

NBER WORKING PAPER SERIES

TIME USE, COLLEGE ATTAINMENT, AND THE WORKING-FROM-HOME REVOLUTION

Benjamin W. Cowan

Working Paper 31439

<http://www.nber.org/papers/w31439>

NATIONAL BUREAU OF ECONOMIC RESEARCH

1050 Massachusetts Avenue

Cambridge, MA 02138

July 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. Nothing to disclose. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

NBER working papers are circulated for discussion and comment purposes. They have not been peer-reviewed or been subject to the review by the NBER Board of Directors that accompanies official NBER publications.

© 2023 by Benjamin W. Cowan. All rights reserved. Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

Time Use, College Attainment, and The Working-from-Home Revolution
Benjamin W. Cowan
NBER Working Paper No. 31439
July 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 fall 2021 weekdays increased by over 90 minutes for college graduates; for non-graduates, it was 17 minutes. The share of work done at home (for those who worked at all) increased by 21% for graduates and 6% for non-graduates. Average minutes worked changed little for either group. Daily time spent traveling (e.g., commuting) fell by 24 minutes for college graduates but did not change for non-graduates. I examine how time-use patterns change for college graduates relative to non-graduates over the same period. Preliminary evidence suggests that time spent with children has risen for college graduates relative to non-graduates, potentially a sign that gaps in children's outcomes by college attainment will be exacerbated by the WFH revolution.

Benjamin W. Cowan
School of Economic Sciences
Washington State University
103E Hulbert Hall
Pullman, WA 99164
and NBER
ben.cowan@wsu.edu

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).² 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 to 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), and, 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

² 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 this switch are also likely to be concentrated among those with college degrees.

Using American Time Use Survey (ATUS) data from the fall (August-December) months of 2015-2019 and 2021, I document that WFH has increased substantially among college graduates but much more modestly among those without a college degree (I refer to these individuals as non-graduates throughout the paper).³ Relative to 2015-19, the number of minutes worked from home on fall 2021 weekdays increased by over 90 minutes for college graduates; for non-graduates, it was 17 minutes. The share of work done at home (for those who worked at all) increased by 21% for graduates and 6% 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 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 relative to prior

³ 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. Because I focus on August-December 2021 as my “post-COVID” period, I focus on the same calendar months in 2015-19 (my “pre-COVID” period).

years. However, there are reasons to believe that such changes are related to WFH, as I argue below.

The largest change that occurs across these 10 categories is in travel—on 2021 weekdays, college graduates spend 27 fewer minutes traveling than do non-graduates (all relative to the same difference in the pre-pandemic period). A little more than half of this reduction is due to a decrease in commuting time specifically. College graduates also spend about 12 fewer minutes per weekday in self-care (e.g., personal grooming) compared to non-graduates in 2021 (again, all compared to the college attainment gap 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 40 minutes per day? No effects on the other 8 categories of time use are statistically significant at conventional levels, though point estimates suggest a roughly 10-15-minute increase in work time, sleep, free time, and caring for others. Notably, when I examine time spent in active engagement with household children, the difference between college graduates and non-graduates grows by a statistically significant 11 minutes (the pre-pandemic difference by college attainment is only about 7 minutes). Effects of college attainment in 2021 on time-use allocations are generally small and insignificant on weekends, though there is evidence of a partial substitution toward more travel on weekends.

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 percent versus 22 percent 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 in fully telework-compatible occupations, 2) college graduates not in such occupations, and 3) non-graduates in in fully telework-compatible occupations, all experienced a substantial rise in WFH in 2021. 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 fall 2021 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 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 fall 2021 is magnified. Many but not all of the time-use variables analyzed follow the same pattern.

Lastly, I examine how these results vary by gender. On average, college-educated men experience a much larger relative change in WFH than do college-educated women. This may be

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>.

partially explained by the fact that a much higher percentage of non-college-educated women hold jobs that can be performed from home (33%) than do similarly situated men (14%). Effects are imprecisely estimated, but point estimates hint at a partial reallocation of household activities from college-educated women to college-educated men, though not with regard to active engagement with household children.

2. Related Literature

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.

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.⁵ Second, I am able to examine detailed time-use categories that pertain to gaps in behavioral health and time spent with children by education

⁵ In particular, better-educated individuals are overrepresented in the G-SWA (Aksoy et al., 2023).

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.

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.

