

# School Re-openings, Childcare Arrangements, and Labor Outcomes During COVID-19

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## **ABSTRACT**

The COVID-19 pandemic, with its associated economic and childcare crises, has the potential to magnify gender differences both in terms of childcare arrangements within the household and in the labor market. In prior work, we found that women carried a heavier load than men in the provision of childcare during the school closures at the beginning of the COVID-19 crisis, even while still working. This division of childcare was associated with a reduction in working hours and an increased probability of transitioning out of employment for working mothers. In the Fall of 2020, schools started to reopen using combinations of in-person, remote learning, and hybrid models. But families across the country have been exposed to different learning options for their school-age children depending on the offering of their local school districts. In this paper, we use 20 waves of data from the Understanding Coronavirus in America tracking survey to measure the gendered impact of this crisis as schools started reopening. We document changes in childcare arrangements and employment outcomes since the spring of 2020 and employ difference-in-differences and triple difference approaches to estimate the effect of public school reopenings and childcare arrangements on the dynamics of labor outcomes. Our preliminary results suggest an increase of childcare responsibilities for mothers, regardless of their work status, in the fall of 2020, as compared to the spring. We also find that the lack of school re-openings could make it harder for parents to recover from employment loss.

**Keywords:** Gender, childcare, labor participation, COVID-19.

**JEL Codes:** J13, J21, I1

## 1. Introduction

The COVID-19 pandemic has disproportionately affected working women compared to men in the United States (Alon et al., 2020). The lockdowns and social-distancing requirements during the Spring of 2020 had the biggest impact on more female-dominated sectors, namely the service industry (Mongey and Weinberg 2020). As a result, women's employment suffered at least as much, if not more, than men's during this crisis (Montenovo et al. 2020, Adams-Prassel et al. 2020). Also, childcare needs soared as schools and daycare centers closed around the country. Besides, social-distancing recommendations, stay-at-home orders, and the higher COVID-19 mortality risk of the elderly made it difficult for informal care providers, such as grandparents or other family members, to help with childcare responsibilities, especially in the early stages of this crisis. Given that women already carried a heavier load than men in the provision of childcare before the crisis (Aguiar and Hurst 2007, Schoonbroodt 2018), it was expected that women will continue to carry a heavier load due to the increased childcare responsibilities that have resulted from the crisis.<sup>1</sup> However, as more parents were required to work from home because of the social distancing measures, it was unclear, a priori, what this would imply for the gender balance in the division of childcare between parents.

In prior work (Zamarro & Prados, 2021) we used data from the USC Dornsife Center for Economic Research Understanding Coronavirus in America (UCA) tracking survey, collected biweekly during the COVID-19 crisis, and corresponding to a nationally representative sample of the U.S., to measure the gendered impact of this crisis in childcare provision, employment and working arrangements when schools closed during the Spring of 2020. Our analysis focused on tracking survey data from March to July 2020 to measure the initial gender differences on the impact of the COVID-19 crisis. We found that the increased need for childcare put a strain on working parents of both genders, but overall, mothers carried a heavier load on the provision of childcare than fathers. Moreover, mothers' working situation appeared to have a limited influence on their childcare responsibilities. Additionally, increased childcare responsibilities in the Spring of 2020 were associated with a reduction of working hours and an increased probability of transitioning out of employment until early Summer.

In this paper, we use data from 20 waves of the UCA tracking survey collected from March to early January 2021, to continue measuring the gendered impact of this crisis in childcare provision, employment, and working arrangements after schools started reopening. In the Fall of 2020, childcare responsibilities remained high. Some schools started to reopen, resulting in a combination of in-person, remote learning, and hybrid models. However, given a lack of centralized decision-making, school districts were often responsible for re-opening decisions. As a result, families across the country have been exposed to different learning options for their school-age children depending on the offering of their local school districts. We first describe transitions in childcare arrangements between the Spring and the Fall of 2020 and the dynamics of employment during this time. We then merge this survey data with unique data on school openings and use difference-in-differences and triple difference estimation approaches to

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<sup>1</sup> It is worth noting that even in the extreme case of the 2007-2009 recession when men's employment was hit harder than women's, and when fathers increased their time devoted to childcare, mothers did not experience significant changes in their time spent in childcare (Gorsuch 2016).

compare the probability of transitioning out of employment and recovery from unemployment in April, among those employed in March, before and after summer, across areas where schools reopened for some in-person education and those that remained fully remote, among those with and without school-age children in the household. Our preliminary results suggest an increase of childcare responsibilities for mothers, regardless of their work status, in the Fall of 2020, as compared to the Spring. We also find that the lack of school re-openings could make it harder for parents to recover from employment loss.

Our paper contributes to the emerging but prolific literature on the gendered labor effects of the COVID pandemic. The early literature highlighted heterogeneous effects of the crisis on labor market outcomes (Adams-Prassl et al. 2020, Beland et al. 2020, Mongey and Weinberg 2020, Zamarro and Prados, 2021). Concerning gender imbalances in childcare, this literature finds that in the U.S., women were more likely to be the main responsible for childcare (Zamarro and Prados, 2021) and spent more time taking care of children than men during the first few months of the pandemic (Adams-Prassl et al. 2020), school-closures in the Spring of 2020 differentially affected the labor status of mothers (Heggeness 2020, Amuedo-Dorantes et al. 2020), and mothers reduced their work hours more than fathers (Collins et al. 2020, Zamarro and Prados 2021). In this paper, we go further and provide evidence of the gendered impact of childcare responsibilities and schooling re-openings on labor market dynamics.

In this literature, only a few studies use survey data collected during the pandemic and they looked mostly at the short-term effects of the COVID crisis. We use rich U.S. tracking survey data, which allows us to evaluate the evolution of work engagement and the labor market attachment of workers as the crisis progresses. We use data collected from March to early January 2021, to measure the longer-term impact of school closures on employment and household arrangements. This is important because it is well known that childcare arrangements are crucial for female labor supply (Heckman 1974, Baker, Gruber and Milligan 2008, Domeij and Klein 2013, Bick 2016, and Zamarro 2020, among others). For all these reasons, and as the COVID-19 crisis continues, it could likely have a major impact on women, especially on their career trajectories and the well-being of working mothers.

This paper is organized as follows. Section 2 describes the data and general descriptive patterns of childcare provision and labor outcomes during the crisis. Section 3 presents our empirical approach and results for estimates of the effect of school re-openings on the evolution of labor outcomes during this crisis. Finally, Section 4 concludes.

## **2. Data, Childcare Arrangements and Employment Dynamics during the COVID-19 Crisis**

### **2.1 The Understanding Coronavirus in America Tracking Survey**

This paper uses data from twenty waves of the Understanding Coronavirus in America (UCA) Tracking Survey,<sup>2</sup> collected approximately every two weeks from March 10, 2020 to January 6,

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<sup>2</sup> <https://covid19pulse.usc.edu/>

2021,<sup>3</sup> administered by the USC Dornsife Center for Economic and Social Research (CESR). Participants in this study are members of the Understanding America Study (UAS).<sup>4</sup> The UAS is a probability-based household internet panel, comprising a nationally representative sample of approximately 9,000 US respondents.<sup>5</sup> All active respondents in the UAS were asked to participate in the ongoing Understanding Coronavirus in America Tracking Surveys. Around 7,000 respondents agreed to participate in the Coronavirus ongoing surveys.

The UAS panel consists of a representative sample of American households using an address-based sample frame. The recruitment of participants is done through several sample batches. The UAS team uses an adaptive sampling design where addresses from zip codes across the US are randomly selected for recruitment. Each sample batch, however, is adjusted to account for differential nonresponse in prior waves, and zip codes with higher proportions of non-responders are sampled more heavily than those with proportions similar or greater than population proportions. The UAS also includes separate oversamples for Native American respondents, respondents from Los Angeles County, and California populations. However, for each completed survey in the UAS, the UAS team provides sample weights. Sample weights are meant to make each survey data set representative of the U.S. population aged 18 and older concerning gender, race/ethnicity, education, and location.

Once a household is selected to be part of the UAS, all adults aged 18 and older in the household are eligible to participate. Although invited, however, not all members of the household decide to participate and as a result, our analysis focuses on data of each respondent individually.<sup>6</sup> As we are interested in studying gender differences on the effects of COVID-19 within households, we focus our analysis on those respondents who reported being married or living together with their partners in the same household. About 66% of our original sample reported being currently married or living together with a partner. We also restrict our sample to working-age respondents who are between 18 and 65 years old. The resulting sample consists of a total of 63,887 observations across the 20 waves of data (4,229 unique respondents). Sample sizes vary by waves from a minimum of 2,826 respondents in wave 2 to a maximum of 4,292 in wave 1 (March).

Table 1 presents descriptive statistics for our analytical sample of respondents who are married or living together with a partner and who are between 18 and 65 years old. All of our results are weighted to the Current Population Survey (CPS) benchmarks, using UAS provided weights, to account for sample design and non-response to maintain national representation to the American population, as described above. Our sample represents all areas of the country with

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<sup>3</sup> See Appendix A.1 for information about the dates of each wave.

<sup>4</sup> The data are publicly available upon registration: <https://uasdata.usc.edu/index.php>

<sup>5</sup> It is important to note that the UAS research team provides internet access and hardware, such as tablets, to those respondents who do not have computer hardware or internet access, so that all households in the sample may participate. UAS respondents usually complete up to 30-minute surveys in waves that occur once or twice per month. Respondents receive compensation for their time spent answering questions at a rate of \$20 per 30 minutes of interview time. The surveys are conducted both in English and Spanish.

