SCHOOLING AND PARENTAL LABOR SUPPLY: EVIDENCE FROM COVID-19 SCHOOL CLOSURES IN THE UNITED STATES

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This article examines 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. The authors collect detailed daily information on school closures at the school-district level, which they merge to individual-level data on labor supply and sociodemographic characteristics from the monthly Current Population Survey spanning from January 2019 through May 2020. Using a difference-in-differences estimation approach, the authors 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.

Over the various COVID-19 waves, the effectiveness of school closures and the move to home-based, online learning to "flatten the curve" became particularly contentious. Whereas school closures appeared to curtail the incidence of influenza (Adda 2016), it remains unclear if the same

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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 article, 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.

Early in the pandemic, then-president Donald 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. 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. 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 2020 academic year. School closures during this period occurred rather unexpectedly, leaving little room for households to prepare for the disruption. 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 children using data from the monthly January 2019 through May 2020 Current Population Survey.

Our article contributes first and foremost to a vast literature aiming to understand parental labor supply responses to child care shocks. Much of this literature focuses on the role played by child care costs and the availability or expansion of child care provision (e.g., Herbst 2017). Our focus is on the role of schools on parental labor supply. Evidence supports that a child's school attendance is positively correlated to parental labor supply (Gelbach 2002; Graves 2013a, 2013b). To our knowledge, however, 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.

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[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).

Our article also contributes to a recent and fast-growing literature assessing the impact of COVID-19 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, Brodeur, and Wright 2020; Cowan 2020; Forsythe, Kahn, Lange, and Wiczer 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 another by 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 to the literature by 1) accounting for other simultaneously adopted social distancing measures; 2) supplementing our primary analysis with an event study to gauge identification; and 3) 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.

Data

We use data on the exact date various NPIs and school closures were implemented, along with individual-level labor market outcomes from the Current Population Survey (CPS). Table A.1 in the Supplemental Online Appendix documents how all these variables are constructed and their summary statistics. (Hereafter, numbering for Online Appendix material is prefaced with an "A.")

Labor Market Outcomes

We use monthly CPS data spanning from January 2019 through May 2020 from the Integrated Public Use Microdata Series (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 seven-day calendar week (Sunday–Saturday) that includes the 12th day of the month. Our main sample consists of working-age (16 to 64 years old), non-institutionalized civilians residing in two-parent households and with school-aged children between 6 and 12 years of age, since that age group requires more parental care and supervision than do older youth (Kalil, Ryan, and Corey 2012). Interviews were conducted exclusively by telephone for most days in March and for all days in April and May (in contrast to 85% of the interviews 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 (BLS) "was still able to obtain estimates that met [their] standards for accuracy and reliability."[2]

We focus on three labor market outcomes. First, we examine respondents' employment status as captured by the variable *employed*, which takes the value 1 if the respondent reported doing any work for profit or working at least 15 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 group is rather small, consisting of individuals who report being temporarily absent from work due to illness, vacation, bad weather, a labor dispute, or other reasons.[3] 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) onward (see Table A.3). Compared to the pre-COVID period, the probability of being employed had declined by about 11% for women in April 2020, and by almost two-thirds that amount (8%) 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% reduction in hours of work for those men who remained at work and a smaller 2.5% reduction in the hours of employed women. Parental work hours during April and May 2020 (approximately 41.4 hours for men and 35.6 hours for women) resembled parental work hours during summer school holidays in previous years (approximately 43.6 hours for men and 35.9 for women), rather than parental work hours during April and May in 2019 (approximately 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).

