Schooling and Parental Labor Supply:

Evidence from COVID-19 School Closures in the United States

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Abstract

We examine changes in parental labor supply in response to the unanticipated closure of schools following the onset of the COVID-19 pandemic in the United States. We collect detailed daily information on school closures at the school-district level, which we merge to individual level data on labor supply and socio-demographic characteristics from the monthly Current Population Survey spanning from January 2019 through May 2020. Using a difference-in-differences estimation approach, we find evidence of non-negligible labor supply reductions. Having a partner at home helped offset the negative effect of school closures, particularly for maternal employment, although respondents' job traits played a more significant role in shaping labor supply responses to school closures. Overall, the labor supply impacts of school closures prove robust to identification checks and to controlling for other coexistent social-distancing measures. In addition, these early school closures seem to have had a long-lasting negative impact on parental labor supply.

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1. Introduction

Over the various COVID-19 waves, the effectiveness of school closures and the move to home-based on-line learning in "flattening the curve" became particularly contentious. Whereas school closures appeared to curtail the incidence of influenza (Adda, 2016), it remains unclear if the same can be said for the earlier variants of the COVID-19 virus (Davies *et al.*, 2020).[1] Yet, school closures can prove extremely damaging for children's development (*e.g.,* Andrew *et al.*, 2020a; Portes, 2020), as well as for parental labor market participation. In this paper, we exploit the unanticipated closure of schools following the onset of the COVID-19 pandemic to estimate the impact of school closures on parental labor supply.

The size of the United States and the lack of federal directives on how to deal with the pandemic guaranteed a high degree of temporal and geographic variation in school closures, which we exploit to identify their role in explaining parental labor supply.[2] We gather daily data on school closures at the school district level during the beginning of the COVID-19 pandemic, which coincides with the end of the academic 2020 year. School closures during this period occurred rather unexpectedly, leaving little room for households to prepare for. We construct a school closures index that considers both the share of the population affected by school closures and the number of days schools were closed in each school district. Difference-in-differences models are estimated to gauge the impact of school closures on the labor supply of couples with young school-aged

[1] In fact, studies have documented higher absenteeism levels of health care workers when schools closed as a result of the COVID-19 pandemic, which could increase mortality rates and offset any reductions stemming from less contagion in school grounds (Bayham and Fenichel, 2020).

[2] Early in the pandemic, President Trump criticized non-pharmaceutical interventions (NPIs) by noting that "the cure cannot be worse than the problem itself" (Haberman and Sanger, 2020). Not surprisingly, NPI approval was divisive, with conservative Republicans expressing more skepticism than liberal Democrats about NPIs (Funk and Tyson, 2020). As a result, the implementation and lifting of NPIs was often driven by political ideology (Willetts, 2020), as opposed to economic conditions more likely correlated to parental labor supply.

children using data from the monthly January 2019 through May 2020 Current Population Survey.

Our paper contributes first and foremost to a vast literature aiming to understand parental labor supply responses to childcare shocks. Much of this literature focuses on the role played by childcare costs and the availability or expansion of childcare provision (*e.g.,* Herbst, 2017). Our focus is on the role of schools on parental labor supply. There is evidence of child's school attendance being positively correlated to parental labor supply (Gelbach, 2002; Graves, 2013a, 2013b). However, to our knowledge, only one study has examined the causal impact of school closures on parental labor supply using teacher strikes as a negative shock to labor supply in Argentina (Jaume and Willén, 2021). In this study, we gauge the causal impact of children's school attendance on parental labor supply using the unanticipated nature of school closures for identification purposes. We also provide suggestive evidence on the mechanisms likely at play at both the extensive and intensive margins.

Our paper also contributes to a recent and fast-growing literature assessing the impact of COVID-19 related social distancing measures on labor supply. Prior studies have examined the effect of stay-at-home orders and business closures on employment and other economic outcomes in the United States (Béland *et al.*, 2020; Cowan, 2020; Forsythe *et al.*, 2020; Gupta *et al.*, 2020; Marcén and Morales, 2021). Less is known about the impact of school closures. The closest exercises to ours include a study by Rojas *et al*. (2020) and Kong and Prinz (2020), which use high frequency data to disentangle the effects of various policy changes that may otherwise confound the school closures effect. In this study, we add by: (1) accounting for other simultaneously adopted social distancing measures; (2) supplementing our primary analysis with an event study to gauge identification; and (3) by exploring the differential impact of school closures based on the age of the children. These analyses are performed while paying close attention to the type of job held by the respondent and his or her partner, as well as to the presence of another partner at home.

The rest of the paper is organized as follows. Sections 2 and 3 describe the data and methodology. Section 4 presents our main findings and identification checks. Section 5 discusses some likely mechanisms at play, while Section 6 presents some long run estimates of the impact of early school closures. Finally, Section 7 concludes the study.

2. Data

We use data on the exact date in which various non-pharmaceutical interventions (NPIs) and school closures were implemented, along with individual-level labor market outcomes from the Current Population Survey. 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). 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 account for seasonality in 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 participation questions that refer to the prior week, which is usually the 7-day calendar week (Sunday–Saturday) that includes the 12th day of the month.[3] Our

[3] 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 Bureau of Labor Statistics "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

main sample consists of working-age, 16 to 64 years old, non-institutionalized civilians residing in two-partnered households and with school-aged children between 6 and 12 years of age, since they are school-age children requiring more parental care and supervision than older youth (Kalil *et al*., 2012).[4]

We focus on *three* labor market outcomes. *First*, we examine respondents' employment status as captured by the variable *employed*, which takes value 1 if the respondent reported doing any work for profit or working at least fifteen hours without pay in a family business or farm. *Second*, we explore if the individual reports having a job but *did not work last week*. Traditionally, this is a rather small group consisting of individuals who report being temporarily absent from work due to illness, vacation, bad weather, a labor dispute, or other reasons.[5][6] During the pandemic, however, some of the individuals in this category might have been in quarantine or self-isolating. Many were furloughed. According to BLS, some workers who were classified as employed but not working should not have been coded as employed but, rather, as unemployed. *Finally*, we look at the number of weekly *work hours* in all jobs by those employed during the week prior to the survey.

Figures 1 to 3 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). Compared to the pre-COVID period, the probability of being employed had declined by about 11 percent for women in April 2020, and by

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[4] For consistency reasons, we select individuals who report information on their occupation and industry in order to construct a respondent's ability to telework and essential status. Our results also prove robust to controlling for whether the interview was done in-person or telephone (see Panel A of Table A2 in the Appendix).

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

[6] 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

almost two thirds that amount (8 percent) for men. For both employed men and women, the probability of not being at work doubled in May 2020, when compared to the pre-COVID period. There was also a 5 percent reduction in hours of work for those men who remained at work and a small 2.5 percent in the case of employed women. Parental work hours during April and May 2020 (around 41.4 hours for men and 35.6 for women) resembled parental work hours during summer school holidays in previous years (around 43.6 hours for men and 35.9 for women), rather than parental work hours during April and May in 2019 (around 43.6 hours for men and 36.3 for women). These statistics are consistent with prior findings in the literature documenting how women reduce their work hours during summer holidays when children are not attending school (Graves, 2013a, 2013b).

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 they started until the end of the school year (Education Week, 2020). We double check state-level information from *Education Week* with routinely-maintained data repository for U.S. state-level distancing policies in response to the 2019 novel coronavirus (SARS-CoV-2) –published by the National Governors Association (NGA) (see Fullman *et al.*, 2020). Finally, we focus on school closures during the 2019-2020 academic year as they are more likely to simulate an unexpected and, for that reason, potentially larger shock to labor market outcomes. Additionally, this is the period during which the information on school districts' decisions was consistently recorded. This changed during the academic year that followed.[7]

[7] For example, as noted by the New York Times (Jan. 21, 2021: "*13,000 School Districts, 13,000 Approaches to Teaching During Covid*"): "there has been no official accounting of how many American students are attending school in person or virtually. We don't know precisely how many remote students are not receiving any live instruction, or how many students have not logged into their classes all year. Nor

Education Week stopped collecting information on school closures (and re-openings) in June 2020. As a result, when examining the impact of school closures occurring later in the pandemic, other authors have either focused on a specific subset of schools (Camp & Zamarro, 2021) or relied on proxies of school closures, as in the case of foot traffic measures (Hansen et al., 2022).

School closures took place at distinct geographic levels (some at the county, others at the state). Additionally, 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 classrooms and 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 during that month. In contrast, Maryland, Michigan, Ohio, and Oregon had closed schools statewide by the end of the month. The latest county to close schools was Oneida county in the state of Idaho on March 23, 2020. Schools remained closed thereafter until the end of the regular academic year.[8]

In order to better capture exposure to school closures, we follow Watson (2014), Amuedo-Dorantes and Lopez (2015), and Amuedo-Dorantes *et al*. (2018). We use school district information on school closures to construct a state-level index.[9] The rationale for using a state-level index stems from the lack of school district identifiers in the CPS or,

has the federal government tracked how many coronavirus cases have been identified in schools or which mitigation methods districts are using."

[8] Some rural school districts intermittently opened schools during May in states like Montana and Wyoming. 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.

[9] Because the CPS does not allow us to identify school districts, we collapse the information on school district closures at a geographic level identifiable for all CPS respondents (*i.e.,* state-level) using the SC index in Equation (1). Then, we merge the collapsed state-level school closures (*i.e*., the state-level SC index) to the individual level data in the CPS by state and month.

for that matter, county identifiers for about half of the sample. To ensure the representability of our sample, as well as the homogenous measurement of school closures across all respondents, the school closure index is constructed at the state level for all observations. The index varies between 0 and 1, and is reflective of the intensity of school closures in state *s* in month *t* as shown below:

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

where $P_{c,2019}$ is the population of county *c,* and $P_{s,2019}$ is the total population of state *s* according to the 2000 U.S. Census.[10] $SC_{d,c}$ is an indicator function that takes value 1 if schools 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 the ELSI-Elementary and Secondary Information System –a web application of the National Center for Education Statistics– to match school districts to counties.[11] We assume that a county closed its schools if a school-district had already done so in the county. In cases where a state closed its schools prior to school districts doing so, we use that date for all counties in the state.

Our index captures the duration (as well as the intensity) of school closures from the 13th of the month to the 12th of the next month, *i.e*., a month prior to the reference week in which the labor market outcomes are collected. We include information on the extent of school closures during the prior month because respondents' labor market responses might be shaped, not only by what happened that week, but also by other changes during the preceding three weeks. That said, we experiment with different time frames for that variable and results prove highly robust (see Panel B in Table A2 in the

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

[11] See https://nces.ed.gov/ccd/elsi/

Appendix). In addition, as noted earlier, 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 can be interpreted as the probability that an individual living in state s may have been exposed to school closures.

