# COVID-19 School Closures and ParentalLabor Supply in the United States

**Catalina Amuedo-Dorantes**
University of California and IZA
**Miriam Marcén**
Universidad de Zaragoza
**Marina Morales**
Universidad de Zaragoza
**Almudena Sevilla**
University College London and IZA

We examine the role of school closures in contributing to the negative labor market impacts of the COVID-19 pandemic. We collect detailed daily information on school closures at the school-district level, which we merge to individual level data on various employment and socio- demographic characteristics from the monthly Current Population Survey from January 2019 through May 2020. Using a difference-in-differences estimation approach, we gauge how the intensity of school closures affects the labor supply of mothers and fathers of young school-age children. We find evidence of non-negligible labor supply reductions, particularly among mothers. These impacts prove robust to endogeneity checks and persist after accounting for other social-distancing measures in place.

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Corresponding author:
Almudena Sevilla
University College
London 55-59 Gordon
Square London WC1H
0NT United Kingdom
E-mail: A.Sevilla@ucl.ac.uk

## 1. Introduction

As a second COVID-19 wave looms, policymakers, researchers, and the public at large are debating which measures help "flatten the curve" the most and how they might affect economic recovery in the long run. The closure of schools and the move to home-based on-line learning have become particularly contentious for a couple of reasons. First, the contribution of school closures to flattening the curve has been questioned due to the lesser incidence and gravity of COVID-19 cases among children.[1] Secondly, the cost of keeping children at home on their development and on parental labor force participation may be non-negligible. After all, parents make up a quarter of all households in the labor force.[2] While the American Academy ofPediatrics was initially open to the reopening of schools during the 2020/2021 academic year (AAP, 2020), reports of widespread contagions during summer camps, as well as when some schools reopened, raised concerns (Szablewski *et al.*, 2020). Many of the large school districts in the country have opted to start online during the 2020/2021 academic year (74% of the 100 largest school districts affecting over 9 million students (Education Week, 2020c)), despitesome state-ordered in-person instruction taking place in four states (*i.e.* Arkansas, Florida, Iowa,and Texas (Education Week, 2020b)). We aim to gain a better understanding of the labor marketimplications of moving from of face-to-face school-based to home-based online learning by examining how school closures due to COVID-19 up to May 2020 impacted parental labor supply in the United States.

To date, we still have a fragmented understanding of the effectiveness of various types of social distancing measures to reduce infection vis-a-vis their immediate impact on economic outcomes. In the absence of vaccines, non-pharmaceutical interventions need to be rigorously implemented during relatively long periods of time to be able to effectively slow down the infection of a contagious disease (Hatchett *et al*., 2007), including COVID-19 (Amuedo-

[1] Recent evidence on summer camps suggested that the incidence, impact and transmission capacity of COVID-19 among children was almost six times lower than among the general population at the time of the study (Götzinger *et al.*, 2020). A recent meta-study of epidemiological and modeling research finds little evidence to support that systematic school closures are effective in coronavirus outbreaks (Viner *et al.*, 2020). Additionally, in countries where schools have reopened, children seem to play a small role in the spread of the virus (Lee and Raszka, 2020).

[2] Authors' own calculations using the Current Population Survey.

Dorantes *et al*., 2020; Fowler *et al*., 2020; Siedner *et al*., 2020). However, social distancing measures can impose large economic costs by curtailing both labor supply and demand –an effect that can only deepen the damage caused by the pandemic (*e.g.*, Barro *et al*., 2020; Chapelle, 2020; Eichenbaum *et al*., 2020; Jones *et al*., 2020; Krueger *et al*., 2020). In the case ofCOVID-19 Béland *et al.* (2020), Cowan (2020), and Gupta, *et al.* (2020) document significant short term employment effects in states that implemented stay-at-home orders.

The trade-off between health and economic outcomes resulting from the COVID-19 epidemic is particularly controversial when it comes to schools. Whereas school closures can reduce the incidence of influenza for a period of about four weeks (Adda, 2016), it is not clear that we can extrapolate those findings to the case of COVID-19, since individuals under the age of 20 appear less likely to spread the disease or become seriously ill (Davies *et al.*, 2020).[3] Yet, the economic consequences of closing schools can be extremely damaging for children and parents. Children's development and later earnings can be compromised as efforts to equalize the home learning experience through the levers available to schools failed to deliver, particularly for low income children (Andrew *et al.*, 2020a; Portes, 2020). School closures can also have negative consequences for parental employment, as working parents cope with additional childcare obligations. For example, Graves (2013a, 2013b) finds that year-round school calendars, which create more frequent and shorter breaks, negatively impact maternal employment. Similarly, evidence from real-time data across several countries from the early days of the pandemic suggests that parents experienced a drop in employment as they assumed greater childcare responsibilities after school closures (Adams-Prassl *et al.* (2020), Andrew *et al*. (2020b) and Sevilla and Smith, (2020) for the U.K.; Del Boca *et al.* (2020) and Biroli *et al*. (2020) for Italy, and Farré *et al*. (2020) for Spain).

The size of the United States and the lack of federal directives on how to deal with the pandemic make the United States an interesting case study. We use the geographical and temporal variation in the implementation of school closures across U.S. states to identify the

[3] In addition, studies have documented higher absenteeism levels of health care workers when schools closed as a result of the COVID-19 pandemic, which can raise mortality rates and offset any reduction stemming from fewer contagion at schools (Bayham and Fenichel, 2020).

effect of children's home on-line learning on parental labor supply. To that end, we construct a comprehensive high-frequency (daily-level) data set of school closures at the school district level from the start of school closures to the end of the academic year. This information is merged to individual level data on employment and socio-demographic characteristics from the monthly January 2019 to May 2020 Current Population Survey.

Unlike other countries, decisions on school closures in the United States were frequently made at the school district level and, in other occasions, at the county or state levels. Schools also closed for different periods of time. In order to better capture individuals' exposureto school closures in a given state and point in time, we construct an index informative of the intensity of school closures, which takes into account the share of the population impacted by school closures, as well as how many days schools were closed. We estimate difference-in- differences models to gauge the impact of school closures on the labor supply of couples with young school-aged children (aged 6-12). Our focus is on individuals' employment propensity;on their propensity to be furloughed if employed; and on the actual number of hours worked by those who report being at work. Our estimation strategy also takes into account other state-level measures implemented at the same time, which likely impacted labor supply during this period, such as the declaration of state of emergency, non-essential and partial business closures and safer-at-home orders.

We find that school closures reduced weekly work hours among fathers and mothers of young school-age children between 11 and 15 percent. The effects are larger for women. Event studies show that the impact of school closures on parental labor supply did not pre-date the policy measures but, rather, occurred in response to the ongoing school closures. Furthermore, the results prove consistent to robustness checks using alternative sample specifications and measures of school closures. We also find that whereas the implementation of NPIs measures, such as business closures and safer at home orders, are associated with employment loses at the extensive margin, school closures seem to have affected employment at the intensive margin by reducing the hours of work of those already employed.

Our findings are consistent with a model in which the closure of schools and the shift to on-line learning imposes a significant burden on parental time, particularly for mothers. We uncover heterogeneous responses to school closures by gender, based on respondents' ability to supply childcare and their childcare needs. School closures appear to have had a greater impact on mothers unable to telework, those who were not considered "essential" workers, as well as among mothers who did not have another adult able to supply childcare in the household. There are no differential effects for fathers, suggesting that mothers might be the ones assuming most of the childcare responsibilities. We fail to see any effect of school closures on the parental labor supply of households with older children, who might require less childcare. Overall, the findings hint on the important role of mothers in responding to emerging childcare responsibilities when children no longer can attend regular face-to-face school.

To date, we lack an understanding of the causal impact of school closures from the COVID-19 pandemic on parental labor supply. Some studies have looked at the effect of other social-distancing measures resulting from COVID-19 –namely, stay-at-home orders and business closures– on employment and other economic outcomes (Béland *et al.*, 2020; Cowan, 2020; Forsythe *et al.*, 2020; Gupta *et al.*, 2020). The closest exercise is found in Rojas *et al*. (2020), who correlate weekly unemployment insurance claims and school closures at the state level to document the historically unprecedented increase in new unemployment insurance claims during the weeks of March 15-21 and March 22-28. They conclude that most of the economic disruption was driven by the health shock itself, rather than school closures. However,the analysis does not consider other simultaneously implemented social distancing measures. Kong and Prinz (2020) exploit the differential timing of the introduction of NPIs across U.S. states on Google searches on how to claim unemployment insurance. They conclude that school closures had no effect on unemployment claim searches. We find that school closures did not affect the probability of holding a job. However, there is robust evidence of school closures and home-based on-line learning curtailing parental work hours.

The rest of the paper is organized as follows. In Section 2, we describe the data used in the analysis. We then present the empirical strategy in Section 3, and discuss our main findings, as well as the results from various identification and robustness checks, in Section 4. In Section

5, we discuss some of the key mechanisms at play, and Section 6 concludes.

