NBER WORKING PAPER SERIES

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Working Paper 31439
http://www.nber.org/papers/w31439

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2023, revised August 2023

I thank Kairon Garcia for her excellent research assistance on this paper. I also thank Virat Agrawal and participants at the 2023 ASHEcon Annual Conference for excellent suggestions. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

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July 2023, revised August 2023
JEL No. I12,I24,J22,J24,J32

ABSTRACT

I demonstrate that the profound change in working from home (WFH) in the wake of the COVID-19 pandemic is concentrated among individuals with college degrees. Relative to 2015-19, the number of minutes worked from home on “post-pandemic” (August 2021-December 2022) weekdays increased by 78 minutes for college graduates; for non-graduates, it was 22 minutes. The share of work done at home (for those who worked at all) increased by 22% for graduates and 7% for non-graduates. Average minutes worked changed little for either group. Daily time spent traveling (e.g., commuting) fell by 21 minutes for college graduates and 6 minutes for non-graduates. I examine how time-use patterns change for college graduates relative to non-graduates over the same period. College graduates experience a relative shift from eating out to eating at home, an increase in free time, and an increase in time spent with children, with the latter effect being concentrated among fathers. Thus, while the gender gap in childcare among college graduates may be diminished by the WFH revolution, gaps in children’s outcomes by parents’ college attainment may be exacerbated by it.

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1. Introduction

The COVID-19 pandemic sharply accelerated a trend toward remote work in the United States and other developed countries. Between 2019 and 2021, the number of U.S. workers primarily working from home tripled to almost 18% (U.S. Census Bureau, 2022). As the pandemic has receded, many workers have remained at home full- or part-time (Chen et al., 2023).[1] The effects of this rapid and seismic shift in work are only beginning to be understood. Because workers typically prefer working from home (WFH) at least part of the week (Aksoy et al., 2022), there are likely to be benefits of WFH that extend beyond individuals' work lives. This study is among the first to investigate how WFH affects individuals' time use outside of work hours. More remote work appears to have slowed the spread of SARS-CoV-2 in the initial phase of the pandemic (Alipour, Fadinger, and Schymik, 2021), but little is known about how WFH affects outcomes that influence health and well-being outside of pandemics.

The focus of this paper is on how WFH has disproportionately affected outcomes for college-educated workers relative to those with less education. This is based on two observations: first, workers with a college degree are substantially more likely to work in jobs that can be performed from home (Bloom, 2020; Dingel and Neiman, 2020). As I later show, college-educated workers account for the lion's share of the increase in WFH since the pandemic. Second, there is longstanding interest in differences in time use by educational attainment since time-intensive activities are key factors in measures of own and children's human capital. Disparities in these outcomes by college attainment are large and, in many cases, have widened over the past several decades (Goldin and Katz, 2018; Galama, Lleras-Muney, and

[1] See, for example, https://wfhresearch.com/wp-content/uploads/2023/02/WFHResearch_updates_February2023.pdf. Data from January 2023 indicates that 27% of paid full-time workdays were from home.

van Kippersluis, 2018; Case and Deaton, 2021; Guryan, Hurst, and Kearney, 2008; Carneiro, Meghir, and Parey, 2013; Doepke, Sorrenti, and Zilibotti, 2019). Since the "WFH revolution" is bound to affect college-educated individuals more than others, any changes in time use outside of work (and downstream outcomes that result from these changes) are also likely to be concentrated among those with college degrees.

Using American Time Use Survey (ATUS) data from 2015-2019 and August 2021-December 2022, I document that WFH has increased substantially following the main pandemic period among college graduates but much more modestly among those without a college degree (I refer to these individuals as non-graduates throughout the paper).[2] Relative to 2015-19, the number of minutes worked from home on "post-pandemic" weekdays increased by 78 minutes for college graduates; for non-graduates, it was 22 minutes. The share of work done at home (for those who worked at all) increased by 22% for graduates and 7% for non-graduates. I then examine how 10 broad categories of time use that are mutually exclusive and sum to approximately 24 hours change for college graduates relative to non-graduates in 2021-22 compared to pre-COVID years. These include sleep, self-care, household tasks, caring for others, work, education, free time, eating and drinking, physical exercise, and traveling (see Cowan, Jones, and Swigert, 2023 for details on how these categories are constructed). It is important to note that because I do not have an exogenous source of variation in WFH, co-occurring trends in time use cannot be directly attributed to the increase in WFH that college graduates experience in 2021-22 relative to prior years. However, there are reasons to believe that such changes are related to WFH, as I argue below.

[2] I do not include January 2020-July 2021 in my analysis because of the direct effect of the COVID pandemic on WFH and other labor-market outcomes. The last state-level restrictions on business activity and group gatherings were lifted by July 2021. The vast majority of schools that were online for all or part of the 2020-21 academic year went back to in-person operations in fall 2021.

One of the largest changes that occurs across these 10 categories is in travel (e.g., driving in a car)—on post-pandemic weekdays, college graduates spend 15 fewer minutes traveling than do non-graduates (relative to the same difference in the pre-pandemic period). Two-thirds of this reduction is due to a decrease in commuting time specifically. College graduates also spend about 7 fewer minutes per weekday in self-care (e.g., personal grooming) compared to non-graduates in 2021-22 (again, compared to the same difference from 2015-2019). These effects are consistent with the idea that when individuals shift work to home, they have fewer reasons to travel or groom/dress for work.

How do college graduates adjust other parts of their daily schedules given the very large increase in WFH and co-occurring decreases in travel and self-care that add up to about 22 minutes per day? The only other significant change in the 10 broad categories is on free time, which increases by about 18 minutes on weekdays (a 10% change from the pre-pandemic mean for college grads). This appears to be the biggest way college graduates use the time savings associated with WFH.

Beneath the (lack of) changes in these 10 broad time-use categories, there are some important changes in specific activities. First, and not surprisingly, time spent eating and drinking shifts from outside to inside the home (on the order of 4-5 minutes, or a 13% change for both categories). This may have health implications if the composition of food also changes, which I discuss further below. Second, when I specifically examine time spent in active engagement with household children, the difference between college graduates and non-graduates grows by about 7 minutes overall and 19 minutes for those with children in the household specifically, which in both cases is a 22% difference relative to the pre-pandemic mean.[3] This effect is important to consider in the context of the skill-building effects of parental time with children and gaps in parental investments by education. I return to these subjects in the Conclusion.

I examine heterogeneity in the main results along three different dimensions. First, I explore the role of occupation in permitting individuals with college degrees to shift more of their work time to WFH. In the ATUS sample, college graduates are almost three times as likely (59% versus 23% for non-graduates) to hold occupations that Dingel and Neiman (2020) classify as ones that can be entirely performed from home. Using their classifications, when I allow for post-COVID differences by college attainment as well as holding such an occupation, I find that 1) college graduates not in fully telework-compatible occupations experience a substantial rise in WFH and 2) college graduates in such occupations see an even larger increase in WFH (relative to grads outside such occupations). This suggests that occupational distinctions by ability to perform a job at home in Dingel and Neiman (2020) capture part, but not all, of what has precipitated the college-graduate-concentrated increase in WFH in the wake of the pandemic.