There is evidence that time-intensive inputs into the development of own and children's human capital 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 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 only use the period August to December in each year I analyze. 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 2021.⁶ Because I focus on August-December 2021 as my “post-COVID” period, I focus on the same calendar months in 2015-19 (my “pre-COVID” period). My main sample is composed of all individuals ages 24 to 59; this includes 13,716 respondents. Summary statistics for economic and demographic variables

⁶ See <https://www.kff.org/other/state-indicator/state-actions-to-mitigate-the-spread-of-covid-19/?activeTab=map¤tTimeframe=0&selectedDistributions=status-of-reopening&sortModel=%7B%22colId%22:%22Location%22,%22sort%22:%22asc%22%7D>.

separated by “pre-COVID” (2015-2019) and “post-COVID” (2021) as well as college attainment are contained in Table 1.

Following Cowan, Jones, and Swigert (2023), I collapse over 400 activity codes in the ATUS into 10 main categories: 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, I examine as dependent variables 1) the 10 categories of time used listed above, 2) commuting 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) 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 time period of study. To do this, I regress WFH (and related variables) on a set of time-related fixed effects (year, month, day of week, holiday) and 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, native born, educational attainment (high-school graduate, some college, college graduate, with less than high school as the omitted category), and detailed industry and occupation dummies.

In Figure 1, I show the results of these regressions run separately for college graduates and non-graduates on weekdays. Each sub-figure contains the coefficients 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 91 minutes relative to 2015) and a much more modest (but still statistically significant) jump for non-graduates (of 17 minutes). 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 21% for college graduates and 6% for non-graduates). Lastly, daily travel time falls after COVID by 24 minutes for college graduates but does not change for non-graduates.

It is clear from these figures that the changes in WFH and related variables in 2021 are due to COVID and its fallout rather than the result of a longer-term trend toward more WFH. In addition, it is clear that as a whole, 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 difference-in-differences (DD) regression model:

$$y_i = \alpha + \beta \cdot (yr21_i \cdot colgrad_i) + X_i\gamma + \epsilon_i \quad (1)$$

where, for individual i , y is minutes spent in a particular time category; $yr21_i$ is an indicator for being interviewed in 2021 (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 in addition to the controls used in the event-study analysis in Figure 1. My coefficient of interest, β , measures the difference in time use for college graduates relative to non-graduates in the post-COVID (fall 2021) period all relative to the same difference in the pre-COVID (fall 2015-fall 2019) period. Equation (1) is estimated on all days, weekdays, and weekends separately. Later in the paper, I discuss modifications to Equation (1) 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.

5. Results

5.1 Baseline estimates

Table 1 shows that demographic/economic variable averages experience at most small changes from the pre- to post-COVID period, and generally such changes are similar for college graduates and non-graduates.⁷ 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 $((131-47) - (34-16))$, or roughly 66 minutes. Reductions in travel time (and commuting time specifically) are concentrated among 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.

⁷ Following national trends, the percentage of college graduates in the ATUS data rises steadily from around 39% in 2015 to 44% by 2021.

To examine changes in these variables in a more systematic way, I analyze regression models represented in Equation (1). In Table 3, I include variables specifically related to WFH. College graduates experience a 57-minute larger increase in WFH after the pandemic than do non-graduates. This effect is fully due to the relative change on weekdays (of 74 minutes) with no change on weekends. With regard to total work time, the DD coefficients are positive overall and on weekdays but relatively small (8 and 13 minutes, respectively) and statistically insignificant.⁸ Relative commuting times for college graduates fall by 10 (all days) and 15 (weekdays) minutes, with no effect on weekends. Changes in total travel time are even larger—on weekdays, the relative change in total travel time (of 27 minutes) is almost twice as large as the change in commuting time. 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 the case of total travel time, there is evidence of partial offsetting on weekends, as travel time increases for college graduates relative to non-graduates in the post-pandemic period (by 13 minutes, which is significant at the 10% level).

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 (obviously, college attainment affects time use through many channels besides WFH, even after controlling for everything in Equation 1). 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).

⁸ It is also the case that college graduates do not experience a differential change in the probability of employment from before to after COVID; the coefficient of the interaction of college graduate and fall 2021 in a regression in which employment (binary) is the dependent variable is -0.003 (SE=0.016).