## 2. Data

We use data on the exact date in which NPIs and school closures were implemented, along with individual-level labor market outcomes from the Current Population Survey. The Table A1 in the Appendix documents how all these variables are constructed and their summary statistics.

### 2.1 Labor Market Outcomes

We use monthly Current Population Surveys (CPS) data spanning from January 2019 through May 2020 from the Integrated Public Use Micro Samples (IPUMS).[4] This extended period allows us to conduct event studies to assess the exogeneity of school closures with respect to parental labor supply, as well as to control for the seasonality of the data by including month fixed effects. CPS interviews and data collection usually take place during the week extending through the 19th of the month. Respondents are asked several labor force participationquestions that refer to the prior week, which is usually the 7-day calendar week (Sunday– Saturday) that includes the 12th of the month.[5] In addition, our results prove robust to controlling for whether the interview was done in-person or telephone (see Appendix Panel A inTable A2). Our main sample consists of working-age, non-institutionalized civilians who are 16 to 64 years old, live in two-partnered households, and have school-aged children 6 to 12 years old, who require more parental care and supervision than older youth.

We focus on *three* labor market outcomes. The *first* outcome is the respondent's employment status as captured by the variable *employed*, which takes value 1 if the respondent reported doing any work at all for pay or profit, or working at least fifteen hours without pay in

[4] According to BLS, of the 8.4 million people employed and not at work during the reference week in May 2020, 1.5 million were included in the "own illness, injury, or medical problems" category (not seasonally adjusted). This share was down from 2.0 million in April, but it was still larger than the 932,000 individuals usually in this category in May of recent years. See: https://cps.ipums.org/cps-action/variables/group?id=h-core_tech

[5] Interviews were conducted exclusively by telephone in the majority of days in March, and in the months of April and May (in contrast to 85% in the pre-COVID period), and response rates were 10 percentage points lower (73%) than in the months preceding the pandemic. Nonetheless, the agency "was still able to obtain estimates that met [their] standards for accuracy and reliability" https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/collecting-data.html

a family business or farm. The *second* outcome is whether the individual reports having a job but *did not work last week*. Focusing on individuals who are employed (at work or furloughed) allows us to study the magnitude of the school closure effect on individuals who are employed, but were not working during the reference week. Traditionally, this group is rather small and consists of individuals who report being temporarily absent from work due to illness, vacation, bad weather, a labor dispute, or other reasons.[6] During the pandemic, however, some of the individuals in this category might have been in quarantine or self-isolating; many were furloughed. However, according to BLS, some workers who were classified as employed butnot working last week should not have been coded as employed. Hence, this category may include individuals who were unemployed. Finally, the *third* outcome we examine is the number of weekly *work hours* across all jobs by those reporting being employed, as well as working during the week prior to the survey.

Figures 1A and 1B document significant employment rate reductions at the intensive and extensive margins from the time the pandemic hit in early March (captured by the March CPS) onwards (see Table A3). While the probability of being employed declined about 14 percent for women, it dropped by almost half of that (8 percent) among men. The probability of not working during the week prior to the survey doubled in May 2020, when compared to the pre-COVID period, for both men and women. There was also a small reduction in hours of workfor those who remained at work of 1 percent. Hours of work during April and May 2020 were closer to the hours of work reported during school holidays in previous years, than to hours of work during the same months of April and May in 2019. This is consistent with the literature on school closures, according to which women reduce hours of work and are more likely to report "not working last week" during the summer holidays when children are not attending school (Graves, 2013a, 2013b).

[6] https://www.bls.gov/cps/employment-situation-covid19-faq-may-2020.pdf

### 2.2 School Closures Data

We gather school closure dates from *Education Week*, which records the closing dates of schools by school district from the time when school closures started until the end of the school year (Education Week, 2020a). We double check state-level information from Education Week sources on the dates of school closures with routinely-maintained data repository for U.S. state-level distancing policies in response to the 2019 novel coronavirus (SARS-CoV-2), which is published by the National Governors Association (NGA) (see Fullman *et al.*, 2020).

School closures took place at distinct geographic levels (some at the county, others atthe state), and schools closed for different periods of time. School closures began on February 26, 2020 in Snohomish county in the state of Washington. By the beginning of March 2020, a total of 347 counties (out of 3,142 counties) had closed their schools. In March, thirty-six states had, at least, one county with schools closed. In many states (Arizona, Georgia, Idaho, Kentucky, Maine, Minnesota, Nevada, South Dakota, Utah, Virginia, and Wisconsin), only one county had closed schools in March. In contrast, Maryland, Michigan, Ohio, and Oregon had closed schools across all counties by the end of March. The latest county to close schools was Oneida county in the state of Idaho on March 23, 2020. Schools remained closed thereafter untilthe end of the academic year at the end of May or beginning of June.[7]

In order to better capture individuals' exposure to school closures, we follow Watson (2014), Amuedo-Dorantes and Lopez (2015), and Amuedo-Dorantes *et al*. (2018), and construct an index that varies between 0 and 1 and is reflective of the intensity of school closures in state *s* in month *t*, given by:

$$(1) \qquad SC_{st} = \frac{1}{P_{s,2019}} \sum_{c \in s} \frac{1}{D} \sum_{d=1}^{D} \mathbf{1}\left(SC_{d,c}\right) P_{c,2019}$$

where $P_{\mathrm{c},2019}$ is the population of county *c*, and $P_{\mathrm{s},2019}$ is the total population of state *s* according to the 2000 U.S. Census.[8] $SC_{\mathrm{d,c}}$ is an indicator function that takes value 1 if schools

[7]Some rural school districts intermittently opened schools during May in states like Montana andWyoming. Information was not systematically collected by Education Week on such instances, and news were suggestive of the reopening of schools being a very rare phenomenon.

[8] https://www.census.gov/data/datasets/time-series/demo/popest/2010s-counties-total.html#par_textimage_70769902

were closed in county *c*, on day *d* of month *t*, whereas *D* is the total number of days in month *t*. We rely on county-level variation due to the lack of data on population figures at the school-district level. We use ELSI-Elementary and Secondary Information System –a web application of the National Center for Education Statistics to match school districts to county, and assume that a county closed a school if a school-district had done so in a given county.[9] In cases where astate closed its schools prior to school districts doing so, we assign that date to all school closures across counties in the state.

To make sure the school closure data refers to the same period for which the labor supply data in the CPS was collected, each month expands from the 13th of the month to the 12th of the next month. We also experiment with different time frames and results prove robust (see Panel B in Table A2). The index takes values ranging between 0 (if no county in the state had closed schools) to 1 (if all counties in the state had closed schools). A value between 0 and 1 canbe interpreted as the probability that an individual living in state *s* may have been exposed to a school closure.

### 2.3 Data on Other Social Distancing Measures

Respondents in various states were also exposed to other COVID19-related non-pharmaceutical interventions that counties and states implemented to curtail contagion and the spread of the pandemic. We follow the literature and control for a variety of such measures – namely, the declaration of state of emergency, partial business closures, non-essential business closures and safer-at-home orders. *Emergency declarations* include the declaration of state of emergency, a public health emergency, and public health disaster declarations. *Partial business closures* incorporate partial closures, such as restrictions or limitations on restaurants, casinos, gyms, fitness centers and entertainment venues. *Non-essential business closures* refer to mandates closing all non-essential businesses. *Safer-at-home orders* refer to mandates for individuals to stay at home for all non-essential activities (Fullman *et al*., 2020).

There were no measures in place until the end of February, when the state of

[9] https://nces.ed.gov/ccd/elsi/

Washington declared the state of emergency on February 29, 2020. Emergency declaration orders were enacted in 34 states during mid-February to mid-March 2020, and West Virginia was the last state to declare the state of emergency on March 16, 2020. Non-essential business closures started on March 19, 2020 in California and Pennsylvania. Mississippi and Oklahoma were the last states to implement them on April 1, 2020. Forty-eight states enacted partial business closures, and 31 states enacted non-essential business closures in April. Safer-at-home measures were in place in 41 states in April. Safer-at-home and shelter-in-place orders startedon March 19, 2020 in California. South Carolina was the last state issuing a safer-at-home order on April 6, 2020.

We also construct a non-pharmaceutical index intended to capture the *intensity* of social distancing measures that an individual is exposed to, depending on how many measures and for how long these measures were in place in a given state at a particular month, *i.e.*:

$$(2) \qquad NPI_{st}^{k} = \sum_{c \in s} \frac{1}{D} \sum_{d=1}^{D} \mathbf{1}\left(NP_{d,s}\right) \text{ for } k = 1 \ldots 4$$

where $NPI_{\mathrm{st}}^{\mathrm{k}}$ is a proxy for the intensity of each one of the 4 measures in each state, where $NP_{\mathrm{d,s}}$ is an indicator function that takes value 1 if NPI *k* in state *s* was in place on day *d* , where *D* is the total number of days in that month. Subsequently, we add the four NPI indices to obtain a single measure of the intensity of social distancing in the state, *i.e.*:

$$(3) \quad TNP_{st} = \sum_{k \in K}^{K} NPI_{st}^{k}$$

The index in equation (3) can take values from 0 (if none of the four NPIs were in place in the state during the month in question) to 4 (if all four measures were in place for the entire month).

