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Thomaz Teodorovicz
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Orit Shaer

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Thomaz Teodorovicz
Harvard University

Raffaella Sadun
Harvard Business School

Andrew L. Kun
University of New Hampshire

Orit Shaer
Wellesley College

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Thomaz Teodorovicz[a]*, Raffaella Sadun[b], Andrew L. Kun[c], and Orit Shaer[d]

[a]Laboratory for Innovation Science at Harvard, Harvard University, Boston, U.S.; [b]Strategy Unit, Harvard Business School, Boston, U.S.; [c]College of Engineering and Physical Sciences, University of New Hampshire, New Hampshire, U.S. ;[d] Computer Science Department, Wellesley College, Wellesley, U.S.

**Corresponding author's contact information: tteodorovicz@hbs.edu; 175 N. Harvard Street, Boston, MA 02134*

Abstract

We assess how the sudden and widespread shift to working from home during the pandemic impacted how knowledge workers allocate time throughout their working day. We analyzed the results from an online time-use survey that collected data on 1,192 knowledge workers in two waves, a pre-pandemic wave collected in August/2019 (615 participants) and a post-pandemic wave collected in August/2020 (577 participants). Our findings indicate that the forced transition to WFH created by the COVID pandemic was associated with a drastic reduction in commuting time, and an increase in time spent in work and/or personal activities. However, this reallocation was heterogeneous across different workers and organizations. Particularly, managers reallocated the entire time gained from commuting into more time spent in meetings, possibly to recoup some of the extemporaneous interactions that typically happen in the office. The transition to WFH did not appear to affect self-reported measures of wellbeing. 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; knowledge workers; managers

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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: while 5-15% of Americans worked from home before the pandemic, 50% of the Americans who were employed pre-COVID reported working from home at April/2020 (Brynjolfsson et al., 2020). While organizations have started to consider extending "working from home" (WFH) arrangements beyond the pandemic (Kelly, 2020), this sudden and exogenous shift has the potential to cause dramatic, and still unknown, effects on workers' behavior, as well as their productivity and wellbeing.

In this research we explore what some of these effects are. Specifically, we assess how the sudden and widespread shift to working from home during the pandemic impacted how knowledge workers--a particular set of occupations that typically focus their activity on problem-solving and related cognitive tasks (Autor & Dorn, 2013; Drucker, 2012) - allocate time throughout their working day. Our study examines: how the forced transition to WFH arrangements changed the allocation of time across different activities (e.g. the relative importance of activities performed alone vs. those that require communication and coordination with others); whether the transition affected how these activities are conducted (for example, length of meetings); whether the changes in time allocation and activity structure varied across knowledge workers with managerial responsibilities vs. individual contributors; and how new work arrangements are correlated with objective and subjective measures of wellbeing. We use this evidence to inform the discussion of two additional and related questions of interest to us, related to human-computer interaction (HCI) technology. In particular, we wanted to understand whether HCI technology might be able to reduce (or even eliminate) the possible negative effects that workers experience due to the shift to working from home; and whether HCI technology can help take advantage of opportunities for improving worker productivity and wellbeing that are made possible by this shift.

We focus our study on knowledge workers for a variety of reasons. First, the importance of these occupations in the U.S. economy has grown significantly over past decades (Autor & Dorn, 2009, 2013) and is expected to continue to grow in importance over time. Second, many knowledge workers engage in activities that can readily be performed at home (Dingel & Neiman, 2020) and that could thus be performed even during the forced shift to WFH due to the pandemic. Third, knowledge workers (managers in particular) typically engage in activities that rely on team-work and social interactions (Deming, 2017). As such, it is important to understand how the loss of the common physical space of interaction such as the office has affected their work. As a corollary, an in-depth examination of the effects of WFH arrangements and, specifically, the understanding of how WFH affects managers vs. independent workers, is important.

To pursue our research objectives, we analyzed 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 during the pandemic in August/2020 (577 participants). Importantly, both waves of knowledge workers commuted to work before the COVID-19 pandemic. 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 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, to investigate whether the changes in time use varied across individuals.

Our findings indicate that the forced transition to WFH created by the COVID pandemic was associated with a drastic reduction in commuting time, and an increase in time spent in work and/or personal activities. However, this reallocation was heterogeneous across different workers and organizations. Particularly, managers appear to have reallocated the entire time gained from commuting into more time spent in meetings, possibly to recoup some of the extemporaneous interactions that typically happen in the office. The transition to WFH did not appear to affect self-reported measures of wellbeing.

We start from these findings to explore implications for technology development in three 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 indicates that there might be new interruptions for knowledge workers to contend with when WFH. We expect that technology can help them navigate transitions between different tasks. Finally, our data provides indications that WFH can have negative effects on workers' mental and physical well-being. We expect that technology can be part of a healthy life for knowledge workers.

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 in the future. We begin with a review of related work.

Related work

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 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 Drucker's view, knowledge workers must pay particular 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). This was especially important for managerial occupations—a specific category within knowledge workers—which involved 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. Recent research has further expanded Mintzberg's work collecting data across a large sample of top managers (Bandiera, Lemos, Prat, & Sadun, 2018; Bandiera, Prat, Hansen, & Sadun, 2020). These studies found evidence of large differences in time allocation, and a direct relationship between time use and firm performance.

This paper expands on earlier work by providing a detailed time use data on a large sample of knowledge workers, and by studying the evolution of time use over time.

Working from Home

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. Patent examiners, however, typically work independently. Therefore, the extent to which the benefits of WFH would extend to occupations characterized by a higher need for team work and coordination, and on managers in particular, is not yet known.

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.). A recent 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).

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 a wider variety of workers and industries, and in providing new evidence on the differences between independent workers and managers. Second, the level of detail of the data collected on the time use of workers involved in WFH is also novel. Thanks to these data, we can investigate variation in the actual time (rather than aggregate recollections) allocated to personal and work-related activities (e.g. work-related meetings, reading/writing reports, personal time) for a large sample of individuals and over time. Third, we examine the effects of the recent shift to WFH caused by the COVID-19 pandemic.