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 statistically insignificant. The effect on eating and drinking overall is also insignificant, but there is a statistically significant decline (at the 5% level) of 5 minutes in time spent eating out on all days. This effect is again concentrated on weekdays, though the coefficient is marginally insignificant at conventional levels. 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 (the effect on eating time at home is positive on all days and weekdays, but it is smaller in magnitude and insignificant). 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 10 (12) 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; effects on free time and caring for others are larger, positive, but also imprecisely estimated. The increase in free time (caring for others) on weekdays of 18 (10) minutes is roughly a 10% (20%) change at the mean. The effect on own educational activities is curiously negative and large relative to the mean on weekdays, but again this is not statistically different from zero.

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 11 minutes on weekdays for college graduates relative to non-graduates following COVID, which is a sizable increase (of roughly 26%). 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 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 effect is statistically significant.

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 larger, though none are precisely estimated at conventional levels.⁹ A comparison of selected effects by presence of household children are contained in Appendix Table 1 (full results available on request).

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 (1) as follows:

⁹ 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.

$$y_i = \alpha + \beta_1 \cdot (yr21_i \cdot colgrad_i) + \beta_2 \cdot (yr21_i \cdot tele_i) + \beta_3 \cdot (tele_i \cdot colgrad_i) + \beta_4 \cdot (yr21_i \cdot tele_i \cdot colgrad_i) + X_i\gamma + \epsilon_i \quad (2)$$

where $tele_i$ is equal to one if an individual works in an occupational with full telework potential according to Dingel and Neiman (2020).^{10 11} That is, I allow for interactions between telework potential and the post-COVID (2021) 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 6.

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 dramatic rise in WFH following COVID compared to non-graduates in such occupations ($\widehat{\beta}_1 = 102$ minutes). Individuals in teleworkable occupations but with no college degree also see a large rise in WFH after COVID compared to non-graduates who do not work in such occupations ($\widehat{\beta}_2 = 86$ minutes). Lastly, what is the post-COVID effect for college graduates in teleworkable occupations compared to non-graduates

¹⁰ 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.

¹¹ 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_bls_codes.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).

outside of those occupations? This would be the sum of $\beta_1, \beta_2,$ and $\beta_4,$ which is 105.4 minutes, hardly bigger than the effect for college graduates outside of teleworkable occupations. Effects on commuting time and all travel time follow a very similar pattern.

How can all of this be interpreted? Within teleworkable occupations, having a college degree conveys a moderate WFH advantage (of 20-25 minutes per day). However, working in a teleworkable occupation conveys very little WFH advantage for college graduates. College graduates outside of these occupations see their WFH increase in the wake of COVID by a similar amount to those graduates inside the teleworkable occupation category. 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, does not capture 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 (2) where all other time-use variables analyzed in the paper serve as the outcomes. Results for eating out, self-care, and caring for household children follow a similar pattern to the one described for WFH. Results pertaining to other uses of time are mixed and imprecisely estimated.

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 (1) as follows:

$$y_i = \alpha + \beta_1 \cdot (yr21_i \cdot colgrad_i) + \beta_2 \cdot (yr21_i \cdot closure_i) + \beta_3 \cdot (closure_i \cdot colgrad_i) + \beta_4 \cdot (yr21_i \cdot closure_i \cdot colgrad_i) + X_i\gamma + \epsilon_i \quad (3)$$

where $closure_i$ is equal to percentage of time during the 2020-21 academic year that schools were closed across the state. 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 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 closures).

Table 7 shows that with a standardized school-closure value of zero (at the mean), WFH is predicted to rise (and travel time predicted to fall) for college graduates following COVID. However, 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 closure raises WFH by

almost 30 minutes and lowers travel time by about 20 minutes, though commuting time specifically is surprisingly unaffected). 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 (3), are all small and statistically insignificant).

Appendix Table 3 shows results from Equation (3) 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 the cases of sleep and eating away from home, as expected. However, I do not see an associated bump in free time or caring for others, including caring for household children. 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

Lastly, 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 (1) for men and women separately. Results pertaining to work and household/care of children variables are contained in Table 8, and results for all other variables are contained in Appendix Table 4.

The increase in WFH for college-educated men is more than 4 times as large as 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, the increase in WFH

among non-college educated women after COVID was substantially larger than it was for similar men (in the raw data, the difference is about 15 minutes). This is consistent with a larger share of non-graduate women (33%) being in teleworkable jobs than non-graduate men (14%).