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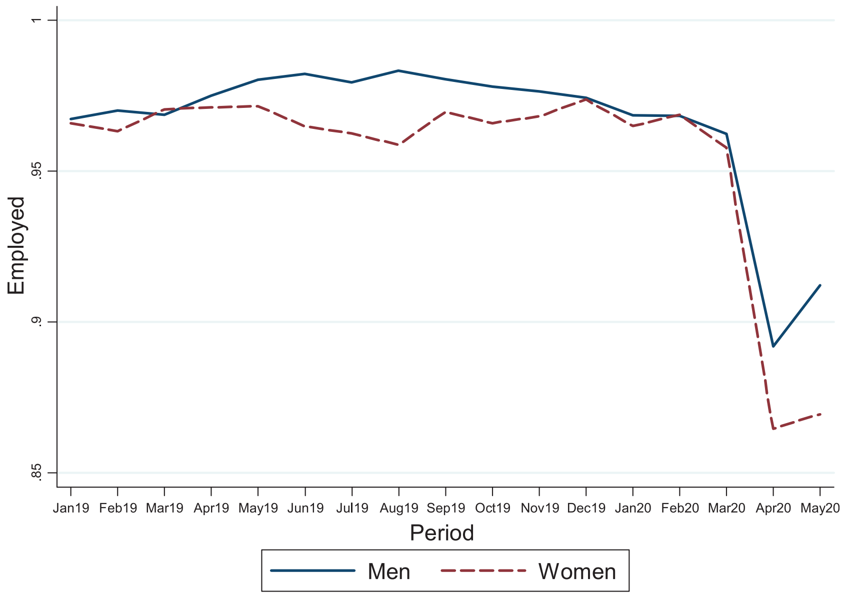
[2]See https://www.census.gov/programs-surveys/cps/technical-documentation/methodology/collecting-data.html. For consistency reasons, we select individuals who report information on their occupation and industry in order to construct a respondent's ability to telework and essential status. Our results also prove robust to controlling for whether the interview was done in-person or by telephone (see Table A.2, panel A).

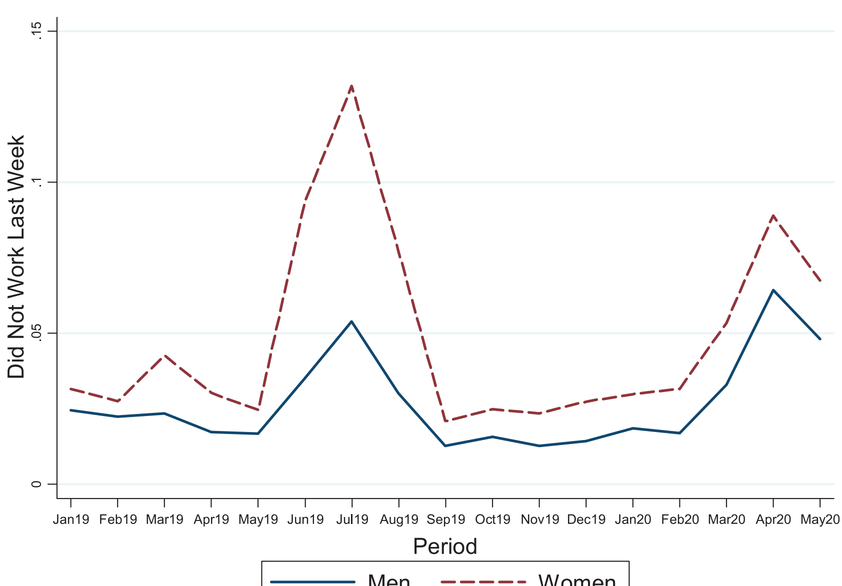
[3]See https://www.bls.gov/cps/employment-situation-covid19-faq-may-2020.pdf. According to the BLS, of the 8.4 million people employed and not at work during the reference week in May 2020, 1.5 million were included in the "own illness, injury, or medical problems" category (not seasonally adjusted). 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.