CSCW Research on Remote Collaboration

Researchers in the field of computer-supported collaborative work (CSCW) have investigated the factors and technologies in support of remote collaboration in the last three decades (e.g. (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. Olson & Olson claim that teams “with high common ground, loosely coupled work, readiness both for collaboration and collaboration technology, have a chance at succeeding with remote work”, while highlighting that deviations in each of these factors might create a strain on the team, which require changes in the work or in collaborative processes to succeed. The paper’s main argument, which is often cited in the CSCW 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 than 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, contrary to findings from Olson & Olson (2000), in software development teams working remotely, closely coupled work tasks encourage remote workers to articulate the work in a way that makes the collaboration function. They also found that managerial practices are critical to making the collaboration function well, highlighting that identifying managerial concerns is essential for CSCW research on distributed work.

While the factors discussed above are still relevant, the forced transition to WFH during COVID-19 introduces additional factors such as increased childcare responsibilities, social isolation, and 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 heterogeneous impact of COVID-19 WFH on different kinds of knowledge workers.

Our study contributes to understanding the time-use of knowledge workers during COVID-19 WFH, while focusing on how the changes in time allocation and activity structure varied across knowledge workers with managerial responsibilities vs. independent workers. The CSCW research discussed above indicates the importance of supporting managers through remote collaboration. Understanding the impact of WFH on managers' activities and time allocation is a critical step in this direction.

Time Use Study of Knowledge Workers

We designed a time-use survey to study whether and how the transition towards "work-from-home" arrangements (WFH), and away from the office, caused by the COVID-19 pandemic affected the use of time of knowledge workers. Specifically, this study addresses the following research questions:

(1) RQ1: How did the forced transition to WFH change the allocation of time across different activities (e.g. activities performed alone vs. those that require communication and coordination with others)?

(2) RQ2: How did the transition to WFH arrangements affect how these activities are conducted (for example, length of meetings)?

(3) RQ3: Are the changes in time allocation and structure different across knowledge workers with and without managerial responsibilities?

(4) RQ4: How has the perceived well-being of knowledge workers changed before and after the shift to WFH?

(5) RQ5: How have the preferences of knowledge workers for working from home changed in the post COVID-19?

We use our results to address the five research questions above, and provide implications for design.

Materials and Methods

Recruitment and Participants

We designed a novel Time-Use survey that we used 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.

In both waves, 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, we set quotas in terms of the gender, annual salary, highest educational degree, and urban profile to create two sample 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).

The only difference in terms of recruitment across both 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 strategy 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.

Table 1 reports the descriptive statistics of the variables used to define the sampling frame across both waves, and the corresponding values in the 2018 U.S. CPS. 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.

INSERT TABLE 1 ABOUT HERE

Although the screening variables are balanced across samples, 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). However, not only are all differences small in magnitude, but to account for any difference in background characteristics, all statistical methods used control for a series of socioeconomic characteristics, work-related characteristics, and noise controls.

As for their work responsibilities, we explore the effects of COVID-19 on managers and non-managers separately. We define managers as participants that report overseeing supervising at least one supervisee at work. In both waves, we achieved a 4:1 ratio of managers to non-managers: 509 (82.8%) participants and 464 (80.4%) participants are managers in the pre- and post-COVID waves, respectively. Is it important to note that the high share of managers across both samples is not detrimental to our results as: (1) the sampling process to collect responses was the same across waves; and (2) our empirical exercises estimate and interpret changes in time allocation within the group of managers (before vs. after COVID-19) and separately interpret changes within the group of non-managers (before vs. after COVID-19).

Data Collection

The survey consisted of five steps. First, potential participants completed a short screening questionnaire. Second, participants meeting the screening conditions were redirected to an online consent form. Third, upon consenting, participants were redirected to a time-use survey where they entered a detailed mapping of the activities they engaged in during the most representative working day of the previous week. Fourth, participants were asked to add additional details for a subset of activities. In the fifth and final step, participants answered a series of additional questions about their well-being, work, and socioeconomic characteristics. Both survey waves were hosted on Qualtrics.

Time Use Survey

Our team developed a new time-use survey by adapting the well-known Daily Reconstruction Method (DRM) (Kahneman et al., 2004) to a distributed, on-line data collection methods. 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 prompted to recall the most "representative" working day from the previous week and were asked to mark which day of the week it was, and at 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 time of the activity. The time-use diary had three different sections, one for each part of the day (morning, afternoon, and evening). In each section, participants entered between 1 and 10 activities that started in that period. Thus, each participant reported up to 30 activities in their diary. We asked participants to report on activities that had lasted at least 15 minutes and that participants felt had been particularly important in their daily routine.

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

INSERT FIGURE 1 ABOUT HERE

Across the pre- and post-COVID waves, participants went through a standard version of the survey tool up to, and including, the filling of the time-use diary. This implies that any data associated with the activities and time allocation are comparable across the pre-and post-COVID waves.

After participants reported all daily activities, and their respective start and end times, the survey instrument asked for further details about a subset of these activities. In the pre-COVID wave we followed the time use questionnaire with additional questions only about 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 final part of the questionnaire across surveys was largely similar. Our team collected the same set of well-being (OECD, 2013), socioeconomic and work-related characteristics across waves, but in the post-COVID wave we added questions about workers' preferences for working-from home.

Data Analysis

Our analysis has multiple steps. We start our analysis by comparing the workday of knowledge workers in the pre- and post-COVID samples in terms of the allocation of time across work, personal, and commuting activities. For this analysis, 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 across the number of, average length of, and total time spent in the 4 following types of detailed 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 model estimates the conditional mean difference between each respective dependent variable and a binary variable indicating whether the respondent is in the post-COVID sample. All models control for the following socioeconomic and work-related characteristics: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, whether the person lives in a large city, 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. 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.

Following the first set of analysis, the next step of the analysis addresses how the nature of the work-day changed within the group of knowledge workers who are also managers, in comparison to the group of knowledge workers who do not have managerial responsibilities. Here, we repeat the same dependent variables and estimation methods as reported above, with the difference being that we replace the binary variable indicating the post-COVID sample by a categorical variable that differentiates (1) managers in the pre-COVID sample, (2) manager in the post-COVID sample, (3) non-managers in the pre-COVID sample, and (4) non-managers in the post-COVID sample. We then report on changes for managers pre-COVID and post-COVID, and for non-managers pre-COVID and post-COVID. This set of analysis enables us to separate the effects of a WFH reality on managers from the effects on non-managers. All estimates control for the same background variables reported above and, as before, all estimated standard errors are White-Huber errors robust to heteroskedasticity, and we report statistical significance using a two-tailed student-t test for the comparison with the benchmark category and for the comparison of coefficients.