In concert with the larger change in WFH, travel time also declines more substantially for college men than for college women. With such men seeing a larger shift toward WFH following COVID, it is interesting to note more positive effects on household tasks, caring for others, and secondary childcare for men (though again, no effects are statistically significant). These changes would go toward shrinking gender gaps (as seen by the differences in pre-COVID means). Time specifically devoted to actively caring for household children, however, is slightly larger for women in spite of a pre-COVID average that is about twice that for men. Appendix Table 4 indicates that accompanying their large change in WFH, college men spend additional time in physical exercise (12 minutes) and free time (27 minutes) to offset less travel and self-care time.

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 fall 2021 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 reduction in time spent eating out and an increase in time spent actively engaged with children. Both 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 Soyatas, 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. As time-use data for 2022 and beyond 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, 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.

Bibliography

Aksoy, Cevat Giray, Jose Maria Barrero, Nicholas Bloom, Steven J. Davis, Mathias Dolls, and Pablo Zarate. *Working from home around the world*. No. w30446. National Bureau of Economic Research, 2022.

Aksoy, Cevat Giray, Jose Maria Barrero, Nicholas Bloom, Steven J. Davis, Mathias Dolls, and Pablo Zarate. *Time savings when working from home*. No. w30866. National Bureau of Economic Research, 2023.

Alipour, Jean-Victor, Harald Fadinger, and Jan Schymik. "My home is my castle—The benefits of working from home during a pandemic crisis." *Journal of Public Economics* 196 (2021): 104373.

Barcellos, Silvia H., Leandro S. Carvalho, and Patrick Turley. "Education can reduce health differences related to genetic risk of obesity." *Proceedings of the National Academy of Sciences* 115, no. 42 (2018): E9765-E9772.

Barrero, Jose Maria, Nicholas Bloom, and Steven J. Davis. *Why working from home will stick*. No. w28731. National Bureau of Economic Research, 2021.

Bloom, Nicholas. "How working from home works out." *Stanford Institute for economic policy research* 8 (2020).

Case, Anne, and Angus Deaton. "The great divide: education, despair, and death." *Annual Review of Economics* 14 (2022): 1-21.

Carneiro, Pedro, Costas Meghir, and Matthias Parey. "Maternal education, home environments, and the development of children and adolescents." *Journal of the European Economic Association* 11, no. suppl_1 (2013): 123-160.

Chen, Yuting, Patricia Cortés, Gizem Koşar, Jessica Pan, and Basit Zafar. *The Impact of COVID-19 on Workers' Expectations and Preferences for Remote Work*. No. w30941. National Bureau of Economic Research, 2023.

Cowan, Benjamin W., Todd R. Jones, and Jeffrey M. Swigert. *Parental and Student Time Use around the Academic Year*. No. w31177. National Bureau of Economic Research, 2023.

Cutler, David M., and Adriana Lleras-Muney. "Understanding differences in health behaviors by education." *Journal of health economics* 29, no. 1 (2010): 1-28.

Dingel, Jonathan I., and Brent Neiman. "How many jobs can be done at home?." *Journal of Public Economics* 189 (2020): 104235.

Doepke, Matthias, Giuseppe Sorrenti, and Fabrizio Zilibotti. "The economics of parenting." *Annual Review of Economics* 11 (2019): 55-84.

Sarah M. Flood, Liana C. Sayer and Daniel Backman. *American Time Use Survey Data Extract Builder: Version 3.1* [dataset]. College Park, MD: University of Maryland and Minneapolis, MN: IPUMS, 2022. <https://doi.org/10.18128/D060.V3.1>

Galama, Titus J., Adriana Lleras-Muney, and Hans Van Kippersluis. "The Effect of Education on Health and Mortality: A Review of Experimental and Quasi-Experimental Evidence." (2018).

Gayle, George-Levi, Limor Golan, and Mehmet A. Soytaş. "What is the source of the intergenerational correlation in earnings?." *Journal of Monetary Economics* 129 (2022): 24-45.

Goldin, Claudia, and Lawrence F. Katz. "The race between education and technology." In *Inequality in the 21st Century*, pp. 49-54. Routledge, 2018.

Guryan, Jonathan, Erik Hurst, and Melissa Kearney. "Parental education and parental time with children." *Journal of Economic perspectives* 22, no. 3 (2008): 23-46.