Table A4 shows the mean and standard deviation of the school closure intensity index at various points in time during the period under analysis. The school closure index was almost 0 in March. This implied that, even though 36 states had at least one county with closed schools, the number of impacted counties was still relatively small (347 out of 3,142 counties). The school closure intensity index increased substantially in April, reaching a value close to 1, at which point most counties had closed schools. By May, this index was 1, signaling all schools had closed. Similarly, with the only exception of emergency declarations, the intensity of the other NPIs was zero in March 2020. It rose in April 2020, ranging from 0.4 (in the case of non-essential business closures) to practically 1 (for emergency declarations and school closures). The indexes continued to rise in May, except the index relating to other business closures, which declined as some businesses were allowed to reopen in some states.

## 3. Methodology

To understand the extent to which school closures adopted in response to the pandemic paused economic activity, we exploit the temporal and geographic variation in the adoption of school closures as follows:

$$(4) \qquad Y_{\text{ist}} = \alpha + \beta SC_{\text{st}} + X_{\text{ist}}\gamma + \varphi TNP_{\text{st}} + \delta_{\text{s}} + \theta_{\text{t}} + \varepsilon_{\text{ist}}$$

where $Y_{\text{ist}}$ captures if the *i*th respondent is employed and, in that case, whether s/he was at work during the week prior. For those reporting being at work during that week, we then model the logarithm of weekly work hours. The variable $SC_{\text{st}}$ is the school closure index capturing the probability that an individual living in state $s$ may have been exposed to a school closure. Our coefficient of interest is $\beta$, which gauges the impact of school closures on parental labor supply. All models account for demographic traits ($X_{\text{ist}}$) known to affect the labor force status, such as gender, age, educational attainment, marital status, and the number of children in the household. When focusing on those reporting to be employed, the vector $X_{\text{ist}}$ also includes controls for the occupation held. In addition, we include the index $TNP_{\text{st}}$, which accounts for other social distancing measures in place potentially affecting labor supply simultaneously. Finally, allmodels include state and time (year, month) fixed-effects ($\delta_{\text{s}}\, and\, \theta_{\text{t}}$) to address observed and unobserved factors potentially affecting economic activity during this extraordinary period.

## 4. Parental Labor Supply during School Closures

### 4.1 Main Findings

Table 1 provides a preliminary assessment of the impact of school closures on the parental labor supply of two-partnered households. We focus on two-partnered households with young school-age children because our aim is to better understand changes in the labor supply of partners as schools close to attend to childrearing and childcaring responsibilities. Roughly 88 percent of school-age children ages 6 to 12 years of age reside in two-partnered households. Nevertheless, we also present estimates on school closures on single-headed households in Table A5 in the appendix.[10] In addition, given our interest on the differential impact of school closures on the labor supply of mothers when compared to fathers, we narrow our focus to heterosexual couples, regardless of their marital status.

As can be seen in Table 1, school closures during the months of March, April and May of 2020 primarily affected the labor supply of mothers and fathers of younger school-age children in two-partnered households through a reduction in their weekly hours of work, which dropped by 11 percent among men and by 15 percent among women. Employment probabilities fell and the probability of not working during the week prior rose, but these coefficients are estimated less efficiently. In sum, the evidence in Table 1 suggests that both mothers and fatherswith young school-age children sought their work hours compromised when schools closed, albeit the impact appears to have been somewhat larger for women.[11]

Other results in Table 1 are as expected. For instance, both mothers and fathers were more likely to be employed if their partners reported to be employed when compared to mothersand fathers whose spouses were not employed, possibly hinting on assortative mating. However,they both reduced their weekly hours of work relative to mothers and fathers whose spouses were not employed, which could be potentially related to household income constraints among the latter. We also observe that older, as well as more educated spouses, are more likely to be employed and, in the case of men, work more hours/week. Importantly, Table 1 controls for the

[10] We do not find a significant impact of school closures on the labor supply of parents in single-headed households. This finding is consistent with single-headed households having a wider network of childcare provision that may have shielded them from the adverse employment effects, at least in the short run, as well as on the household's probable reliance on that parent's income.

[11] Because individuals of working age are either employed, unemployed or not in the labor force, based on the findings from Table 1, where the propensity to be employed remained unchanged by school closures, we might expect offsetting impacts of school closures on the propensity to be unemployed or notin the labor force or, alternatively, close to null impacts. Table A6 shows the results from this exercise. The unemployment and the out of the workforce propensities of fathers do not seem to have significantly changed with school closures. However, school closures seem to have tripled mothers' unemployment propensity (raising it by 6 percentage points), while decreasing their likelihood of being out the workforce by 4 percentage points, although this effect is only marginally statistically significant.

adoption of others social distancing measures, including business closures and stay-at-home orders. Whereas school closures affect labor market outcomes at the intensive margin, other non-pharmaceutical measures seem to affect labor market outcomes at the extensive margin. An increase in the NPI index equal to 2 (close to the index average during April and May) was associated with a 4.5 percent and an 8.2 percent reduction in the employment propensity of fathers and mothers, respectively.

### 4.2 Identification

A reasonable concern with the results in Table 1 refers to the possibility that our coefficients of interest might be biased due to the unlikely random closure of schools. While no policy is ever adopted arbitrarily (Allcott *et al.*, 2020), our concern is if factors responsible for the closing of schools are correlated with the labor market outcomes of interest. To assess if the adoption of school closures measures is endogenous to the labor market outcomes of interest herein, we conduct an event study for each of those outcomes. This allows us to gauge if any impact of school closures on parental labor supply predated the adoption of the policy in question. In addition, we can assess whether school closures led to a significant break in the parental labor supply trend. Because our identification relies on changes in the probability of being exposed to a school closure, leads are defined as the periods prior to the $SC_{st}$ index first

turning positive, whereas the lags are interacted with $SC_{st}$ to capture the intensity of school closures, as in recent literature utilizing a continuous treatment variable, *e.g.* Clemens *et al.* (2018) and Goodman-Bacon (2018). Specifically, the event-study takes the following form:

(5) $$Y_{ist} = \alpha + \sum_{j=-15}^{-2} \tau_j 1(SC_{st} > 0) + \sum_{j=0}^{2} \rho_j [1(SC_{st} > 0) \cdot SC_{st}] + X_{ist}\gamma + \varphi TNP_{st} + $$
$$+\delta_s + \theta_t + \varepsilon_{ist}$$

where $Y_{ist}$ is the outcome for individual *i* in state *s* and month *t*. The indicator function $1(SC_{st} > 0)$ represents the *t*th month before or after the $SC_{st}$ index first turned positive in state *s*. We examine the existence of pre-trends during the fifteen months prior, as captured by coefficients $\tau_j$. The coefficients $\rho_j$ measure the dynamics of school closure effects, and they are interacted with the $SC_{st}$ index to capture the intensity effects.

Figure 2 displays the coefficients from the event study for our main sample of two-partnered households, along with 95 percent confidence intervals. All estimates for the months prior to the school closures are close to zero, strongly supporting the assumption of no pre- trends. There are no clear breaks in the employment or in the employed-not at work trends. However, there is evidence of a clear break in the trend in the weekly hours at work reported by both men and women around the closure of schools (estimates are provided in Table A7). The estimates are also statistically different from zero one and two months after the school closures (coinciding with April and May), signaling the break in the trend in economic activity accompanying the closing of schools.

In addition to the event study described above, to address endogeneity concerns stemming from reverse causality, we model the timing of school closures in a given state as a function of the state's parental labor supply *prior to* such closures. This enables us to assess if, while non-random, the policy adoption can be predicted by our outcome of interest. Table A8 shows that we are unable to predict the timing of school closures based on the pre-COVID state employment rate of parents, the share of employed parents not at work during the prior week, ortheir average weekly work hours for those at work. As such, while the policies might not be randomly adopted, their adoption does not appear to have been correlated to parental labor supply.

## 5. Mechanism: Competing Work and Child Care Responsibilities

The negative impact of school closures on parental labor supply may originate from the need to care for children during the hours they are no longer at school. During COVID closures, the impact of school closures was further magnified by the need to also supervise and help children with home schooling. Real-time data across several countries from the early days of thepandemic suggests that parents experienced a drop in employment as they assumed greater childcare responsibilities as school closed their doors (*e.g.* Adams-Prassl *et al*. 2020, Andrew *et al*. 2020b, and Sevilla and Smith, 2020 for the U.K.; Del Boca *et al.* 2020 and Biroli *et al*., 2020 for Italy; and Farré *et al*., 2020 for Spain). In this section, we explore the legitimacy of this hypothesized mechanism, which we envision as primarily responsible for the negative impact of school closures on the labor supply of parents with young school-age children.