To assess whether the need for coordination could explain potential differences across pre-COVID and post-COVID behaviors for managers and non-managers, we re-estimate the models above using either only individuals that reported working in large firms (firms with at least 250 employees) or only workers from small firms (firms with at most 249 employees). 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 knowledge workers from large firms.

To assess potential changes in well-being, we repeat the models above using two measures of worker's well-being (0-10 score on life satisfaction and % of reported workday that the worker was in a more positive than negative mood). Finally, we report simple descriptive statistics collected exclusively in the post-COVID sample about workers' perceptions about WHF arrangements.

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

Results

In this section we summarize results from the responses of the 1192 knowledge workers in our sample (615 in the pre-COVID sample and 577 in the post-COVID sample). Within this sample, 973 participants were managers (509 in the pre-COVID sample and 464 in the post-COVID sample) and 219 not managers (106 in the pre-COVID sample and 113 in the post-COVID sample).

Time Diaries

Participants entered an average of 14.1 daily activities (SD = 7.3). Including time allocated to sleeping, participants reported an average of 1191.9 minutes of time spent on different activities (SD = 209.3 minutes); this translates to just under 20 hours spent on the reported activities. Participants reported their activities for Mondays (37.8%), Tuesdays (24.8%), Wednesdays (17.9%), Thursdays (10.1%), and Fridays (9.6%). All models control for which day of the week was reported.

Time allocation pre- vs. post-COVID

Figure 2 summarizes how participants 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 knowledge workers post-COVID. First, as expected, commuting time (represented by the red area) is compressed to almost zero throughout the day. Second, the compressed commuting time is replaced by personal activities, especially in the morning (represented by the expansion of the green area between 6AM and 9AM). Third, working days are longer and more dispersed over the day (blue area expands between 6PM and 10PM).

INSERT FIGURE 2 ABOUT HERE

Table 2 provides further details on time use by reporting the average difference in time allocation across activity types in the post-COVID vs. the pre-COVID samples while adjusting for differences in socioeconomic and work-related characteristics of participants (as detailed in the methods section, results are estimated by multivariate Ordinary Least Squares regressions and we assess statistical significance via a two-tailed t-test). Participants report a -31.4 minutes decline in the time allocated to commuting events (p-value < 0.01) in the post-COVID sample, an increase in +24.2 minutes allocated to personal time (p-value < 0.01), and no increase in total time allocated to work-related activities (difference of +7.2 minutes, p-value = 0.35). These results suggest that respondents reallocated commuting time towards personal activities rather than expanding their working time.

Column [4] in Table 2 shows that the structure of the workday changed post-COVID. The work-day span (the difference between the start of the first work activity and the end of the last work activity) increased by +43.2 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 ABOUT HERE

The structure of work pre- vs. post-COVID

Tables 3 and 4 explore in more detail changes in the structure of work post-COVID. Table 3 focuses on the frequency of the 4 types of work-related main 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).

Table 3 reports the results of a multivariate regression model comparing the counts of each type of work-related activities. Participants reported a higher number of work-related activities post-COVID (+1.4 activities, p-value < 0.01). These 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).

INSERT TABLE 3 ABOUT HERE

Table 4 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. In other words, the time that workers spend on an average task, before they switch to another task, is shorter post-COVID. Conditional on engaging in an activity, the average engagement in a work activity was -11.6 minutes shorter in the post-COVID sample (p-value < 0.01). We see this change across average email/social media activity (-6.7 minutes (p-value < 0.05) and solo cognitive activity (-14.3 minutes, p-value < 0.01), and marginally so for interactive activities (-6.8 minutes, p-value = 0.053).

INSERT TABLE 4 ABOUT HERE

Overall, the data suggest that WFH has resulted in a proliferation and greater fragmentation of tasks during the working day. These two changes increase in frequency of activities, but the reduction in average length of activities balances off such that the total time dedicated to each of these activities is not statistically different across the pre- and post-COVID samples (Table 5). In other words, workers spend the same total amount of time on these tasks post-COVID as they did pre-COVID. But, post-COVID they do this through a larger number of shorter engagements than pre-COVID.

INSERT TABLE 5 ABOUT HERE

Heterogeneous change in the nature and structure of knowledge work across managers and non-managers

While all knowledge workers are likely to engage in activities that rely on team-work and social interactions to a certain degree, the role of coordinative and interactive tasks is especially important for managers (Deming, 2017; Drucker, 1963). We see this in our time-use data as well. Conditional on all control variables described in the methods section, managers in our dataset (combining pre-COVID and post-COVID data) devote +29.0 more minutes of the working day to interactive activities (p-value < 0.01), more time to strategic solo-cognitive tasks (e.g. planning for meetings, preparing materials, or thinking about work-related problems) than non-managers (+ 21.1 minutes, p-value < 0.05). Symmetrically, we also see that managers spend on average less time in more operational solo-cognitive tasks as writing/editing/programming (-28.8 minutes, p-value < 0.01).

Given the importance that interactive activities for managers, we turned to explore whether the forced transition to WFH affected managers differently relative to independent contributors. In particular, we hypothesized that managers might have needed to spend an even greater fraction of their time in meetings while WFH, to compensate for the loss of the many extemporaneous and unstructured interactions that would typically take place in an office.

To look at this question, in Table 6 we break the sample down between managers and non-managers. That is, instead of simply comparing all knowledge workers before and after COVID as we did in Table 2, we compare managers and non-managers to their pre-COVID baselines. Column [1] shows that both managers and non-managers reduced the time spent commuting in the post-COVID sample when compared to the pre-COVID period (-27.3 minutes, p-value < 0.01, and -48.4 minutes, p-value < 0.01, for managers and non-managers post-COVID, respectively). However, as shown in columns [2] and [3], there are significant differences in how the commuting time was reallocated by managers vs non-managers. Non-managers reallocated the foregone commuting time towards personal activities (+80.0-minute difference in comparison to non-managers pre-COVID, with p-value < 0.01) and reduced work-related time (-31.6-minute difference in comparison to non-managers pre-COVID, with p-value < 0.05). In contrast, for managers we see no statistically significant increase in personal time (+10.9 minutes, p-value = 0.23) and a marginal increase in work-related time (+16.4 minutes, p-value = 0.06). Furthermore, Column [4] indicates that the longer work span reported in table 2 is entirely driven by managers, who clocked a 58.2 minutes longer work-span (p-value<0.01), while there was no statistically significant difference in work-span for non-managers (-19.9 minutes, p-value = 0.27).