Panels A-B in Figure 4 show the roll out of school closures between March 2020 and May 2020. Lighter colors correspond to fewer school closures (captured by the school closure index, SC_{st}) in each state and month. The school closure index went from 0 to 1 over this period, but there was substantial geographical variation across states due to differences in the number of counties closing schools. For instance, the index had a low value during March 2020 in most states. Although 36 states had at least one county with closed schools, the number of impacted counties within a given state was still relatively small (347 counties had closed schools out of 3,142 counties). There was also great variation across states, with some states that had no school closures, such as Alabama, and other states with more than 75 percent of their schools closed, such as Connecticut or Washington DC. The index increased in value in April 2020, getting closer to 1 as schools closed in most counties, but still displayed substantial variation across states depending on how long schools had been closed. By May 2020, the index had reached the value of one in all states (see Table 1).

2.3 Data on Other Social Distancing Measures

In addition to school closures, respondents in various states were exposed to other COVID19-related non-pharmaceutical interventions (NPIs) implemented by counties and states to curtail contagion. 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 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, and Mississippi and Oklahoma were the last states to adopt them on April 1, 2020. Altogether, forty-eight states enacted partial business closures, and 31 states enacted non-essential business closures in April 2020. Safer-at-home and shelter-in-place orders started on March 19, 2020, in California and were last adopted in South Carolina on April 6, 2020. Safer-at-home and shelter-in-place orders were in place in 41 states in April 2020. To account for the multiplicity of measures in place, we construct a non-pharmaceutical index aimed at capturing the overall *intensity* of social distancing measures to which respondents were exposed to depend on how many measures were in place and for how long in each state and month, *i.e.*:

(2) $NPI_{st}^{k} = \sum_{c\epsilon s} \frac{1}{D} \sum_{d=1}^{D} \mathbf{1}\left(NP_{d,s}\right)$ for k=1….4

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

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

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 during the entire month).

Table 1 shows that, except for emergency declarations, the intensity of the other NPIs (as captured by TNP_{st}) was zero in March 2020. However, it rose during April 2020, when it ranged 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 for the index of business closures, which declined as businesses reopened in some states.

3. Methodology

To understand the extent to which school closures may have hindered parental labor supply, we exploit their temporal and geographic variation by estimating the following benchmark model specification separately for each labor supply outcome:

(4) $Y_{ist} = \alpha + \beta SC_{st} + X_i\gamma + \varphi TNP_{st} + \delta_s + \theta_t + \varepsilon_{ist}$

where Y_{ist} captures the ith respondent labor supply outcome, *i.e.*, employed, did not work last week, and log (weekly work hours). The subindex *s* denotes state, whereas *t* indicates the month. When modeling weekly work hours, we focus on employed respondents.[12] The variable SC_{st} is the school closure index, which captures the extent to school closures at the (state, month) level. Our coefficient of interest is β, which gauges the impact of school closures on parental labor supply. All models account for demographic traits (X_i) known to affect the labor force status, such as age, educational attainment, cohabitation

[12] We also gauge if our school closures' impact significantly differs when we include non-working parents in the estimation of weekly work hours using, as our dependent variable, the logarithm of weekly work hours plus one. As shown in Table A4 in the Appendix, our main findings remain qualitatively the same.

status, race, the number of children in the household, the presence of children under the age of 6 years in the household and whether the partner is at home. When focusing on those employed, the vector X_i also includes controls for the occupation held. Depending on the model specification being estimated, dummy variables indicative of the respondent's classification as an essential worker or ability to telework are added. In addition, we include the index TNP_{st}, which accounts for the intensity and duration of other social distancing measures in place simultaneously affecting labor supply. Finally, all models include state and time (year, month) fixed effects (δ_s and θ_t) to account for observed and unobserved factors affecting economic activity during this period.

4. Parental Labor Supply during Early School Closures

4.1 Main Findings

Table 2 provides a preliminary assessment of the impact of school closures on the parental labor supply of two-partnered households. As noted earlier, our focus is on two-partnered households with young school-age children. Roughly 88 percent of school-age children 6 to 12 years old reside in such households. In addition, given our interest on assessing any gender differences in the impact of school closures on parental labor supply, we focus on heterosexual couples regardless of their marital statuses.

As shown in Table 2, school closures during the months of March, April and May of 2020 affected the labor supply of parents of younger school-age children at both the extensive and intensive margins. Specifically, as school closed, both mothers and fathers significantly cut down their work hours by 15 percent and 12 percent, respectively. In addition, the employment likelihood of mothers dropped by 8 percentage points on account of school closures –a reduction significantly greater than the one experienced by fathers as revealed by the *p*-values at the bottom of Table 2.[13] However, school closures do not appear to have significantly altered the propensity of not being at work during the prior week for neither fathers nor mothers. Heggeness (2020) looks at labor supply impacts at the beginning of the pandemic using a similar diff-in-diff strategy; yet, the findings are not directly comparable to ours as the study does not distinguish between school closures and stay at home orders, nor does it consider the impact of other non-pharmaceutical measures.

In sum, both mothers and fathers with young school-age children saw their work hours compromised when schools closed their doors; however, mothers were disproportionally affected by school closures through a significant reduction of their employment likelihood.[14] The asymmetric response of men and women in Table 2 is consistent with findings from the parental time investments literature, which has documented how parental childcare responsibilities fell primarily on mothers shortly after the onset of the pandemic, with the additional childcare provided by women being less sensitive to their employment than the childcare provided by men (Adams-Prassl *et al.*, 2020; Alon *et al.*, 2020; Sevilla and Smith, 2020; Zamarro and Prados, 2021).[15]

The models in Table 2 controls for the adoption of other social distancing

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[13] The displayed *p*-values correspond to a generalized Hausman specification test testing whether the *SC* estimates for men and women are statistically different from each other. These tests are performed using the *Stata* command *suest*.

[14] Because individuals of working age are either employed, unemployed or not in the labor force, based on the findings from Table 2, where the propensity to be employed remained unchanged by school closures, we might expect offsetting or close to null impacts of school closures on the propensity to be unemployed or not in the labor force. Table A5 in the Appendix looks at whether that was the case. The unemployment and the out of the workforce propensities of fathers do not seem to have significantly changed with school closures. However, mothers' unemployment propensity (raising it by 6 percentage points) tripled upon school closures at a marginally statistically significance level.

[15] This finding is hard to square with standard economic models of the household, which would suggest a symmetric response ceteris paribus. Instead, they can be rationalized in light of social norms that consider childcare is primarily a female responsibility (Akerlof and Kranton, 2000; Bertrand *et al.*, 2015; Sevilla-Sanz, 2010).

measures, including business closures and stay-at-home orders. The coefficient on the NPI index suggests that these measures further dampened employment in the short-term. Specifically, an increase in the NPI index equal to 2 (close to the index average during April and May) is associated with a 1.5 percentage point reduction in the employment propensity of fathers. These findings are consistent with those from Kong and Prinz (2020), who use daily Google searches to disentangle the impacts of various policy changes.[16] In contrast to school closures, which negatively impacted work hours, NPIs did not. These results are suggestive of school closures primarily curtailing individual labor supply, and NPIs firm labor demand.

Other results in Table 2 are as expected. For instance, possibly due to assortative mating and spousal preferences to spend time together (Hamermesh, 2002), mothers are 1 percentage point less likely to be employed if their partners reported being home. Additionally, fathers and mothers appear more likely to report not working during the prior week if their spouses were at home.

4.2 Identification

A reasonable concern with the results in Table 2 refers to the possibility for the estimated impacts to be biased due to the nonrandom closure of schools. While no policy is ever arbitrarily adopted (Allcott *et al.*, 2020), our concern should be focused on factors associated to school closures potentially correlated with parental labor market supply. To gauge the endogeneity of school closures with respect to parental labor supply, we conduct event studies that enable us to gauge if the estimated impacts predated the closure of schools. In addition, we can assess if school closures led to a significant break in the

[16] As in Kong and Prinz (2020), we also run our models excluding California, Washington, and New York –states with many cases in the early stages of the pandemic. As shown in Table A6 in the Appendix, our main findings prove robust to the use of this alternative sample. Results also prove robust to excluding May 2020 (when some policies started reversing) from our sample. See Table A7 in the Appendix.

parental labor supply trend. Because our identification relies on changes to 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 the SC_{st} index, as in recent literature utilizing a continuous treatment variable (Clemens *et al.,* 2018; Goodman-Bacon, 2018). Specifically, the event-study takes the following form:

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

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 τ_j. The coefficients ρ_j measure the dynamics of school closure effects, and they are interacted with the SC_{st} index to capture intensity impacts.

Figure 5 displays the coefficients from the event study 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 differential pre-trends. However, there are no clear breaks in the employment trends, albeit a small decline among women. In contrast, there is evidence of a break in the trend of hours worked by mothers and fathers following school closures (see estimates in Table A8 in the Appendix), with the impact remaining statistically different from zero during one to two months after.

In addition to the above-described event studies, we address reverse causality concerns by modeling the timing of school closures in each state as a function of the state's parental labor supply *prior to* the school closures. This exercise enables us to assess if, while non-random, school closures could be predicted by our outcomes of interest. As shown in Table A9 in the Appendix, the timing of school closures appears unrelated to the employment rate of parents, the share of employed parents not at work, or their average weekly work hours prior to the onset of the pandemic. As such, while school closures were not fortuitous, their adoption appears unrelated to parental labor supply prior to the COVID epidemic.

5. Assessing Mechanisms: Competing Work and Childcare Responsibilities

The negative impact of school closures on parental labor supply may originate from the need to care for and assist children with home schooling. 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 (*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*., 2021 for Italy; and Farré *et al*., 2021 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 parental labor supply.

5.1 Differences by Respondents' Job Traits: *Remote* and *Essential* Work

During the pandemic, *remote* or *telework* became a saving grace for many working parents with young children, as it enabled them to cope with both childcare and work responsibilities. We merge the Standard Occupational Classification (SOC) and 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 equal to 1 if a worker's occupation is amenable to telework, and 0 otherwise.[17] Forty percent of fathers and 55 percent of mothers in our sample could telework. To identify the role that being an essential worker might have played in shaping parental labor supply responses to school closures, we use the classification of essential workers of two states Pennsylvania

[17] See Montenovo *et al.* (2021) for alternative specifications of remote work.

and Delaware provided by the NGA, which utilizes 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.