<sup>6</sup> In our analytical sample including those respondents younger than 65 years old, married or living together with a partner, about 55% of respondents are the only one in the household participating in the UAS. As a result, less than half of the households in our data would have both partners in the couple responding to the surveys.

about half of respondents being women and half of the respondents being men. The average age of respondents in the sample is about 44 years old with a majority (65%) being white. Ten percent are African American, 20% are Hispanic or Latino and 6% are of other races. About 49% of respondents in our sample reported having school-age children. In our analysis, a respondent is considered to have children in the household if he/she reports living with a school-age child (Kindergarten to 12th grade) or with a child enrolled in daycare or preschool.<sup>7</sup> About 41% of respondents reported holding an Associates College degree or higher college education and about 64% reported having a job as of March 2020.

In the next subsections, we describe our measures of childcare arrangements, schooling options, and choices, and labor market outcomes that are available in the UAS and show descriptive patterns in the data along these dimensions. In Section 3, we further formalize our analytical approach to study the effect of school re-openings and childcare arrangements on the evolution of employment outcomes.

## 2.2. Childcare Arrangements

Respondents in the UAS who reported living with school-age children were asked in four waves (early April, April, early May, and October of 2020) about childcare responsibilities within the household. In particular, they were asked to identify who was primarily responsible for providing childcare and help with schoolwork.<sup>8</sup> Respondents could answer within the following categories, choosing all that apply: “You,” “your spouse or partner,” “a sibling,” “another extended family member,” “a paid childcare provider,” “a childcare facility not in the home,” or “other.” We then used this information to create the following childcare provision responsibilities indicators: *Only me* if a respondent only indicated “You” as their answer to the question; *Only my partner* if the respondent only indicated “Your spouse or partner” as their answer; *Only Both* if the respondent indicated only both “You” and “Your spouse or partner” as their answer; and *Others Help* if the respondent indicated other options including “a sibling, another extended family member, a paid childcare provider, a childcare facility not in the home, or other” in their response.

Figure 1 shows the patterns of childcare responsibilities by respondents’ gender among those living in two-partner households, both in the Spring (April) and in the Fall (October) of 2020. The data indicates that the gender gap in childcare responsibilities widened, even among working parents. As panels (a) and (c) in Figure 1 show, women have been carrying a heavier load of childcare during this COVID-19 crisis than men. 44.5 and 52 percent of mothers, in April and October respectively, report being the sole provider of care for their children compared with 14 and 12 percent of fathers. These patterns remain even when we condition on those respondents currently working, as it is shown in Figure 1, panels (b) and (d). In this case, 33 percent and 47 percent of working mothers report, in April and October respectively, that they are the only provider of care for their children compared with about 10.5 and 9 percent of

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<sup>7</sup> Throughout this article, we refer to women and men who are part of a couple living with children in the household as mothers and fathers.

<sup>8</sup> By late March 2020, most states in the U.S. had ordered or recommended school closures for the rest of their academic year. In the Fall 2020, some school districts required school closures to remain in effect while other school districts allowed for some in-person options.

working fathers. Amongst those who were working in March 2020, 38.3 percent of mothers have continued to be the caregiver of children at their household both in Spring and Fall of 2020, while this number is only 2.8 percent for fathers.

When we consider the dynamics of childcare responsibilities within the household, we find that caregiving responsibilities, if anything, appear to have increased for mothers from the Spring to the Fall. Figure 2 shows the percentage of mothers and fathers, within each category of childcare arrangements in the Spring (May 2020), who became the sole providers of care in October 2020. We find that women were much more likely to become the main childcare provider by October than men, regardless of what the childcare arrangement was like in May. Less than 30% of mothers who reported being the sole provider of care in May (*Only me*) said they no longer are the only source of care. On the other hand, a sizeable fraction of women who were not the main childcare provider in May are so in October: 38% of mothers who were sharing responsibility with a partner last spring, plus 31% who were sharing responsibility with someone else, and 28% of those whose partners were caring for the children are now reporting being the sole providers of care. In contrast, roughly the same proportions of fathers assumed sole responsibility and left sole responsibility for childcare in October as compared to May, leaving the overall proportion of sole-providing fathers mostly unchanged at 9%.

It is worth noting that the time burden of childcare and help with schoolwork may not be directly comparable in the Spring and Fall, as approximately half of the respondents have access to some amount of in-person instruction for their children. (See Section 2.3 for a description of the schooling situation in the Fall of 2020.) But in any case, it does appear that mothers have continued to carry a heavier load of childcare responsibilities than fathers during the second half of 2020. Figure 3 presents households' childcare arrangements by gender by their children's learning options (i.e. fully remote learning versus some in-person learning). Although it does appear that families whose children continued to learn fully remotely in the fall had more childcare help from others, mothers remain the main responsible for childcare independently of school instruction type, with 57% of mothers in households with children receiving some in-person instruction and 49% of mothers in households with children only receiving online instruction being the main responsible for childcare.<sup>9</sup> The gender gap in caregiving is wide under both types of schooling modalities.

When considering the transitions in childcare responsibilities by the children's school modality, we find that 70% of mothers who were primary responsible in the Spring continue being primary responsible in the Fall in households with some in-person learnings. The situation is similar in households with fully remote instruction, with 66% of mothers who were primary responsible in the Spring continuing with that role in the Fall.

## 2.2. Employment

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<sup>9</sup> When combined, 22% of all households in fully remote mode have others' help versus 15.6% of all households with some in-person learning.

UAS respondents answered questions about their employment status in every wave. Figure 4 presents the percentage of workers who declare being out of employment by gender over time, conditional on being employed in March 2020. Among those who were employed in March 2020, 19% of women lost their employment in April of that year, compared with 15% of men. Of these, 15.5% of women remained without a job in early January 2021 as compared with about 10% of men. In our sample of partnered couples, women have lost jobs at a higher rate than men, and twice as many remain unemployed in January 2021.

When considering childcare responsibilities, in Table 2, column (a) we observe that, amongst those who had a job in March of 2020, parents who were the main responsible for childcare in the Spring and Fall of 2020 were less likely to be employed in Fall (78% of those mainly responsible for childcare in Spring and Fall versus 90% for those not responsible for childcare at both times). We also find that, amongst those who had a job in March of 2020, parents who were the main responsible for childcare in the Spring and Fall of 2020 were more likely to have reduced their work hours at some point between April 2020 and January 2021 if they remained employed (Table 2, column b) or after July 2020 (Table 2, column c).

### **2.3. School Re-openings**

In March of 2020, with the hope of containing the pandemic, all schools across the United States closed for in-person attendance and students moved to remote learning for the rest of the academic year. Schools started to reopen in the fall of 2020 using different combinations of in-person, remote learning, and hybrid models. But, given a lack of centralized decision-making, school districts were often ultimately responsible to decide on re-opening decisions. As a result, students across the country have been exposed to different learning options depending on the offering of their local school districts. Figure 5 presents the percentage of households with children receiving different modes of instruction according to our data collected in October 2020. As it can be seen in this figure, a majority of respondents declare some sort of remote learning (fully remote or hybrid) for their children during the fall.

Districts that have remained closed for in-person learning appear to be more low-income, urban, and serve a more diverse population (Belsha et al., 2020; Smith & Reeves, 2020). However, the response to the pandemic appears to have been driven to a great extent by politics (Shao & Hao, 2020). Hartney & Finger (2020) use data from a large sample of school districts and conclude that a local conservative political leaning was the strongest predictor of districts' decisions to open for in-person learning. Local COVID-19 incidence rates appear to have had little impact on school districts' decisions of opening for in-person learning. Using data from a nationally representative sample of American parents, Henderson, Peterson, and West (2020) found that the availability of in-person learning options to parents was unrelated to COVID-19 incidence rates at the start of the 2020-2021 school year. If anything, they found that by November 2020 students were more likely to be attending school fully in-person in areas with higher levels of incidence.



Most school districts made their re-opening plans at the start of the 2020-2021 school year and remained with those plans until at least December 2020. Gross, Opalka, and Gundapaneni (2020) study a nationally representative sample of 477 school districts and document that a majority of school districts (81%) remained with their offered learning model between early November and December. About 15% of school districts moved to more remote learning and only 3.6% moved to more in person. This pattern has not changed until recently when, following President Joe Biden's focus on reopening schools for in-person learning, in February and March 2021 there has been an increase of public-school districts across the country re-opening for in-person learning.

In this paper, we exploit geographic differences in the availability of in-person learning in public school districts during the Fall of 2020 and study their influence on childcare arrangements and labor outcomes within partnered couples. For this purpose, we merge the Understanding America Study Survey data with estimates of learning option supply at the census-tract level when possible and county level when we are unable to merge at the tract-level<sup>10</sup>. Data for these supply estimates comes from MCH Strategic Data<sup>11</sup>, which has regularly collected information of school district re-openings options (either only remote learning available as well as the preferred model of learning if multiple options are available) since the Summer of 2020 and has obtained information of 92% of school districts in the country. This is, to our knowledge, the most comprehensive source of information on school re-openings and supply of learning options.

We use MCH survey data at the beginning of the fall semester of 2020 as reported in October 2020. At this point, MCH had collected and processed reopening plan data for 78% of districts nationwide. As school reopening plans might have changed over time, we interpret our estimates as intent to treat estimates. Thus, we construct census-tract/county-level estimates of learning options exposure for each tract as the proportion of students in the tract school districts that are offered a given learning option. We then build a variable indicating the percentage of students in a respondents' census tract/county whose public schools opened for any kind of in-person learning (fully in-person learning or hybrid options) as opposed to those school districts that continued to only offer remote learning to their students. Figure 6 presents a map with our county-level estimates of the percentage of students whose public schools only offered remote learning options. As we can see in this map there is considerable regional variation in the opportunity to attend school in person in the fall of 2020. Overall, 33% of respondents in our sample live in areas where there were no in-person learning options and learning was then fully remote. In contrast, 52% of respondents live in areas where all public school districts offer some sort of in-person learning. When offering in-person learning most school districts preferred mode of opening was a hybrid model (39% of respondents live in areas where all public school districts preferred a hybrid model).