INSERT TABLE 6 ABOUT HERE

Table 7 reports how the count of different types of work-related activities during the reported day changed for managers and for non-managers post-COVID (this is analogous to the results in Table 3 which reported on changes for all workers). Table 7 shows once again that managers were the most affected by working-from-home post-COVID—especially in activities associated with coordination. In the post-COVID sample, managers engaged in more work-related activities across multiple types of activities. On average, they engaged in 1.41 more work-related activities (p-value <0.01), +0.47 email/social media activities (p-value < 0.01), +0.41 interactive activities (p-value < 0.01), and +0.57 solo-cognitive activities (p-value < 0.01). For non-managers, the increase in the number of work activities was concentrated in solo-cognitive work (+0.80 activity, p-value < 0.01). The increase in the count of events devoted to work-related email/social media was also greater for managers.

INSERT TABLE 7 ABOUT HERE

Tables 8 and 9 show the post- vs. pre-COVID changes across managers and non-managers in the average time of different types of work activity and on total time dedicated to each activity. Table 8 shows that, while the duration of the average work activity declined for both managers (-10.7 minutes, p-value < 0.01) and non-managers (-15.3 minutes, p-value = 0.063), the types of activities affected were different. Managers saw a marginal decrease in the duration of solo cognitive (-8.7 minutes shorter, p-value = 0.07) and other work activities (-10.4 minutes shorter, p-value = 0.08), but not in interactive activities. In contrast, non-managers experienced a reduction in the duration across both solo and interactive work activities: -40.9 minutes in the average duration of solo cognitive activities (p-value < 0.01), -20.9 minutes in the average duration of interactive activities (p-value < 0.05), and -18.2 minutes in the average duration of email/social media activities (p-value < 0.05).

INSERT TABLE 8 ABOUT HERE

Table 9 shows that managers and non-managers did not increase the time focused to specific types of work activities, with exception of a marginal increase in time allocated to work-related interactive activities by managers (+11.6 minutes, p-value = 0.08), a decrease in "other" type of work activities by managers (- 16.7 minutes, p-value < 0.01), and decrease in time dedicated to email/social work by non-managers (-34.9 minutes, p-value <0.01).

INSERT TABLE 9 ABOUT HERE

The data show that the differences between managers and non-managers are even larger in large and complex organizations, where the need for coordination is presumably greater. We report these results in Tables 10 and 11, where we show the coefficients of regression models analogous to those from tables 5-9, but estimated separately according to the size of the firm where the respondent worked. Table 10 reports the results using a subsample of 847 respondents working in large firms (694 managers and 153 non-managers), 417 in the pre-COVID (342 managers and 75 non-managers) and 430 in the post-COVID (352 managers and 78 non-managers) samples. Table 11 reports the results using the remaining subsample of 345 respondents working in small firms (279 managers and 66 non-managers), 198 respondents in the pre-COVID (167 managers and 31 non-managers) and 147 in the post-COVID (112 managers and 35 non-managers) samples. These results show that managers working in large companies experienced a greater change in the workday structure relative to all other respondents. Columns [1]-[4] from both tables 10 and 11 show that, although the reduction in commuting time was similar for small and large organizations, managers from large organizations were the only category that did not recoup personal time in the post-COVID world (+1.3 minute, p-value = 0.91) and the only category that effectively increased total minutes working (+24.9 minutes, p-value < 0.05) and total work span (+74.7 minutes, p-value < 0.01). Columns [5] and [6] from table 10 also show that the increased fragmentation of work activities was also driven by knowledge workers from large firms: managers from large firms reported +2.1 work activities in a day (p-value < 0.01) with a shorter average duration by -13.0 minutes (p-value < 0.01), and non-managers from large firms reported +1.5 work activities in a day (p-value < 0.05), with a shorter average duration by -17.2 minutes (p-value < 0.01). Finally, columns [7]-[10] from table 10 show that the type of work conducted by managers from large firms changed towards more interactive activities (+24.5 minutes in meetings, phone-call, and alike activities, p-value < 0.01). Knowledge workers (both managers and non-managers) from small firms, however, exhibited no statistically significant change in the structure of the workday (columns [5]-[10] from table 11).

INSERT TABLE 10 ABOUT HERE

INSERT TABLE 11 ABOUT HERE

The well-being and preferences for WFH arrangements of knowledge workers post-COVID

We also analyzed whether our data exhibited differences in self-perceived overall life well-being, and on the share of time participants reporting being in a "positive mood" in the day measured in the survey. We do not see any statistically significant difference before and after COVID in terms of either overall well-being (-0.04 points in a 0-10 scale, p-value = 0.668), or mood (-2.5% of day in a good mood, p-value = 0.102). Although the absence of an effect on well-being was not surprising for non-managers--who have substituted commuting time for more personal time--this results was surprising for managers--who did not see any increase in personal time after the transition to WFH. One potential explanation for the lack of an effect on wellbeing is that knowledge workers may have started to see other new benefits in WFH that more than compensate for the longer work-day span and time spent in interactions. To verify whether this was the case, we asked respondents from the post-COVID wave about how their perception about working from home changed after COVID. Figure 3 shows that 65.8% of knowledge workers in the post-COVID survey reported having improved their perception about working-from-home arrangements post-COVID, and Figure 4 shows that this positive change in perception occurs across both managers and non-managers: 69.2% of managers and 52.2% of non-managers have now a more positive perspective about working-from-home than they had before COVID. However, this difference is not statistically significant after controlling for socioeconomic characteristics.

INSERT FIGURE 3 ABOUT HERE

INSERT FIGURE 4 ABOUT HERE

Discussion and Implication for Design

One of the most important findings to emerge from our study is that in post-COVID WFH arrangements, managers do not seem to be able to reallocate commuting time to personal time, probably because in the absence of a common office space, they have to spend more time coordinating their employees and teams (RQ1). We also found that the workdays of knowledge workers are more fragmented post-COVID, with an increase in the number of activities, with shorter activity durations, and with activities that are more dispersed across the day, resulting in a longer workday (RQ2). More generally, this study reinforces the notion that the effects of WFH arrangements during COVID-19 are heterogeneous across workers and firms (RQ3).