Using the information on respondents' job traits, we re-estimate the model in Table 2 including interaction terms between those job traits and the school closure index to gauge the role that parental job traits might have played in shaping their labor supply responses to schools closing their doors. To facilitate the interpretation of our findings, we compute the impact of school closures when respondents can either telework or are classified as essential workers. Such impacts are then compared to the coefficient on school closures in the first row of Table 3 reflecting the labor supply response of parents unable to telework or classified as non-essential to learn about the impact of respondents' job traits on their labor supply response. A couple findings are worth noting.

First, school closures had a much smaller disruptive impact on parental labor supply when mothers and fathers were able to *telework*. For instance, fathers unable to telework became 9 percentage points less likely to be employed when schools closed their doors. In contrast, those able to work remotely did not experience a statistically significant reduction of their employment propensity. Similarly, fathers unable to telework cut their work hours by 15 percent as schools closed, whereas their counterparts able to work remotely did so by 12 percent.

Being able to telework was particularly helpful for mothers. Those unable to telework became 18 percentage points less likely to be employed when schools closed their doors (vs. 10 percentage points in the case of mothers able to work remotely). Furthermore, work hours of mothers able to telework dropped by 17 percent as schools closed their doors, relative to the 23 percent reduction in work hours experienced by mothers unable to work remotely. Overall, these results are consistent with Kalenkoski and Pabilonia (2021), who find that remote work mitigated some of the negative labor market impacts of the pandemic.

Second, as with remote work, respondents' classification as *essential* workers proved critical in shaping their labor supply responses to school closures. Fathers performing jobs classified as non-essential became 9 percentage points less likely to be employed, whereas the employment likelihood of their counterparts with jobs classified as essential did not significantly change. In addition, as schools closed their doors, fathers with non-essential jobs reduced their weekly work hours by 15 percent, as opposed to 11 percent in the case of fathers with essential jobs.

The reduction in maternal employment in response to school closures was also less pronounced when mothers held jobs classified as essential. Those moms became 8 percentage points less likely to be employed following the school closures –a figure in sharp contrast with the 19-percentage points reduction in the employment propensity of mothers with non-essential jobs. Likewise, when schools closed, mothers with essential jobs cut their weekly work hours by 16 percent vs. 23 percent in the case of mothers with non-essential jobs.

In sum, we find that both the ability to telework and the classification of one's job as essential played a critical role in parental labor supply responses to school closures. Yet, as displayed by the *p*-values at the bottom of Table 3, the mitigating role of respondents' job traits was not sufficient to erase the negative impact of school closures on maternal employment, which remained less likely after schools closed their doors when compared to fathers' employment, hinting on mothers' prominent role as child caretakers as a possible explanation. In what follows, we investigate this hypothesis further by assessing the compounded role of personal job traits and having a partner at home –defined as a spouse or partner who is at home because s/he is able to telework, was not at work during the week prior to the interview, is unemployed, or is out of the workforce– played on parental labor supply in response to school closures.

5.2 Differences by Households' Ability to Care for Children

The fact that responses school closures had a much smaller disruptive impact on parental labor supply when mothers and fathers were able to *telework* further suggests that childcare may be a possible explanation for the labor supply reductions of mothers and fathers with young school-age children following the school closures. If that is the case, we would expect the *presence of another adult in the household* hypothetically able to supervise the children to make a significant difference.

The estimates in Table 3 have documented the important role that respondents' ability to telework and the classification of their jobs as essential play in taming parental labor supply reductions as school closed their doors. Next, in Tables 4 and 5, we gauge the added value of having a partner at home. To that end, we add triple interaction terms and, to facilitate the interpretation of the results, compute the overall impact of school closures on the labor supply of mothers and fathers able to work remotely or with jobs classified as essential, when compared to their counterparts without a partner at home.[18]

Based on the estimates in Table 4, respondents' ability to telework played a more important role in shaping their labor supply than the presence of the partner at home. Nevertheless, teleworking mothers no longer experienced a significant reduction in their propensity to be employed if their partners were at home, whereas their teleworking

[18] As noted by Wooldridge (2003), the coefficients on the interaction terms should not be interpreted in isolation but, rather, jointly with other relevant coefficients in the model. One unexpected finding in Table 4 refers to the negative coefficient for *Partner at home x SC* which, interpreted jointly with the coefficients on *Partner at home* and *SC*, yields a negative and statistically significant estimate. A closer inspection distinguishing according to the labor force status of the partner at home (see Tables A10 to A13 in the Appendix) reveals how this effect is driven by unemployed partners, pointing to the non-random incidence of unemployment across households during the pandemic. In other words, possibly due to assortative matching and the fact that many couples meet while studying or working, both men and women appear less likely to be employed if their partners were unemployed amid the pandemic, which is when schools closed.

counterparts without a partner at home did (their employment likelihood dropped by 8-percentage points). That said, having a partner at home did not have a differential impact on the hours worked by mothers and fathers able to telework.

Table 5 repeats the same exercise focusing, instead, on the added value of having a partner at home if the respondent has a job classified as *essential*. To facilitate the interpretation of the estimates, we compute the overall impact of school closures on the labor supply of parents with essential jobs, distinguishing between those with and without a partner at home. Having a partner at home had a differential impact on mothers with essential jobs, when compared to their male counterparts, helping erase the damaging impact of school closures on their employment likelihood. However, the presence of a partner at home did not have a differential impact on the hours worked by mothers vs. fathers with essential jobs. This is true even though the work hours of fathers with essential jobs dropped by 10 percent, as opposed to 14 percent, when having a partner at home; in contrast, the reduction in work hours of mothers with essential jobs remained unaffected.

Overall, the results in Tables 3 through 5 seem to underscore the more important role of respondents' job traits in shaping their labor supply responses to school closures. Partners' ability to stay at home played a secondary role, even though the endogenous nature of parental labor supply decisions with regards to household structure and composition prevents us from fully disentangling such impacts. Finally, both personal job traits and the presence of a partner at home appear to have had a greater impact on the labor supply of mothers than on the labor supply of fathers.

5.3 Parental Labor Supply Responses when Children are Older

To conclude, with the purpose of further gauging the relevance of *childcare needs* on parental labor supply, Table 6 includes a placebo check looking at parental labor supply when children are older, as in the case of those over 13-year-olds. These children are less likely to need the type of parental supervision required by younger school-age children (Kalil *et al.*, 2012). If the captured impact of school closures on parental labor supply was due to the need to supervise children when not at school, we should observe a smaller change in parental labor supply in this case.

As shown therein, we find no significant impact of school closures on the labor supply of mothers and fathers when children are older, supporting the notion that the labor supply impacts of school closures in Table 2 were mainly driven by the need to supervise younger children when schools closed. We obtain similar results when we conduct the analysis focusing on men and women in two-partnered households without children.[19]

6. An Exploration of Longer-term Implications of Early School Closures

Our focus thus far has been on the impact on school closures on parental labor supply during the 2019-2020 academic year, exploiting the unanticipated closing of schools during the remaining part of the 2019-2020 academic year. As noted earlier, descriptive data from around the world during the early days of the pandemic suggests that parents reduced their work hours as they assumed greater childcare responsibilities after school closures.[20] In this final section, we link long-run employment outcomes to early school closures to assess longer-term adjustments of parental employment to the shock.

Figures 6 and 7 show that, for the sample of mothers and fathers with children between 6 and 12 years old, employment and work hours had recovered by October 2021

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[19] See the results in Table A14 in the Appendix.

[20] See, for instance, Zamarro and Prados (2021) and Adams-Prassl *et al.,* (2020) for evidence in the United States; Andrew *et al*., (2020b) and Sevilla and Smith (2020) for evidence in the U.K.; Yamamura and Tsustsui (2021) for evidence in Japan; Del Boca *et al.,* (2020) and Biroli *et al*., (2021) for evidence in Italy; and Farré *et al*. (2021) for evidence in Spain.

(with respect to their February 2019 levels). While the probability of being employed declined by 8 percent for men and 11 percent for women from the pre-COVID period to April 2020, it rose by 9 and 11 percent, respectively, between April 2020 and October 2021. Similarly, there was a 2.5 percent and a 5 percent reduction in weekly work hours of employed men and women from before the pandemic to April 2020; nevertheless, hours recovered to reach their pre-COVID levels by October 2021.

This full recovery of parental labor supply does not mean that school closures do not have long run labor market effects. To address that inquiry, we examine how parental employment in recent months appears to have been shaped by early school closures adopted over one year ago following the onset of the pandemic. The long-term impact of initial school closures on parental labor supply depends, not only on the duration of school closures, but also on families' ability to accommodate their work schedules to such a shock. Parents able to rely on extended family members or older siblings for child supervision, those able to pay for private schooling, learning pods or tutors, or parents with jobs offering remote-work options, might not have endured long-lasting labor supply reductions. However, less fortunate parents lacking such options might have experienced significant work effort reductions or stopped working altogether.

To gauge the long-term impact of early school closures following the onset of the COVID-19 pandemic on parental labor supply, we correlate the state-level SC index in April 2020 (which captures school closures that are unanticipated, as shown in section 4.2) with the latest available labor supply outcomes in October 2021 (employment and work hours) in the spirit of Correia *et al.*, (2020).[21] Figure 8 presents the relationship

[21] Specifically, we estimate the following model: (6) $Y_{is}^{Oct\ 2021} = \alpha + \beta SC_s^{April2020} + \varepsilon_{ist}$ where Y_{is}^{2021} captures if the *i*th respondent is employed during the week prior in October 2021. For those reporting being at work during that week, we then model the logarithm of weekly work hours. The variable SC_s^{2020} is the school closure index in April 2020, capturing the extent of school closures at the state level during the early months of the pandemic. Our coefficient of interest is β, which captures the long-term response to dissimilarities in the initial intensity of the school closures on parental labor supply.

between labor market outcomes in October 2021 and the SC index. States that closed earlier and for a longer period at the beginning of the pandemic lagged in terms of employment in October 2021. While these estimates need to be interpreted with caution due to omitted variable biases –notably, data on school re-openings, they are suggestive of early school closures being inversely related to parental labor supply a year later, particularly at the intensive margin.[22] While purely descriptive, this evidence underscores the vital role of schools in explaining parental labor supply, as confirmed by the disproportionate increase in childcare responsibilities borne by mothers during the pandemic (*e.g.,* Zamarro and Prados, 2021).

7. Summary and Conclusions

We explore the impact of unanticipated school closures in the spring of 2020 on the labor supply of partnered parents with young school-aged children. Using the monthly Current Population Survey and a state-level index capturing the intensity of school closures, we find evidence of significant reductions in the hours worked by mothers and fathers of young school-age children when classrooms closed, even after accounting for other contemporaneous non-pharmaceutical interventions. Identification checks support a causal interpretation of our findings, while robustness checks using different model specifications confirm the reliability of our estimates.