I next see whether the relative changes in WFH and other variables for college graduates in 2021-22 were larger in states that likely experienced larger shocks to WFH during COVID. Because some states' policies led to longer business and school closures during 2020 and early 2021, individuals in such states were perhaps more likely to shift to WFH during that time. These arrangements may have persisted even after closures and other mandates were lifted given many workers' preference to spend at least part of their work week from home.[4] I use state averages of

[3] The pre-pandemic difference by college attainment in active time with children (for those with children in the household) is also only about 19 minutes per day.

[4] Though nearly all public schools had returned to in-person learning by fall 2021, there were short-term disruptions for COVID outbreaks at the school or district level throughout the 2021-22 academic year. See https://about.burbio.com/school-opening-tracker.

the percentage of the 2020-21 K-12 school year that was not in-person as a proxy for the degree of state closures during COVID. The results suggest that in states with longer closures, the relative increase in WFH for college graduates in 2021-22 is magnified.

Lastly, I examine how these results vary by gender. On average, college-educated men experience a larger relative change in WFH than do college-educated women. This may be partially explained by the fact that a much higher percentage of non-college-educated women hold jobs that can be performed from home (34%) than do similarly situated men (15%). The associated increase in active time with children is fully concentrated among men, which implies a reallocation of childcare from (college-educated) women to men: the increase for men of about 12 minutes per day is just over 40% of the pre-COVID gap in active childcare time by gender. Thus, the WFH revolution has the potential to further narrow differences in household roles that have diminished over the past several decades but remain entrenched (Parker and Wang, 2013).

2. Background

A series of papers using the Global Survey of Working Arrangements (G-SWA) and the Survey of Working Arrangements and Attitudes (SWAA) have documented several notable findings regarding shifts in WFH in the wake of the pandemic (Barrero, Bloom, and Davis, 2021; Aksoy et al., 2022; Aksoy et al., 2023). In work that is most relevant for this paper, Aksoy et al. (2023) asked respondents how long they spent commuting to work prior to the pandemic. For those primarily working from home in the wake of the pandemic, respondents were then asked how they spent the time they saved by not commuting (6 total activity categories, where answers were to be given as percentages of the time saved). The authors find that the average daily time savings from not commuting on WFH days is 72 minutes, with an average of 40% of that time being reallocated to work activities, 34% to leisure activities, and 11% to caregiving.[5]

This paper goes beyond the analysis in Aksoy et al. (2023) in several ways. First, by using American Time Use Survey (ATUS) data, I am able to see how individuals allocate their time based on a detailed 24-hour time diary. The data is also nationally representative of the U.S. population, whereas the G-SWA is not.[6] Second, I am able to examine detailed time-use categories that pertain to gaps in behavioral health and time spent with children by education level. Third, I can examine trends in time use in WFH and other variables by educational level prior to the pandemic as well as after it.

My paper also builds on a recent literature using individual survey data such as ATUS to examine the association between WFH and various time allocations before, during, and after COVID (Massar et al., 2023; Pabilonia and Vernon, 2022, 2023; Restrepo and Zeballos, 2022). These papers provide conditional correlations between WFH and many activities, but a concern is that they do not account for selection into being a remote worker or the decision to work from home on a particular day. For those papers examining changes in time use by WFH status from before to during/after the pandemic, one major difficulty is that the pandemic very likely affected the composition of remote workers/WFH days. By focusing on college attainment rather than WFH status itself, I can overcome some of these challenges, as I detail in Section 4.

Regarding my interest in the relationship between college attainment, WFH, and time use, there is evidence that time-intensive inputs into the development of own and children's

[5] Time savings from forgoing a commute is not the only way that WFH may affect time allocations. WFH may introduce more flexibility in switching between work and other activities throughout the day, moving some traditionally non-work activities into the traditional workday, and vice versa. It is not clear *a priori* how this would affect overall time allocations between work and other activities. With WFH, it is also possible that individuals are able to multitask (e.g., by doing other activities while working) in ways that are not possible when working outside of the home.

[6] In particular, better-educated individuals are overrepresented in the G-SWA (Aksoy et al., 2023).

human capital generally rise with education. College-educated individuals are more likely to exercise regularly, get high-quality sleep, and have better nutrition (Cutler and Lleras-Muney, 2010; Hiza et al., 2013; Barcellos, Carvalho, and Turley, 2018; Sheehan et al., 2020; Park and Kim, 2023). Differences in these outcomes help to explain why college attainment is a strong predictor of health outcomes like obesity and longevity (Cutler and Lleras-Muney, 2006). College attainment is also strongly correlated with time spent with own children including educational activities; this is in spite of the fact that parents with higher levels of education tend to work more hours (Guryan, Hurst, and Kearney, 2008; Carneiro, Meghir, and Parey, 2013). Doepke, Sorrenti, and Zilibotti (2019) find that since the 1970's, childcare time for college-educated parents has increased much more than it has for those with less education.

WFH has the potential to widen these gaps in time-intensive human capital inputs by freeing up additional time for college-educated workers—who are much more likely to be in jobs that allow for WFH—to spend on activities that enhance health and wellbeing. For example, cooking meals at home (rather than eating out) and finding time throughout the day to exercise might be easier when one is working from home. Of course, on the other hand, WFH could cause workers to be more sedentary or spend more time on activities that detract from health (such as overconsumption of drugs, alcohol, or social media). Lastly, part of the reason WFH may be strongly preferred by many workers is because it reduces stresses associated with either work or family life, which could promote activities that have short-term costs but long-term benefits (such as sticking to a healthy sleep schedule). Ultimately, the question of how WFH affects time spent in health-related activities is empirical.

3. Data

I use the 2015-2019 and 2021-2022 versions of the American Time Use Survey (ATUS) obtained via IPUMS (Flood, Sayer, and Backman, 2022). The ATUS is a 24-hour time diary, where the respondent reports the activities they were doing between 4:00 am of the first day and 4:00 am of the following day. Respondents are randomly sampled from individuals who completed the Current Population Survey (CPS) and take the ATUS between two and five months after their final CPS interview. I exclude all of 2020 and January-July 2021 to avoid measuring direct effects of the COVID-19 pandemic and associated policies on time use. The last state-level restrictions on business activity and group gatherings were lifted by July 2021.[7] Thus, I consider August 2021-December 2022 as my "post-COVID" period and all of 2015-2019 as my "pre-COVID" period. My main sample is composed of all individuals ages 24 to 59; this includes 36,204 respondents. Summary statistics for economic and demographic variables separated by "pre-COVID" (2015-2019) and "post-COVID" (2021) as well as college attainment are contained in Table 1.[8]

Following Cowan, Jones, and Swigert (2023), I collapse over 400 activity codes in the ATUS into 10 main categories based on the primary activity being performed at any given time: 1) sleep; 2) self-care; 3) household tasks; 4) caring for others; 5) work; 6) education; 7) free time; 8) eating; 9) exercise; and 10) travel. Working from home (WFH) is defined as any work activities performed from one's own residence. In addition to WFH in minutes and the share of overall work time spent at home (conditional on working a positive amount on a given day), I examine as dependent variables 1) the 10 categories of time used listed above, 2) commuting

[7] See https://www.kff.org/other/state-indicator/state-actions-to-mitigate-the-spread-of-covid-19/?activeTab=map&currentTimeframe=0&selectedDistributions=status-of-reopening&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D.