Our results complement existing work—and in particular Yang et al. (2020)—by showing changes in time allocation for a broad set of knowledge workers employed by firms that may be less technology-enabled than Microsoft. 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. Reassuringly, our findings are consistent with those found by Yang et al. among Microsoft's employees—in particular the increase in overall time allocated to interactive activities, a reduction in average activity length, and fewer uninterrupted work hours found among managers.

We did not find indication of changes in perceived wellbeing post-COVID (RQ4). And while it is too early to know whether the changes documented in this study will persist in a post-pandemic world, there are clear indications that at least some of them will–after all, almost half of our respondents told us that they would prefer to continue primarily working from home (RQ5). Considering this, organizations should consider how they can use technology to better support WFH arrangements. In the next section we discuss three key areas where technology can play a critical role in supporting this transition.

Implications for Design

Technology for improving time allocation in support of work and wellbeing

Our data 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, reducing 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 gives us new impetus to focus on it.

One specific area where technology could help is with 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 by handling routine coordination tasks such as scheduling meetings and sharing access to resources as well as locating needed information.

Our data also indicates that for some workers WFH means interleaving work and personal life. The way that workers allocate time to work and personal tasks means that they spread their work beyond the hours that they would usually spend at the office, perhaps so as to fit in non-work tasks during the day. This might indicate that, for these workers, work and personal life will collide, with the barriers between the two blurring. Technology can help workers maintain barriers between work and personal life, which in turn can help maintain their overall 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. For example, some workers might decide to take an hour each morning to help their children with school and compensate by working for an hour after dinner. Others might do the same but only when a child requests help. This type of removal of barriers (help each morning), or blurring (help when needed) of barriers, between work and personal tasks might lead to the longer post-COVID workdays that we observed. 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 workers 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 workers 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 workers’ 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 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 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).

Technology can also support workers in completing multiple tasks when working from home. The home office introduces interruptions that differ from those in the office: for example, in the home environment knowledge workers might be interrupted by children needing help, roommates doing dishes, and dogs barking. Of course work-related interruptions have been common for knowledge workers well before COVID (González & Mark, 2004). Still, as the amount of communication increases for managers with WFH, this increase in communication 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, all of these interruptions, from those that pull knowledge workers to personal tasks, to work-related (and particularly communication-related) tasks, are one possible explanation for the reduction in the average length of engagement in work tasks (see Tables 8 and 10).

Interruptions can also negatively affect performance—after all there is a cognitive cost to resuming an interrupted activity. 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 workers 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, Iqbal, Kun, & Donker, 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, the 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 workers 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). Looking at our data, it is possible that some workers benefit from the new interruptions when WFH, and this might be one reason that we found no dropoff in perceived wellbeing post-COVID.

Technology to support mental and physical wellbeing

At the beginning of this section we discussed how technology can help with time allocation when WFH, and how this can support both work tasks and mental wellbeing. Technology can support workers' mental wellbeing in additional ways. For example, while we know that spending time in nature can support mental wellbeing, the lack of commuting that we document, along with other COVID-related movement restrictions, mean fewer opportunities for workers to see nature. Wooller et al. (2018) found that simulated nature experiences can reduce stress in a laboratory setting. Ongoing work by our team is exploring if exposure to simulated nature experiences at home can improve creativity (Kun, Shaer, Sadun, Boyle, & Lee, 2020). Another simple way that technology can help: Butler and Jaffe (2020) found that simply reflecting each night about things one can be grateful for can help workers be satisfied with their day. Finally, playing digital games can help recovery from work (Collins & Cox, 2014; Collins, Cox, Wilcock, & Sethu-Jones, 2019). However, it would be important to assess the combined impact of games and the changing work-life boundaries of WFH. For example, what is the effect of playing digital games after work, now that the work day has been extended for some workers (such as in our sample)?

Finally, it is important for us to consider how technology can support the physical wellbeing of workers. One aspect of physical wellbeing is physical movement. Unfortunately, even before COVID-19 knowledge workers were likely to spend much of their work hours seated. For example administrative workers in a study conducted by Clemes et al. (2014) spent around 70% of their time at work in sedentary activities. Unfortunately, WFH might result in further reduction in physical movement. And while our data does not explore how sedentary behaviors might have changed post-COVID, we see indications that, in workers' personal life, sedentary behaviors might have increased with the shift to WFH. Specifically, we found that post-COVID workers spent more time on personal tasks that they describe as sleep, relaxing, social media/email, phone call, and TV/video. Considering this, it is interesting to consider the work of Haliburton and Schmidt (2020), who argue for developing technology to allow working while walking. In a sense, this approach constitutes flexible blurring of barriers between work and personal goals, as discussed by Ciolfi and Lockley (2018). Of course, any technology that supports walking and working must be carefully designed for safety, because walking outside, and especially around vehicles, is a safety-critical activity. But, if a person is walking and working, there is a potential that this person's ability to safely participate in traffic could suffer (Neider et al., 2011).

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, 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. To test the validity of our approach in recovering "stable" time allocation decisions, we conducted a validation exercise where we collected longitudinal data for 203 participants, reporting on one day of their week over three consecutive weeks in June/2020. That data validated that working days were already substantially stable within-workers by June/2020 and reassured our team that the DRM is able to capture persistent different in work behavior.

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 kids, 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 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, our sample focuses on knowledge workers in the US, and we know many aspects of their work (such as managerial status and company size) there are certainly unobserved differences across individuals that we cannot fully account for. It is also important to deploy this study in other countries where cultural and structural factors might result in differences in knowledge workers’ 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.

Conclusion

The sudden and widespread shift to WFH due to the COVID-19 pandemic presents two important questions. First, it is important to understand the effect of this shift on the structure and intensity of different activities that knowledge workers engage in during WFH. Our results show that all workers commute significantly less post-COVID, but that other effects of the pandemic are heterogeneous across workers with different roles (manager vs. non-manager) and 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? And what will be the role of local and global factors, such as customs, social norms, and the developing health situation? 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]
Background characteristics	2018 US CPS	Pre-Covid Sample (N = 615)	Post-Covid Sample (N = 577)	Difference	p-value
Gender					0.427
Female	47.90%	49.27%	46.97%	-2.30%	
Male	52.10%	50.73%	53.03%	2.30%	
Education (highest degree)					0.469
Less than a college degree	20.90%	13.66%	12.48%	-1.18%	
College degree	48.30%	49.43%	45.93%	-3.50%	
Graduate School	30.80%	36.91%	41.59%	4.68%	
Annual Salary (in USD)					0.131
$39,999 or lower	5.90%	-	-		
$40,000 to $60,000	21.60%	19.84%	19.41%	-0.43%	
$60,000 to $80,000	31.10%	25.69%	20.28%	-5.41%	
$80,000 to $100,000	23.40%	19.19%	20.80%	1.61%	
$100,000 or higher	18.10%	35.28%	39.51%	4.23%	
Lives in a large city (population of at least 500,000)	N/A	75.61%	73.83%	-1.78%	0.48

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 do not match the variable used by our research team.