We also document how parental labor supply responded differently to school closures depending on parents' gender and occupational traits. While school closures curtailed the hours worked by both mothers and fathers, the impacts appear to have been more noticeable among mothers. Mothers became 8 percentage points less likely to be employed as schools closed their doors, though fathers did not. The damaging impact of

[22] The *p*-values for hours worked by men and women equal 0.000 and 0.064, respectively. Employment impacts are less precisely estimated.

school closures on parental labor supply was somewhat lessened by the ability of mothers and fathers to work remotely, as well as by their employment in essential jobs, possibly for distinct reasons. Remote work allowed for greater flexibility when caring for school-age children, whereas essential employment required employees to be present at work. At the end of the day, however, mothers were still less likely to be employed after school closures than fathers, even if they were able to work remotely or held essential jobs.

Finally, having a partner at home helped offset the negative labor supply impact of school closures, particularly among mothers, although respondents' job traits played a more significant role in shaping labor supply responses to school closures. The overall greater impact of school closures on maternal employment suggests they probably assumed most childcare responsibilities. In fact, placebo tests focusing on parents with children over 13 years of age, as well as on men and women without children, provide suggestive evidence of the reduction in parental work hours following school closures being primarily led by increased childcare responsibilities at home.

The data used in the main analysis expands from January 2019 through May 2020. In an extension of the analysis using data from October 2021, we gauge the long-term impact of school closures in the Spring of 2020 on parental labor supply a year later. A correlational analysis is suggestive of a (marginally significant) negative long-lasting effect of early school closures on parental labor supply. Overall, the findings underscore the significant labor supply impact of school closures on families, particularly mothers, highlighting the urgency to re-integrate them into the workforce and expand childcare programs and telework opportunities.

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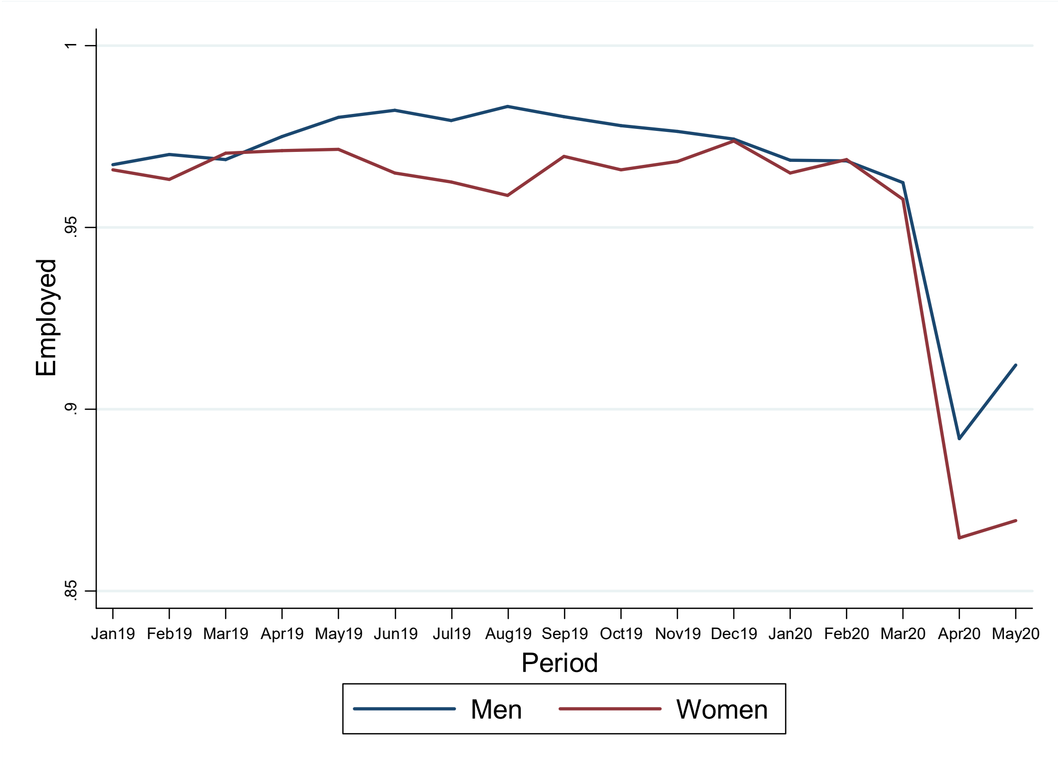
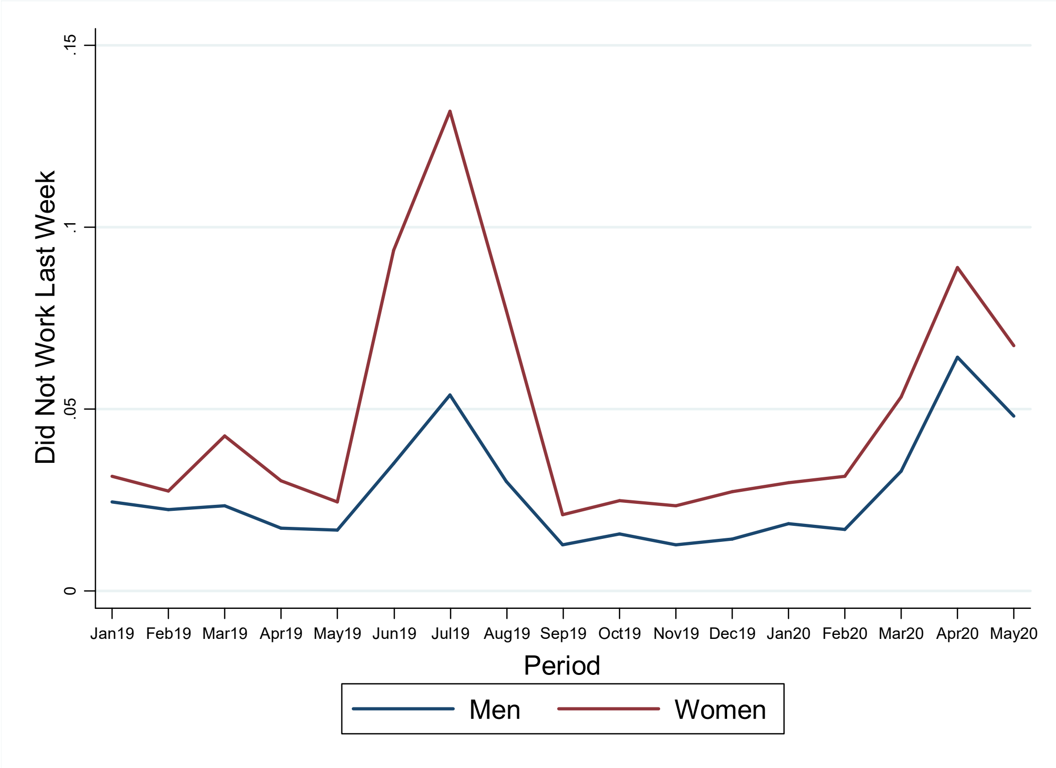
Figure 1
Employment for Two-Partnered Households by gender



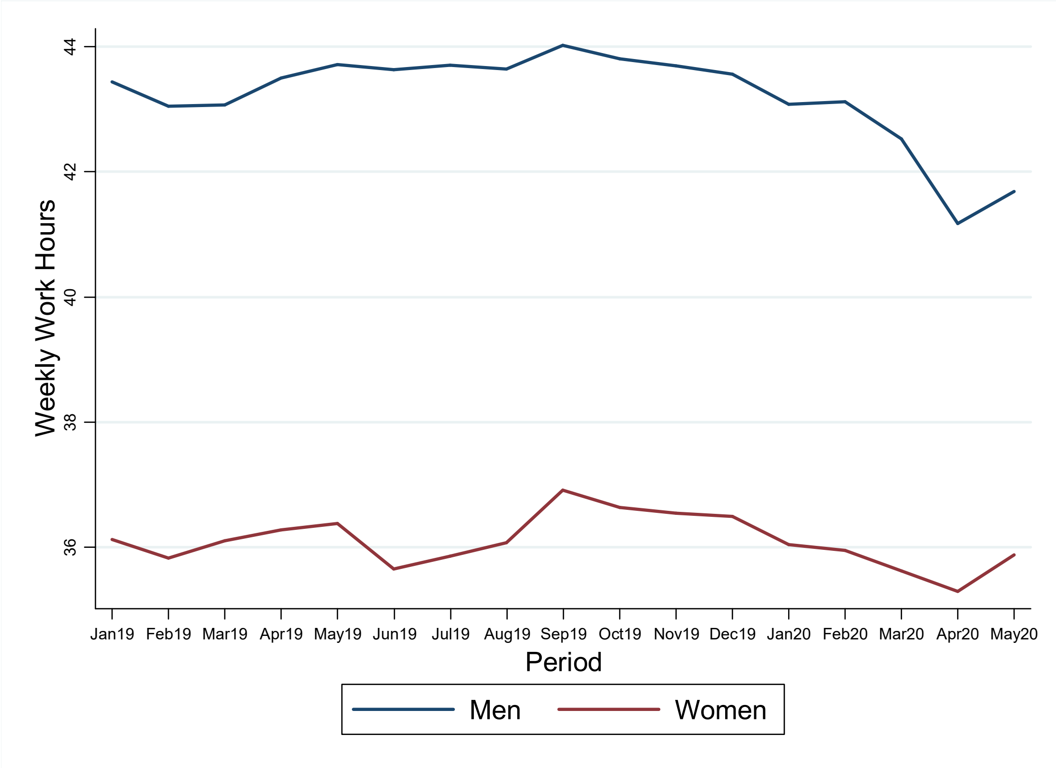
Notes: This figure plots the evolution of the mean of our labor outcome variable "Employed" by gender from January 2019 to May 2020. The sample includes individuals between 16 and 64 years old from two-partnered households with at least one child aged 6-12 years old. Employment is analyzed using a sample of civilian, not institutionalized individuals.

Figure 2
Did Not Work Last Week for Two-Partnered Households by gender



Notes: This figure plots the evolution of the mean of our labor outcome variable "Did not Work Last Week" from January 2019 to May 2020. The sample includes individuals between 16 and 64 years old from two-partnered households with at least one child aged 6-12 years old. 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).