[8] College graduates are overrepresented in the ATUS data, and this appears to be somewhat larger after COVID (2021-22), though of course the share of college graduates gradually increases in the data following national trends. Sample weights correct for this overrepresentation, and I use these weights throughout my analysis.

time (travel specifically related to one's work), 3) eating at home versus eating away from home, 4) time spent actively engaged with household children (such as reading to/with children, taking them to appointments, playing a sport with them, etc.), and 5) secondary childcare (time spent monitoring children while actively engaged in a different primary activity). Summary statistics for each of these time-use variables separated by "pre-COVID" (2015-2019) and "post-COVID" (2021-2022) periods as well as college attainment are contained in Table 2.

4. Empirical Strategy

I begin by examining how trends in WFH and related variables have changed over the study period. To do this, I regress WFH (and related variables) on a set of individual characteristics for college graduates and non-graduates separately:

$$y_{i(t)} = \alpha_t + Z_{i(t)}\delta + \epsilon_{i(t)} \qquad (1)$$

where, for each individual i surveyed in year t, $y_{i(t)}$ is an outcome measured in minutes per day.[9] α_t is an indicator for the year in which an individual is interviewed, and $Z_{i(t)}$ contains other time-related fixed effects (month, day of week, holiday) as well as demographic/economic controls, which include state fixed effects, a quadratic in age, MSA size dummies, marital status, number of household children, sex, race (black, Asian, other, with white as the omitted category), Hispanic ethnicity, an indicator for being born in the U.S., educational attainment dummies, and detailed industry and occupation dummies (4-digit Census codes).

In Figure 1, I show the results of the regression represented in Equation (1) run separately for college graduates and non-graduates on weekdays. Each sub-figure contains the coefficients

[9] All time-use variables in the ATUS data are nonnegative whole numbers (in minutes) with (in several cases) heaping at zero. Because these data are thus clearly not normally distributed, some have suggested transforming the data (e.g., with the inverse hyperbolic sine function). However, recent work by Mullahy and Norton (2022) shows that estimates of marginal effects obtained from regressions using such transforms can be biased, particularly in the presence of many zeros. In their applications, one way they obtain roughly unbiased marginal effect estimates is by performing OLS with the untransformed outcome as the dependent variable, which I follow here.

on each year dummy (with 2015 as the base year) and 95% confidence intervals for the following outcomes: 1) daily time spent working from home, or WFH (in minutes), 2) daily total time spent working (in minutes), 3) daily percentage of time spent working from home (for those who worked at all on a given day), and 4) daily time spent traveling, including commuting (in minutes).

As seen in Figure 1, there is little change in WFH for either college graduates or non-graduates in the pre-COVID period (2015-2019). In the fall of 2021, there is a huge jump in WFH for college graduates (of about 95 minutes relative to 2015); in 2022, the difference shrinks but is still very large compared to the pre-COVID period (71 minutes). There are much more modest (but still statistically significant) jumps for non-graduates of 19 and 23 minutes in 2021 and 2022, respectively.

There are no significant post-COVID differences for either group in total time spent working. As a result, the daily share of time spent working (for those who worked at all) also increases markedly in 2021 (by around 22-23% for college graduates and 6-8% for non-graduates). Lastly, daily travel time falls after COVID by 20-24 minutes for college graduates and 0-11 minutes for non-graduates.

It is clear from Figure 1 that college graduates have experienced the lion's share of the increase in WFH post-COVID. I thus turn attention to examining how time use patterns have changed by college attainment from before to after COVID using a slightly more parsimonious difference-in-differences (DD) regression model:

$$y_i = \alpha + \beta \cdot (yr21\_22_i \cdot colgrad_i) + X_i\gamma + \epsilon_i \qquad (2)$$

where, for individual i, y_i is minutes spent in a particular time category; $yr21\_22_i$ is an indicator for being interviewed in 2021 or 2022 (as opposed to 2015-2019), $colgrad_i$ is an indicator for having a college degree, and X is a vector of control variables including a full sets of month-by-year dummies (rather than separate year and month effects) in addition to the other controls used in the event-study analysis in Figure 1. I combine both post-COVID years into a single treatment due to the abbreviated period for 2021 that can be considered "post-pandemic" and the fact that estimates for 2021 and 2022 displayed in Figure 1 are not statistically distinguishable at conventional levels for either college graduates or non-graduates.

Equation (2) is estimated on all days, weekdays, and weekends separately. Later in the paper, I discuss modifications to Equation (2) including interaction terms for the telework potential of occupations, state-level differences in the fraction of time that public K-12 schools were closed during the 2020-21 academic year, and gender. Standard errors are clustered at the state level to account for potential intrastate correlations in errors owing to policy differences in COVID responses across states, but simple heteroskedasticity-robust standard errors are very similar to those reported in the tables below.

The coefficient of interest in Equation (2), β, measures the difference in time use for college graduates relative to non-graduates in the post-COVID (2021-22) period all relative to the same difference in the pre-COVID (2015- 2019) period. This coefficient identifies the differential impact of COVID on a particular category of time use for college graduates under standard "parallel trends" and "no anticipation" assumptions. One way the parallel trends assumption could fail is if the composition of college graduates is changing over time in a way that would have affected time use even without COVID. In addition, if COVID caused the composition of college graduates to change, it is hard to tell whether time-use effects are due to a change in composition or a change in behavior at the individual level.

Because college attainment is very likely a pre-determined characteristic for the great majority of individuals in the sample given the age restriction (24-59), the scope for compositional change is limited. Nevertheless, the percentage of college graduates in the data is increasing over my sample period. However, the increase in college attainment from 2015 to 2022 is gradual, while the changes in time use shown in Figure 1 are sudden following the pandemic. Indeed, Figure 1 suggests that the changes in WFH and related variables in 2021-2022 are due to COVID and its fallout rather than the result of a longer-term trend toward more WFH.

To further analyze the extent to which the composition of college grads/non-grads may change following COVID, I run the Equation (2) regression using the dependent variables of 1) employment (binary), 2) family income, and 3) occupational telework compatibility (binary; defined in the next section). If college graduates experienced differential changes in these variables in 2021-22, it would suggest that the composition of the college/non-college groups changed in ways that may affect estimation of the β's in Equation (2). As shown in Appendix Table 1, the coefficient of the interaction of college graduate and an indicator for post-pandemic in these regressions are all modest and not significantly different from zero.

