working in a "knowledge worker" occupation.

Individuals meeting all the above criteria were invited to start the survey.

In addition to the participation criteria, our team set quotas in terms of the gender, annual salary, highest educational degree, and urban profile to create two samples of knowledge workers whose average socioeconomic characteristics approximated the characteristics of knowledge workers described in the US Census' 2018 Current Population Survey (CPS) (United States Census Bureau, 2018). We report those variables in the main text.

The only difference in terms of recruitment across the two waves was that in the pre-COVID wave we set a quota for knowledge workers who reported that they commuted to work between 4 to 5 days per week, whereas in the post-COVID wave we set a quota in terms of knowledge workers who reported that they commuted to work between 4 to 5 days a week before the COVID pandemic. This approach was designed to select knowledge workers in the post-COVID sample who were expected to commute to work in case the COVID pandemic had not forced organizations to swiftly adjust their operations to a working-from-home reality.

A2 – Specifications underlying Figures 3 and 4

To assess whether the need for coordination could explain potential differences across pre-COVID and post-COVID behaviors, we estimate two differences-in-differences regression models. In Figure 3, we continue using the sample of managers and a specification similar to the one described in the main text and used for the results on Table 3, but including adding the binary variable indicating post-COVID observations and a binary variable indicating whether a firm is large (i.e. it has 250 employees or more), it further adds an interaction term between the post-COVID binary variable and the large-firm binary variable. The coefficient of the interaction term provides information on how the average change in time allocation of managers from large firms post-COVID is different from the average change in time allocation of managers from small/medium-sized firms. If any observed effect is due to a higher need for coordination in a context where workers work from home, we would expect results to be driven by managers workers from large firms. In Figure 4, we estimate an analogous differences-in-differences specifications, but using a sample that includes non-managers and managers from large firms and adding an interaction term between the post-COVID binary variable and a binary variable indicating whether the knowledge worker is also a manager (beyond these variables being reported separately).

A3 – Additional robustness analyses by subsamples

In Table A1, we report robustness analyses where we replicate the main specifications reported in Tables 2 and 3, but estimating the models separately for the subsample of managers from large organizations (panel A) and for the subsample of managers from small/medium-sized organizations (panel B). While managers from large firms recouped no personal time post-COVID (-2.2 minutes, p-value = 0.85) and increased work-time (+29.2 minutes, p-value < 0.01), managers from small or medium-sized firms effectively increased their personal time (+39.1 minutes, p-value < 0.01) and did not increase their work-time (-6.4 minutes, p-value = 0.67). We observe that all the differences in the pre- and post-COVID allocation of managerial time use on Tables 2-5 concentrate on the sample of managers from large firms. These managers have a +78.2-minute longer work-span (p-value < 0.01), fragment their work in more activities (+2.2 activities/day, p-value < 0.01), reduce the length of the average work activity (-13.9 minutes, p-value < 0.01), and increase the time spent on interactive activities (+25.4 minutes, p-value < 0.01).

In Table A2, we report another set of robustness analyses analogous to those reported on Table A1, but focused on the sample of 219 knowledge workers that are not managers but that also participated in the broader sample of 1192 knowledge workers in our broader sample. Unlike managers (from large firms, in particular), non-managers work less hours (-47.8 minutes, p-value < 0.01), allocate more time to more personal activities (+97.8 minutes, p-value < 0.01), marginally reduce the length of their working day (-30.7 minutes, p-value < 0.1), and do not spend more time in meetings (-16.8 minutes, p-value = 0.29).

Table A1. Comparison of main changes between managers from large firms and managers from small or medium-sized firms