Hiza, Hazel AB, Kellie O. Casavale, Patricia M. Guenther, and Carole A. Davis. "Diet quality of Americans differs by age, sex, race/ethnicity, income, and education level." *Journal of the Academy of Nutrition and Dietetics* 113, no. 2 (2013): 297-306.

Lachat, Carl, E. Nago, Roosmarijn Verstraeten, Dominique Roberfroid, John Van Camp, and Patrick Kolsteren. "Eating out of home and its association with dietary intake: a systematic review of the evidence." *Obesity reviews* 13, no. 4 (2012): 329-346.

Park, Kiwoong, and Jinho Kim. "Longitudinal association between perceived discrimination and sleep problems among young adults in the United States: Tests of moderation by race/ethnicity and educational attainment." *Social Science & Medicine* 321 (2023): 115773.

Parolin, Zachary, and Emma K. Lee. "Large socio-economic, geographic and demographic disparities exist in exposure to school closures." *Nature human behaviour* 5, no. 4 (2021): 522-528.

Sheehan, Connor M., Katrina M. Walsemann, and Jennifer A. Ailshire. "Race/ethnic differences in educational gradients in sleep duration and quality among US adults." *SSM-population health* 12 (2020): 100685.

Figure 1:

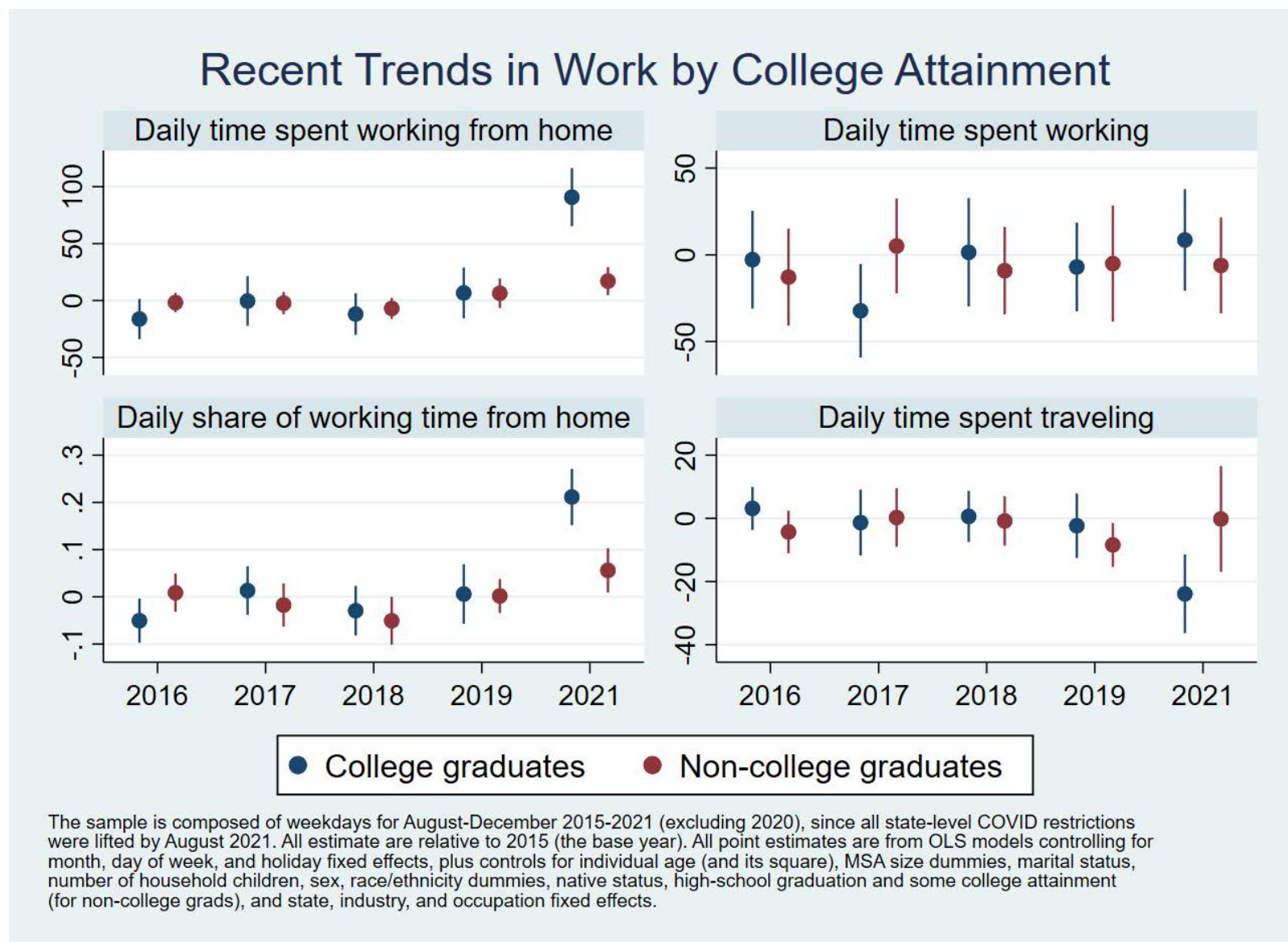


Table 1: Summary statistics by time period and college attainment

	2015-2019 (pre-COVID)				2021 (post-COVID)			
	Non-graduates		College graduates		Non-graduates		College graduates	
	mean	sd	mean	sd	mean	sd	mean	sd
Number of household children	0.93	1.23	0.88	1.13	0.94	1.25	0.82	1.07
Age	41.87	10.81	40.79	10.23	41.56	10.50	40.81	10.03
State-wide fraction of 2020-21 academic year schools were closed	N/A		N/A		0.39	0.18	0.42	0.17
Employed	0.75		0.88		0.77		0.89	
Occupation has full telework potential	0.22		0.59		0.24		0.58	
High-school graduate	0.40		N/A		0.44		N/A	
Some college	0.41		N/A		0.38		N/A	
White	0.79		0.79		0.79		0.78	
Black	0.15		0.09		0.14		0.09	
Asian	0.02		0.10		0.04		0.11	