Table 2. Change in Daily Time Allocated 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	-31.3621***	24.1717***	7.1904	43.2214***
	[0.0000]	[0.0025]	[0.3513]	[0.0002]
Observations	1192	1192	1192	1192
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 alone, 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. Change in number of work-related activities (pre vs. post-COVID surveys)

	[1]	[2]	[3]	[4]	[5]
	Total work-related activities (count)	Total work-related email/social media activities (count)	Total work-related interactive activities (count)	Total work-related solo-cognitive activities (count)	Total other work-related activities (count)
Post vs. Pre-COVID change	1.3699*** [0.0000]	0.3798*** [0.0006]	0.3754*** [0.0001]	0.6123*** [0.0002]	0.0025 [0.9730]
Observations	1192	1192	1192	1192	1192
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 alone, 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 4. Change in average duration of work-related activities (pre vs. post-COVID surveys)

	[1]	[2]	[3]	[4]	[5]
	Time of average work-related activity (minutes)	Time of average work-related email/social media activity (minutes)	Time of average work-related interactive activity (minutes)	Time of average work-related solo-cognitive activity (minutes)	Time of average work-related other activity (minutes)
Post vs. Pre-COVID change	-11.5729***	-6.7108**	-6.7751*	-14.2876***	-3.9175
	[0.0004]	[0.0492]	[0.0530]	[0.0012]	[0.5160]
Observations	1189	1015	879	1013	548
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 alone, 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. [5] The mean of the dependent variables (pre-COVID) were: 89.4 minutes, 61.3 minutes, 71.2 minutes, 96.2 minutes, and 64.9 minutes, for columns 1 through 5, respectively.

Table 5. Change in daily time allocated to different types of work-related activities (pre vs. post-COVID surveys)

	[1]	[2]	[3]	[4]
	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	-0.2849	7.3705	8.9874	-8.8826
	[0.9588]	[0.2240]	[0.2781]	[0.1496]
Observations	1192	1192	1192	1192
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 alone, 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 6. Change in Daily Time Allocated Across Activity Types (pre vs. post-COVID surveys, by managerial status)

	[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 (Managers)	-27.3246***	10.9337	16.391*	58.1868***
	[0.0000]	[0.2277]	[0.0618]	[0.0000]
Post vs. Pre-COVID change (Non-Managers)	-48.3952***	80.0198***	-31.6246**	-19.9136
	[0.0000]	[0.0000]	[0.0260]	[0.2685]
Observations	1192	1192	1192	1192
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] The coefficient "Post vs Pre-COVID change (Managers)" is the difference in the dependent variable when comparing the mangers in the post-COVID survey to managers in the pre-COVID survey. The coefficient "Post vs Pre-COVID change (Non-Managers)" is computed in two steps. First, we estimate the difference between non-managers pre-COVID and managers pre-COVID (difference 1) and the difference between non-managers post-COVID to managers pre-COVID (difference 2), i.e. we use managers pre-COVID as a baseline. In a second step, we estimate "Post vs. Pre-COVID change (Non-Managers)" by computing the difference between difference 2 and difference 1 (difference 3), which results in a comparison of non-managers post-COVID to non-managers pre-COVID. [3] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, and whether the person lives in a large city. [4] 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. [5] 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. [6] A two-tailed t-test confirms that all within-manager and within-non-managers changes are different from one another (p-value < 0.01 for all).

Table 7. Change in number of work-related activities (pre vs. post-COVID surveys, by managerial status)

	[1]	[2]	[3]	[4]	[5]
	Total work-related activities (count)	Total work-related email/social media activities (count)	Total work-related interactive activities (count)	Total work-related solo-cognitive activities (count)	Total other work-related activities (count)
Post vs. Pre-COVID change (Managers)	1.4113***	0.4669***	0.4139***	0.5674***	-0.0369
	[0.0001]	[0.0004]	[0.0002]	[0.0029]	[0.6608]
Post vs. Pre-COVID change (Non-Managers)	1.1951**	0.0120	0.2127	0.8016***	0.1688
	[0.0125]	[0.9378]	[0.2376]	[0.0033]	[0.2680]
Observations	1192	1192	1192	1192	1192
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] The coefficient "Post vs Pre-COVID change (Managers)" is the difference in the dependent variable when comparing the mangers in the post-COVID survey to managers in the pre-COVID survey. The coefficient "Post vs Pre-COVID change (Non-Managers)" is computed in two steps. First, we estimate the difference between non-managers pre-COVID and managers pre-COVID (difference 1) and the difference between non-managers post-COVID to managers pre-COVID (difference 2), i.e. we use managers pre-COVID as a baseline. In a second step, we estimate "Post vs. Pre-COVID change (Non-Managers)" by computing the difference between difference 2 and difference 1 (difference 3), which results in a comparison of non-managers post-COVID to non-managers pre-COVID. [3] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, and whether the person lives in a large city. [4] 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. [5] 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. [6] A two-tailed t-test confirms that the within-manager and within-non-managers changes are different for total count of email/social media activities (p-value < 0.05), With our sample, we do not have statistical power to assess whether the within-manager changes in the other categories are different from within non-manager changes. However, the direction of the differences is as expected, with managers engaging in more interactive activities and non-managers more in solo-cognitive activities.