### 5.1 Parental Ability to Respond to Increased Childcare Needs

During the pandemic, telework became a saving grace for many working parents with young children, as it enabled them to cope with both childcare and work responsibilities and, possibly, keep their jobs. We merge the Standard Occupational Classification (SOC) codes and the CPS occupational codes with the equivalence provided by the BLS in 2019 and 2020, and follow Dingel and Neiman (2020) to construct an indicator variable that takes value 1 if a worker's occupation is amenable to telework, and 0 otherwise. Forty percent of fathers and 55 percent of mothers in our sample can telework. Panels A and B in Table 2 show how the labor supply of mothers and fathers responded differently to school closures depending on their ability to telework. While both endured reductions in their weekly hours of work, mothers who were able to telework did not experience a significant reduction in their employment propensity (Panel A), whereas those unable to telework did (by about 13 percent, see Panel B). In addition, mothers able to telework did not reduce their hours of work as much as mothers unable to telework. These results are consistent with Kalenkoski and Pabilonia (2020), who find that remote work mitigated some of the negative effects on employment and hours.

In Panels C and D of Table 2, we further explore the role played by whether the respondent is an "essential" worker. We use the classification of essential workers of two states Pennsylvania and Delaware provided by the NGA, which uses the official North American Industry Classification System (NAICS) codes. These codes can be easily matched with the CPS Codes using BLS equivalence for the years 2019 and 2020. Perhaps the most striking finding is how being classified as an "essential" worker makes a difference in how mothers' labor supply responds to school closures. Relative to mothers who were not essential workers, mothers who were experienced a smaller reduction in their employment propensity (9 percentvs. 16 percent), did not stop working, and did not curtail their weekly work hours. These differences are not observed among fathers, whose labor supply reacted similarly to school closures regardless of whether they were essential workers or not. Finally, among non-essential workers –by far, the largest group of workers in the workforce– labor supply reductions in response to school closures were significantly more acute among mothers than fathers. Mothers reduced their employment likelihood, increased their propensity of not being at work, and cut down their weekly work hours by 30 percent as schools closed. In contrast, fathers only reduced their weekly work hours by 11 percent.

### 5.2 Household's Ability to Respond to Increased Childcare Needs

If childrearing is the main explanation for the uneven impact of school closures on the labor supply of mothers with young school-age children relative to fathers, we would expect the presence of an adult in the household to make a significant difference. Results in Panel A and B in Table 3 show that the presence of an adult in the household, other than the spouse, seems to have helped fathers maintain their labor supply more than it assisted mothers. Fathers were significantly less likely to be on furlough or not at work as schools closed if there was an adult (other than the mother) in the household. Furthermore, those fathers did not reduce their work hours, whereas fathers without an adult in the household did by about 12 percent. In other words, the presence of an adult in the household enabled fathers to maintain their labor supply patterns despite ongoing school closures. In a similar vein, mothers with an adult (other than the father) in the household did not reduce their weekly hours of work when schools closed, whereas their counterparts without an adult in the household did by 14 percent. However, their propensity to be on furlough or not at work rose, albeit by a marginally statistically significant level.

Panels C and D in Table 3 further look at how school closures might have impacted parental labor supply differently depending on whether the other spouse was at home –working or not. While the labor supply response of fathers to school closures was the same regardless of whether mothers were at home (in both instances, fathers reduced their weekly work hours by11 percent), that was not the case for mothers. Mothers whose partners were at home cut their weekly work hours by 11 percent as schools closed –just as fathers did. However, motherswhose spouses were *not* at home reduced their weekly hours of work by almost double that amount (20 percent) as schools closed.

To conclude, Panel E shows the results of a placebo check where we look at the labor supply responses of parents with older school-aged children, such as those with teenagers 15 to 17 years old. These children are less likely to need the type of parental supervision required by younger school-age children. If the captured impact of school closures on parental labor supply is due to the need to care and supervise children when not at school, we should not see as much of a change in parental labor supply in that case. As shown in Panel E, we find no significant impact of school closures on the labor supply of either mothers or fathers when children were older. This suggests that the found labor supply impacts of school closures in Table 1, 2 and 3 were mainly driven by the need to care and supervise younger children when schools closed.

## 6. Summary and Conclusions

We examine how school closures following the breakout of the COVID-19 pandemic have impacted parental labor supply in the United States. Even after accounting for other policies happening during this time, we find evidence of significant reductions in the weekly work hours by both mothers and fathers of young school-age children in two-partnered households when face-to-face or physical school was place on hold. Identification checkssupport a causal interpretation of our findings, and robustness checks confirm the reliability of our estimates.

Whereas school closures have primarily lowered the weekly work hours of both fathers and mothers of young school-aged children in two-partnered households, the labor supply impacts of school closures have been more noticeable among mothers, particularly if they were unable to telework, were non-essential workers or did not have an adult (partner or else) in the household. These results underscore the significant labor supply impact of school closures on families and, in particularly, on mothers, who seem to have borne the brunt of childcareresponsibilities. As such, the findings highlight the urgency to come out with solutions for families, which might range from expanding telework opportunities, to alternative childcare arrangements.

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**Figure 1**
**Employment Outcomes for Two-Partnered Households by gender**

**Figure 1A: Men**

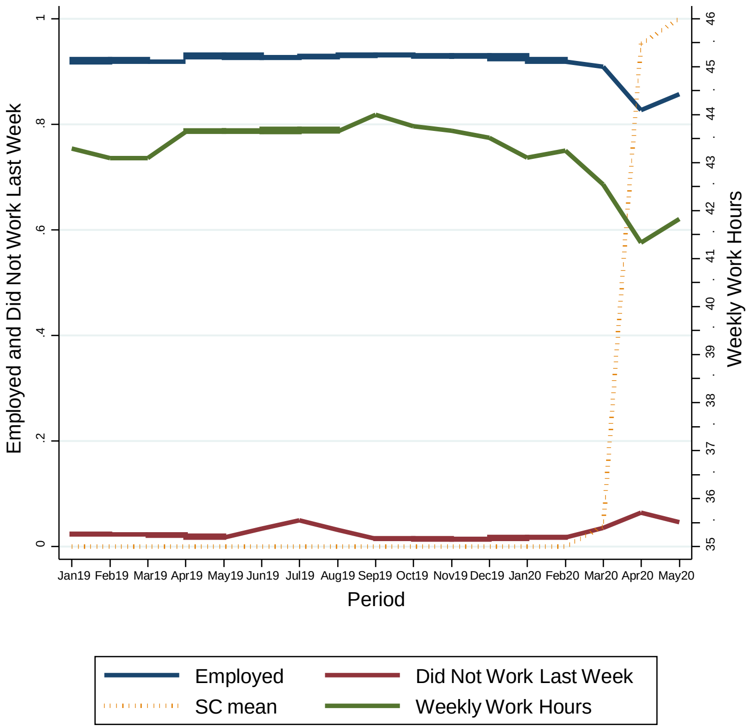
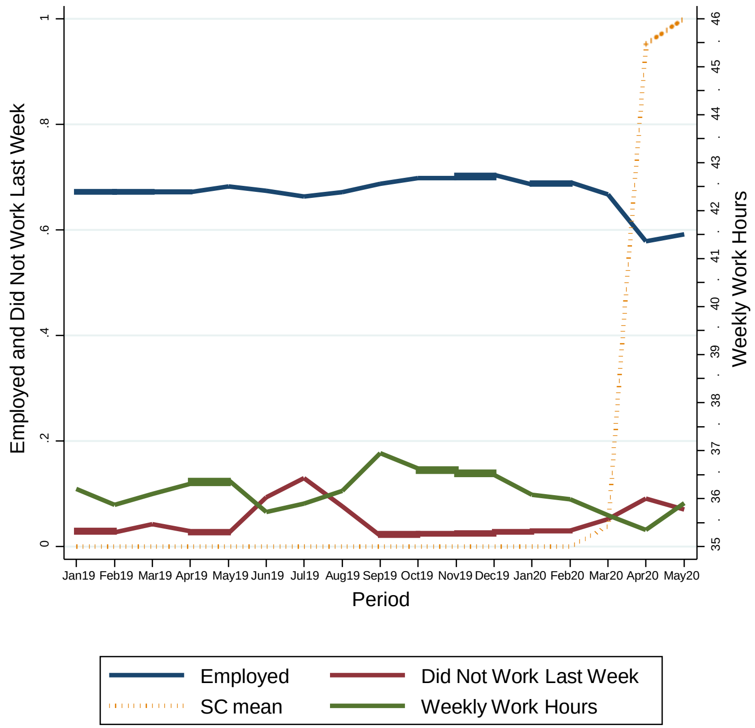