Other race	0.03		0.02		0.03		0.02	
Hispanic ethnicity	0.24		0.09		0.29		0.11	
Married	0.54		0.65		0.52		0.64	
Native-born	0.78		0.80		0.74		0.77	
Female	0.49		0.54		0.49		0.53	

Notes: All estimates are weighted by ATUS sample weights. N=13,716.

Table 2: Summary statistics by time period and college attainment

	2015-2019 (pre-COVID)				2021 (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	85	79	71	107	68	84
Work	250	269	292	266	252	270	303	270
Self-care	45	59	44	45	53	83	41	35
Household tasks	137	150	129	135	141	148	132	136
Free time	272	208	228	174	262	203	226	172
Caring for others	46	97	47	93	42	86	51	102
Eating and drinking	58	47	70	53	59	46	71	50
Education	8	57	12	73	9	53	9	60
Physical activity	14	54	19	50	11	39	21	43
Sleep	526	144	501	114	531	147	511	104
Detailed time-use categories								
Working from home (WFH)	16	81	47	128	34	121	131	222
Share of work time at home	0.10	0.29	0.24	0.40	0.17	0.35	0.47	0.48
Caring for household children	34	82	41	87	31	75	44	97
Commuting	22	39	25	41	22	40	15	29
Eating at home	35	37	39	37	39	38	48	39
Eating away from home	22	38	31	49	20	35	23	42
Secondary childcare	122	227	117	216	118	225	120	227

Notes: All estimates are weighted by ATUS sample weights. N=13,716.

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

	Time spent working from home	Time spent working at all	Commuting time	All travel time
All days (N=13,716)				
College graduate*(year=2021)	56.538*** (9.463)	8.174 (11.942)	-10.161*** (2.209)	-15.748** (6.197)
College grad pre-COVID mean	47	292	25	85
R-square	0.256	0.493	0.291	0.119
Weekdays (N=6,840)				
College graduate*(year=2021)	74.206*** (13.901)	12.709 (15.407)	-14.537*** (3.263)	-27.306*** (9.422)
College grad pre-COVID mean	56	378	33	86
R-square	0.337	0.526	0.316	0.173
Weekends (N=6,876)				
College graduate*(year=2021)	-0.106 (5.471)	-15.158 (13.599)	0.698 (1.319)	13.188* (6.594)
College grad pre-COVID mean	25	78	5	83
R-square	0.174	0.309	0.232	0.159