Table 8. Change in average duration of work-related activities (pre vs. post-COVID surveys, by managerial status)

	[1]	[2]	[3]	[4]	[5]
	Time of average work-related activity (minutes)	Time of average work-related email/social media activity (minutes)	Time of average work-related interactive activity (minutes)	Time of average work-related solo-cognitive activity (minutes)	Time of average work-related other activity (minutes)
Post vs. Pre-COVID change (Managers)	-10.6859***	-4.1542	-4.2357	-8.7231*	-10.4291*
	[0.0022]	[0.2545]	[0.2530]	[0.0677]	[0.0778]
Post vs. Pre-COVID change (Non-Managers)	-15.3242*	-18.1522**	-20.9922**	-40.9569***	33.2322*
	[0.0627]	[0.0326]	[0.0326]	[0.0001]	[0.0539]
Observations	1189	1015	879	1013	548
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] The coefficient "Post vs Pre-COVID change (Managers)" is the difference in the dependent variable when comparing the mangers in the post-COVID survey to managers in the pre-COVID survey. The coefficient "Post vs Pre-COVID change (Non-Managers)" is computed in two steps. First, we estimate the difference between non-managers pre-COVID and managers pre-COVID (difference 1) and the difference between non-managers post-COVID to managers pre-COVID (difference 2), i.e. we use managers pre-COVID as a baseline. In a second step, we estimate "Post vs. Pre-COVID change (Non-Managers)" by computing the difference between difference 2 and difference 1 (difference 3), which results in a comparison of non-managers post-COVID to non-managers pre-COVID. [3] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, and whether the person lives in a large city. [4] 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. [5] 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. [6] A two-tailed t-test confirms that the within-manager and within-non-managers changes are different for average duration of solo-cognitive work (p-value < 0.01) and other work-related activities (p-value < 0.05).

Table 9. Change in daily time allocated to different types of work-related activities (pre vs. post-COVID surveys, by managerial status)

	[1]	[2]	[3]	[4]
	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 (Managers)	7.9287	11.6146*	13.6248	-16.7772***
	[0.1845]	[0.0821]	[0.1185]	[0.0056]
Post vs. Pre-COVID change (Non-Managers)	-34.9363***	-10.5343	-10.5766	24.4227
	[0.0078]	[0.4698]	[0.6385]	[0.1772]
Observations	1192	1192	1192	1192
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] The coefficient "Post vs Pre-COVID change (Managers)" is the difference in the dependent variable when comparing the mangers in the post-COVID survey to managers in the pre-COVID survey. The coefficient "Post vs Pre-COVID change (Non-Managers)" is computed in two steps. First, we estimate the difference between non-managers pre-COVID and managers pre-COVID (difference 1) and the difference between non-managers post-COVID to managers pre-COVID (difference 2), i.e. we use managers pre-COVID as a baseline. In a second step, we estimate "Post vs. Pre-COVID change (Non-Managers)" by computing the difference between difference 2 and difference 1 (difference 3), which results in a comparison of non-managers post-COVID to non-managers pre-COVID. [3] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, and whether the person lives in a large city. [4] 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. [5] 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. [6] A two-tailed t-test confirms that the within-manager and within-non-managers changes are different for time-use exclusively dedicated to work-related email/social media (p-value < 0.01) and other work-related activities (p-value < 0.01). With our sample, we do not have statistical power to assess whether the within-manager changes in interactive activities (p-value = 0.169) or in solo-work activities (0.315) are statistically different from one another. However, the direction is as expected, with within-manager changes being towards more time dedicated to interactive activities.

Table 10. Summary of changes for knowledge workers working in large firms (firms with at least 250 employees)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	Time in commuting activities (minutes)	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/socia l 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 (Managers)	-26.2*** [0.0000]	1.3 [0.9127]	24.9** [0.0237]	74.7*** [0.0000]	2.1*** [0.0000]	-13.0*** [0.0019]	6.9 [0.3275]	24.5*** [0.0013]	10.3 [0.3279]	-16.7** [0.0160]
Post vs. Pre-COVID change (Non-Managers)	-46.8*** [0.0000]	78.1*** [0.0000]	-31.3* [0.0687]	-19.9 [0.3720]	1.5** [0.0189]	-17.2* [0.0714]	-43.5*** [0.0061]	-7.1 [0.6455]	-38.5 [0.1401]	57.9*** [0.0084]
Observations	847	847	847	847	847	845	847	847	847	847
Noise controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Work-related controls	Yes	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] The coefficient "Post vs Pre-COVID change (Managers)" is the difference in the dependent variable when comparing the mangers in the post-COVID survey to managers in the pre-COVID survey. The coefficient "Post vs Pre-COVID change (Non-Managers)" is computed in two steps. First, we estimate the difference between non-managers pre-COVID and managers pre-COVID (difference 1) and the difference between non-managers post-COVID to managers pre-COVID (difference 2), i.e. we use managers pre-COVID as a baseline. In a second step, we estimate "Post vs. Pre-COVID change (Non-Managers)" by computing the difference between difference 2 and difference 1 (difference 3), which results in a comparison of non-managers post-COVID to non-managers pre-COVID. [3] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, and whether the person lives in a large city. [4] 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. [5] 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 11. Summary of changes for knowledge workers working in small firms (firms with at most 249 employees)

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
	Time in commuting activities (minutes)	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 (Managers)	-31.5***	34.5**	-2.7	10.6	-0.4	-6.7	9.4	-18.6	21.6	-15.1
	[0.0001]	[0.0162]	[0.8567]	[0.6527]	[0.4321]	[0.3739]	[0.4323]	[0.2212]	[0.2109]	[0.2384]
Post vs. Pre-COVID change (Non-Managers)	-46.1***	80.3***	-34.3	-33.5	-0.0	-1.7	-16.6	-12.3	63.6	-68.9**
	[0.0006]	[0.0045]	[0.1745]	[0.2851]	[0.9659]	[0.9088]	[0.5057]	[0.7081]	[0.1221]	[0.0199]
Observations	345	345	345	345	345	344	345	345	345	345
Noise controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Work-related controls	Yes	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] The coefficient "Post vs Pre-COVID change (Managers)" is the difference in the dependent variable when comparing the mangers in the post-COVID survey to managers in the pre-COVID survey. The coefficient "Post vs Pre-COVID change (Non-Managers)" is computed in two steps. First, we estimate the difference between non-managers pre-COVID and managers pre-COVID (difference 1) and the difference between non-managers post-COVID to managers pre-COVID (difference 2), i.e. we use managers pre-COVID as a baseline. In a second step, we estimate "Post vs. Pre-COVID change (Non-Managers)" by computing the difference between difference 2 and difference 1 (difference 3), which results in a comparison of non-managers post-COVID to non-managers pre-COVID. [3] All columns report models that control for the following socioeconomic variables: age, gender, income, highest educational degree, marital status, whether the person lives alone, whether the person lives with children, and whether the person lives in a large city. [4] 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. [5] 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.