5. Results

5.1 Baseline estimates

Table 1 shows that demographic/economic variable averages experience some modest changes from the pre- to post-COVID period. Changes with respect to employment/occupational telework potential and most demographics are similar for college graduates and non-graduates. College graduates become slightly more racially and ethnically diverse over time, while the composition of non-graduates remains similar. Table 2 shows a marked increase in mean WFH for both groups. The simple DD estimate of the pandemic on WFH by college attainment is

((116-44) - (36-17)), or roughly 53 minutes. Reductions in travel time (and commuting time specifically) are larger for college graduates. Consistent with these changes, the reduction (rise) in time spent eating away from home (at home) is also larger for those with college degrees. Caring for others (and caring for household children specifically) ticks down for non-graduates but up for graduates, while free time does the opposite.

To examine changes in these variables in a more systematic way, I analyze regression models represented in Equation (2). In Table 3, I include variables specifically related to WFH. College graduates experience a 45-minute larger increase in WFH after the pandemic than do non-graduates. This effect is fully due to the relative change on weekdays (of 60 minutes) with no change on weekends, as expected. With regard to total work time, the DD coefficients are negative overall and on weekdays but very small (5-7 minutes) and statistically insignificant. Relative commuting times for college graduates fall by 7 (all days) and 10 (weekdays) minutes, with no effect on weekends. Changes in total travel time are modestly larger—on weekdays, the relative change in total travel time is 15 minutes. This suggests that when individuals do not need to commute, they also choose to spend less time traveling for other purposes (such as running errands). In no case is there evidence of weekend offsetting of WFH-related weekday effects.

How do these notable changes in individuals' work lives translate into how they allocate their time? Because I do not have an instrument for WFH, I cannot claim that any changes in time use are caused by changes in WFH. In other words, even if the reduced-form differential effects of the pandemic on WFH and other time uses for college grads vs. non-grads are well-identified given the assumptions outlined in Section 4, WFH may not be the only channel by which the pandemic affected (relative) time use. Nevertheless, relative changes in college graduates' schedules after the pandemic are suggestive, particularly when they coincide with intuition on how an increase in WFH should operate (such as with the results in Table 3 on commuting and all travel time).

In Table 4, I show relative changes in college graduates' time use in areas that most directly affect physical health. Regarding exercise and sleep, effects are positive but small and statistically insignificant. The effect on eating and drinking overall is also insignificant, but there is a statistically significant decline (at the 10% level) of 4 minutes in time spent eating out on weekdays and increase of almost 5 minutes in time spent eating at home. Once again, this accords with intuition regarding shifts to WFH: if workers are spending more of their workdays at home, they are less likely to eat out since it is relatively easier to eat at home. Substitution from eating out to eating at home could have health benefits in the form of lower caloric/fat intake (Lachat et al., 2012), though the ATUS data are not suitable for analyzing food intake in different settings and how WFH affects those choices.

Table 5 shows effects on all other time-use variables examined in the paper, all of which pertain to personal and household activities. There is a 5 (7) minute reduction in self-care time on all days (weekdays) for college graduates following COVID (relative to the same difference for non-graduates). This is likely explained by a decrease in dressing and grooming for work on days those individuals work from home. Effects on household tasks are small and statistically insignificant. The effect on free time is positive and significant (5% level) and equal to just less than a 10% change relative to the pre-COVID college graduate mean. The effect on all caring for others is positive but insignificant on weekdays, and effects on education time are small and insignificant.

In the last two columns of Table 5, I examine two variables related to household children specifically. The first is time directly engaged with household children (one of the categories included in the broader “caring for others”). This variable increases by 7 minutes on weekdays for college graduates relative to non-graduates following COVID, which is a sizable increase (of roughly 17%). Thus, the entire increase (and more) in caring for others overall is explained by the increase in caring for household children specifically. The last column of Table 5 displays results for secondary childcare for household children, which is time spent monitoring children while engaged in a different primary activity (such as work). Naturally, there is a rise in this variable for college graduates in 2021-22 that is larger on weekdays; this is consistent with the idea that when individuals with household children work from home, they are likely to have children at home with them for at least part of the day. However, neither the overall effect nor the effect on weekdays is statistically significant.

A comparison of weekday effects related to work and personal/household/care of children variables by presence of household children are contained in Table 6.[10] Not surprisingly, when I restrict the sample to only those with children in the household, the effects on caring for others, caring for household children, and secondary childcare for household children all get substantially larger.[11] The effect on caring for household children is nearly 19 minutes (a 22% difference at the mean) and the effect on secondary childcare is 23 minutes (a 12% difference). The effect on WFH time is larger for those with children at home, though the travel time reduction is similar across the two groups. There is a (somewhat surprising) large reduction in time spent in household tasks for those with children at home, and the positive effect on free time is larger for this group. One possible explanation for the household-tasks effect is that when parents are working from home, they can multitask (such as by doing laundry or

[10] Full results for all outcomes considered in the paper are available on request.
[11] In the cases of time with household children and secondary childcare for household children, coefficients get larger mechanically for those with children in the household, since those variables are zero if there are no children in the household.

dishes while working) in ways that are not available when working outside the home. If work is considered the primary activity during such times (by the respondent), they would be coded as work time rather than time spent in household tasks. However, it is not clear why this effect would not also be present (to some degree) for childless individuals.

5.2 Interactions with occupational characteristics

In this sub-section, I address the issue of how the ability to telework based on one's job characteristics moderate the baseline results discussed above. To do so, I modify Equation (2) as follows:

$$y_i = \alpha + \beta_1 \cdot (yr21\_22_i \cdot colgrad_i) + \beta_2 \cdot (yr21\_22_i \cdot tele_i) + \beta_3 \cdot (tele_i \cdot colgrad_i) + \beta_4 \cdot (yr21\_22_i \cdot tele_i \cdot colgrad_i) + X_i\gamma + \epsilon_i \qquad (3)$$

where $tele_i$ is equal to one if an individual works in an occupational with full telework potential according to Dingel and Neiman (2020).[12] [13] That is, I allow for interactions between telework potential and the post-COVID (2021-22) dummy as well as college attainment (note that level effects of all three variables are subsumed by year-by-month fixed effects, occupational fixed effects, and educational attainment fixed effects, all of which are included in X_i). For this and subsequent analyses, I focus on weekdays exclusively. The results of this exercise are contained in Table 7.

[12] Dingel and Neiman (2020) propose an index between 0 and 1 for each occupation (based on the characteristics of the job) where 0 means telework is impossible and 1 means it is fully possible. Because roughly 90% of individuals in my data have a value of 0 or 1 for their occupation, I focus on a binary variable that is equal to 1 if the Dingel and Neiman (2020) index is equal to 1 and is equal to zero otherwise.

[13] To assign the Dingel and Neiman (2020) index to each occupation in the ATUS data, I first use the Standard Occupational Classification (SOC) crosswalk provided by the authors at https://github.com/jdingel/DingelNeiman-workathome/blob/master/onet_to_BLS_crosswalk/output/onet_teleworkable_blscodes.csv. I then use a crosswalk from SOC codes to Census occupation codes found at https://www.census.gov/topics/employment/industry-occupation/guidance/code-lists.html (2018 Census Occupation Code Lists).