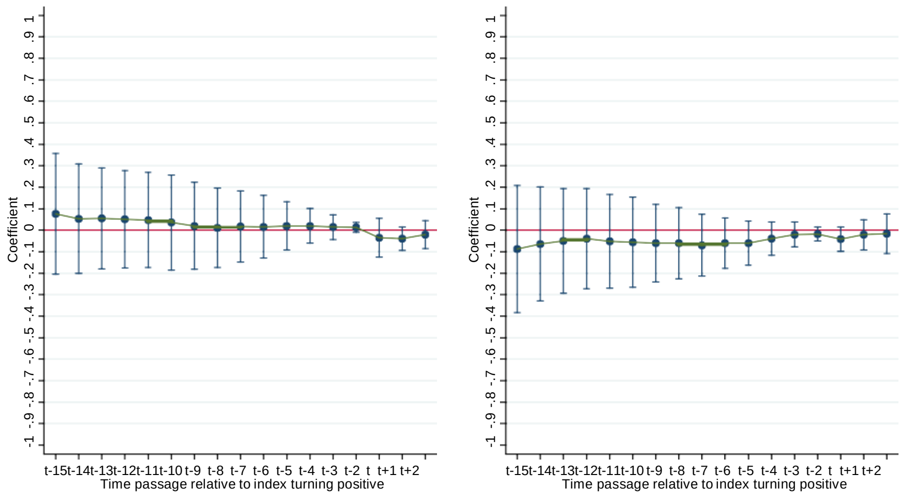

**Figure 1B: Women**




**Notes:** This figure plots the evolution of the mean of our labor outcome variables from January 2019 to May 2020. The sample in all columns includes individuals between 16 and 64 years old from two-partnered households with at least one child aged 6-12 years old. Employment is analyzed using a sample of civilian, not institutionalized individuals. We use a sample of individuals currently employed when studying “Did not Work Last Week” (those at work and those who has a job and did not work the last week). We consider a sample of individuals who report being at work during the prior week when we analyze the “Weekly Work Hours”. Women are plotted on the right and men on the left.

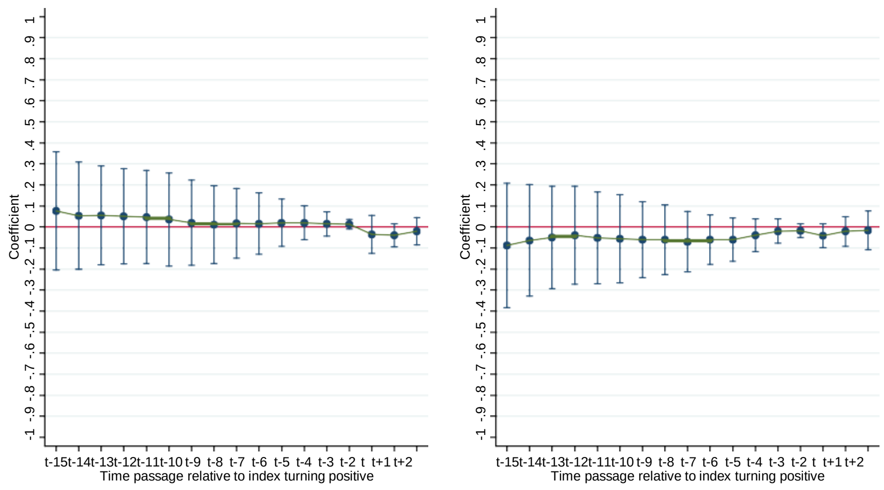
**Figure 2 Event Study**
**Employed**

**Men** **Women**



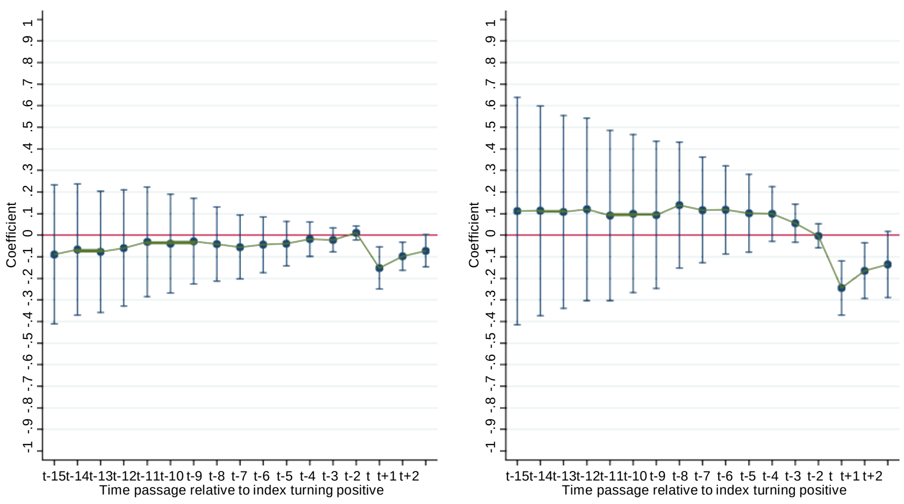

**Did not work last week**

**Men** **Women**




**Log(Weekly work hours)**

**Men** **Women**




**Notes:** These figures display the coefficients from the event study for our main sample of two-partnered households, along with 95 percent confidence intervals. Estimates are provided in Appendix A in Table A7.

**Table 1**
**Labor Supply Response to School Closures of Two-Partnered Households with Children Ages 6-12**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Employed** | | **Did not Work Last Week** | | **Log (Weekly Work Hours)** | |
| | **Men** | **Women** | **Men** | **Women** | **Men** | **Women** |
| SC | -0.025 | -0.018 | 0.012 | 0.028 | -0.110*** | -0.152*** |
| | (0.027) | (0.027) | (0.016) | (0.021) | (0.022) | (0.051) |
| Partner employed, not at work last week | 0.019** | 0.045*** | 0.202*** | 0.376*** | -0.067*** | -0.137*** |
| | (0.007) | (0.014) | (0.012) | (0.018) | (0.016) | (0.023) |
| Partner employed, at work last week | 0.004 | 0.036*** | -0.010*** | 0.000 | -0.009** | -0.057*** |
| | (0.004) | (0.012) | (0.001) | (0.003) | (0.004) | (0.014) |
| Age | 0.021*** | 0.038*** | -0.001 | -0.002 | 0.006* | -0.002 |
| | (0.002) | (0.004) | (0.001) | (0.001) | (0.003) | (0.005) |
| $Age^2/100$ | -0.027*** | -0.044*** | 0.001 | 0.002 | -0.008** | 0.003 |
| | (0.003) | (0.005) | (0.001) | (0.002) | (0.004) | (0.006) |
| Number of children | 0.000 | -0.054*** | 0.000 | 0.005*** | 0.004** | -0.045*** |
| | (0.002) | (0.004) | (0.001) | (0.001) | (0.002) | (0.006) |
| High School | 0.025*** | 0.158*** | -0.002 | -0.004 | 0.049*** | 0.005 |
| | (0.009) | (0.013) | (0.003) | (0.009) | (0.013) | (0.018) |
| College | 0.044*** | 0.239*** | -0.002 | 0.005 | 0.057*** | -0.052** |
| | (0.012) | (0.010) | (0.003) | (0.010) | (0.012) | (0.021) |
| More college | 0.090*** | 0.306*** | -0.005 | 0.000 | 0.065*** | -0.040* |
| | (0.011) | (0.015) | (0.003) | (0.009) | (0.013) | (0.022) |
| TNP | -0.021** | -0.028*** | 0.006 | 0.004 | 0.012 | 0.034* |
| | (0.009) | (0.009) | (0.005) | (0.007) | (0.008) | (0.018) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean 01/2019-02/2020 | 0.93 | 0.68 | 0.02 | 0.04 | 3.73 | 3.50 |
| Observations | 80,787 | 82,696 | 74,125 | 56,472 | 72,153 | 53,783 |
| R-squared | 0.037 | 0.092 | 0.065 | 0.106 | 0.025 | 0.055 |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The samplein columns (3) and (4) are individuals currently employed. The sample in column (5) and (6) are employed individuals who are currently working, and who were at work during the prior week. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). We also control for the type of occupation in columns (3) to (6). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include The Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