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=13,716)					
College graduate*(year=2021)	3.774 (2.543)	6.798 (7.294)	-3.099 (2.418)	-5.269** (2.490)	1.931 (2.128)
College grad pre-COVID mean	19	501	70	31	39
R-square	0.093	0.204	0.143	0.141	0.157
Weekdays (N=6,840)					
College graduate*(year=2021)	3.927 (2.799)	11.046 (10.642)	-3.863 (3.929)	-6.582 (4.442)	2.499 (2.633)
College grad pre-COVID mean	17	482	67	30	37
R-square	0.139	0.230	0.184	0.205	0.205
Weekends (N=6,876)					
College graduate*(year=2021)	3.794 (4.758)	-0.109 (9.531)	1.011 (4.361)	2.504 (3.164)	-1.892 (3.416)
College grad pre-COVID mean	26	549	80	34	45
R-square	0.221	0.186	0.215	0.198	0.215

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=13,716)							
College graduate*(year=2021)	-9.882** (4.144)	-2.916 (8.290)	10.338 (10.038)	7.468 (4.979)	-3.822 (4.731)	8.413** (4.082)	16.714 (11.896)
College grad pre-COVID mean	44	129	228	47	12	41	117
R-square	0.110	0.225	0.301	0.246	0.106	0.309	0.424
Weekdays (N=6,840)							
College graduate*(year=2021)	-12.219** (5.068)	-4.968 (9.924)	17.918 (11.679)	9.614 (6.865)	-7.937 (6.610)	11.419** (5.467)	19.621 (15.591)
College grad pre-COVID mean	45	108	188	45	13	40	92
R-square	0.158	0.319	0.302	0.315	0.143	0.371	0.423
Weekends (N=6,876)							
College graduate*(year=2021)	-3.986 (4.418)	-3.060 (15.821)	-5.951 (22.827)	10.267 (7.385)	5.234 (3.946)	5.147 (6.942)	13.452 (14.450)
College grad pre-COVID mean	41	180	328	52	9	43	178
R-square	0.119	0.208	0.243	0.235	0.160	0.272	0.518

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 work-related time use after COVID by college attainment and occupational telework potential

	Time spent working from home	Time spent working at all	Commuting time	All travel time
College graduate*(year=2021)	101.609*** (21.331)	13.053 (25.028)	-19.240** (7.977)	-37.552*** (11.103)
(Telework=1)*(year=2021)	86.210*** (22.489)	-9.572 (35.343)	-14.289* (7.348)	-32.661*** (8.347)
College graduate*(telework=1)	-11.853 (10.401)	-3.405 (19.868)	-2.516 (3.748)	-0.129 (6.346)
College graduate*(year=2021)*(telework=1)	-82.408** (33.588)	-4.248 (41.731)	9.554 (10.608)	34.338** (14.740)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays. N=5,547 (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 7: 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	Commuting time	All travel time
College graduate*(year=2021)	69.032*** (12.137)	9.958 (16.194)	-13.655*** (3.437)	-25.098*** (8.505)
(School closure)*(year=2021)	-2.367 (5.150)	1.427 (12.483)	-1.796 (2.007)	7.378 (7.941)
College graduate*(school closure)	3.900 (2.871)	-3.261 (5.557)	-1.075 (0.844)	-0.913 (2.116)
College graduate*(year=2021)*(school closure)	29.038*** (8.854)	13.061 (17.267)	-2.242 (3.129)	-20.156** (9.390)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays (N=6,840). 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- 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	Household tasks	Caring for others	Caring for household children	Secondary childcare for HH children
Men (N=3,208)							
College graduate*(year=2021)	111.424*** (22.832)	3.866 (23.752)	-36.174** (14.768)	2.713 (12.476)	9.597 (6.748)	5.030 (5.979)	21.636 (15.936)
College grad pre-COVID mean	61	437	90	76	29	26	67
Women (N=3,632)							
College graduate*(year=2021)	26.103* (15.420)	18.414 (19.493)	-15.835 (10.679)	-14.157 (10.573)	0.331 (9.796)	8.399 (8.900)	-0.900 (25.892)
College grad pre-COVID mean	52	327	82	136	59	52	113

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 time use after COVID by college attainment and presence of household children

	Self-care	Household tasks	Free time	Caring for others	Caring for household children	Secondary childcare for HH children
Individuals with household children (N=3,781)						
College graduate*(year=2021)	-18.306** (8.297)	-8.089 (14.440)	32.074* (17.790)	15.696 (11.793)	17.766 (11.371)	36.635 (31.280)
College grad pre-COVID mean	41	113	157	90	85	196
R-square	0.168	0.406	0.324	0.351	0.353	0.369
Individuals without household children (N=3,059)						
College graduate*(year=2021)	-3.467 (6.310)	-5.216 (16.026)	20.170 (20.957)	2.859 (8.746)	N/A	N/A
College grad pre-COVID mean	48	103	214	6	N/A	N/A
R-square	0.374	0.388	0.392	0.216		