As stated previously, individuals with college degrees are much more likely to be in occupations with full telework potential. This could mean that effects noted earlier for college graduates operate purely through telework potential, in which case we would expect $\beta_1 = \beta_4 = 0$ and $\beta_2 > 0$ (if the dependent variable is WFH). As shown in Table 6, college graduates who do not work in "teleworkable" occupations still see a large rise in WFH following COVID compared to non-graduates in such occupations ($\widehat{\beta_1}$ =47 minutes). Individuals in teleworkable occupations but with no college degree also see a (more muted) rise in WFH after COVID compared to non-graduates who do not work in such occupations ($\widehat{\beta_2}$ =26 minutes). Lastly, what is the post-COVID effect for college graduates in teleworkable occupations compared to non-graduates outside of those occupations? This would be the sum of $\widehat{\beta_1}, \widehat{\beta_2}$, and $\widehat{\beta_4}$, which is 102 minutes. Effects on commuting time and all travel time are also larger for this group.

How can all of this be interpreted? Within teleworkable occupations, having a college degree conveys a post-COVID WFH advantage of about 76 minutes ($\widehat{\beta_1} + \widehat{\beta_4}$); among college graduates, working in a teleworkable occupation conveys a WFH advantage of about 55 minutes ($\widehat{\beta_2} + \widehat{\beta_4}$) after COVID. This suggests that the telework potential index proposed by Dingel and Neiman (2020), though predictive of an increase in WFH for non-graduates in 2021-22, does not capture all of what allows college graduates as a group to increase their WFH after COVID. This is perhaps because of within-occupation heterogeneity in ability to work from home (which would not be described by the index) that is correlated with educational attainment.

Appendix Table 2 shows results for Equation (3) where all other time-use variables analyzed in the paper serve as the outcomes. Effects for college graduates not in teleworkable occupations ($\widehat{\beta_1}$) are similar in sign and magnitude to their counterparts in Tables 4 and 5 for all college grads (though they are less precisely estimated in some cases). Estimates of β_2 and β_4, however, are all imprecisely estimated and sometimes wrong-signed compared to what is predicted by the results in Table 7.

5.3 Interactions with state-level COVID school closures

I now examine whether college graduates living in states with more stringent social distancing policies (in the form of school closures) experienced even larger changes in WFH than those living in states with more lax policies. With longer school closures (as well as other social distancing policies that were correlated with school closures, such as non-essential business closures), individuals may have been more likely to transition to WFH for the first time during late 2020 and early 2021. By the time such policies were lifted in summer 2021, WFH arrangements may have become entrenched. To examine this possibility, I modify Equation (2) as follows:

$$y_i = \alpha + \beta_1 \cdot (yr21_i \cdot colgrad_i) + \beta_2 \cdot (yr21_i \cdot closure_i) + \beta_3 \cdot (closure_i \cdot colgrad_i) + \beta_4 \cdot (yr21_i \cdot closure_i \cdot colgrad_i) + X_i\gamma + \epsilon_i \qquad (4)$$

where $closure_i$ is equal to the percentage of time during the 2020-21 academic year that schools were closed across the state.[14] Regarding WFH as the dependent variable, my hypothesis is that $\beta_4 > 0$, or that WFH increases in fall 2021 were even larger for college graduates living in states with longer school closures.

To measure school closures at the state level, I use *Safegraph* mobile phone location data from Parolin and Lee (2021). The authors track year-over-year changes in the number of visitors to each individual K-12 school in each month relative to the same month in 2019 (the pre-pandemic baseline). Institutions are considered "closed" if there is at least a 50 percent year-over-year decline in the number of in-person visits. I then use the share of closed institutions in

[14] This value stays the same over the entire panel; it would thus be colinear with state fixed effects if it entered the model in levels, though its interactions with other variables are identified.

each state in each month during the 2020-21 academic year (August-May) and average over those months to construct my school-closure variable. The largest value for school closures in the data is about 0.84 (District of Columbia) and the smallest value is about 0.12 (Arkansas). This variable is then converted into standard deviation units for easier interpretation (one standard deviation is about an 18-percentage point change in closure share).

Table 8 shows that with a standardized school-closure value of zero (i.e., the mean value), WFH is predicted to rise (and travel time predicted to fall) for college graduates following COVID. WFH rises further still for college graduates when schools were closed longer over the 2020-21 academic year: a one-standard-deviation increase in school closures raises the post-pandemic college graduate WFH effect ($\widehat{\beta_4}$) by almost 16 minutes. Interestingly, the same change in school closures leads to a reduction in total work time for college graduates in 2021-22, also by about 16 minutes (though this effect is much smaller in percentage terms than the WFH effect). Commuting and travel time are each reduced by almost an additional 4 minutes, though the latter effect is insignificant. These results provide some support for the notion that WFH gained a greater foothold in areas where social distancing policies were more stringent. Notably, college graduates were the only ones to experience a greater post-COVID boost in WFH with longer school closures (the estimated interaction effects between school closure and an indicator for fall 2021, which correspond with β_2 in Equation (4), are generally small and statistically insignificant).

Appendix Table 3 shows results from Equation (4) with other time-use variables serving as the outcomes. With a greater school-closure value, the post-COVID effect for college graduates is accentuated in cases where significant baseline effects were found earlier: eating away from home and eating at home, self-care, free time, and active caring for household children. However, none of the triple interaction (β_4) estimates are statistically significant. As was the case for the analysis by occupational characteristics, my ability to make strong conclusions based on the results is limited by imprecision in the estimates.

5.4 Results by gender

In my last analysis, I examine how my main results differ for men and women given well-documented background differences in work patterns and time use by gender. To do so, I simply run Equation (2) for men and women separately. Results pertaining to work and personal/household/care of children variables are contained in Table 9.[15]

The weekday increase in WFH for college-educated men following COVID is about 20 minutes larger than it is for college women. This is likely due to a few reasons: first, with a greater percentage of men than women in the sample working in the first place (and generally working more hours), there is greater scope for COVID to lead to a larger shift in WFH for men. Second, a larger share of non-graduate women (34%) work in teleworkable jobs than non-graduate men (15%); the percentage of college graduates working in such jobs is very similar across gender at 58-60%.

In concert with the larger change in WFH, travel time and self-care also decline more substantially for college men than for college women. College men also reduce their work time by almost 25 minutes a day, while (if anything) college women see a slight increase; however, neither effect is statistically significant. With men seeing a larger shift toward WFH (and perhaps away from work) following COVID, it is interesting to note that while the free time effects are similar across gender (at 18-20 minutes), only men see a rise in caring for others/household children specifically (of 12-15 minutes). Because the pre-COVID mean values are more than

[15] Full results for all outcomes considered in the paper are available on request.

twice as high for women as they are for men, this change has the effect of shrinking the gender gap in childcare. The increase in time actively engaging with children for college-educated men represents more than 40% of the pre-pandemic difference in this variable across gender.