Figure 1. Employment for Two-Parent Households by Gender



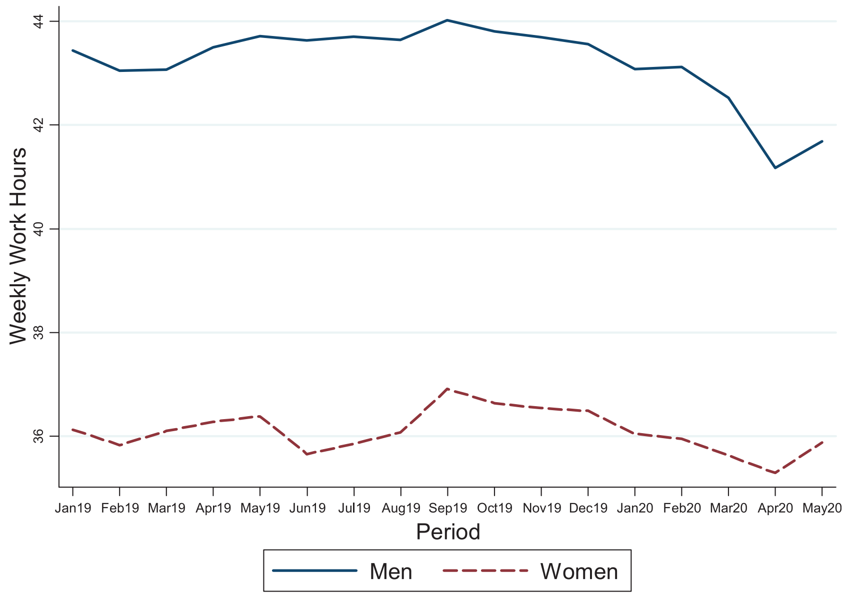
Notes: This figure plots the evolution of the mean of our labor outcome variable "Employed" by gender from January 2019 to May 2020. The sample includes individuals between 16 and 64 years old from two-parent households with at least one child between 6 and 12 years old. Employment is analyzed using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

Figure 2. Did Not Work Last Week for Two-Parent 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-parent households with at least one child between 6 and 12 years old. We use a sample of individuals currently employed when studying "Did Not Work Last Week" (those at work and those who have a job but did not work the last week).

Figure 3. Weekly Work Hours for Two-Parent 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-parent households with at least one child between 6 and 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."

School Closures Data

We gather school closure dates from Education Week (2020), which records the closing dates of schools by school district from the date classes started until the end of the school year. We compare state-level information from Education Week with a routinely maintained data repository for US 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. 2021). Finally, we focus on school closures during the 2019–2020 academic year as those years are more likely to simulate an unexpected and, for that reason, potentially larger shock to labor market outcomes. Additionally, during this time frame the information on school districts' decisions was consistently recorded. This consistency changed during the academic year that followed. For example, as noted in the *New York Times*,[4] "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 has the federal government tracked how many coronavirus cases have been

[4]Kate Taylor, "13,000 School Districts, 13,000 Approaches to Teaching During Covid," *New York Times* (January 21, 2021).

identified in schools or which mitigation methods districts are using." 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 and Zamarro 2021) or relied on proxies of school closures, as in the case of foot traffic measures (Hansen, Sabia, and Schaller 2022).

School closures took place at distinct geographic levels (some at the county, others at the state). Additionally, schools closed for varied 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 36 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. By 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.[5]

To better capture exposure to school closures, we follow Watson (2014), Amuedo-Dorantes and Lopez (2015), and Amuedo-Dorantes, Arenas-Arroyo, and Sevilla (2018). We use school district information on school closures to construct a state-level index.[6] The rationale for using a state-level index stems from the lack of school district identifiers in the CPS or, for that matter, county identifiers for approximately 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:

$$SC_{st} = \frac{1}{P_{s,2019}} \sum\nolimits_{c \epsilon s} \frac{1}{D} \sum\nolimits_{d=1}^{D} \mathbf{1}(SC_{d,c}) P_{c,2019} \tag{1}$$

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 US Census.[7] The $SC_{d,c}$ is an indicator function that takes the value 1 if schools were closed in county c on day d of

[5]Some rural school districts intermittently opened schools during May, for example, in Montana and Wyoming. Information was not systematically collected by Education Week on such instances, and news reports were suggestive of the re-opening of schools being a very rare phenomenon.

[6]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 school closure (SC) index in Equation (1). Then, we merge the collapsed state-level school closures (i.e., the state-level SC index) with the individual-level data in the CPS by state and month.

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

month t, whereas D is the total number of days in month t. We rely on county-level variation because of the lack of data on population figures at the school-district level. We use the Elementary/Secondary Information System (ELSi)—a web application of the National Center for Education Statistics (NCES)—to match school districts to counties.[8] 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, that is, 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 Table A.2, panel B). 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.