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<sup>10</sup> 4.8% of respondents were merged at the county level instead of the census-tract level. Unfortunately, we were unable to merge any learning options supply information for 2.2% of respondents.

<sup>11</sup> <https://www.mchdata.com/covid19/schoolclosings>

### 3. School Re-openings, childcare arrangements, and Labor Outcomes During the COVID-19 Crisis

We employ Difference in Differences (DD) and Triple Difference (DDD) approaches to study the relationship between school re-openings for in person learning in the fall of 2020 and employment outcomes among partnered respondents.

#### 3.1. Methods

Our DD approach focuses on data from parents of school-age children who had a job in March 2020 and compares their labor outcomes before and after summer (i.e. before and after wave 10, July 2020) across areas where schools reopened for some in-person education and those that remained fully remote. For this analysis, we use data collected up to January 6<sup>th</sup>, 2021 (wave 20) to avoid the effect of the recent wave of re-openings that have occurred since then. Thus, we use discrete logit models following this type of specification:

$$\text{logit}(Y_{it}) = \beta_0 + \gamma_t + \beta_1 X_i + \beta_2 \text{SinPerson}_i + \beta_3 \text{SinPerson} \times \text{AfterSummer}_i + \varepsilon_i \quad (1)$$

Our first model studies transitions out of employment among those who had a job in March 2020. In this case the outcome variables ( $Y_{it}$ ) is a dummy variable that takes value 1 if the respondent is observed out of employment in a given wave since March 2020. Next, we study recovery from employment loss. In this case, the outcome variable ( $Y_{it}$ ) is also a dummy that takes value 1 if the respondent is observed out of employment in a given month, but the sample only includes those who had a job in March 2020 and lost it in April 2020.

$X_i$  includes controls for the respondent being female, three regional dummies for the region of residence of the respondent (Midwest, Northeast, and South), four dummies for the respondent's age group (age 18-29, age 30-39, age 40-49 and age 50-59), and three dummies for the respondent's race/ethnicity (African American, Hispanic and other non-white). We control for the respondent having a college degree or higher education allowing for a different effect for women. Finally, we also control for the prevalence of private schools in the state of residence of the respondent to capture the fact that a majority of private schools have continued to offer full in-person learning options even in areas where public schools only offered remote learning options.  $\gamma_t$  includes a set of wave fixed effects.

The variable  $\text{SinPerson}_i$  captures the proportion of students in the respondent's census tract or county whose public school districts offer some sort of in-person learning (i.e. fully in person or hybrid options) as opposed to census tracts where only a remote learning option is offered. Finally, our coefficient of interest is  $\beta_3$  which is the coefficient of the interaction between  $\text{Sinperson}_i$  and a dummy variable that takes value 1 for survey waves after 10 (after July 2020), when school re-opening plans started to be discussed.  $\beta_3$  then captures differences in employment outcomes across parents, before and after the summer, across areas with public schools that re-opened for in person learning and areas who did not. We also study heterogeneous effects by gender including an interaction term with a dummy for the respondent being female. Finally, we also explore heterogeneous effects by childcare arrangements during the Spring of 2020 including the direct effect and an interaction term with an indicator variable for the

respondent being the sole provider of care and school support for children in the household when schools were closed in Spring 2020.<sup>12</sup>

We also estimate models using a DDD approach which further controls for potential differences between areas that re-opened their schools for in-person learning and those who remained fully remote by subtracting the observed differences in the outcome variables, before and after summer, among those without school-age children in the household and that should not be then affected by school re-openings. In this case, we estimate the model using data from both parents of school-age children and non-parents but who held a job in March. Our DDD models then follow this type of discrete logit model specification:

$$\text{logit}(Y_{it}) = \beta_0 + \gamma_t + \beta_1 X_i + \beta_2 \text{SinPerson}_i + \beta_3 \text{SinPerson} \times \text{AfterSummer}_i + \beta_4 \text{Kids}_i + \beta_5 \text{Kids} \times \text{AfterSummer}_i + \beta_6 \text{Kids} \times \text{SinPerson}_i + \beta_7 \text{Kids} \times \text{SinPerson} \times \text{AfterSummer}_i + \varepsilon_i \quad (2)$$

Where the variables are defined as in (1) above but the sample includes respondents living with a partner but without school-age children in the household. The model then includes a dummy for the respondent living with children in the household (*Kids*), an interaction of this variable with a dummy for waves after July 2020, i.e. waves 10 and above, (*AfterSummer*), and the interaction of this variable with *SinPerson*, capturing the availability of in-person learning options in the respondent’s census tract of residence, as described above. Finally, our coefficient of interest in this model is the coefficient of the triple interaction between the variables *Kids*, *SinPerson*, and *AfterSummer* ( $\beta_7$ ). This coefficient captures the differences in employment outcomes, across respondents with school-age children, before and after summer, in areas with schools offering in-person learning in the fall and those who don’t, as compared to differences in employment outcomes across respondents without school-age children in the household, before and after summer, in areas with schools offering in-person learning and those with only remote learning options.

### 3.2. Results

Table 3 presents the results for our DD estimates following the specifications described in (1) above. Columns 1, 3, and 5 correspond to the analysis of discrete duration models on the probability of reporting being out of employment among those who reported holding a job in March. Our baseline DD specification results as described in (1) are presented in column 1. In Column 3 we present results when we allow for the effect of school re-openings after summer to be different for women with an additional interaction term of the treatment effect with the female variable. Finally, the results in column 5 include a variable for the respondent declaring being the sole provider of care of their children during the school closures of Spring 2020 and the interaction of the treatment effect with this sole care variable to allow for differential effects by care responsibilities early in the pandemic. Overall, looking at the results in columns 1 and 3, we observe that moms present a higher probability of about 7 to 8 percentage points of being out of employment than dads. However, looking at the results presented in column 5, it appears that this

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<sup>12</sup> We use childcare arrangements in the spring as opposed to the fall to avoid issues of endogeneity due to the simultaneous nature of caregiving decisions.

higher probability of being out of employment for moms might be driven by increased care responsibilities early in the pandemic as the dummy for female is insignificant in this case. At the same time, being the sole provider of care during the Spring of 2020 is associated with an increased probability of being out of employment in later waves of about 10 percentage points. Having a college degree helps reduce the probability of leaving employment. Respondents with a college degree or higher present a lower probability of between 7 and 10 percentage points of being out of employment. Concerning school re-openings for in-person learning, we do not find a statistically significant effect of school re-opening after the summer on the probability of being without employment in this case.

Columns 2, 4, and 6 of Table 3 present our DD estimates for the analysis of discrete duration models on recovering from employment loss. That is, our outcome variable, in this case, continues to be a dummy for being out of employment, but our sample is made of those respondents who declared holding a job in March but lost or left their jobs in April 2020. Structured as in the previous set of results, column 2 contains our baseline DD specification following the model described in (1), column 4 allows for school-reopenings after the summer to have a different effect for women with an additional interaction term with female, and column 6 includes a dummy for being the sole provider of childcare in the household during the school closures of Spring 2020 and allows for a differential effect of school reopenings by these care responsibilities. Overall, we find that the areas where schools reopened for in-person learning are areas where, on average, respondents transitioned out of employment at higher rates. Those respondents living in areas where 100% of students in public schools were offered some sort of in-person learning present a higher probability of remaining out of employment after having lost their jobs of about 22 percentage points. However, looking at our DD coefficient of interest (School In Person\*After Summer), in column (2), we observe that, after the summer, as schools reopened for in-person learning, the probability of remaining out of employment is reduced by about 13 percentage points, on average. The results in column (4) indicate that this decrease in the probability of remaining out of employment appears to be driven by dads and not so much for moms. Dads present a reduced probability of 26 percentage points of remaining out of employment after the summer if schools reopened for in-person instruction, while moms have a more persistent out-of-employment status and only present a reduction of about 5 percentage points if schools reopened. Finally, being the sole provider of childcare during the Spring of 2020 is associated with a higher probability of remaining without employment of about 13 percentage points although this effect is only marginally significant in this case.

Table 4 presents the results of our DDD estimates following the specification presented in (2) above. Again, columns 1, 3, and 5 present estimates of duration models for the probability of being out of employment among those employed in March 2020. Columns 2, 4, and 6 present estimates for the probability of remaining out of employment for those employed in March but who lost their employment in April, 2020. Our results are very similar to those using a DD specification presented in Table 3. Overall, women present a higher probability of reporting being out of employment of about 7 percentage points and of remaining without employment after losing it in April of about 13 percentage points. Part of this effect for women on the probability of being out of employment among those employed in March appears to be related to

the increased childcare responsibilities of moms during the school closures of Spring 2020. Again, having a college degree helps protect against transitions out of employment in this case. Our coefficient of interest here is the interaction between having school-age children living in the household and living in an area where schools re-opened for some in-person learning after the summer (K12 Kids\* S. in Person\*After Summer). We observe that among those who lost their employment in April and who live with school-age children in the household, the reopening of schools for some in-person learning reduced the probability of remaining without employment between about 20 and 25 percentage points and we do not observe differential effects for men and women in this case.

### **3.3 Threats to Internal Validity and Robustness Checks**

As stressed by Goodman-Bacon and Marcus (2020), there are certain threats to internal validity to consider when using a DD research design in the context of the COVID-19 crisis. A first concern is that other policies might have been in place that could correlate with the re-opening of school districts for in-person education. This concern would reflect itself in observed differences between treated and control areas that would lead to a violation of the common-trends assumption thus threatening the validity of our DD design. To explore this possibility, we expanded the models presented in (1) and (2) to allow for differential leads and lag effects for the different waves of data.