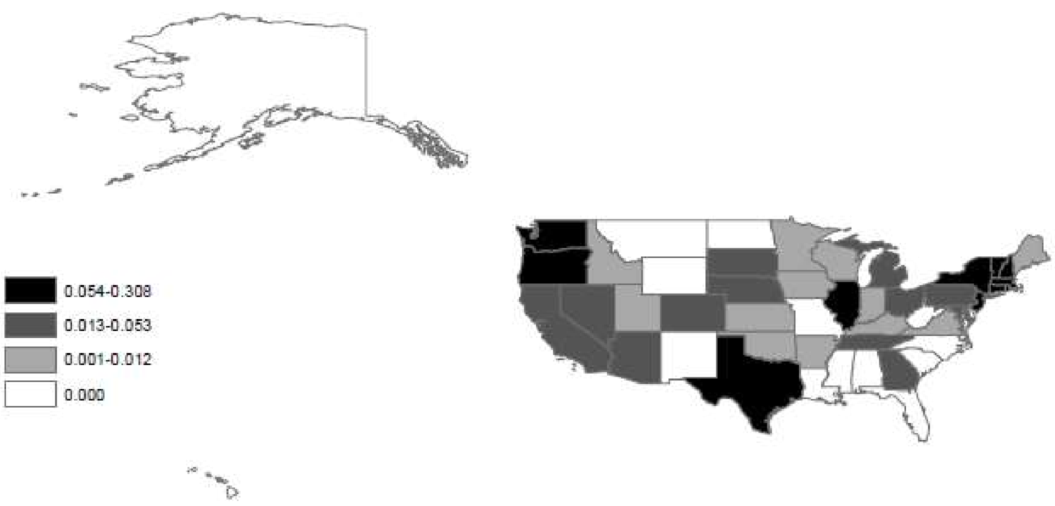
Figure 3
Weekly Work Hours for Two-Partnered Households by gender



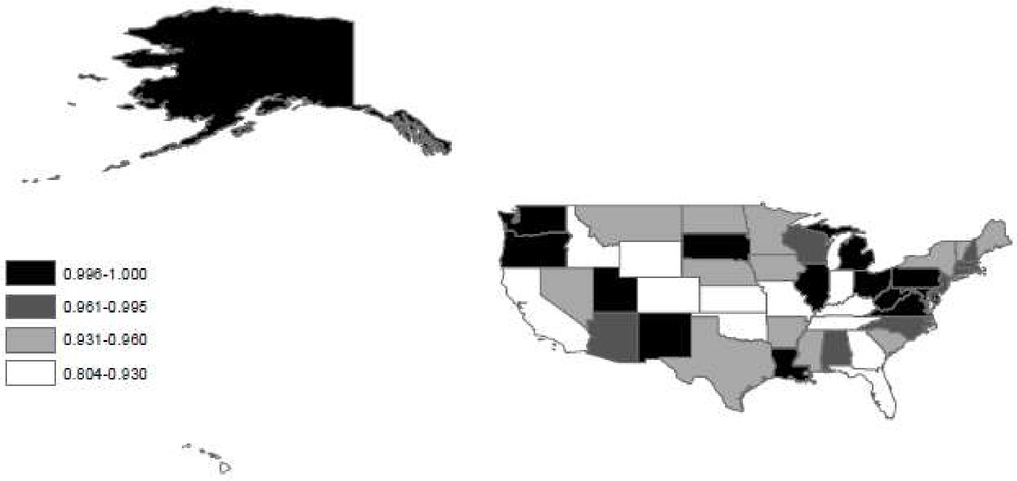
Notes: This figure plots the evolution of the mean of our labor outcome "Weekly Work Hours" from January 2019 to May 2020. The sample includes individuals between 16 and 64 years old from two-partnered households with at least one child aged 6-12 years old. We consider a sample of individuals who report being at work during the prior week when we analyze the "Weekly Work Hours".

Figure 4: Geographic variation in the SC index over time

A) 13th March to 12th April (2020)



B) 13th April to 12th May (2020)

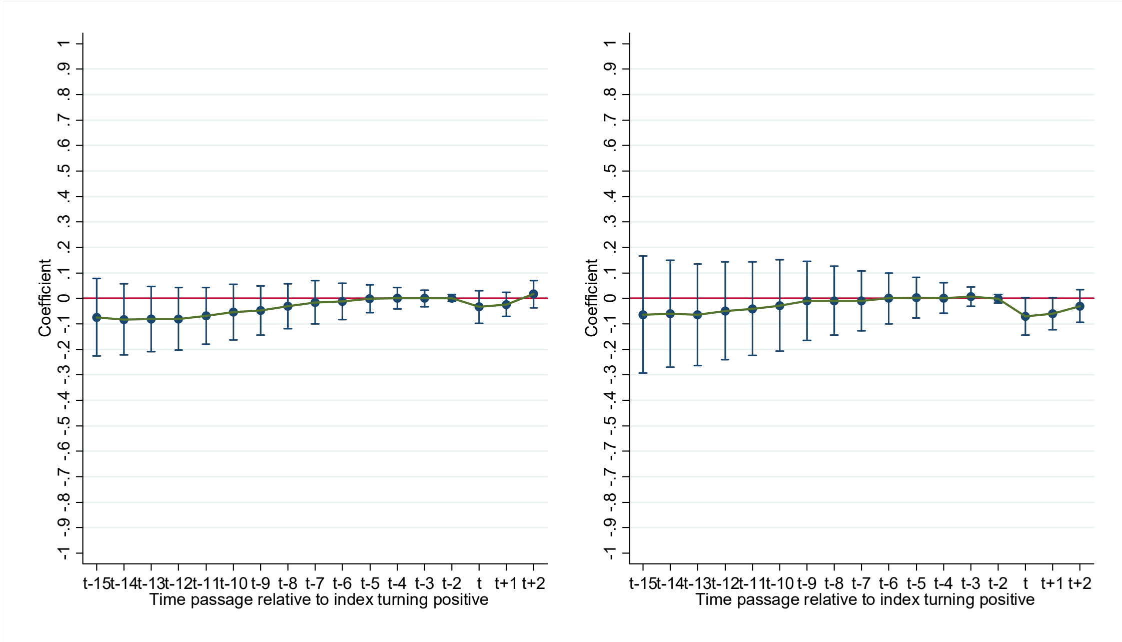


Notes: Darker colors correspond to higher levels of SC index (higher levels of the SC index means that more counties in the state had closed schools) in each state and month (see Table 1).

Figure 5: Event Study

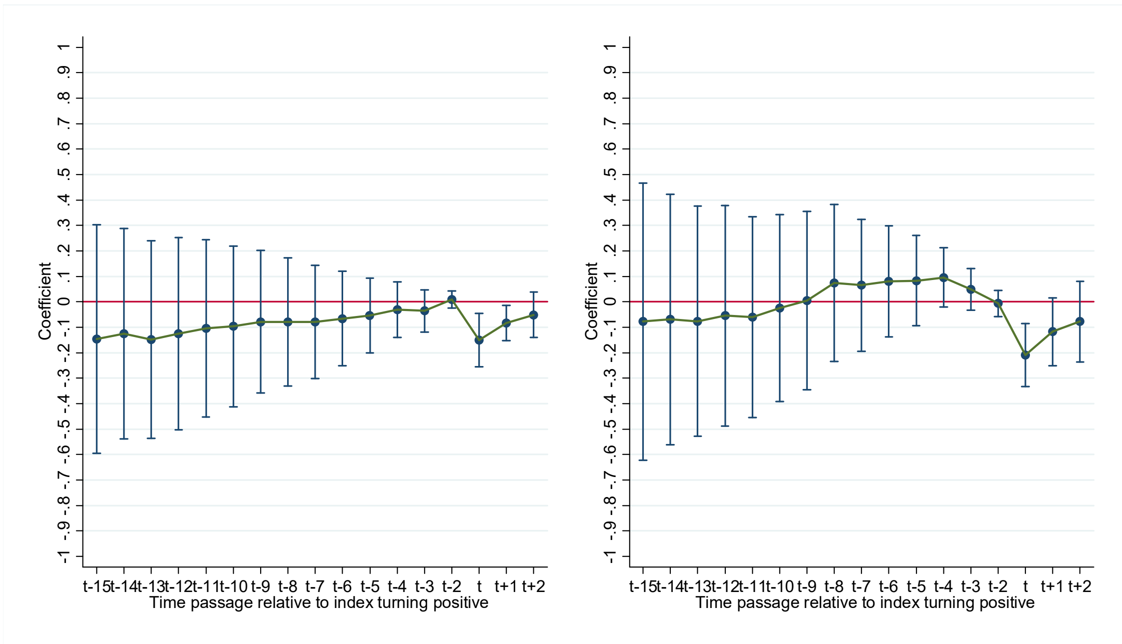
Employed

Men **Women**



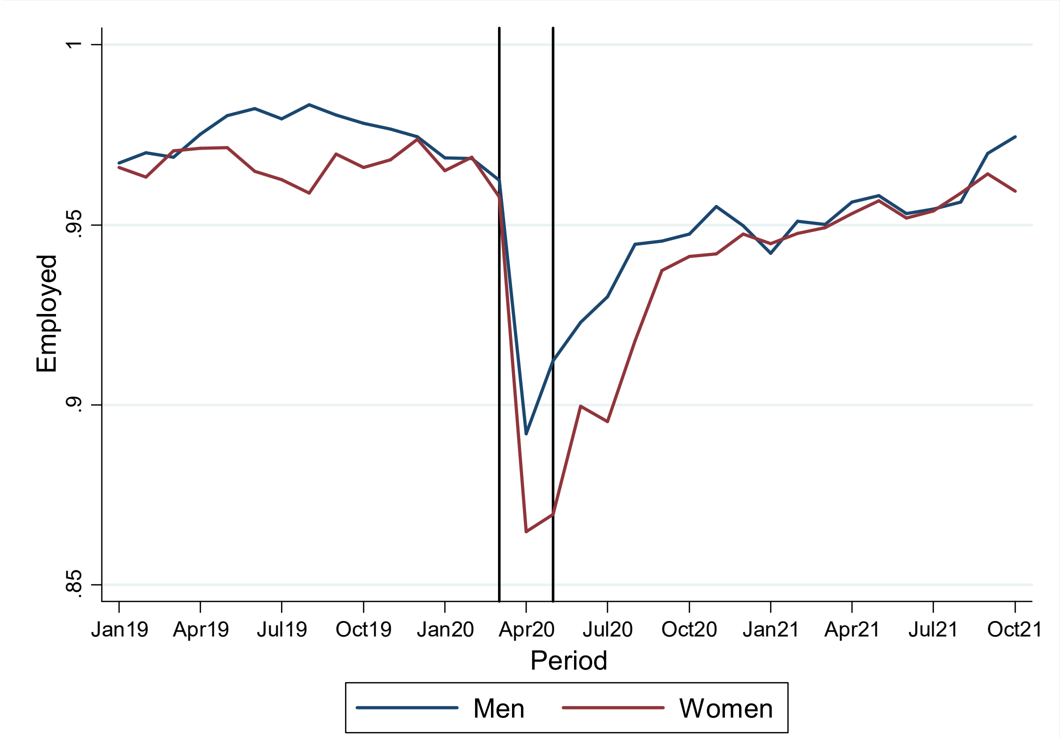
Log(Weekly work hours)