**Table 2**
**Mechanisms #1: Heterogeneous Responses according to the Respondent's Ability to Supply Childcare**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Respondent is Amenable to Telework** | | | | | | |
| | **Employed** | | **Did not Work Last Week** | | **Log (Weekly Work Hours)** | |
| | **Men** | **Women** | **Men** | **Women** | **Men** | **Women** |
| SC | -0.028 | -0.060 | 0.014 | 0.036 | -0.126*** | -0.132** |
| | (0.027) | (0.041) | (0.020) | (0.022) | (0.039) | (0.059) |
| Mean 01/2019-02/2020 | 0.98 | 0.97 | 0.02 | 0.05 | 3.74 | 3.52 |
| Observations | 30,814 | 32,308 | 30,261 | 31,282 | 29,582 | 29,744 |
| R-squared | 0.016 | 0.029 | 0.020 | 0.057 | 0.023 | 0.061 |
| **Panel B: Respondent is Not Amenable to Telework** | | | | | | |
| SC | -0.021 | -0.090*** | 0.012 | 0.019 | -0.093*** | -0.167** |
| | (0.029) | (0.033) | (0.021) | (0.047) | (0.028) | (0.069) |
| Mean 01/2019-02/2020 | 0.97 | 0.96 | 0.02 | 0.04 | 3.72 | 3.47 |
| Observations | 45,645 | 26,623 | 43,864 | 25,190 | 42,571 | 24,039 |
| R-squared | 0.038 | 0.052 | 0.014 | 0.024 | 0.029 | 0.059 |
| **Panel C: Essential Worker** | | | | | | |
| SC | -0.014 | -0.060** | 0.015 | -0.006 | -0.119*** | -0.046 |
| | (0.019) | (0.026) | (0.015) | (0.023) | (0.032) | (0.057) |
| Mean 01/2019-02/2020 | 0.98 | 0.97 | 0.02 | 0.03 | 3.74 | 3.53 |
| Observations | 38,629 | 30,223 | 37,571 | 29,152 | 36,611 | 28,133 |
| R-squared | 0.024 | 0.034 | 0.010 | 0.012 | 0.023 | 0.063 |
| **Panel D: Non-essential Worker** | | | | | | |
| SC | -0.046 | -0.106** | 0.021 | 0.080* | -0.105*** | -0.296*** |
| | (0.036) | (0.050) | (0.030) | (0.040) | (0.029) | (0.076) |
| Mean 01/2019-02/2020 | 0.98 | 0.96 | 0.02 | 0.06 | 3.72 | 3.46 |
| Observations | 37,830 | 28,708 | 36,554 | 27,320 | 35,542 | 25,650 |
| R-squared | 0.041 | 0.057 | 0.018 | 0.063 | 0.032 | 0.058 |
| *For all* | | | | | | |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The sample in columns (3) and (4) are individuals currently employed. The sample in column (5) and (6) are employed individuals who are currently working, and who were at work during the prior week. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). We also control for the type of occupation in columns (3) to (6). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include the Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

**Table 3**
**Mechanisms #2: Heterogeneous Responses according to the Household's Ability to Supply Childcare**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Other Adults in the Household (excluding own children)** | | | | | | |
| | **Employed** | | **Did not Work Last Week** | | **Log (Weekly Work Hours)** | |
| | **Men** | **Women** | **Men** | **Women** | **Men** | **Women** |
| SC | -0.139 | -0.042 | -0.125** | 0.120* | 0.038 | -0.405 |
| | (0.118) | (0.093) | (0.053) | (0.066) | (0.087) | (0.313) |
| Mean 01/2019-02/2020 | 0.90 | 0.68 | 0.02 | 0.04 | 3.70 | 3.50 |
| Observations | 4,896 | 4,962 | 4,286 | 3,341 | 4,157 | 3,188 |
| R-squared | 0.091 | 0.116 | 0.144 | 0.193 | 0.048 | 0.132 |
| **Panel B: No Other Adults in the Household** | | | | | | |
| SC | -0.022 | -0.017 | 0.021 | 0.023 | -0.119*** | -0.138*** |
| | (0.025) | (0.030) | (0.017) | (0.021) | (0.023) | (0.045) |
| Mean 01/2019-02/2020 | 0.93 | 0.68 | 0.02 | 0.04 | 3.73 | 3.50 |
| Observations | 75,891 | 77,734 | 69,839 | 53,131 | 67,996 | 50,595 |
| R-squared | 0.035 | 0.093 | 0.062 | 0.102 | 0.026 | 0.055 |
| **Panel C: Partner at Home (Working or Not)** | | | | | | |
| SC | -0.019 | -0.036 | 0.025 | 0.040 | -0.114*** | -0.109* |
| | (0.037) | (0.043) | (0.023) | (0.035) | (0.022) | (0.061) |
| Mean 01/2019-02/2020 | 0.09 | 0.08 | 0.03 | 0.05 | 3.73 | 3.51 |
| Observations | 52,647 | 38,620 | 48,923 | 30,654 | 47,386 | 28,978 |
| R-squared | 0.044 | 0.082 | 0.016 | 0.050 | 0.025 | 0.061 |
| **Panel D: Partner Working Outside the Home** | | | | | | |
| SC | -0.032 | -0.068 | -0.015 | 0.011 | -0.106** | -0.200*** |
| | (0.028) | (0.050) | (0.022) | (0.027) | (0.048) | (0.069) |
| Mean 01/2019-02/2020 | 0.94 | 0.78 | 0.01 | 0.03 | 3.72 | 3.48 |
| Observations | 26,877 | 33,053 | 25,202 | 25,818 | 24,767 | 24,805 |
| R-squared | 0.026 | 0.094 | 0.015 | 0.027 | 0.027 | 0.054 |
| **Panel E: Two-Partnered Households with Children 15-17 Years Old** | | | | | | |
| SC | 0.014 | -0.025 | -0.040 | 0.029 | -0.058 | 0.006 |
| | (0.043) | (0.087) | (0.034) | (0.028) | (0.035) | (0.061) |
| Mean 01/2019-02/2020 | 0.90 | 0.75 | 0.03 | 0.04 | 3.74 | 3.56 |
| Observations | 18,896 | 19,449 | 16,919 | 14,745 | 16,437 | 14,168 |
| R-squared | 0.057 | 0.080 | 0.099 | 0.142 | 0.035 | 0.057 |
| *For all* | | | | | | |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The sample in columns (3) and (4) are individuals currently employed. The sample in column (5) and (6) are employed individuals who are currently working, and who were at work during the prior week. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). We also control for the type of occupation in columns (3) to (6). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include the Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