Figure 7 presents our estimated effects for our DD analysis of transitions out of employment while Figure 8 presents the estimated effects for the analysis of employment recovery among those working in March but who lost their employment in April. Looking at Figure 7, overall, we do not find statistically significant lag effects (before Wave 10) for the analysis of transitions out of employment among all those employed in March. We also do not find statistically significant effects after the summer (waves 10 and above) generally, in this case. For the analysis of employment recovery among those who lost employment in April, presented in Figure 8, we do find statistically significant effects after the summer (waves 10 and above) with those living in areas that re-opened schools for some in-person learning having a decrease in the probability of remaining out of employment. However, we also find two statistically significant anticipation lag effects for waves 6 and 8. And so, these estimates should be interpreted with caution. Note, that our DDD design would be robust to these observed anticipation effects as long as they are experienced similarly for those living with and without school age children in the household. The fact that our results are similar in the DDD specification is then reassuring. In any case, we plan to further explore alternative selection processes for our control group (e.g. building a synthetic control) as well as recent methods described in the literature to further address issues due to the potential violation of the common threat assumption in our DD models (Rambachan and Roth,2020).

Another concern comes from the potential endogeneity of school reopening decisions. As it was described in the results section above, we do find that areas that reopened schools for some in-person learning appear to be areas with overall higher probabilities of being out of employment. According to the literature described above, school reopening decisions did not appear to be very much driven by COVID-19 incidence rates and were more of a political

decision. But we are collecting information on COVID-19 incidence rates to include in our analysis as a control to better address this concern. However, again, our DDD approach should not be affected by this issue if those with and without school-age children in the household are affected similarly.

Another important issue has to do with the potential for anticipation effects. Most schools' academic years start sometime between mid-August and early September. School districts started discussing their plans for re-openings as early as July 2020. We consider wave 10 (July 22 - August 19, 2020) as our start of the treatment period, allowing for some anticipation effects. We also run specifications that consider wave 7 (June 10 - July 8, 2020) as the beginning of the treatment period instead and results were robust to this change.<sup>13</sup> Finally, we also estimated specifications excluding the waves of data corresponding to July (waves 7, 8, and 9). The estimated results are presented in Appendix A.2. Results were overall robust to excluding this month of data from the analysis.

Similarly, changes in reopening plans over time would be an additional concern for the validity of our DD and DDD estimates. As explained above, most schools set up their opening plans early in the academic year and they kept their plans at least until January 2021. To avoid the confounding of results derived from the latest wave of school re-openings for in-person learning since the new government of President Joe Biden, we restrict our analysis data to the first 20 waves just up to the beginning of January 2021. We have received access of school re-openings data across time and not just in October and we plan to study if there are significant changes observed in our data. We are also exploring the possibility of using phone mobility data to build an alternative measure of school re-openings (i.e. Bravata et al., 2021) to check the stability of school re-opening decisions and the robustness of our results to alternative re-opening measures.

Finally, parents might be voluntarily taking precautions during the pandemic and might not be willing to send their kids for in-person learning despite school districts' offerings if they feel it is not safe. Indeed, Camp and Zamarro (2021) show that families are responsive to local COVID-19 in the choosing of in-person learning options for their children. If parents are not sending their kids for in-person learning regarding school re-openings our estimates would represent only an intent to treat estimate in the context of the current pandemic conditions. As we have data on actual families' school modality choices, we plan to use this information along with school re-openings in an instrumental variables approach to estimate the local-average treatment effect of in-person learning on labor outcomes.

## 4. Conclusions

The unprecedented school-closures and social distancing measures derived from the current COVID-19 pandemic have the potential to drastically magnify gender differences in terms of both childcare arrangements and work. In prior work, we documented how women carried a

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<sup>13</sup> Results available from the authors upon request.

heavier load than men in the provision of childcare during the school closures of Spring of 2020, even while still working. This division of childcare was associated with a reduction in working hours and an increased probability of transitioning out of employment for working mothers.

In the Fall of 2020, schools started to reopen using combinations of in-person, remote learning, and hybrid models. But childcare responsibilities remained high as there was considerable variation across the U.S on school districts' learning options offered to parents and a majority of families in the country continued to use some sort of remote learning option for their children.

In this study, we analyze 20 waves of data, from March 2020 to early January 2021, from a nationally representative sample of the U.S. collected through the Understanding Coronavirus in America tracking survey. We document changes in childcare arrangements and employment outcomes during the current crisis and exploit geographic differences in the availability of in-person learning in public school districts during the Fall of 2020 to study their influence on employment outcomes within partnered couples.

Our preliminary results show that mothers have continued to carry a heavier load of childcare responsibilities than fathers during this pandemic. We also find that the lack of school re-openings could have made it harder for parents to recover from employment loss. Moreover, the transitions out of employment for mothers who were working before the onset of the pandemic seem to be more persistent than for fathers in similar conditions. Although our results are preliminary and there are important robustness checks described in the paper that we plan to implement, our DDD specifications should be more robust to potential bias and results appear to confirm our DD estimates. In ongoing work, we will also study changes in working hours as a function of childcare responsibilities and school re-openings for those who kept their jobs.

## References

- Adams-Prassl, A., Boneva, T., Golin, M., & Rauh, C. (2020). Inequality in the impact of the coronavirus shock: Evidence from real time surveys. IZA Discussion Paper No. 13183, April 2020. <http://ftp.iza.org/dp13183.pdf>.
- Aguiar, M., & Hurst, E. (2007). Measuring trends in leisure: The allocation of time over five decades. *The Quarterly Journal of Economics*, 122(3), 969-1006.
- Alon, T. M., Doepke, M., Olmstead-Rumsey, J., & Tertilt, M. (2020). The impact of COVID-19 on gender equality. National Bureau of Economic Research Working Paper No. 2697. <https://www.nber.org/papers/w26947>.
- Amuedo-Dorantes, C., Marcén, M., Morales, M., & Sevilla, A. (2020). COVID-19 School Closures and Parental Labor Supply in the United States. IZA Discussion Paper No. 13827, Available at SSRN: <https://ssrn.com/abstract=3726429>
- Baker, M., Gruber, J., & Milligan, K. (2008). Universal child care, maternal labor supply, and family well-being. *Journal of Political Economy*, 116(4), 709-745.
- Beland, L. P., Brodeur, A., & Wright, T. (2020). COVID-19, stay-at-home orders and employment: Evidence from CPS data. IZA Discussion Paper No. 13282, May 2020. <http://ftp.iza.org/dp13282.pdf>.
- Belsha, K., Rubinkam, M., LeMarr LeMee, G., & Fenn, L. (2020, September 11). A nationwide divide: Hispanic and Black students more likely than white students to start the year online. Chalkbeat. <https://www.chalkbeat.org/2020/9/11/21431146/hispanic-and-black-studentsmore-likely-than-white-students-to-start-the-school-year-online>
- Bick, A. (2016). The quantitative role of child care for female labor force participation and fertility. *Journal of the European Economic Association*, 14(3), 639-668.
- Bravata, D., Cantor, J. H., Sood, N. & Whaley, C. M. (2021). Back to school: The effect of school visits during Covid-19 on Covid-19 transmissions. NBER Working Paper Series. Working paper 28645.
- Camp, A. & Zamarro, G. (2021). Determinants of Ethnic Differences in School Modality Choices during the COVID-19 Crisis. (EdWorkingPaper: 21-374). Retrieved from Annenberg Institute at Brown University: <https://doi.org/10.26300/pmyy-nh92>
- Collins, C., Landivar, L. C., Ruppner, L., & Scarborough, W. J. (2020). COVID-19 and the Gender Gap in Work Hours. *Gender, Work & Organization*, <https://doi.org/10.1111/gwao.12506>.
- Domeij, D., & Klein, P. (2013). Should day care be subsidized?, *Review of Economic Studies*, 80(2), 568-595.
- Goodman-Bacon, A. & Marcus, J. (2020). Using difference-in-differences to identify causal effects of COVID-19 policies. Manuscript retrieved here: [https://cdn.vanderbilt.edu/vu-my/wp-content/uploads/sites/2318/2020/05/11154933/Covid-DD\\_v2.pdf](https://cdn.vanderbilt.edu/vu-my/wp-content/uploads/sites/2318/2020/05/11154933/Covid-DD_v2.pdf)



Gorsuch, M. M. (2016). Decomposing the increase in men's time on childcare during the great recession. *Review of Economics of the Household*, 14(1), 53-82.

Gross, B., Opalka, A., & Gundapaneni, P. (2020). U-turn: Surge of Covid cases reverse reopening progress in America's school districts. Center on Reinventing Public Education. [https://www.crpe.org/sites/default/files/u\\_turn\\_brief\\_jan\\_2020\\_0.pdf](https://www.crpe.org/sites/default/files/u_turn_brief_jan_2020_0.pdf)

Hartney, M. T., & Finger, L. K. (2020). Politics, markets, and pandemics; Public education's response to Covid-19 (EdWorkingPaper No. 20-304). Annenberg Institute at Brown University. <https://doi.org/10.26300/8ff8-3945>

Heckman, J. J. (1974). Effects of child-care programs on women's work efforts, *The Journal of Political Economy*, 82 (2), S136-S163.

Henderson, M. B., Peterson, P.E., & West, M. (2020). Pandemic Parent Survey Finds Perverse Pattern: Students Are More Likely to Be Attending School in Person Where Covid Is Spreading More Rapidly. ED Next Poll 2020 Public Opinion Vol. 21 (2). Retrieved here: <https://www.educationnext.org/pandemic-parent-survey-finds-perverse-pattern-students-more-likely-to-be-attending-school-in-person-where-covid-is-spreading-more-rapidly/>

Heggeness, M. (2020). Why is mommy so stressed? Estimating the immediate impact of the COVID-19 shock on parental attachment to the labor market and the double bind of mothers. Federal Reserve Bank of Minneapolis Institute Working Paper No. 33. <https://www.minneapolisfed.org/institute/working-papers-institute/iwp33.pdf>.