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	Time in personal activities (minutes)	Time in work-related activities (minutes)	Time in work span (minutes)	Total work-related activities (count)	Time of average work-related activity (minutes)	Time in work-related email/social media activities (minutes)	Time in work-related interactive activities (minutes)	Time in work-related solo-cognitive activities (minutes)	Time in other work-related activities (minutes)
	Panel A – Subsample of managers from large firms (250 employees or more)								
Post vs. Pre-COVID change	-2.1995	29.2262***	78.2069***	2.2353***	-13.8991***	6.6932	25.4117***	11.0885	-13.9672**
	[0.8516]	[0.0089]	[0.0000]	[0.0000]	[0.0012]	[0.3530]	[0.0011]	[0.2928]	[0.0402]
Observations	694	694	694	694	693	694	694	694	694
	Panel B – Subsample of managers from small and medium-sized firms (249 employees or less)								
Post vs. Pre-COVID change	36.0905***	-6.3929	-6.3929	-0.4276	-6.395	6.3282	-16.4267	15.6826	-11.9769
	[0.0093]	[0.6681]	[0.6681]	[0.3843]	[0.3894]	[0.6004]	[0.2852]	[0.3614]	[0.3557]
	279	279	279	279	278	279	279	279	279
Noise controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Work-related controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: [1] *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1. All coefficients are estimates via ordinary least square regression models and all estimated standard errors are White-Huber errors robust to heteroskedasticity and we report the p-value of a two-tailed student-t test under brackets. [2] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] All columns report models that control for the following work-related variables: whether the person lives 6 miles or 12 miles away from work, whether the person works in a firm with more than 249 employees, whether the person works in the service sector, and tenure in the firm. [4] All columns report models that control for the following noise control variables: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary.

Table A2. Main changes in the working day of non-managers

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	Time in personal activities (minutes)	Time in work-related activities (minutes)	Time in work span (minutes)	Total work-related activities (count)	Time of average work-related activity (minutes)	Time in work-related email/social media activities (minutes)	Time in work-related interactive activities (minutes)	Time in work-related solo-cognitive activities (minutes)	Time in other work-related activities (minutes)
Post vs. Pre-COVID change	97.8342***	-47.7560***	-30.7713*	0.7506*	-17.8106*	-30.7397**	-16.8325	-17.7104	17.5266
	[0.0000]	[0.0016]	[0.0858]	[0.0786]	[0.0644]	[0.0277]	[0.2943]	[0.4742]	[0.3861]
Observations	219	219	219	219	218	219	219	219	219
Noise controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Work-related controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: [1] *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1. All coefficients are estimates via ordinary least square regression models and all estimated standard errors are White-Huber errors robust to heteroskedasticity and we report the p-value of a two-tailed student-t test under brackets. [2] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] All columns report models that control for the following work-related variables: whether the person lives 6 miles or 12 miles away from work, whether the person works in a firm with more than 249 employees, whether the person works in the service sector, and tenure in the firm. [4] All columns report models that control for the following noise control variables: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary.

Table A3. Robustness analyses: change in daily time allocated by managers across activity types (pre vs. post-COVID surveys) as new control variables are added in the model

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
	Panel A – Main activities								
	Time in personal activities (minutes)			Time in work-related activities (minutes)			Time in work span (minutes)		
Post vs. Pre-COVID change	7.9206 [0.3933]	9.3243 [0.2997]	8.9613 [0.3249]	22.2787** [0.0129]	18.9631** [0.0296]	18.2396** [0.0391]	74.4586*** [0.0000]	58.2953*** [0.0000]	60.8869*** [0.0000]
Observations	973	973	973	973	973	973	973	973	973
Adjusted R-squared	0.4	0.41	0.4	0.34	0.35	0.34	0.04	0.12	0.13
	Panel B – Main work-related activities								
	Time in work-related email/social media activities (minutes)			Time in work-related interactive activities (minutes)			Time in work-related solo-cognitive activities (minutes)		
Post vs. Pre-COVID change	4.957 [0.3890]	5.275 [0.3730]	7.4135 [0.2244]	16.4869** [0.0121]	16.0544** [0.0174]	12.0126* [0.0772]	14.3272* [0.0929]	12.02 [0.1641]	13.1328 [0.1335]
Observations	973	973	973	973	973	973	973	973	973
Adjusted R-squared	0.01	0.02	0.02	0.07	0.08	0.09	0.12	0.13	0.13
Noise controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Work-related controls	No	No	Yes	No	No	Yes	No	No	Yes

Notes: [1] *** p-value < 0.01; ** p-value < 0.05; * p-value < 0.1. All coefficients are estimates via ordinary least square regression models and all estimated standard errors are White-Huber errors robust to heteroskedasticity and we report the p-value of a two-tailed student-t test under brackets. [2] Socioeconomic control variables are: age, gender, income, highest educational degree, marital status, whether the person lives with children, and whether the person lives in a large city. [3] Work-related control variables are: whether the person lives 6 miles or 12 miles away from work, whether the person works in a firm with more than 249 employees, whether the person works in the service sector, and tenure in the firm. [4] Noise control variables are: total time filling in the survey, day of week that was reported, and total unreported time within the day reported in the time-use diary.