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 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)	-6.904 (5.298)	20.060 (12.935)	-3.627 (4.450)	-7.261** (3.223)	3.124 (2.711)	-14.952** (6.602)
College graduate*(telework=1)	-3.402 (3.279)	6.805 (9.240)	1.078 (3.535)	1.215 (3.118)	-0.472 (2.740)	-5.069 (3.073)
(Telework=1)*(year=2021)	-3.068 (4.543)	7.730 (17.200)	-4.790 (7.087)	-5.445 (5.833)	0.285 (4.654)	-11.272 (11.352)
College graduate*(year=2021)*(telework=1)	12.727* (7.019)	-24.406 (17.456)	10.461 (8.883)	6.742 (7.978)	4.134 (6.108)	18.936 (11.374)
	Household tasks	Free time	Caring for others	Education	Caring for household children	Secondary childcare for HH children
College graduate*(year=2021)	5.811 (15.621)	33.473* (16.672)	6.602 (8.903)	-12.663* (6.696)	14.288** (6.643)	22.183 (21.500)
College graduate*(telework=1)	-3.099 (9.255)	-2.903 (11.469)	11.060* (5.806)	4.868 (4.820)	9.091 (5.652)	11.491 (11.734)
(Telework=1)*(year=2021)	-1.231 (22.762)	56.426*** (17.056)	11.655 (11.127)	-9.640 (7.731)	10.489 (10.011)	-2.761 (18.463)
College graduate*(year=2021)*(telework=1)	-7.384 (26.160)	-59.297** (23.573)	-3.774 (14.380)	15.448 (10.973)	-8.966 (13.075)	-23.894 (21.764)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays. N=5,547 (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)	3.870 (2.893)	10.289 (9.458)	-3.311 (3.263)	-5.920 (3.553)	2.412 (2.783)	-12.429** (5.182)
College graduate*(school closure)	1.299 (1.433)	-0.827 (3.460)	-1.364 (1.605)	-0.995 (1.471)	-0.516 (1.347)	-2.377* (1.275)
(School closure)*(year=2021)	-1.412 (2.034)	-13.461* (7.230)	6.104*** (2.149)	3.406* (1.840)	2.458 (1.791)	3.154 (4.550)
College graduate*(year=2021)*(school closure)	1.783 (2.270)	20.221** (9.459)	-9.975** (3.774)	-7.364* (3.869)	-2.421 (2.719)	-2.319 (3.712)
	Household tasks	Free time	Caring for others	Education	Caring for household children	Secondary childcare for HH children
College graduate*(year=2021)	-4.771 (9.445)	18.918 (11.645)	9.588 (6.684)	-8.544 (6.281)	11.360** (5.448)	20.544 (15.667)
College graduate*(school closure)	1.572 (4.292)	1.181 (5.027)	3.944 (2.370)	-3.373 (2.621)	2.621 (2.085)	10.009 (6.630)
(School closure)*(year=2021)	-5.407 (6.623)	-3.581 (11.161)	-0.984 (4.757)	7.146* (4.191)	0.791 (3.548)	-2.389 (7.865)
College graduate*(year=2021)*(school closure)	5.225 (10.663)	-1.068 (14.658)	0.694 (5.821)	-4.903 (7.072)	-1.061 (4.620)	-3.497 (12.099)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Sample is composed of weekdays (N=6,840). 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 4: Differences in other time use after COVID by college attainment and gender

	Physical exercise	Sleep	Eating and drinking	Self-care	Free time	Education
Men (N=3,208)						
College graduate*(year=2021)	11.619*	8.128	-5.254	-14.227*	27.440	-9.902
	(6.091)	(14.194)	(6.777)	(7.837)	(19.449)	(11.563)
College grad pre-COVID mean	20	473	69	36	189	12
Women (N=3,632)						
College graduate*(year=2021)	3.084	14.314	-3.646	-8.216	6.676	-1.157
	(2.665)	(15.366)	(3.926)	(10.331)	(16.592)	(5.265)
College grad pre-COVID mean	14	490	64	53	186	14

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.