Mongey, S., & Weinberg, A. (2020). Characteristics of workers in low work-from-home and high personal-proximity occupations. Becker Friedman Institute for Economic White Paper, April 2020. <https://bfi.uchicago.edu/working-paper/characteristics-of-workers-in-low-work-from-home-and-high-personal-proximity-occupations/>.

Montenovo, L., Jiang, X., Rojas, F. L., Schmutte, I. M., Simon, K. I., Weinberg, B. A., et al. (2020). Determinants of disparities in covid-19 job losses. National Bureau of Economic Research Working paper No. 27132. <https://www.nber.org/papers/w27132>. Rambachan, A. &

Roth, J. (2020). An honest approach to parallel trends. Manuscript retrieved here: [https://scholar.harvard.edu/jroth/publications/Roth\\_JMP\\_Honest\\_Parallel\\_Trends](https://scholar.harvard.edu/jroth/publications/Roth_JMP_Honest_Parallel_Trends)

Schoonbroodt, A. (2018). Parental child care during and outside of typical work hours. *Review of Economics of the Household*, 16(2), 453-476.

Shao, W., & Hao, F. (2020). Confidence in political leaders can slant risk perceptions of Covid-19 in a highly polarized environment. *Social Science & Medicine*, 261. <https://doi.org/10.1016/j.socscimed.2020.113235>

Smith, E., & Reeves, R. V. (2020, September 23). Students of color most likely to be learning online: Districts must work even harder on race equity. The Brookings SCHOOL MODALITY CHOICES DURING COVID 25 Institution Blog. <https://www.brookings.edu/blog/how->

werise/2020/09/23/students-of-color-most-likely-to-be-learning-online-districtsmust-work-even-harder-on-race-equity/

Zamarro, G. (2020). Family Labor Participation and Childcare Decisions: The Role of Grannies. *SERIEs*, 11, 287-312.

Zamarro, G. & Prados, M. J. (2021). Gender differences in couples' division of childcare, work and mental health during COVID-19. *Review of Economics of the Household*, 19, 11-40.

## APPENDIX

### A.1. Dates for each wave of the Understanding America Study Covid Tracking Survey

Wave 1 (March) was collected from March 10, 2020 to March 31, 2020; Wave 2 (Early April) was collected from April 1 to April 28, 2020; Wave 3 (April) was collected from April 15, 2020 to May 12, 2020; Wave 4 (Early May) was collected from April 29, 2020 to May 26, 2020; Wave 5 (Late May) was collected from May 13 to June 9, 2020; Wave 6 (Early June) was collected from May 27 to June 23, 2020; Wave 7 (Late June) was collected from June 10 to July 8, 2020; Wave 8 (Early July) was collected from June 24 to July 22, 2020; Wave 9 (July) was collected from July 8 to August 5, 2020; Wave 10 (Early August) was collected from July 22 to August 19, 2020; Wave 11 (August) was collected from August 5 to September 2, 2020; Wave 12 (Early September) was collected from August 19 to September 16, 2020; Wave 13 (September) was collected from September 2 to September 30, 2020; Wave 14 (Early October) was collected from September 16 to October 14, 2020; Wave 15 (October) was collected from September 30 to October 27, 2020; Wave 16 (Early November) was collected from October 14 to November 11, 2020; Wave 17 (November) was collected from October 28 to November 25, 2020; Wave 18 (Early December) was collected from November 11 to December 9, 2020; Wave 19 (December) was collected from November 25 to December 23, 2020; Wave 20 (Early January) was collected from December 9, 2020 to January 6, 2021.

## A.2. Robustness Check: Eliminating Data From July 2020 (Waves 7, 8 and 9)

Table A.2.1. DD Estimates -Eliminating July Waves

<i>VARIABLES</i>	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Out of Employment after March</i>	<i>Out of Employment After April- Among Unemployed in April</i>	<i>Out of Employment after March</i>	<i>Out of Employment After April- Among Unemployed in April</i>	<i>Out of Employment after April</i>	<i>Out of Employment After April- Among Those Unemployed in April</i>
Female	0.076*** (0.028)	0.041 (0.072)	0.082*** (0.027)	-0.038 (0.071)	0.010 (0.028)	-0.006 (0.077)
College	-0.065** (0.029)	0.130 (0.086)	-0.065** (0.029)	0.134 (0.089)	-0.087*** (0.029)	0.132 (0.084)
Female*College	-0.026 (0.040)	-0.077 (0.111)	-0.026 (0.040)	-0.074 (0.111)	0.006 (0.039)	-0.108 (0.118)
School In Person	0.012 (0.025)	0.251*** (0.067)	0.012 (0.025)	0.245*** (0.065)	0.017 (0.025)	0.223*** (0.062)
School In Person*After Summer	-0.012 (0.024)	-0.170** (0.070)	-0.002 (0.034)	-0.282*** (0.102)	-0.029 (0.030)	-0.124 (0.092)
School In Person*After Summer* Female			-0.017 (0.035)	0.179* (0.103)		
Care Only Me-Spring 2020					0.111*** (0.022)	0.158** (0.064)
Care Only Me-Spring 2020*S. In Person*A. Summer					0.020 (0.033)	-0.041 (0.100)
Prevalence Private Schools	-0.003 (0.005)	-0.000 (0.013)	-0.003 (0.005)	-0.001 (0.013)	-0.003 (0.005)	-0.001 (0.014)
Observations	14,378	3,027	14,378	3,027	13,267	2,786

Note: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Wave dummies, Age, Race and Region Dummies also included. Results weighted using population weights to the CPS benchmarks.

**Table A.2.2. DDD Estimates -Eliminating July Waves**

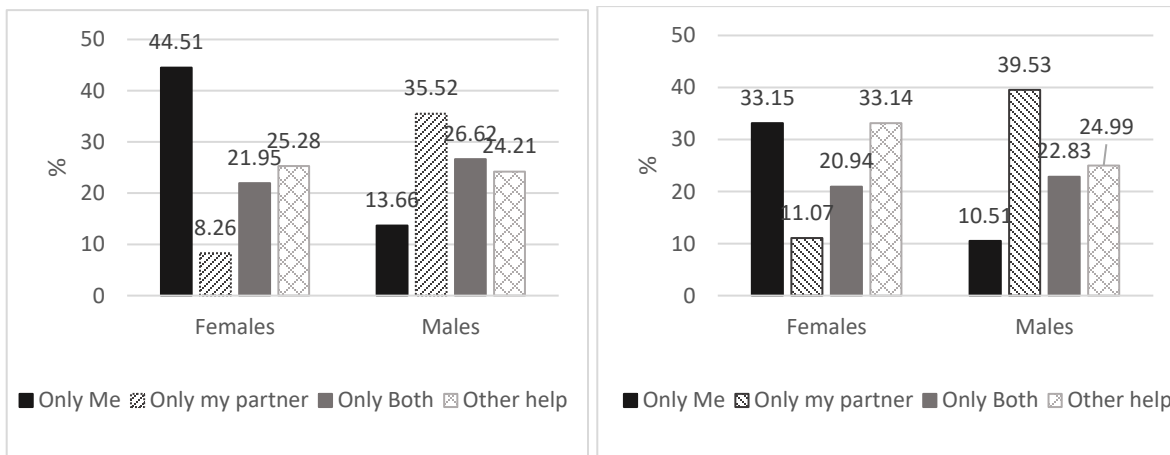
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	<i>Out of Employment after March</i>	<i>Out of Employment After April- Among Unemployed in April</i>	<i>Out of Employment after March</i>	<i>Out of Employment After April- Among Unemployed in April</i>	<i>Out of Employment after April</i>	<i>Out of Employment After April- Among Those Unemployed in April</i>
Female	0.068*** (0.021)	0.115** (0.053)	0.067*** (0.022)	0.096* (0.056)	0.040* (0.022)	0.102* (0.054)
College	-0.070*** (0.024)	0.015 (0.065)	-0.070*** (0.024)	0.015 (0.065)	-0.078*** (0.024)	0.010 (0.066)
Female*College	-0.021 (0.031)	-0.054 (0.086)	-0.021 (0.031)	-0.048 (0.086)	-0.010 (0.032)	-0.071 (0.088)
School In Person	0.047* (0.029)	-0.013 (0.068)	0.047* (0.029)	-0.014 (0.068)	0.044 (0.028)	-0.022 (0.067)
School In Person*After Summer	-0.020 (0.026)	0.004 (0.079)	-0.020 (0.026)	0.003 (0.079)	-0.020 (0.026)	0.004 (0.078)
K12 Kids	0.014 (0.029)	-0.128* (0.072)	0.014 (0.029)	-0.122* (0.071)	-0.045 (0.031)	-0.197** (0.089)
K12 Kids*After Summer	-0.023 (0.029)	0.065 (0.084)	-0.023 (0.029)	0.065 (0.084)	-0.022 (0.030)	0.045 (0.090)
K12 Kids* School in Person	-0.037 (0.036)	0.204** (0.093)	-0.037 (0.036)	0.203** (0.092)	-0.027 (0.036)	0.193** (0.094)
K12 Kids* S. in Person*After Summer	0.005 (0.038)	-0.182* (0.108)	0.003 (0.045)	-0.241* (0.127)	-0.016 (0.043)	-0.169 (0.127)
K12 Kids*S. in Person*A. Summer*Female			0.003 (0.040)	0.090 (0.105)		
Prevalence Private Schools	0.001 (0.003)	-0.009 (0.009)	0.001 (0.003)	-0.008 (0.009)	0.001 (0.003)	-0.007 (0.010)