## APPENDIX

**Table A1**
**Data Appendix: Summary Statistics of Controls from CPS; Table of Definitions of CPS Variables**

| Name | CPS variable | Definition | Mean (Men) | S.D. (Men) | Mean (Women) | S.D. (Women) |
|---|---|---|---|---|---|---|
| **A. Individual characteristics** | | | | | | |
| Age | Individual's Age | Years | 41.1 | 7.39 | 38.75 | 6.75 |
| Number of children | NCHILD counts the number of own children (of any age or marital status) residing with each individual. NCHILD includes step-children and adopted children as well as biological children. Persons with no children present are coded 0. | Number of own children residing with each individual | 2.49 | 1.1 | 2.49 | 1.1 |
| High school | EDUC indicates respondents' educational attainment, as measured by the highest year of school or degree completed. Note that completion differs from the highest year of school attendance; for example, respondents who attended 10th grade but did not finish were classified in EDUC as having completed 9th grade. Values of this variable: | Dummy variable equal to 1 if EDUC==73 | 0.26 | 0.44 | 0.21 | 0.4 |
| College | None or preschool 2<br>Grades 1, 2, 3, or 4 10<br>Grades 5 or 6 20<br>Grades 7 or 8 30<br>Grade 9 40<br>Grade 10 50<br>Grade 11 60<br>12th grade, no diploma 71 | Dummy variable equal to 1 if EDUC=81 or EDUC=91 or EDUC=92 | 0.25 | 0.43 | 0.26 | 0.44 |
| More college | High school diploma or equivalent 73 | Dummy variable | 0.39 | 0.49 | 0.45 | 0.5 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | Some college but no degree<br>Associate's degree, occupational/vocational<br>Associate's degree, academic program<br>Bachelor's degree<br>Master's degree<br>Professional school degree<br>Doctorate degree | 81<br>91<br>92<br>111<br>123<br>124<br>125 | equal to 1 if EDUC=111 or EDUC=123 or EDUC=124 or EDUC=125 | | | | |
| Telework | We classify the feasibility of working at home (telework) for all occupation categories following the classification of Dingel & Neiman (2020) for each of the Standard Occupational Classification (SOC) codes, which we merge with the CPS occupational codes with the equivalence provided by the BLS in 2019 and 2020. | | Dummy variable equal to 1 if the individual can telework | 0.40 | 0.49 | 0.55 | 0.50 |
| Essential worker | We use the classification of essential workers of two states Pennsylvania and Delaware (this information is provided by the NGA) that use the official NAICS codes which can be easily matched with the CPS Codes using BLS equivalence for the years 2019 and 2020. We define essential workers as those working in an industry classified as essential by both states, and as non-essential otherwise. We admit likely measurement error because not all states use the same classification of essential workers, but this is a much more precise way of determining essential industries than a possible subjectivepartial classification made manually from the CISA.<br><br>The official industry guidelines issued by the Department of Homeland Security through the Cybersecurity and Infrastructure Security Agency (CISA) provided an advisory guidance to identify the critical infrastructure sectors and the essential workers. However, the CISA classification (without any official codification) cannot be easily<br><br>merged with the detailed Industry Classification Codes of the CPS. | | Dummy variable equal to 1 if the individual is an essential worker | 0.50 | 0.50 | 0.51 | 0.50 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Partner employed, not at work last week | EMPSTAT indicates whether persons were part of the labor force--working or seeking work--and, if so, whether they were currently unemployed. The variable also provides information on the activity (*e.g.*, doing housework, attending school,) or status (*e.g.*, retired, unable to work) of persons not in the labor force, as well as limited additional information on those who are in the labor force (*e.g.* members of the Armed Forces, those with a job, but not at work last week). | Dummy variable equal to 1 if EMPSTAT=12 (has job, but did not work last week) | 0.03 | 0.18 | 0.02 | 0.15 |
| Partner employed, at work last week | | Dummy variable equal to 1 if EMPSTAT=10 (at work) | 0.65 | 0.48 | 0.87 | 0.33 |
| **B. Employment Outcomes** | | | | | | |
| Employed | EMPSTAT indicates whether persons were part of the labor force--working or seeking work--and, if so, whether they were currently unemployed. The variable also provides information on the activity (*e.g.*, doing housework, attending school,) or status (*e.g.*, retired, unable to work) of persons not in the labor force, as well as limited additional information on those who are in the labor force (*e.g.* members of the Armed Forces, those with a job, but not at work last week). Values of this variable:<br><br>At work 10<br>Has job, not at work last week 12<br>Unemployed, experienced worker 21<br>Unemployed, new worker 22<br>NILF, unable to work 32<br>NILF, other 34<br>NILF, retired 36 | Dummy variable equal to 1 if EMPSTAT=10 (at work), or if EMPSTAT=12 (has job, but did not work last week) | 0.92 | 0.28 | 0.68 | 0.47 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Did not Work Last Week | See EMPSTAT above | Dummy variable equal to 1 if EMPSTAT=12 (has job but did not work last week) | 0.03 | 0.16 | 0.05 | 0.21 |
| Log (Weekly Work Hours) | AHRSWORKT reports the total number of hours the respondent was at work during the previous week. For employers and the self-employed, this includes all hours spent attending to their operation(s) or enterprise(s). For employees, it is the number of hours they spent at work. For unpaid family workers, it is the number of hours spent doing work directly related to the family business or farm (not including housework). The universe is Civilians age 15+ at work last week. | Logarithm of hours worked last week | 3.73 | 0.37 | 3.48 | 0.56 |
| NILF | See EMPSTAT above | Dummy variable equal to 1 if EMPSTAT=32 or EMPSTAT=34 or EMPSTAT=36 | 0.06 | 0.23 | 0.3 | 0.46 |
| Unemployed | See EMPSTAT above | Dummy variable equal to 1 if EMPSTAT=21 or EMPSTAT=22 | 0.03 | 0.16 | 0.02 | 0.15 |

**Table A2**
**Robustness checks**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **Panel A: Main Results Controlling for whether the Interview was done In-Person or by Telephone** | | | | | | |
| | **Employed** | | **Did not Work Last Week** | | **Log (Weekly Work Hours)** | |
| | **Men** | **Women** | **Men** | **Women** | **Men** | **Women** |
| SC | -0.028 | -0.020 | 0.012 | 0.028 | -0.110*** | -0.141*** |
| | (0.027) | (0.028) | (0.016) | (0.021) | (0.022) | (0.050) |
| In-person | -0.007 | -0.006 | -0.001 | -0.001 | 0.000 | 0.033*** |
| | (0.004) | (0.005) | (0.001) | (0.003) | (0.003) | (0.006) |
| Mean 01/2019-02/2020 | 0.93 | 0.68 | 0.02 | 0.04 | 3.73 | 3.50 |
| Observations | 80,787 | 82,696 | 74,125 | 56,472 | 72,153 | 53,783 |
| R-squared | 0.037 | 0.092 | 0.065 | 0.106 | 0.025 | 0.056 |
| **Panel B: Merging School Closure Data to the 7th Day of the Month** | | | | | | |
| SC | -0.028 | -0.024 | 0.014 | 0.023 | -0.106*** | -0.161*** |
| | (0.026) | (0.027) | (0.015) | (0.022) | (0.023) | (0.047) |
| Mean 01/2019-02/2020 | 0.93 | 0.68 | 0.02 | 0.04 | 3.73 | 3.50 |
| Observations | 80,787 | 82,696 | 74,125 | 56,472 | 72,153 | 53,783 |
| R-squared | 0.037 | 0.092 | 0.065 | 0.106 | 0.025 | 0.055 |
| *For all* | | | | | | |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The sample in columns (3) and (4) are individuals currently employed. The sample in column (5) and (6) are employed individuals who are currently working, and who were at work during the prior week. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). We also control for the type of occupation in columns (3) to (6). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include the Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

**Table A3**
**Summary Statistics of Employment Variables by Gender**

| | 01-2019/02-2020 | | March 2020 | | April 2020 | | May 2020 | | May 2020 - pre-COVID19 | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** | **S.D.** | **Diff** | **p-value** |
| **Panel A1: Men from Two-Partnered Households** | | | | | | | | | | |
| Employed | 0.93 | 0.26 | 0.91 | 0.29 | 0.83 | 0.38 | 0.86 | 0.35 | -0.06*** | <0.01 |
| Did Not Work Last Week | 0.02 | 0.15 | 0.04 | 0.18 | 0.06 | 0.24 | 0.05 | 0.21 | 0.02*** | <0.00 |
| Log (Weekly Work Hours) | 3.74 | 0.36 | 3.71 | 0.4 | 3.66 | 0.47 | 3.69 | 0.4 | -0.05*** | <0.01 |
| **Panel A2: Women from Two-Partnered Households** | | | | | | | | | | |
| Employed | 0.68 | 0.47 | 0.67 | 0.47 | 0.58 | 0.49 | 0.59 | 0.49 | -0.08*** | <0.01 |
| Did Not Work Last Week | 0.04 | 0.2 | 0.05 | 0.22 | 0.09 | 0.29 | 0.07 | 0.26 | 0.02*** | <0.01 |
| Log (Weekly Work Hours) | 3.49 | 0.54 | 3.45 | 0.61 | 3.43 | 0.66 | 3.47 | 0.6 | -0.03** | <0.01 |

**Notes:** The sample includes individuals between 16 and 64 years old who have at least one child aged 6-12 years old. Please refer to the Data Appendix for a detailed description of each variable. The sample for employed is civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data. The sample for did not work last week are individuals currently employed. Finally, we use those individuals who report being at work during the prior week when analyzing Weekly Work Hours.

**Table A4**
**Social Distancing Measures**

| | 01-2019/02-2020 | | March 2020 | | April 2020 | | May 2020 | |
|---|---|---|---|---|---|---|---|---|
| | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** | **S.D.** | **Mean** | **S.D.** |
| School Closure Index (SC) | 0.000 | 0.000 | 0.039 | 0.065 | 0.952 | 0.050 | 1.000 | 0.000 |
| Emergency declaration sub-index | 0.000 | 0.000 | 0.091 | 0.105 | 0.994 | 0.019 | 1.000 | 0.000 |
| Partial business closure sub-index | 0.000 | 0.000 | 0.000 | 0.000 | 0.785 | 0.232 | 0.707 | 0.281 |
| Non-essential business closure sub-index | 0.000 | 0.000 | 0.000 | 0.000 | 0.395 | 0.330 | 0.488 | 0.431 |
| Safer-at-home sub-index | 0.000 | 0.000 | 0.000 | 0.000 | 0.450 | 0.263 | 0.677 | 0.387 |
| Non-pharmaceutical Index (TNP) | 0.000 | 0.000 | 0.091 | 0.105 | 2.624 | 0.661 | 2.871 | 0.900 |
| | | | **Number of States with SC>0** | | | | | |
| School Closure Index (SC)>0 | 0 | | 36 | | 51 | | 51 | |
| Emergency declaration sub-index >0 | 0 | | 34 | | 51 | | 51 | |
| Partial business sub-index >0 | 0 | | 0 | | 48 | | 48 | |
| Non-essential business sub-index >0 | 0 | | 0 | | 31 | | 31 | |
| Safer-at-home sub-index>0 | 0 | | 0 | | 41 | | 41 | |
| Non-pharmaceutical Index (TNP) >0 | 0 | | 34 | | 51 | | 51 | |

**Notes:** Number of states with a social distancing measure in place by the 12th day of each month. The School Closure Index ranges from 0 to 1. All the sub-indexes capturing other SD measures range from 0 to 1. The Non-Pharmaceutical Index, which is constructed as the sum of four sub-indexes, ranges from 0 to 4.