Men **Women**



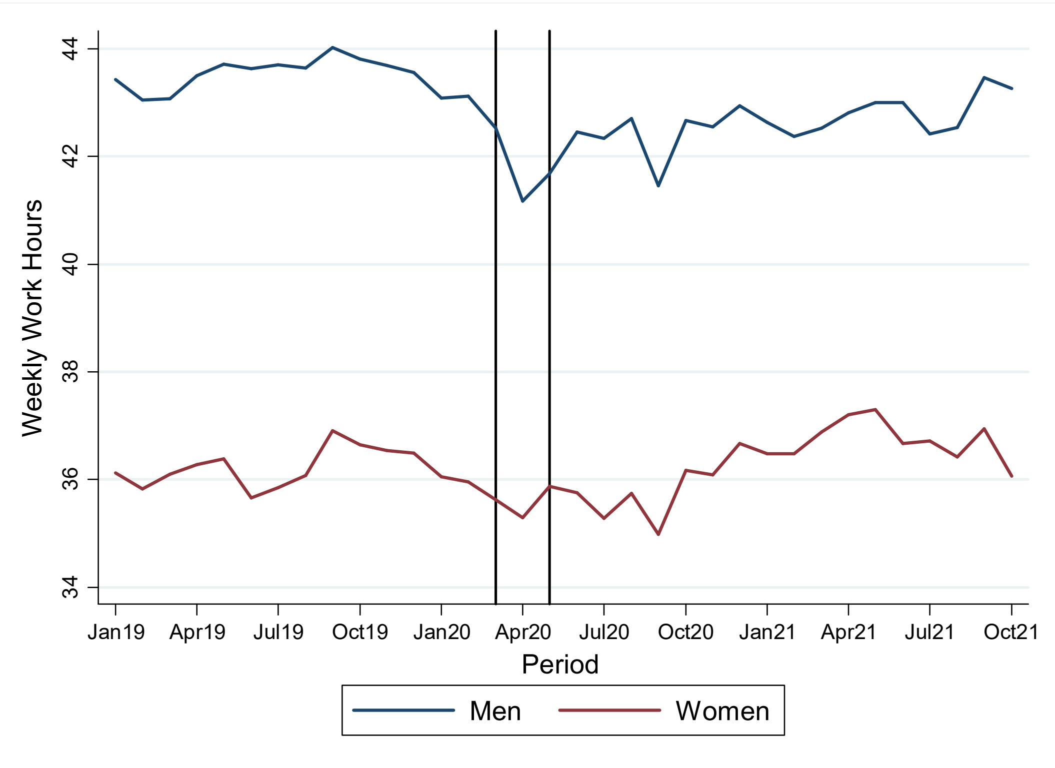
Notes: These figures display the coefficients from the event study for our main sample of two-partnered households, along with 95 percent confidence intervals. Estimates are provided in Appendix A in Table A8.

Figure 6
Employment for Two-Partnered Households by gender (Jan. 2019- Oct. 2021)



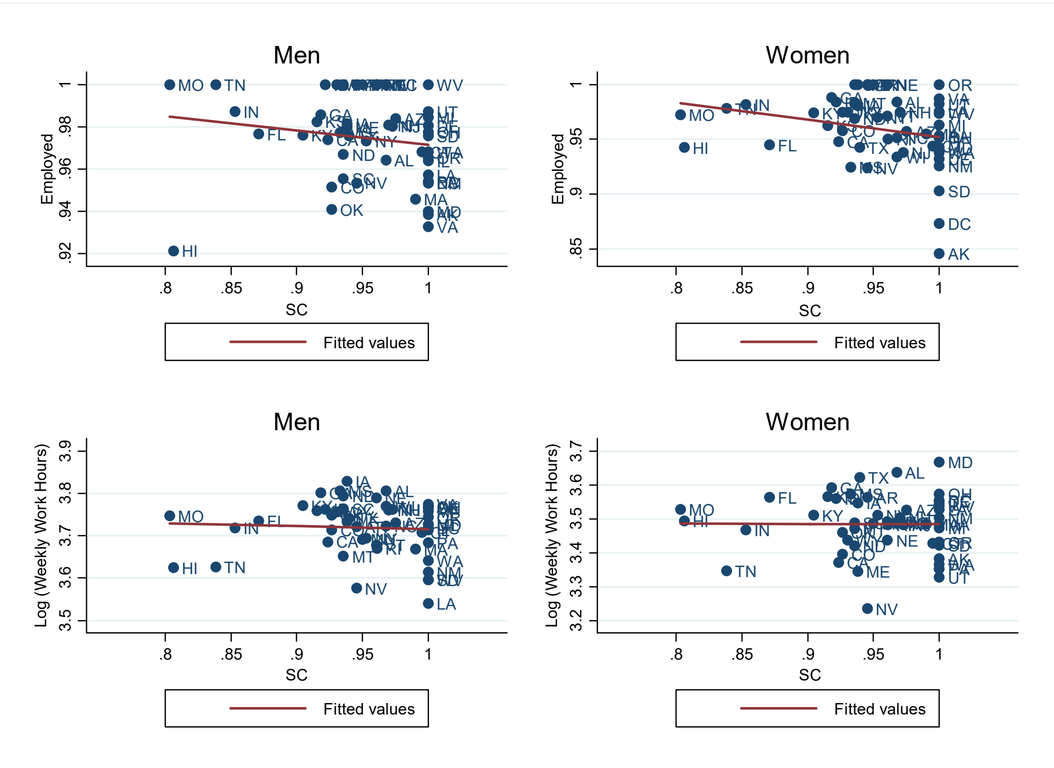
Notes: This figure plots the evolution of the mean of our labor outcome variable from January 2019 to October 2021. The sample includes individuals between 16 and 64 years old from two-partnered households with at least one child aged 6-12 years old.

Figure 7
Weekly Work Hours for Two-Partnered Households by gender (Jan. 2019- Oct. 2021)



Notes: This figure plots the evolution of the mean of our labor outcome "Weekly Work Hours" from January 2019 to October 2021. The sample includes individuals between 16 and 64 years old from two-partnered households with at least one child aged 6-12 years old. We consider a sample of individuals who report being at work during the prior week when we analyze the "Weekly Work Hours".

Figure 8
Long-term Implications of Early School Closures



Notes: These figures display the coefficients from estimating the equation in footnote no. 21 for our main sample of two-partnered households. The *p*-values for hours worked by men and women equal 0.000 and 0.064, respectively.

Table 1
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 social distancing measures>0

	01-2019/02-2020	March 2020	April 2020	May 2020
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 2
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	-0.033	-0.077**	0.018	0.032	-0.117***	-0.146***
	(0.025)	(0.031)	(0.019)	(0.024)	(0.026)	(0.052)
TNP	-0.015**	-0.010	0.008	0.006	0.014	0.033*
	(0.007)	(0.009)	(0.006)	(0.007)	(0.009)	(0.018)
Partner at home	-0.003	-0.010***	0.018***	0.016***	0.004	-0.002
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.011)
Age	0.008***	0.013***	-0.001	-0.002	0.004	-0.004
	(0.002)	(0.002)	(0.001)	(0.001)	(0.004)	(0.005)
$Age^2/100$	-0.009***	-0.015***	0.002	0.002	-0.006	0.006
	(0.002)	(0.002)	(0.001)	(0.002)	(0.004)	(0.006)
Number of children	-0.001	-0.004***	0.000	0.004***	0.006***	-0.042***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.006)
High School	0.028***	0.048***	-0.003	-0.002	0.048***	-0.001
	(0.007)	(0.010)	(0.003)	(0.009)	(0.014)	(0.020)
College	0.036***	0.057***	-0.003	0.005	0.053***	-0.054**
	(0.008)	(0.009)	(0.003)	(0.009)	(0.013)	(0.023)
More college	0.049***	0.076***	-0.006*	-0.002	0.062***	-0.038
	(0.007)	(0.008)	(0.004)	(0.009)	(0.013)	(0.025)
Black	-0.026***	-0.005	0.005*	-0.001	-0.031***	0.110***
	(0.006)	(0.005)	(0.003)	(0.005)	(0.010)	(0.012)
Other race	-0.010***	-0.006	0.011***	0.001	-0.027***	0.032**
	(0.003)	(0.007)	(0.003)	(0.004)	(0.006)	(0.013)
Unmarried	-0.033***	-0.018***	0.005	-0.001	-0.026***	0.051***
	(0.006)	(0.006)	(0.004)	(0.005)	(0.008)	(0.010)

Children under 6 years in the HH	0.001	0.002	-0.002	0.007**	-0.008*	-0.037***
	(0.002)	(0.004)	(0.002)	(0.003)	(0.005)	(0.010)
Mean 01/2019-02/2020	0.98	0.97	0.02	0.04	3.73	3.50
Observations	64,716	57,066	62,710	54,748	61,081	52,144
R-squared	0.036	0.040	0.017	0.035	0.026	0.058
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
p-value SC (1)=(2)	0.0159					
p-value SC (3)=(4)			0.4594			
p-value SC (5)=(6)					0.5687	

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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. 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 **Heterogenous Responses Based on Respondents' Ability to Telework or Classification as Essential**

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.092***	-0.182***	-0.145***	-0.227***
	(0.027)	(0.035)	(0.026)	(0.055)
Amenable to telework	0.005*	0.013***	-0.027***	0.022
	(0.002)	(0.003)	(0.007)	(0.014)
Amenable to telework x SC	0.071***	0.081***	0.029*	0.062***
	(0.010)	(0.014)	(0.016)	(0.022)
Essential worker	0.002	0.009**	0.016***	0.049***
	(0.003)	(0.004)	(0.004)	(0.013)
Essential worker x SC	0.060***	0.103***	0.031**	0.072***
	(0.009)	(0.017)	(0.013)	(0.026)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.042	0.051	0.027	0.060
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
***SC* effect if respondent is:**				
Amenable to Telework (SC + telework x SC)	-0.021	-0.101***	-0.116***	-0.165***
p-value	(0.4355)	(0.0058)	(0.0002)	(0.0032)
p-value (1)=(2)	0.0001			
p-value (3)=(4)			0.3268	