6. Conclusion

This paper is among the first to examine differences in working-from-home (WFH) and time use by college attainment following the COVID-19 shock to the U.S. economy. College graduates experienced the lion's share of the shift to WFH by 2021-2022 as well as reductions in travel and self-care time that accompanied that change. The most precisely estimated downstream changes in time use are a shift from time spent eating out to eating at home and an increase in free time and time spent actively engaged with children. Such changes may have health and human-capital benefits: in the latter case, parental time with children has been identified as a key driver of the intergenerational correlation in earnings (Gayle, Golan, and Soytas, 2022). This suggests that differences in health and human-capital investments by college attainment, which have grown stronger in recent decades, may be further magnified if the sharp changes in WFH in the wake of COVID persist.[16] As time-use data for additional years becomes available, it will be possible to examine how not only WFH but other time-use variables analyzed in this paper evolve in a post-COVID world.

Though a lack of plausibly exogenous variation in WFH prevents me from ascribing changes in time use by college graduation status to the "WFH revolution," evidence presented throughout the paper suggests that WFH has played an important role in changing time-use patterns for college graduates compared with non-graduates. This includes the fact that variables most directly related to shifts in work from the office to home (travel time, time spent eating out,

[16] Bonacini, Gallo, and Scicchitano (2021) also predict that an increase in WFH feasibility in Italy is likely to increase wage inequality by favoring more highly educated and highly paid workers.

etc.) see the most robust relative changes following COVID. In addition, WFH and associated variable changes are even larger in states that had longer school closures (and, likely, other lockdown policies) during the previous school year. Nevertheless, it will be important to corroborate this evidence with different empirical designs, especially those that harness exogenous variation in WFH to trace out causal effects on downstream outcomes.

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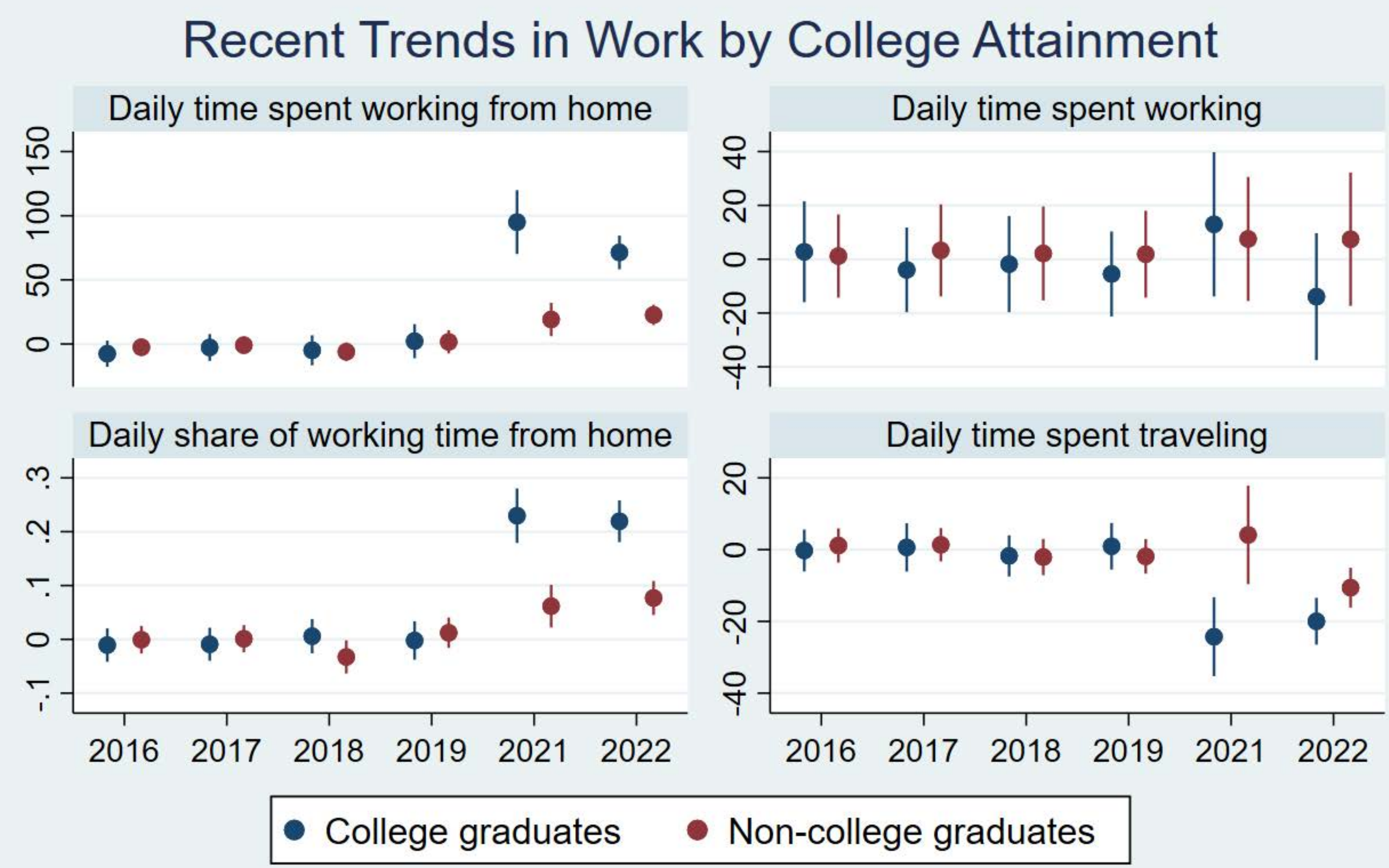
Figure 1:



The sample is composed of weekdays for 2015-2022 (excluding January 2020-July 2021), since all state-level COVID restrictions were lifted by August 2021. All estimate are relative to 2015 (the base year). All point estimates are from OLS models controlling for month, day of week, and holiday fixed effects, plus controls for individual age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment (for non-college grads), and state, industry, and occupation fixed effects.

Table 1: Summary statistics by time period and college attainment

	2015-2019 (pre-COVID)				2021-2022 (post-COVID)			
	Non-graduates		College graduates		Non-graduates		College graduates	
	mean	sd	mean	sd	mean	sd	mean	sd
Number of household children	0.92	1.22	0.85	1.10	0.93	1.22	0.82	1.09
Age	41.96	10.75	40.43	10.29	41.63	10.67	40.68	10.00
State-wide fraction of 2020-21 academic year schools were closed	**N/A**		**N/A**		0.39	0.18	0.42	0.18
Employed	0.75		0.88		0.78		0.89	
Occupation has full telework potential	0.23		0.59		0.24		0.59	
High-school graduate	0.40		**N/A**		0.42		**N/A**	
Some college	0.41		**N/A**		0.39		**N/A**	
White	0.79		0.79		0.79		0.75	
Black	0.15		0.09		0.14		0.11	
Asian	0.03		0.10		0.03		0.12	
Other race	0.03		0.02		0.04		0.02	
Hispanic ethnicity	0.24		0.09		0.29		0.11	
Married	0.54		0.64		0.51		0.62	
Native-born	0.77		0.80		0.74		0.77	
Female	0.49		0.54		0.47		0.54	
Observations	16,740		13,195		3,058		3,211	

Notes: All estimates are weighted by ATUS sample weights.