**Table A5**
**Labor Supply Response to School Closures of Single-Headed Households with Children Ages 6-12**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Employed** | | **Did not Work Last Week** | | **Log (Weekly Work Hours)** | |
| | **Men** | **Women** | **Men** | **Women** | **Men** | **Women** |
| SC | -0.151 | -0.064 | 0.028 | -0.062** | -0.074 | 0.006 |
| | (0.115) | (0.070) | (0.087) | (0.031) | (0.113) | (0.078) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Mean 01/2019-02/2020 | 0.85 | 0.78 | 0.03 | 0.04 | 3.69 | 3.57 |
| Observations | 3,904 | 19,344 | 3,318 | 14,802 | 3,201 | 14,224 |
| R-squared | 0.096 | 0.083 | 0.055 | 0.028 | 0.059 | 0.057 |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in Two-Partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The sample in columns (3) and (4) are individuals currently employed. The sample in column (5) and (6) are employed individuals who are currently working, and who were at work during the prior week. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). We also control for the type of occupation in columns (3) to (6). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include the Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

**Table A6**
**Other Responses to School Closures of Two-Partnered Households with Children Ages 6-12**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | **Unemployed** | | **Not in the Labor Force** | |
| | **Men** | **Women** | **Men** | **Women** |
| SC | 0.020 | 0.060*** | 0.005 | -0.042* |
| | (0.023) | (0.019) | (0.014) | (0.025) |
| State FE | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes |
| Mean 01/2019-02/2020 | 0.02 | 0.02 | 0.05 | 0.03 |
| Observations | 80,787 | 82,696 | 80,787 | 82,696 |
| R-squared | 0.026 | 0.026 | 0.023 | 0.083 |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include the Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level,
** Significant at the 5% level, * Significant at the 10% level.

**Table A7: Event Study**
**Labor Supply Response to School Closures of Two-Partnered Households with Children Ages 6-12**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | **Employed** | | **Did not Work Last Week** | | **Log (Weekly Work Hours)** | |
| | **Men** | **Women** | **Men** | **Women** | **Men** | **Women** |
| 15 months before the event | 0.077 | -0.085 | 0.185** | 0.061 | -0.091 | 0.109 |
| | (0.139) | (0.148) | (0.088) | (0.201) | (0.160) | (0.263) |
| 14 months before the event | 0.055 | -0.062 | 0.167** | 0.048 | -0.069 | 0.111 |
| | (0.126) | (0.133) | (0.082) | (0.184) | (0.151) | (0.242) |
| 13 months before the event | 0.056 | -0.048 | 0.156** | 0.044 | -0.079 | 0.105 |
| | (0.117) | (0.121) | (0.075) | (0.168) | (0.140) | (0.223) |
| 12 months before the event | 0.052 | -0.037 | 0.137* | 0.038 | -0.061 | 0.117 |
| | (0.113) | (0.116) | (0.072) | (0.164) | (0.135) | (0.211) |
| 11 months before the event | 0.048 | -0.050 | 0.126* | 0.039 | -0.034 | 0.089 |
| | (0.109) | (0.109) | (0.065) | (0.150) | (0.126) | (0.197) |
| 10 months before the event | 0.036 | -0.056 | 0.109* | 0.036 | -0.041 | 0.098 |
| | (0.110) | (0.104) | (0.059) | (0.139) | (0.114) | (0.183) |
| 9 months before the event | 0.020 | -0.059 | 0.102* | 0.003 | -0.029 | 0.093 |
| | (0.101) | (0.089) | (0.054) | (0.124) | (0.098) | (0.170) |
| 8 months before the event | 0.012 | -0.060 | 0.088* | -0.012 | -0.043 | 0.138 |
| | (0.092) | (0.082) | (0.047) | (0.097) | (0.085) | (0.146) |
| 7 months before the event | 0.016 | -0.069 | 0.081** | 0.026 | -0.056 | 0.116 |
| | (0.082) | (0.071) | (0.040) | (0.079) | (0.074) | (0.122) |
| 6 months before the event | 0.016 | -0.061 | 0.064* | 0.025 | -0.045 | 0.117 |
| | (0.072) | (0.058) | (0.033) | (0.068) | (0.064) | (0.102) |
| 5 months before the event | 0.020 | -0.060 | 0.046* | 0.017 | -0.040 | 0.101 |
| | (0.056) | (0.051) | (0.027) | (0.058) | (0.051) | (0.090) |
| 4 months before the event | 0.020 | -0.039 | 0.035* | 0.016 | -0.019 | 0.098 |
| | (0.040) | (0.039) | (0.020) | (0.046) | (0.040) | (0.063) |
| 3 months before the event | 0.015 | -0.019 | 0.020 | 0.014 | -0.022 | 0.055 |
| | (0.029) | (0.029) | (0.015) | (0.036) | (0.028) | (0.044) |
| 2 months before the event | 0.012 | -0.017 | 0.011 | 0.005 | 0.010 | -0.003 |
| | (0.012) | (0.016) | (0.008) | (0.020) | (0.016) | (0.028) |
| The month of the event x SC | -0.033 | -0.043 | 0.005 | 0.023 | -0.141*** | -0.242*** |
| | (0.043) | (0.026) | (0.019) | (0.032) | (0.047) | (0.060) |
| 1 month after the event x SC | -0.036 | -0.023 | -0.015 | 0.028 | -0.086*** | -0.162** |
| | (0.025) | (0.033) | (0.014) | (0.034) | (0.029) | (0.062) |
| 2 months after the event x SC | -0.014 | -0.015 | -0.039** | 0.011 | -0.061* | -0.136* |
| | (0.031) | (0.045) | (0.019) | (0.041) | (0.034) | (0.076) |
| State FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Month FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 80,787 | 82,696 | 74,125 | 56,472 | 67,372 | 50,668 |
| R-squared | 0.037 | 0.092 | 0.065 | 0.106 | 0.023 | 0.051 |

**Notes:** The sample includes civilian, not institutionalized individuals from January 2019 to May 2020 Monthly CPS data living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The sample in columns (3) and (4) are individuals currently employed. The sample in column (5) and (6) are employed individuals who are currently working, and who were at work during the prior week. We estimate Equation (5). All regressions include demographic controls for age, age squared, number of children, educational attainment, and partner's work status (ref category: not employed). We also control for the type of occupation in columns (3) to (6). Please refer to Table A1 in the Appendix for a detailed description of each variable. We also include the Non-pharmaceutical Index (TNP) to control for other social measures. Estimates are weighted using CPS weights. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.

**Table A8: Identification Check**
**Predicting School Closures (Days between First COVID-19 Death and First SD Measure)**

| | (1) | (2) |
|---|---|---|
| **Panel A: Employment** | | |
| | **Men** | **Women** |
| Share Employed | 1.984 | -22.741 |
| | (25.026) | (19.099) |
| Observations | 51 | 51 |
| R-squared | 0.135 | 0.176 |
| Region FE | Yes | Yes |
| **Panel B: Did not work last Week** | | |
| Share of Employed Individuals Who Did Not Work Last Week | 103.875 | 14.393 |
| | (105.485) | (58.443) |
| Observations | 51 | 51 |
| R-squared | 0.176 | 0.137 |
| Region FE | Yes | Yes |
| **Panel C: Log (Weekly work hours)** | | |
| Log (Weekly Work Hours) | 30.831 | 2.541 |
| | (20.653) | (19.896) |
| Observations | 51 | 51 |
| R-squared | 0.173 | 0.136 |
| Region FE | Yes | Yes |

**Notes:** We estimate $\text{Date of first SC}_s = \alpha + Y_s^0\vartheta + Z_s^0\vartheta + \rho_r + \varepsilon_s$, where $\text{Date of first SC}_s$ is constructed as the date when the index first turns positive for a given state. The vector $Y_s^0$ represents the average level of economic activity in the state prior to the school closures. Employment outcomes have been collapsed at the state level for the period January 2019 to February 2020. $Z_s^0$ includes the average age, average gender, marriage rate, average education levels, and rate of having children before the SC index turns positive in a state. The model also includes fixed effects, $\rho_r$, for each of the 9 U.S. regions (New England, Middle Atlantic, East North Central, West North Central, South Atlantic, East South Central, West South Central, Mountain, Pacific). Standard errors are clustered at the state level. The proportion of employed individuals by state is calculated using a sample of civilian, not institutionalized individuals living in two-partnered households between 16 and 64 years old who have at least one child aged 6-12 years old. The share of employed individuals who did not work last week is calculated using a sample of individuals currently employed and we use those individuals who are currently working, and who were at workduring the prior week. The regression includes a constant term. Estimates are weighted. Robust standard errors are clustered at the state level and reported in parentheses. *** Significant at the 1% level, ** Significant at the 5% level, * Significant at the 10% level.