Is essential worker (SC + essential x SC)	-0.032	-0.079***	-0.114***	-0.155***
p-value	(0.1939)	(0.0085)	(0.0001)	(0.0035)
p-value (1)=(2)	0.0389			
p-value (3)=(4)			0.4337	

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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 4: Heterogenous Responses Among Parents Able to Telework Based on Having a Partner at Home

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.032	-0.081***	-0.105***	-0.166***
	(0.020)	(0.030)	(0.031)	(0.055)
Partner at home	-0.004	-0.033***	0.009	-0.028*
	(0.004)	(0.006)	(0.005)	(0.015)
Partner at home x SC	-0.045**	-0.070**	-0.038*	0.016
	(0.019)	(0.031)	(0.021)	(0.045)
Resp able to telework	-0.001	-0.005	-0.028**	0.008
	(0.004)	(0.005)	(0.012)	(0.018)
Resp able to telework x SC	0.040*	0.000	-0.033	0.036
	(0.021)	(0.030)	(0.037)	(0.042)
Partner at home x	0.006	0.032***	0.003	0.033
Resp able to telework	(0.004)	(0.008)	(0.012)	(0.021)
Partner at home x	0.043*	0.101**	0.080*	-0.012
Resp able to telework x SC	(0.025)	(0.044)	(0.040)	(0.053)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.040	0.046	0.057	0.028
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
***SC* effect if respondent teleworks, plus:**				
Partner at Home (SC + Resp able to telework x SC + Partner at Home x SC)	0.0006	-0.050	-0.096***	-0.126**
p-value	(0.8081)	(0.1713)	(0.0020)	(0.0181)

	(1)	(2)	(3)	(4)
p-value (1)=(2)	0.0044			
p-value (3)=(4)			0.5528	
Partner NOT at Home (SC + Resp able to telework x SC)	0.008	-0.081**	-0.138***	-0.130**
p-value	(0.7966)	(0.0167)	(0.0025)	(0.0498)
p-value (1)=(2)	0.0065			
p-value (3)=(4)			0.9178	

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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 5 **Heterogenous Responses Among Essential Workers Based on Having a Partner at Home**

	(1)	(2)	(3)	(4)
	Employed		Log (Weekly Work Hours)	
	Men	Women	Men	Women
SC	-0.070**	-0.162***	-0.139***	-0.235***
	(0.027)	(0.034)	(0.035)	(0.067)
Partner at home	0.001	-0.008*	0.009	-0.022
	(0.003)	(0.004)	(0.007)	(0.017)
Partner at home x SC	0.009	0.057**	0.008	0.085*
	(0.020)	(0.022)	(0.026)	(0.050)
Resp essential	0.006	0.009*	0.022***	0.033*
	(0.003)	(0.006)	(0.007)	(0.017)
Resp essential x SC	0.063***	0.121***	0.037	0.108**
	(0.020)	(0.020)	(0.029)	(0.050)
Partner at home x	-0.007**	-0.004	-0.010	0.031*
Resp essential	(0.003)	(0.005)	(0.008)	(0.016)
Partner at home x	-0.016	-0.059***	-0.013	-0.079
Resp essential x SC	(0.020)	(0.019)	(0.033)	(0.058)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.038	0.046	0.027	0.060
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
***SC* effect if respondent has an essential job, plus:**				
Partner at Home (SC + Resp essential x SC + Partner at Home x SC)	-0.014	-0.043	-0.107***	-0.121**
p-value	(0.6014)	(0.2112)	(0.0002)	(0.0178)

p-value (1)=(2)	0.1913			
p-value (3)=(4)			0.8013	
Partner NOT at Home (SC + Resp essential x SC)	-0.007	-0.041	-0.102***	-0.127**
p-value	(0.7395)	(0.1735)	(0.0016)	(0.0291)
p-value (1)=(2)	0.1114			
p-value (3)=(4)			0.6573	

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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 6 **Two-Partnered Households with Only Children 13+ Years Old**

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.021	-0.040	-0.044	-0.038
	(0.052)	(0.045)	(0.060)	(0.062)
Mean 01/2019-02/2020	0.98	0.98	3.74	3.53
Observations	10,197	9,435	9,637	8,748
R-squared	0.025	0.045	0.037	0.077
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
p-value SC (1)=(2)	0.8103			
p-value SC (3)=(4)			0.9301	

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 over 13 years old and no child aged 6-12. The sample in column (3) and (4) 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, race (ref category: white), cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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	7.20	39.10	6.53
Number of children	NCHILD counts the number of own children (of any age or marital status) residing with each individual. NCHILD includes stepchildren and adopted children as well as biological children. Persons with no children present are coded 0.	Number of own children residing with each individual	2.44	1.06	2.37	1.10
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	0.18	0.38
College	None or preschool 2 Grades 1, 2, 3, or 4 10 Grades 5 or 6 20 Grades 7 or 8 30 Grade 9 40 Grade 10 50 Grade 11 60 12th grade, no diploma 71	Dummy variable equal to 1 if EDUC=81 or EDUC=91 or EDUC=92	0.26	0.44	0.26	0.44
More college	High school diploma or equivalent 73		0.40	0.49	0.51	0.50

	Some college but no degree	81					
	Associate’s degree, occupational/vocational	91	Dummy variable equal to 1 if EDUC=111 or EDUC=123 or EDUC=124 or EDUC=125				
	Associate’s degree, academic program	92					
	Bachelor’s degree	111					
	Master’s degree	123					
	Professional school degree	124					
	Doctorate degree	125					
	RELATE reports an individual's relationship to the head of household or householder: See AGE above.						
Children under 6 years old in the HH	Head	101	Dummy variable equal to 1 if RELATE==301 and age<6	0.35	0.48	0.32	0.47
	Spouse	201					
	Opposite sex spouse	202					
	Same sex spouse	203					
	Child	301					
	Stepchild	303					
	Parent	501					
	Sibling	701					
	Grandchild	901					
	Other relative, n.s.	1001					
	Unmarried partner	1114					
	Housemate/roomate	1115					
	Opposite sex unmarried partner	1116					

	Same sex unmarried partner	1117					
	Roomer/boarder/lodger	1241					
	Foster children	1242					
	Other nonrelatives	1260					
Black	RACE indicates individual's Race		Dummy variable equal to 1 if RACE==200	0.07	0.26	0.07	0.26
	White	100					
	Black	200					
	American	300					
Other race	Asian	650	Dummy variable equal to 1 if RACE>200	0.09	0.29	0.10	0.30
	Other race	700					
	Two or more races	800					
Unmarried	MARST gives each person's current marital status, including whether the spouse was currently living in the same household		Dummy variable equal to 1 if MARST>2	0.08	0.28	0.08	0.27
	Married, spouse present	1					
	Married, spouse absent	2					
	Separated	3					

	Divorced	4				
	Widowed	5				
	Never married/single	6				
	Widowed or Divorced	7				
	NIU	9				
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	0.41	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 subjective partial classification made manually from the CISA. 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 merged with the detailed Industry Classification Codes of the CPS.	Dummy variable equal to 1 if the individual is an essential worker	0.51	0.50	0.51	0.50

	See classification for telework and essential worker above. Partner refers to a spouse or unmarried partner. See also RELATE above.					
Partner at home	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: At work 10 Has job, not at work last week 12 Unemployed, experienced worker 21 Unemployed, new worker 22 NILF, unable to work 32 NILF, other 34 NILF, retired 36	Dummy variable equal to 1 if (RELATE=201 | RELATE=202 | RELATE=203 | RELATE=1114 | RELATE=1116 | RELATE=1117) & EMPSTAT>10 (not at work), or if EMPSTAT=10 & telework=1 (at work, but able to telework)	0.60	0.50	0.53	0.50
B. Employment Outcomes						
Employed	See EMPSTAT above	Dummy variable equal to 1 if EMPSTAT=10 (at work), or if EMPSTAT=12 (has job, but did not work last week)	0.97	0.17	0.96	0.20
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	0.003	0.06	0.01	0.09
Unemployed	See EMPSTAT above	Dummy variable equal to 1 if EMPSTAT=21 or EMPSTAT=22	0.03	0.16	0.03	0.18

Table A2
Robustness checks

	(1)	(2)	(3)	(4)
Panel A: Main Results Controlling for whether the Interview was done In-Person or by Telephone				
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.033	-0.076**	-0.117***	-0.136**
	(0.025)	(0.031)	(0.026)	(0.052)
In-person	0.001	0.003*	0.001	0.032***
	(0.002)	(0.002)	(0.004)	(0.006)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.036	0.040	0.026	0.059
p-value SC (1)=(2)	0.0179			
p-value SC (3)=(4)			0.7079	
Panel B: Merging School Closure Data to the 7th Day of the Month				
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.037*	-0.081**	-0.114***	-0.155***
	(0.024)	(0.031)	(0.028)	(0.049)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.035	0.040	0.026	0.058
For all:				
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
p-value SC (1)=(2)	0.0252			
p-value SC (3)=(4)			0.4213	

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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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

Panel A: Men from Two-Partnered Households										
	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**
Employed	0.97	0.16	0.96	0.19	0.89	0.31	0.91	0.29	-0.05***	<0.01
Did Not Work Last Week	0.02	0.15	0.03	0.18	0.06	0.25	0.05	0.21	0.02***	<0.00
Log (Weekly Work Hours)	3.73	0.35	3.70	0.40	3.66	0.47	3.65	0.47	-0.05***	<0.01
Panel B: Women from Two-Partnered Households										
	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**
Employed	0.97	0.18	0.96	0.20	0.86	0.34	0.87	0.34	-0.09***	<0.01
Did Not Work Last Week	0.04	0.20	0.05	0.22	0.09	0.29	0.07	0.25	0.02***	<0.01
Log (Weekly Work Hours)	3.50	0.53	3.46	0.60	3.44	0.64	3.48	0.58	-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
Labor Supply Response to School Closures of Two-Partnered Households with Children Ages 6-12