Care Only Me-Spring 2020					0.122***	0.167**
					(0.024)	(0.077)
Care*School in Person*After Summer					0.019	-0.007
					(0.038)	(0.118)
Observations	29,725	6,381	29,725	6,381	28,614	6,140

Note: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Wave dummies, Age, Race and Region Dummies also included. Results weighted using population weights to the CPS benchmarks

**Figure 1. Childcare arrangements in the household during the COVID-19 crisis.**

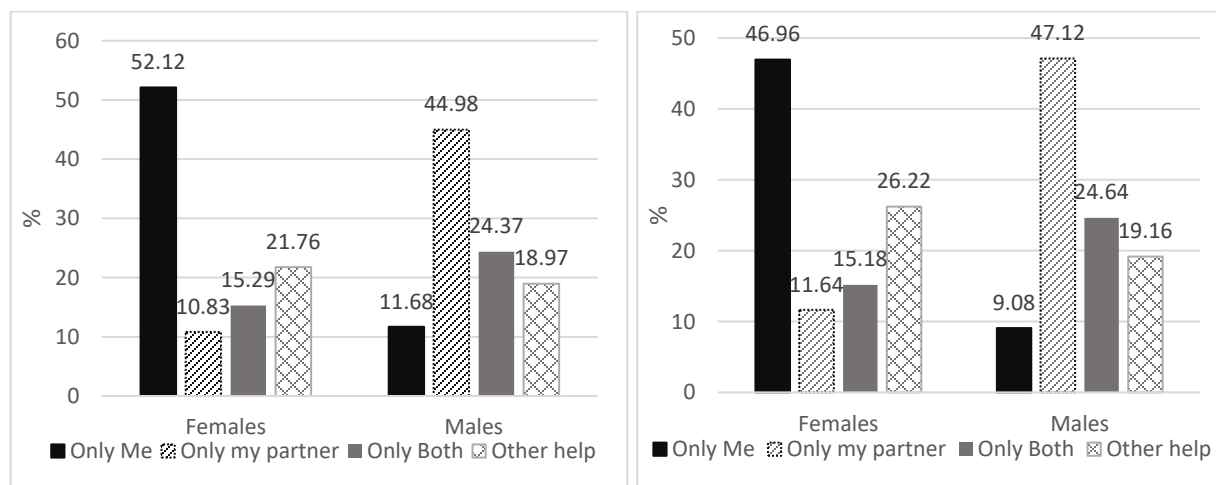
**April 2020**



**(a) All Parents**

**(b) Working Parents**

**October 2020**

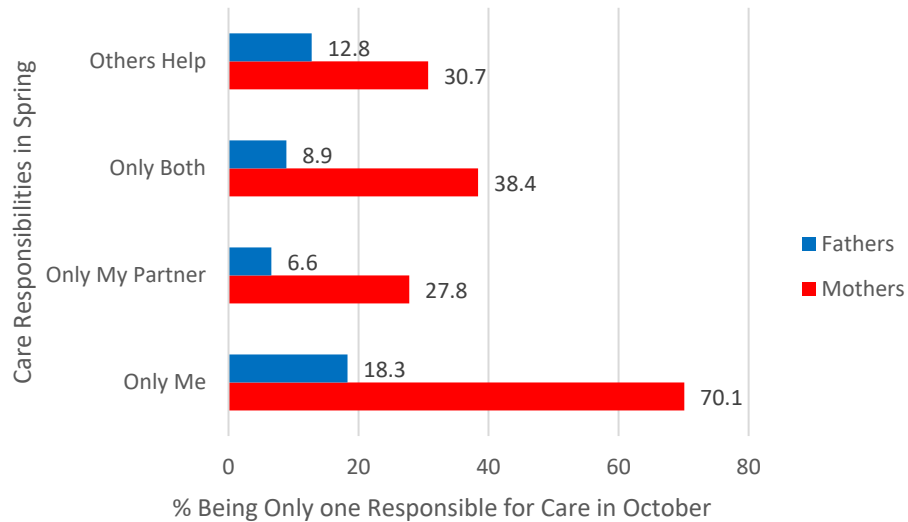


**(c) All Parents**

**(d) Working Parents**

**Note:** This figure presents the proportion of respondents in two-adult households with children who declare to be the main responsible for childcare and help with homework (“Only me”), or who declare their partner is the main responsible (“Only my partner”), or both are (“Only both”), or others are (“Other help”), by gender. Panels (a) and (c) includes all adults in two-parent households with children in April and October of 2020 respectively, and panels (b) and (d) only include working adults in these households, in April and October of 2020 respectively. Results weighted using population weights to the CPS benchmarks

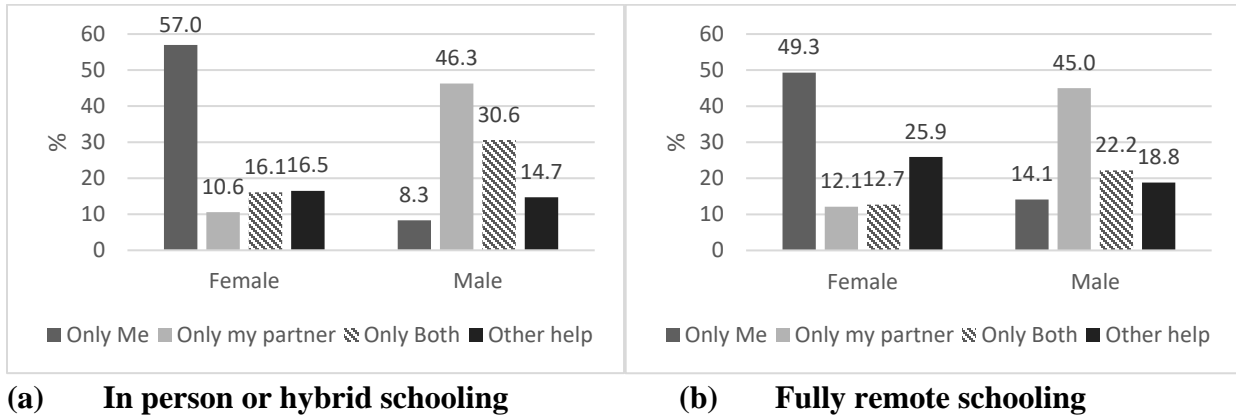
**Figure 2. Percentage of Parents within Each Category of Childcare Responsibilities in Spring 2020 Who Became Primarily Responsible for Care and Help with Schoolwork in October 2020**



**Note:** This figure presents the percentage of parents in each childcare arrangement in the spring of 2020, by gender, who transitioned to become the main responsible for childcare in the household in October of that year (“Only me”). For example, it shows that 30.7% of mothers who had others (non-partner) in charge of childcare in the spring of 2020 became the main responsible for childcare in the subsequent fall, while only 12.8% of fathers who had others (non-partner) in charge of childcare in the spring of 2020 became main responsible in the fall of that year. Results weighted using population weights to the CPS benchmarks

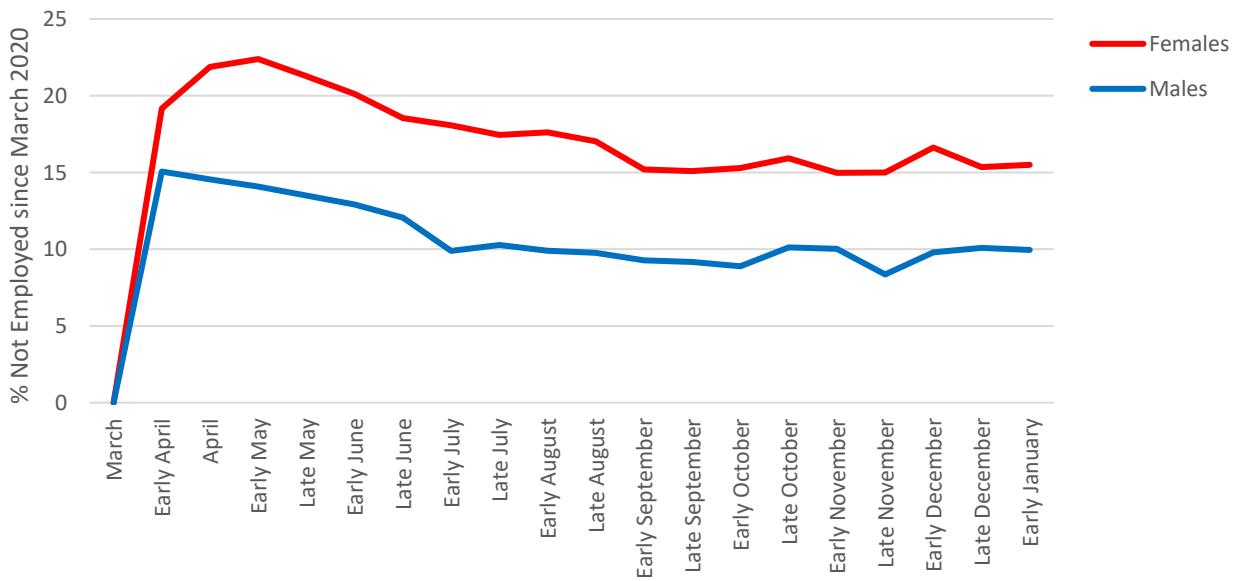


**Figure 3. Percentage of Parents within Each Category of Childcare Responsibilities in October 2020, by Children Learning Modality**