Table 2: Summary statistics by time period and college attainment

	2015-2019 (pre-COVID)				2021-2022 (post-COVID)			
	Non-graduates		College graduates		Non-graduates		College graduates	
	mean	sd	mean	sd	mean	sd	mean	sd
Main time-use categories								
Traveling	**72**	73	**86**	82	**65**	84	**68**	81
Work	**251**	269	**294**	264	**259**	270	**289**	263
Self-care	**46**	61	**44**	43	**49**	74	**42**	41
Household tasks	**137**	151	**128**	133	**139**	155	**129**	137
Free time	**275**	209	**226**	171	**262**	202	**232**	178
Caring for others	**44**	95	**47**	93	**41**	91	**49**	99
Eating and drinking	**58**	47	**70**	51	**61**	46	**72**	51
Education	**8**	53	**11**	66	**6**	48	**9**	60
Physical activity	**13**	50	**21**	52	**11**	39	**21**	51
Sleep	**526**	144	**504**	113	**536**	149	**518**	113
Detailed time-use categories								
Working from home (WFH)	**17**	84	**44**	122	**36**	124	**116**	205
Share of work time at home	**0.11**	0.29	**0.23**	0.39	**0.17**	0.36	**0.44**	0.48
Caring for household children	**33**	82	**41**	88	**30**	76	**43**	94
Commuting	**22**	39	**25**	39	**20**	38	**15**	30
Eating at home	**35**	37	**38**	36	**41**	38	**48**	41
Eating away from home	**22**	38	**32**	48	**20**	37	**24**	44
Secondary childcare	**123**	230	**116**	216	**122**	227	**118**	224
Observations	16,740		13,195		3,058		3,211	

Notes: All estimates are weighted by ATUS sample weights.

Table 3: Differences in work-related time use after COVID by college attainment

	Time spent working from home	Time spent working at all	Share of work time from home	Commuting time	All travel time
			All days (N=36,204)		
College graduate*(year>=2021)	44.858***	-6.879	0.136***	-7.398***	-11.180***
	(4.901)	(10.409)	(0.017)	(1.011)	(3.094)
College grad pre-COVID mean	44	294	0.23	25	86
			Weekdays (N=18,120)		
College graduate*(year>=2021)	60.338***	-5.225	0.147***	-9.863***	-14.590***
	(6.848)	(11.739)	(0.018)	(1.380)	(3.833)
College grad pre-COVID mean	52	381	0.17	33	86
			Weekends (N=18,084)		
College graduate*(year>=2021)	4.165	-6.045	0.058	-0.929	-3.742
	(2.844)	(9.205)	(0.038)	(0.580)	(4.341)
College grad pre-COVID mean	24	75	0.57	5	86

Notes: *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Table 4: Differences in physical health-related time use after COVID by college attainment

	Physical exercise	Sleep	Eating and drinking	Eating and drinking away from home	Eating and drinking at home
			All days (N=36,204)		
College graduate*(year>=2021)	2.369	4.118	-0.179	-4.233**	3.915***
	(1.456)	(4.366)	(1.448)	(1.665)	(1.222)
College grad pre-COVID mean	21	504	70	32	38
			Weekdays (N=18,120)		
College graduate*(year>=2021)	2.339	6.932	0.805	-3.992*	4.703***
	(1.594)	(6.480)	(1.834)	(2.159)	(1.551)
College grad pre-COVID mean	18	486	66	30	36
			Weekends (N=18,084)		
College graduate*(year>=2021)	4.421	-2.653	-1.552	-3.633*	1.714
	(2.668)	(6.356)	(2.439)	(1.932)	(1.444)
College grad pre-COVID mean	27	550	80	36	45

Notes: *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Table 5: Differences in time use on other variables after COVID by college attainment

	Self-care	Household tasks	Free time	Caring for others	Education	Caring for household children	Secondary childcare for HH children
				All days (N=36,204)			
College graduate*(year>=2021)	-5.443***	-3.078	15.579**	5.225*	-0.502	5.509**	5.472
	(1.719)	(5.683)	(6.978)	(2.854)	(2.477)	(2.505)	(5.174)
College grad pre-COVID mean	44	128	226	47	11	41	116
				Weekdays (N=18,120)			
College graduate*(year>=2021)	-6.644***	-5.517	17.736**	5.421	-1.591	6.902*	9.295
	(2.355)	(6.159)	(7.496)	(4.501)	(3.198)	(3.766)	(6.472)
College grad pre-COVID mean	46	106	186	45	11	40	88
				Weekends (N=18,084)			
College graduate*(year>=2021)	-1.795	1.430	3.422	5.739	1.710	3.050	2.144
	(2.756)	(7.550)	(13.380)	(4.468)	(2.554)	(3.415)	(7.181)
College grad pre-COVID mean	41	181	325	53	10	45	184

Notes: *** p<0.01, ** p<0.05, * p<0.1. All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Table 6: Differences in time use after COVID by college attainment and presence of household children

	Time spent working from home	Time spent working at all	All travel time	Self-care	Household tasks	Free time	Caring for others	Caring for household children	Secondary childcare for HH children
				Individuals with household children (N=9,800)					
College graduate *(year>=2021)	68.423***	-12.483	-14.283***	-6.030	-20.160**	22.187**	19.538**	18.859***	23.422*
	(9.452)	(13.748)	(5.160)	(3.627)	(7.626)	(8.661)	(7.947)	(6.938)	(12.311)
College grad pre-COVID mean	52	367	90	42	114	161	91	87	194
				Individuals without household children (N=8,320)					
College graduate *(year>=2021)	49.330***	-5.085	-15.319***	-7.754**	6.385	11.693	-2.894	N/A	N/A
	(9.376)	(16.726)	(5.375)	(3.688)	(8.346)	(12.044)	(4.027)		
College grad pre-COVID mean	52	393	83	48	100	206	6	N/A	N/A

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays. All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Table 7: Differences in work-related time use after COVID by college attainment and occupational telework potential

	Time spent working from home	Time spent working at all	Share of work time from home	Commuting time	All travel time
College graduate*(year>=2021)	47.268***	-2.874	0.106***	-9.410***	-17.938***
	(9.165)	(14.631)	(0.022)	(2.381)	(4.627)
(Telework=1)*(year>=2021)	26.373*	6.605	0.060**	-7.840**	-20.414**
	(15.088)	(18.738)	(0.028)	(3.512)	(8.263)
College graduate*(telework=1)	-6.395	-11.476	-0.009	-2.210	0.031
	(6.671)	(9.985)	(0.018)	(2.183)	(2.874)
College graduate*(year>=2021)*(telework=1)	28.342**	-6.370	0.067**	-2.224	8.557
	(12.268)	(15.108)	(0.028)	(2.719)	(5.255)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays. N=14,714 (only those with a Census occupation code appear in the regression). All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Table 8: Differences in work-related time use after COVID by college attainment and state school closure length