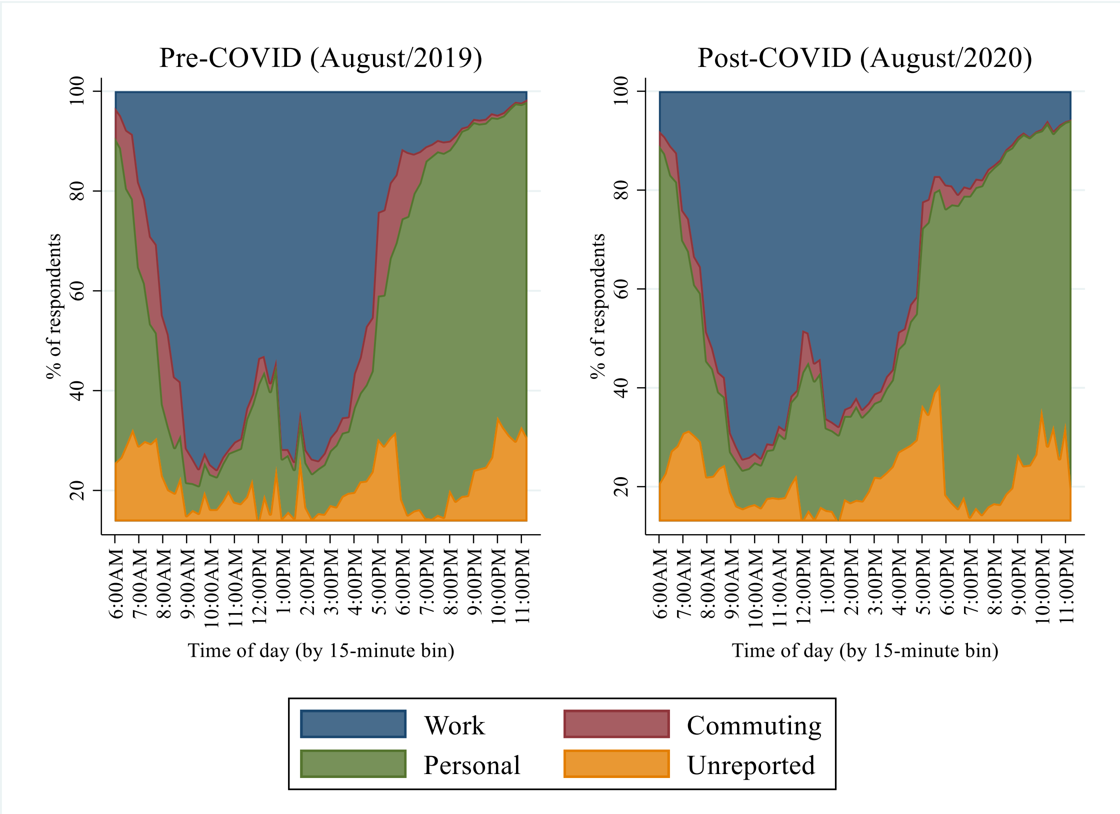

Figure 3. Change in perceptions about working-from-home arrangements (post-COVID sample)

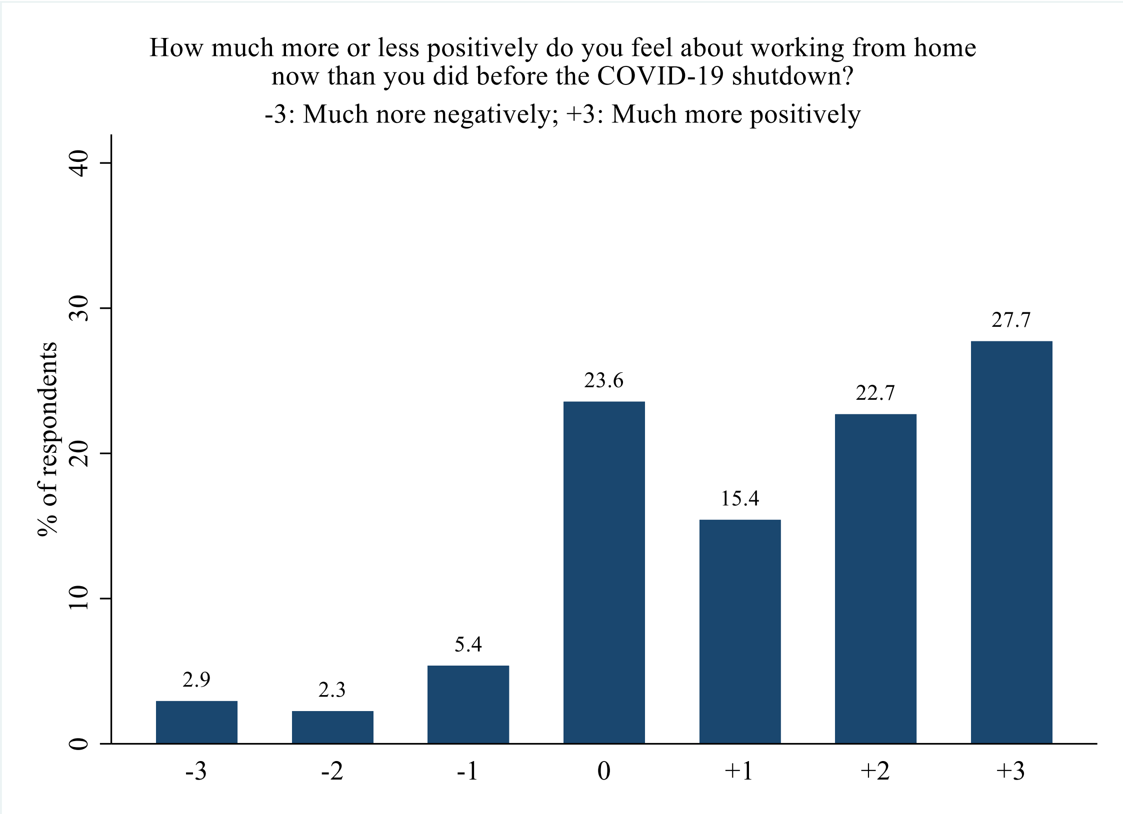

Figure 4. Change in perceptions about working-from-home arrangements (post-COVID sample, by managerial status)