	(1)	(2)
	Log (1+Weekly Work Hours)	
	Men	**Women**
SC	-0.293**	-0.485***
	(0.134)	(0.146)
TNP	-0.064	-0.019
	(0.040)	(0.041)
Partner at home	-0.082***	-0.101***
	(0.014)	(0.022)
Age	0.034***	0.043***
	(0.008)	(0.010)
$Age^2/100$	-0.042***	-0.050***
	(0.010)	(0.013)
Number of children	0.001	-0.062***
	(0.005)	(0.008)
High School	0.134***	0.101***
	(0.021)	(0.034)
College	0.150***	0.036
	(0.025)	(0.030)
More college	0.193***	0.119***
	(0.019)	(0.031)
Black	-0.136***	0.072***
	(0.027)	(0.026)
Other race	-0.104***	-0.002
	(0.017)	(0.021)
Unmarried	-0.154***	-0.007
	(0.023)	(0.023)
Children under 6 years	0.005	-0.053***
in the HH	(0.010)	(0.015)
State FE	Yes	Yes
Year FE	Yes	Yes
Month FE	Yes	Yes
Mean 01/2019-02/2020	3.58	3.27
Observations	64,716	57,066
R-squared	0.056	0.072
p-value SC (1)=(2)	0.0280	

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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, the presence of the partner at home, and the type of occupation. 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 A5
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	0.028	0.081***	0.005	-0.004
	(0.025)	(0.030)	(0.005)	(0.006)
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	0.003	0.01
Observations	64,716	57,066	64,716	57,066
R-squared	0.035	0.040	0.002	0.004
p-value SC (1)=(2)	0.0023			
p-value SC (3)=(4)			0.1239	

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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. 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
Excluding CA, WA, and NY

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.036	-0.081**	-0.126***	-0.105**
	(0.026)	(0.034)	(0.030)	(0.051)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	55,728	49,504	52,724	45,288
R-squared	0.033	0.039	0.028	0.063
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
p-value SC (1)=(2)	0.0320			
p-value SC (3)=(4)			0.6600	

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 column (3) and (4) are employed individuals who are currently working, and who were at work during the prior week. We exclude the states of California, Washington, and New York from our sample. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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
Excluding May 2020

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.004	-0.032	-0.121***	-0.143
	(0.022)	(0.039)	(0.043)	(0.090)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	61,568	54,320	58,299	49,889
R-squared	0.032	0.031	0.025	0.059
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
p-value SC (1)=(2)	0.3219			
p-value SC (3)=(4)			0.8052	

Notes: The sample includes civilian, not institutionalized individuals from January 2019 to April 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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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
Event Study

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
15 months before the event	-0.074	-0.064	-0.147	-0.078
	(0.076)	(0.114)	(0.224)	(0.271)
14 months before the event	-0.083	-0.060	-0.125	-0.070
	(0.069)	(0.105)	(0.206)	(0.245)
13 months before the event	-0.082	-0.065	-0.148	-0.076
	(0.064)	(0.099)	(0.193)	(0.225)
12 months before the event	-0.081	-0.049	-0.125	-0.055
	(0.061)	(0.096)	(0.188)	(0.215)
11 months before the event	-0.069	-0.040	-0.105	-0.061
	(0.055)	(0.091)	(0.173)	(0.197)
10 months before the event	-0.054	-0.028	-0.097	-0.026
	(0.054)	(0.089)	(0.157)	(0.183)
9 months before the event	-0.047	-0.009	-0.078	0.004
	(0.048)	(0.077)	(0.139)	(0.175)
8 months before the event	-0.031	-0.009	-0.080	0.074
	(0.044)	(0.068)	(0.125)	(0.154)
7 months before the event	-0.015	-0.010	-0.080	0.065
	(0.042)	(0.059)	(0.111)	(0.129)
6 months before the event	-0.011	-0.000	-0.066	0.080
	(0.036)	(0.050)	(0.092)	(0.109)
5 months before the event	-0.002	0.003	-0.054	0.083
	(0.027)	(0.040)	(0.073)	(0.088)
4 months before the event	0.001	0.001	-0.031	0.096
	(0.021)	(0.030)	(0.054)	(0.058)
3 months before the event	-0.000	0.006	-0.036	0.049
	(0.016)	(0.019)	(0.042)	(0.041)
2 months before the event	0.001	-0.001	0.010	-0.007
	(0.007)	(0.008)	(0.017)	(0.026)
The month of the event x SC	-0.034	-0.071*	-0.151***	-0.209***
	(0.032)	(0.037)	(0.052)	(0.061)
1 month after the event x SC	-0.024	-0.060*	-0.084**	-0.118*
	(0.023)	(0.031)	(0.035)	(0.067)
2 months after the event x SC	0.017	-0.030	-0.052	-0.078
	(0.027)	(0.032)	(0.044)	(0.079)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	64,716	57,066	61,081	52,144
R-squared	0.036	0.041	0.027	0.059

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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. 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 A9
Identification Check:
Predicting School Closures (Days between First COVID-19 Death and First SD Measure)

Panel A: Predicting School Closures with the Share Employed		
	(1)	**(2)**
	Men	**Women**
Share Employed	75.938	8.010
	(70.755)	(89.765)
Observations	51	51
R-squared	0.349	0.402
Region FE	Yes	Yes
Panel B: Predicting School Closures with the Log (Weekly work hours)		
Log (Weekly Work Hours)	33.881	-13.353
	(26.987)	(15.778)
Observations	51	51
R-squared	0.350	0.421
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, rate of having children, rate for the presence of the partner at home, rate of black individuals, rate of individuals with other race, rate of unmarried individuals, rate of HH with children under 6 years old before the SC index turns positive in a state. The model also includes fixed effects, ρ_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 logarithm of weekly work hours is calculated using a sample of individuals currently employed and we use those individuals who are currently working, and who were at work during 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.

Table A10:
Responses Among Parents Able to Telework Based on Having an Unemployed Partner

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.037*	-0.095***	-0.121***	-0.171***
	(0.021)	(0.026)	(0.026)	(0.053)
Unemployed partner	-0.101***	-0.140***	-0.027	-0.039
	(0.021)	(0.027)	(0.020)	(0.029)
Unemployed partner x SC	-0.119***	-0.070	-0.016	0.112*
	(0.044)	(0.053)	(0.037)	(0.061)
Resp able to telework	0.002	-0.000	-0.022***	0.016
	(0.002)	(0.002)	(0.007)	(0.012)
Resp able to telework x SC	0.050***	0.049***	0.021	0.044**
	(0.008)	(0.014)	(0.017)	(0.021)
Unemployed partner x	0.035	0.108***	0.034	0.101**
Resp able to telework	(0.033)	(0.027)	(0.033)	(0.040)
Unemployed partner x	0.043	-0.157**	-0.007	-0.144
Resp able to telework x SC	(0.043)	(0.062)	(0.060)	(0.087)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.040	0.046	0.057	0.028
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 A11:
Responses Among Parents Able to Telework Based on Having a Partner Not in the LF

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.050**	-0.103***	-0.116***	-0.165***
	(0.024)	(0.030)	(0.027)	(0.053)
NILF partner	0.013***	-0.027**	0.010	0.106***
	(0.003)	(0.013)	(0.007)	(0.026)
NIL partner x SC	-0.024	-0.033	-0.038	-0.058
	(0.018)	(0.044)	(0.031)	(0.068)
Resp able to telework	0.003	0.000	-0.026***	0.019
	(0.003)	(0.002)	(0.007)	(0.013)
Resp able to telework x SC	0.061***	0.052***	0.012	0.034
	(0.011)	(0.013)	(0.015)	(0.021)
NILF partner x	-0.004	0.019	0.027**	-0.009
Resp able to telework	(0.005)	(0.020)	(0.011)	(0.027)
NILF partner x	0.005	0.016	0.060	0.080
Resp able to telework x SC	(0.025)	(0.060)	(0.042)	(0.087)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.039	0.042	0.027	0.059
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 A12:
Responses Among Parents Able to Telework Based on Having a Partner Able to Telework

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.062**	-0.103***	-0.127***	-0.163***
	(0.025)	(0.029)	(0.028)	(0.051)
Partner able to telework	-0.003	-0.000	0.020***	-0.070***
	(0.004)	(0.007)	(0.006)	(0.019)
Partner able to telework x SC	0.050***	-0.003	0.016	-0.049
	(0.018)	(0.033)	(0.038)	(0.082)
Resp able to telework	0.000	-0.001	-0.017	0.010
	(0.003)	(0.004)	(0.011)	(0.017)
Resp able to telework x SC	0.043***	-0.007	0.032*	0.052*
	(0.015)	(0.024)	(0.019)	(0.029)
Partner able to telework	0.005	0.003	-0.020	0.067***
Resp able to telework	(0.005)	(0.009)	(0.013)	(0.023)
Partner able to telework x	-0.004	0.093**	-0.026	0.022
Resp able to telework x SC	(0.025)	(0.040)	(0.037)	(0.080)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.040	0.044	0.027	0.059
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 A13:
Responses Among Parents Able to Telework Based on Having an Employed Partner not Working During the Last Week

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.060**	-0.107***	-0.122***	-0.168***
	(0.025)	(0.030)	(0.026)	(0.052)
Partner furloughed	-0.005	-0.004	-0.053**	-0.074
	(0.008)	(0.008)	(0.021)	(0.048)
Partner furloughed x SC	0.106***	0.024	-0.014	0.178**
	(0.026)	(0.044)	(0.060)	(0.076)
Resp able to telework	0.002	0.001	-0.021***	0.019
	(0.002)	(0.002)	(0.007)	(0.013)
Resp able to telework x SC	0.069***	0.054***	0.017	0.041*
	(0.010)	(0.014)	(0.017)	(0.021)
Partner furloughed	0.003	0.015	-0.034	-0.094
Resp able to telework	(0.010)	(0.009)	(0.037)	(0.081)
Partner able to telework x	-	-0.015	0.145**	-0.007
Resp able to telework x SC	(0.036)	(0.047)	(0.072)	(0.154)
Mean 01/2019-02/2020	0.98	0.97	3.73	3.50
Observations	64,716	57,066	61,081	52,144
R-squared	0.040	0.044	0.027	0.059
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	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 column (3) and (4) 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, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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 A14
Labor Supply Response to School Closures of Two-Partnered Households without children

	(1)	(2)	(3)	(4)
	Employed		**Log (Weekly Work Hours)**	
	Men	**Women**	**Men**	**Women**
SC	-0.018	-0.018	-0.043	-0.083
	(0.035)	(0.037)	(0.044)	(0.060)
Mean 01/2019-02/2020	0.98	0.97	3.72	3.55
Observations	26,607	26,983	24,913	24,807
R-squared	0.028	0.043	0.032	0.036
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
p-value SC (1)=(2)	0.9876			
p-value SC (3)=(4)			0.5402	

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 no children in the HH. The sample in column (3) and (4) are employed individuals who are currently working, and who were at work during the prior week. We exclude the states of California, Washington, and New York from our sample. We estimate Equation (4). All regressions include demographic controls for age, age squared, number of children, educational attainment, race (ref category: white), the presence of children under 6 years old in the HH, cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). 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.