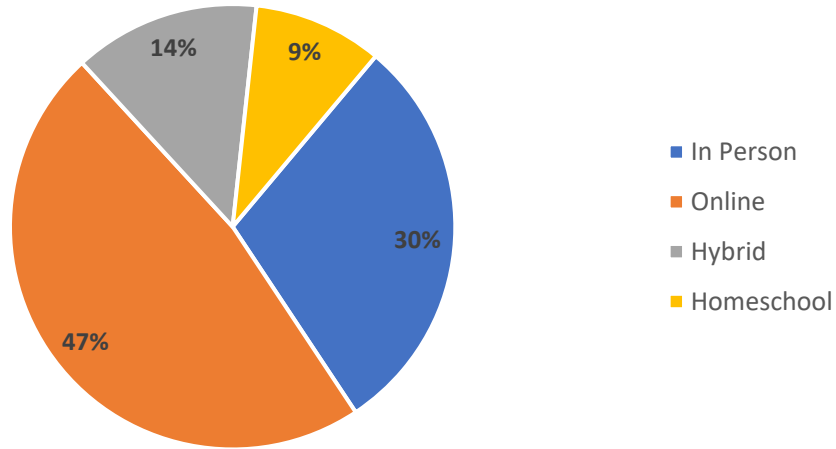
*Note:* This figure presents the percentage of parents in each childcare arrangement category in October of 2020, by gender. Panel (a) presents the results for households with children attending school in person or with a hybrid modality, and panel (b) presents the results for households with children only engaged in online learning. Results weighted using population weights to the CPS benchmarks

**Figure 4. Percentage of Respondents Employed in March 2020 Who Are No Longer Employed, By Gender**



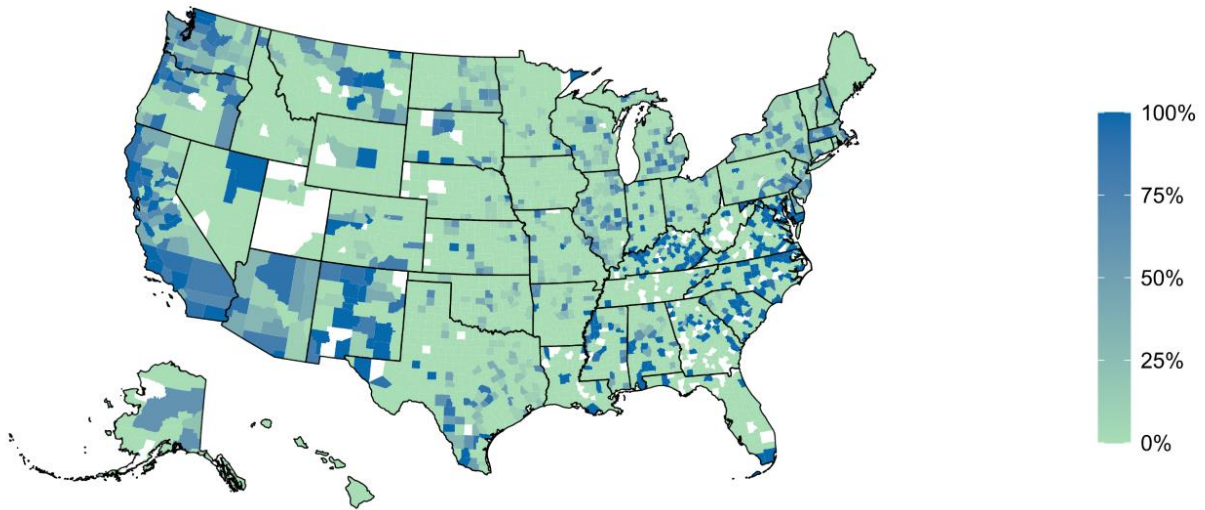
*Note:* Results weighted using population weights to the CPS benchmarks

**Figure 5. Percentage of households with children receiving different types of school instruction, October 2020**



*Note:* Percentage of survey respondents which declare the K-12 children in their household to be enrolled in each of the following schooling options: In person, fully remote (online), hybrid (mix of in-person and remote) and homeschooled. Results weighted using population weights to the CPS benchmarks.

**Figure 6. Remote Only Learning- By County, October 2020**

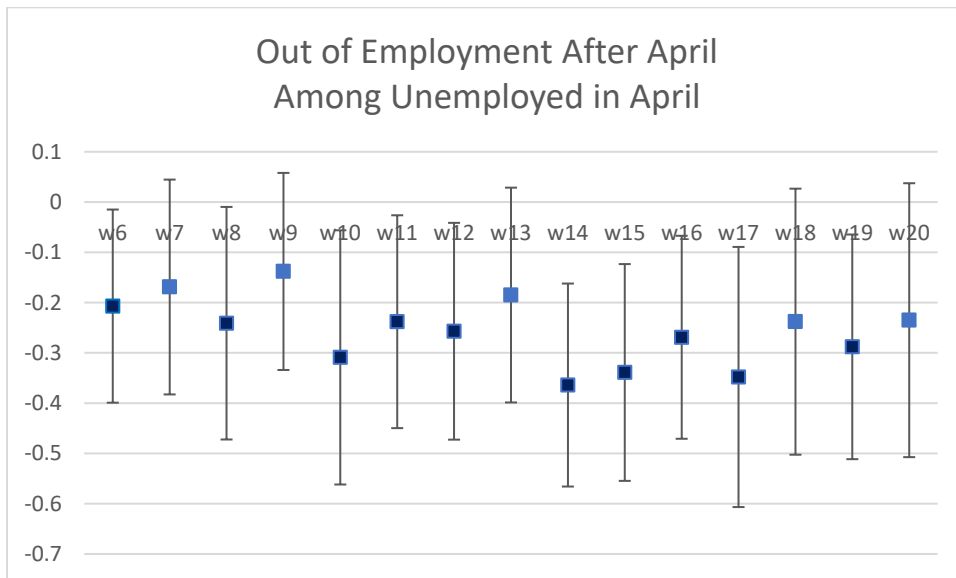


Source: MCH Strategic data (<https://www.mchdata.com/covid19/schoolclosings>)

**Figure 7. Leads and Lags Estimated Effects DD Model**



**Figure 8. Leads and Lags Estimated Effects DDD Model**



Note: Dark blue represents statistically significant estimated effects at the 95% confidence level.

**Table 1. Descriptive statistics**

	<i>Mean</i>	<i>Standard Deviation</i>
<i>Female</i>	0.51	0.50
<i>Age</i>	44.27	11.67
<i>West</i>	0.23	0.42
<i>Midwest</i>	0.21	0.40
<i>Northeast</i>	0.17	0.37
<i>South</i>	0.40	0.49
<i>White</i>	0.65	0.48
<i>African American</i>	0.10	0.30
<i>Hispanic</i>	0.19	0.40
<i>Other Race</i>	0.06	0.23
<i>College</i>	0.41	0.49
<i>Working in March</i>	0.64	0.48
<i>School Age Kids</i>	0.49	0.50

Note: Total number of observations was 63,887 observations across the 20 waves of data (4,292 unique respondents). Results weighted using population weights to the CPS benchmarks.

**Table 2. Labor market outcomes by childcare responsibility**

(a)			(b)			©		
Childcare: Only me Spring and Fall	% employed in Fall 2020 (with job in March)		Childcare: Only me Spring and Fall	% ever reduced hours (with job in March)		Childcare: Only me Spring and Fall	% reduced hours during Fall '20 (with job in March)	
	Row %	95% CI		Row %	95% CI		Row %	95% CI
No (n=4,475)	90.3	[87.4,92.6]	No (n=4,314)	38.1	[33.1,43.3]	No (n=4,185)	12	[8.7,16.4]
Yes (n=1,235)	78	[68.3,85.4]	Yes (n=1,129)	49.8	[39.0,60.6]	Yes (n=1,047)	17.9	[10.5,29.0]
Total (n=5,710)	87.9	[84.9,90.3]	Total (n=5,443)	40.2	[35.6,45.0]	Total (n=5,232)	13	[9.8,17.1]

**Table 3. DD Estimates of the Probability of Being Out of Employment-Those Employed in March, 2020**

<i>VARIABLES</i>	(1) <i>Out of Employment after March</i>	(2) <i>Out of Employment After April- Among Unemployed in April</i>	(3) <i>Out of Employment after March</i>	(4) <i>Out of Employment After April- Among Unemployed in April</i>	(5) <i>Out of Employment after April</i>	(6) <i>Out of Employment After April- Among Those Unemployed in April</i>
w3-(April 15, 2020 – May 13, 2020)	0.014 (0.010)		0.014 (0.010)			
w4-(April 29, 2020 – May 26, 2020)	0.019* (0.010)		0.019* (0.010)			
w5-(May 13 - June 9, 2020)	0.008 (0.013)		0.008 (0.013)			
w6-(May 27 - June 23, 2020)	0.001 (0.013)	-0.068 (0.048)	0.001 (0.013)	-0.067 (0.048)	-0.010 (0.009)	-0.103** (0.047)
w7-(June 10 - July 8, 2020)	-0.019 (0.015)	-0.160*** (0.049)	-0.019 (0.015)	-0.159*** (0.049)	-0.031*** (0.010)	-0.205*** (0.046)
w8- (June 24 - July 22, 2020)	-0.027* (0.015)	-0.244*** (0.052)	-0.027* (0.015)	-0.242*** (0.051)	-0.038*** (0.012)	-0.278*** (0.049)
w9-(July 8 - August 5, 2020)	-0.018 (0.015)	-0.212*** (0.046)	-0.018 (0.015)	-0.210*** (0.047)	-0.026** (0.012)	-0.227*** (0.050)
w10-(July 22 - August 19, 2020)	-0.021 (0.018)	-0.197*** (0.063)	-0.021 (0.018)	-0.197*** (0.062)	-0.030* (0.017)	-0.233*** (0.067)
w11-(August 5 - September 2, 2020)	-0.029 (0.020)	-0.208*** (0.063)	-0.029 (0.020)	-0.206*** (0.063)	-0.035* (0.018)	-0.231*** (0.072)
w12-(August 19 - September 16, 2020)	-0.043** (0.020)	-0.248*** (0.063)	-0.043** (0.020)	-0.250*** (0.063)	-0.052*** (0.019)	-0.276*** (0.073)
w13-(September 2 - September 30, 2020)	-0.056*** (0.021)	-0.289*** (0.061)	-0.056*** (0.021)	-0.285*** (0.062)	-0.063*** (0.019)	-0.319*** (0.070)
w14-(September 16 - October 14, 2020)	-0.049**	-0.250***	-0.049**	-0.251***	-0.063***	-0.278***