	Time spent working from home	Time spent working at all	Share of work time from home	Commuting time	All travel time
College graduate*(year>=2021)	57.431***	-3.267	0.138***	-9.102***	-13.818***
	(6.617)	(9.909)	(0.012)	(1.421)	(3.809)
(School closure)*(year>=2021)	4.483	8.504	0.006	-2.149	-2.436
	(5.249)	(9.462)	(0.013)	(1.414)	(4.568)
College graduate*(school closure)	1.124	2.968	0.002	-0.341	-0.584
	(1.371)	(3.626)	(0.005)	(0.581)	(1.021)
College graduate*(year>=2021)*(school closure)	15.893***	-16.395**	0.057***	-3.708***	-3.615
	(5.230)	(7.119)	(0.013)	(0.860)	(3.140)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays (N=18,120). All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Table 9: Differences in work- and care-related time use after COVID by college attainment and gender

	Time spent working from home	Time spent working at all	All travel time	Self-care	Household tasks	Free time	Caring for others	Caring for household children	Secondary childcare for HH children
					Men (N=8,408)				
College graduate*(year>=2021)	68.152***	-24.893	-18.569***	-7.442**	2.905	20.103*	14.872***	11.657***	9.759
	(10.927)	(18.286)	(5.248)	(3.262)	(8.630)	(11.722)	(3.978)	(4.066)	(7.200)
College grad pre-COVID mean	57	445	88	38	73	184	28	25	64
					Women (N=9,712)				
College graduate*(year>=2021)	48.546***	6.931	-10.448**	-4.349	-10.978	18.261**	-3.376	2.101	9.620
	(8.192)	(14.926)	(4.376)	(3.560)	(8.221)	(7.991)	(6.818)	(5.365)	(12.738)
College grad pre-COVID mean	47	326	84	52	136	187	59	52	110

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays. All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Appendix Table 1: Differences in employment outcomes after COVID by college attainment

	Employed	Family income ($)	Log family income	Teleworkable occupation
College graduate*(year>=2021)	-0.009	2,991.613	-0.012	-0.018
	(0.011)	(2,401.396)	(0.029)	(0.014)
College grad pre-COVID mean	0.88	113,732	11.43	0.59

Notes: *** p<0.01, ** p<0.05, * p<0.1. N=36,204. All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, and state fixed effects. Columns 2 and 3 regressions also control for detailed industry and occupation fixed effects, and the Column 4 regression controls for detailed industry fixed effects (N=29,256 in this regression since the outcome is not defined for those who do not have an occupation in the data). Family income is an approximate continous measure derived from categorical responses (16 categories; the midpoints of each category range are used except for the top category, $150k and over, in which case $200k is used). Standard errors are clustered at the state level.

Appendix Table 2: Differences in other time use after COVID by college attainment and occupational telework potential

	Physical exercise	Sleep	Eating and drinking	Eating and drinking away from home	Eating and drinking at home	Self-care
College graduate*(year>=2021)	1.018	10.386	0.224	-3.156	3.234	-10.747***
	(3.161)	(6.457)	(2.272)	(2.117)	(2.009)	(3.119)
(Telework=1)*(year>=2021)	0.240	0.820	0.241	1.942	-1.650	-0.861
	(2.891)	(11.836)	(3.958)	(4.649)	(3.053)	(4.690)
College graduate*(telework=1)	1.708	9.877*	1.036	0.399	0.751	-5.236
	(2.174)	(5.657)	(2.176)	(2.099)	(1.634)	(3.272)
College graduate	-0.732	-9.570	4.739*	0.185	4.420*	4.489
(year>=2021)(telework=1)	(3.776)	(6.566)	(2.510)	(3.507)	(2.481)	(3.192)

	Household tasks	Free time	Caring for others	Education	Caring for household children	Secondary childcare for HH children
College graduate*(year>=2021)	1.392	13.636*	6.806	-2.250	8.790**	8.085
	(7.566)	(7.894)	(4.218)	(2.936)	(3.355)	(9.145)
(Telework=1)*(year>=2021)	-5.944	16.851	5.359	-0.970	5.666	-3.914
	(11.541)	(13.216)	(5.936)	(4.630)	(5.416)	(8.596)
College graduate*(telework=1)	-1.938	-4.360	10.228***	0.672	4.967*	10.624*
	(5.506)	(7.262)	(2.844)	(3.024)	(2.778)	(6.049)
College graduate	0.504	-2.259	-2.028	1.045	-2.447	-3.740
(year>=2021)(telework=1)	(7.431)	(9.778)	(4.589)	(3.044)	(4.192)	(9.532)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays. N=14,714 (only those with a Census occupation code appear in the regression). All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.

Appendix Table 3: Differences in other time use after COVID by college attainment and state school closure length

	Physical exercise	Sleep	Eating and drinking	Eating and drinking away from home	Eating and drinking at home	Self-care
College graduate*(year>=2021)	2.498	6.239	0.704	-3.772*	4.386***	-6.695***
	(1.618)	(6.126)	(1.883)	(1.944)	(1.399)	(2.404)
(School closure)*(year>=2021)	-0.872	-5.277	3.566***	1.342	2.180**	2.099
	(1.473)	(4.502)	(1.219)	(1.111)	(1.016)	(2.977)
College graduate*(school closure)	1.329*	-2.844	0.120	0.746	-0.689	-2.455***
	(0.722)	(2.370)	(0.706)	(1.027)	(0.905)	(0.815)
College graduate *(year>=2021)*(school closure)	-0.720	7.027*	-1.022	-2.063	1.040	-0.401
	(1.172)	(3.561)	(1.605)	(2.408)	(1.529)	(1.347)

	Household tasks	Free time	Caring for others	Education	Caring for household children	Secondary childcare for HH children
College graduate*(year>=2021)	-5.927	16.690**	4.980	-1.824	6.425*	8.823
	(6.060)	(7.267)	(4.506)	(3.247)	(3.822)	(6.421)
(School closure)*(year>=2021)	-1.447	-6.028	-0.905	3.901*	0.585	-4.273
	(3.774)	(8.392)	(3.438)	(2.232)	(2.912)	(6.433)
College graduate*(school closure)	0.303	-0.538	1.426	-1.624	1.213	3.405
	(3.060)	(2.298)	(1.433)	(1.151)	(1.262)	(2.989)
College graduate *(year>=2021)*(school closure)	3.189	9.334	3.010	-0.188	2.576	4.561
	(4.611)	(5.791)	(3.114)	(2.206)	(2.463)	(4.417)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays (N=18,120). All regressions are weighted by ATUS sample weights. All regressions include controls for year by month, day of week, and holiday fixed effects, controls for age (and its square), MSA size dummies, marital status, number of household children, sex, race/ethnicity dummies, native status, high-school graduation and some college attainment, state fixed effects, and detailed industry and occupation fixed effects. Standard errors are clustered at the state level.