	(0.019)	(0.062)	(0.019)	(0.062)	(0.018)	(0.072)
w15-(September 30 - October 27, 2020)	-0.029	-0.225***	-0.029	-0.228***	-0.041**	-0.246***
	(0.020)	(0.065)	(0.020)	(0.065)	(0.019)	(0.073)
w16-(October 14 - November 11, 2020)	-0.028	-0.230***	-0.028	-0.228***	-0.036*	-0.242***
	(0.020)	(0.061)	(0.020)	(0.062)	(0.019)	(0.071)
w17- (October 28 - November 25, 2020)	-0.042**	-0.263***	-0.042**	-0.264***	-0.057***	-0.304***
	(0.020)	(0.064)	(0.020)	(0.065)	(0.019)	(0.068)
w18-(November 11 - December 9, 2020)	-0.017	-0.182***	-0.018	-0.181***	-0.030	-0.208***
	(0.019)	(0.070)	(0.020)	(0.070)	(0.020)	(0.076)
w19-(November 25 - December 23, 2020)	-0.029	-0.225***	-0.029	-0.230***	-0.038*	-0.236***
	(0.020)	(0.068)	(0.020)	(0.068)	(0.020)	(0.077)
w20-(December 9, 2020 - January 6, 2021)	-0.031	-0.239***	-0.031	-0.241***	-0.041**	-0.266***
	(0.020)	(0.071)	(0.020)	(0.071)	(0.019)	(0.076)
Female	0.071**	0.008	0.076***	-0.083	-0.015	-0.047
	(0.028)	(0.094)	(0.027)	(0.096)	(0.031)	(0.100)
College	-0.072**	0.102	-0.072**	0.098	-0.089***	0.093
	(0.030)	(0.103)	(0.029)	(0.106)	(0.031)	(0.107)
Female*College	-0.012	-0.021	-0.012	-0.014	0.037	-0.033
	(0.040)	(0.136)	(0.040)	(0.136)	(0.040)	(0.148)
School In Person	0.005	0.228***	0.005	0.222***	0.009	0.217**
	(0.025)	(0.088)	(0.025)	(0.085)	(0.026)	(0.088)
School In Person*After Summer	-0.008	-0.126**	0.003	-0.258***	-0.023	-0.126
	(0.020)	(0.059)	(0.030)	(0.091)	(0.026)	(0.089)
School In Person*After Summer* Female			-0.018	0.209**		
			(0.032)	(0.100)		
Prevalence Private Schools	-0.003	0.005	-0.003	0.005	-0.003	0.001
	(0.005)	(0.015)	(0.005)	(0.015)	(0.005)	(0.016)
Care Only Me-Spring 2020					0.104***	0.133*
					(0.023)	(0.078)
Care Only Me-Spring 2020*S. In Person*A. Summer					0.028	0.017
					(0.030)	(0.099)

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Observations	18,322	3,179	18,322	3,179	13,992	2,918
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Note: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Age, Race and Region Dummies also included. Results weighted using population weights to the CPS benchmarks

**Table 4. DDD Estimates of the Probability of Being Out of Employment-Those Employed in March, 2020**

<i>VARIABLES</i>	(1) <i>Out of Employment after March</i>	(2) <i>Out of Employment After April- Among Unemployed in April</i>	(3) <i>Out of Employment after March</i>	(4) <i>Out of Employment After April- Among Unemployed in April</i>	(5) <i>Out of Employment after April</i>	(6) <i>Out of Employment After April- Among Those Unemployed in April</i>
w3-(April 15, 2020 – May 13, 2020)	0.011 (0.008)		0.011 (0.008)			
w4-(April 29, 2020 – May 26, 2020)	0.010 (0.008)		0.010 (0.008)			
w5-(May 13 - June 9, 2020)	0.005 (0.010)		0.005 (0.010)			
w6-(May 27 - June 23, 2020)	-0.001 (0.009)	-0.054* (0.032)	-0.001 (0.009)	-0.053* (0.032)	-0.008 (0.006)	-0.070** (0.031)
w7-(June 10 - July 8, 2020)	-0.012 (0.011)	-0.127*** (0.034)	-0.012 (0.011)	-0.127*** (0.034)	-0.019*** (0.007)	-0.147*** (0.033)
w8- (June 24 - July 22, 2020)	-0.024** (0.011)	-0.199*** (0.036)	-0.024** (0.011)	-0.198*** (0.036)	-0.030*** (0.008)	-0.213*** (0.036)
w9-(July 8 - August 5, 2020)	-0.024** (0.011)	-0.208*** (0.035)	-0.024** (0.011)	-0.208*** (0.035)	-0.029*** (0.009)	-0.216*** (0.037)
w10-(July 22 - August 19, 2020)	-0.009 (0.019)	-0.295*** (0.062)	-0.009 (0.019)	-0.294*** (0.062)	-0.021 (0.017)	-0.309*** (0.061)
w11-(August 5 - September 2, 2020)	-0.013 (0.019)	-0.312*** (0.063)	-0.013 (0.019)	-0.311*** (0.063)	-0.024 (0.017)	-0.321*** (0.063)
w12-(August 19 - September 16, 2020)	-0.024 (0.020)	-0.335*** (0.064)	-0.024 (0.020)	-0.334*** (0.064)	-0.036** (0.018)	-0.345*** (0.064)
w13-(September 2 - September 30, 2020)	-0.028 (0.019)	-0.366*** (0.063)	-0.028 (0.019)	-0.364*** (0.063)	-0.039** (0.018)	-0.375*** (0.062)
w14-(September 16 - October 14, 2020)	-0.029	-0.362***	-0.029	-0.360***	-0.043**	-0.372***



	(0.019)	(0.064)	(0.019)	(0.064)	(0.018)	(0.063)
w15-(September 30 - October 27, 2020)	-0.019	-0.355***	-0.019	-0.354***	-0.033*	-0.364***
	(0.020)	(0.064)	(0.020)	(0.064)	(0.018)	(0.064)
w16-(October 14 - November 11, 2020)	-0.020	-0.347***	-0.020	-0.345***	-0.031*	-0.351***
	(0.020)	(0.064)	(0.020)	(0.063)	(0.018)	(0.063)
w17- (October 28 - November 25, 2020)	-0.031	-0.385***	-0.031	-0.384***	-0.046**	-0.399***
	(0.020)	(0.065)	(0.020)	(0.065)	(0.018)	(0.063)
w18-(November 11 - December 9, 2020)	-0.017	-0.361***	-0.017	-0.359***	-0.031*	-0.371***
	(0.020)	(0.066)	(0.020)	(0.065)	(0.019)	(0.064)
w19-(November 25 - December 23, 2020)	-0.023	-0.382***	-0.023	-0.381***	-0.036*	-0.386***
	(0.020)	(0.065)	(0.020)	(0.064)	(0.019)	(0.064)
w20-(December 9, 2020 - January 6, 2021)	-0.024	-0.384***	-0.024	-0.383***	-0.037**	-0.393***
	(0.020)	(0.064)	(0.020)	(0.064)	(0.018)	(0.062)
Female	0.069***	0.143**	0.069***	0.127*	0.041*	0.131**
	(0.021)	(0.063)	(0.022)	(0.066)	(0.023)	(0.064)
College	-0.070***	0.027	-0.070***	0.027	-0.072***	0.021
	(0.024)	(0.078)	(0.024)	(0.078)	(0.026)	(0.080)
Female*College	-0.014	-0.055	-0.014	-0.049	0.003	-0.067
	(0.032)	(0.103)	(0.032)	(0.103)	(0.033)	(0.106)
School In Person	0.044	-0.074	0.044	-0.075	0.032	-0.081
	(0.028)	(0.083)	(0.028)	(0.083)	(0.028)	(0.082)
School In Person*After Summer	-0.014	0.066	-0.014	0.065	-0.006	0.066
	(0.022)	(0.068)	(0.022)	(0.067)	(0.021)	(0.067)
K12 Kids	0.012	-0.207**	0.012	-0.202**	-0.045	-0.289**
	(0.028)	(0.096)	(0.028)	(0.095)	(0.031)	(0.115)
K12 Kids*After Summer	-0.017	0.140*	-0.017	0.139*	-0.008	0.148*
	(0.024)	(0.074)	(0.024)	(0.073)	(0.024)	(0.078)
K12 Kids* School in Person	-0.042	0.230*	-0.042	0.229*	-0.029	0.238*
	(0.035)	(0.119)	(0.035)	(0.118)	(0.036)	(0.122)
K12 Kids* S. in Person*After Summer	0.005	-0.197**	0.005	-0.250**	-0.020	-0.232**
	(0.032)	(0.090)	(0.040)	(0.117)	(0.037)	(0.117)
K12 Kids*S. in Person*A. Summer*Female			-0.001	0.082		

			(0.038)	(0.109)		
Prevalence Private Schools	0.000	-0.007	0.000	-0.007	-0.000	-0.007
	(0.003)	(0.011)	(0.003)	(0.011)	(0.003)	(0.011)
Care Only Me-Spring 2020					0.108***	0.134
					(0.025)	(0.088)
Care*School in Person*After Summer					0.027	0.048
					(0.035)	(0.116)
Observations	37,885	6,738	37,885	6,738	30,311	6,477

Note: Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Age, Race and Region Dummies also included. Results weighted using population weights to the CPS benchmarks