Figure 4, panels A and B, show the rollout 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 affected counties within a given state was still relatively small (347 counties had closed schools out of 3,142 counties). A high degree of variation occurred across states: Some states had no school closures, such as Alabama. Other states, such as Connecticut, along with the District of Columbia, had more than 75% of their schools closed. The index increased in value in April 2020, moving closer to 1 as schools closed in most counties but still displaying substantial variation across states depending on how long schools had been closed. By May 2020, the index had reached the value of 1 in all states (see Table 1).

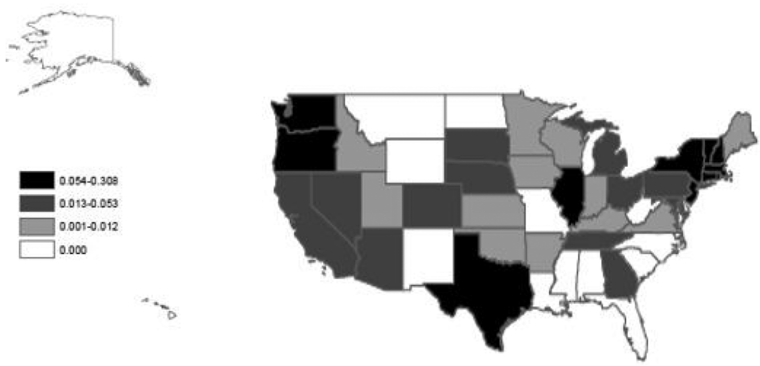
Data on Other Social Distancing Measures

In addition to school closures, respondents in various states were exposed to other COVID-19–related NPIs implemented by counties and states to curtail contagion. We follow the literature and control for a variety of such

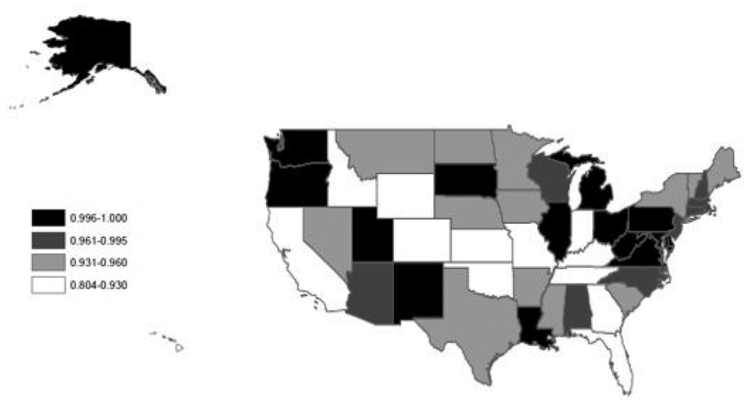
[8] See https://nces.ed.gov/ccd/elsi/.

Figure 4. Geographic Variation in the SC Index over Time

A March 13 to April 12 (2020)



B April 13 to May 12 (2020)



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

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 a 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. 2021).

No such measures were 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

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 subindex	0.000	0.000	0.091	0.105	0.994	0.019	1.000	0.000
Partial business closure subindex	0.000	0.000	0.000	0.000	0.785	0.232	0.707	0.281
Non-essential business closure subindex	0.000	0.000	0.000	0.000	0.395	0.330	0.488	0.431
Safer-at-home subindex	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 subindex >0	0	34	51	51
Partial business subindex >0	0	0	48	48
Non-essential business subindex >0	0	0	31	31
Safer-at-home subindex>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 subindexes capturing other standard deviation (S.D.) measures range from 0 to 1. The non-pharmaceutical index, which is constructed as the sum of four subindexes, ranges from 0 to 4.

the state of emergency on March 16, 2020. Non-essential business closures started on March 19, 2020, in California and Pennsylvania; Mississippi and Oklahoma were the last states to adopt them on April 1, 2020. Altogether, 48 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 an NPI index aimed at capturing the overall *intensity* of social distancing measures to which respondents were exposed, depending on how many measures were in place and for how long in each state and month:

$$NPI_{st}^{k} = \sum\nolimits_{c \epsilon s} \frac{1}{D} \sum\nolimits_{d=1}^{D} \mathbf{1}(NP_{d,s}) \text{ for } k = 1 \ldots .4 \tag{2}$$

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:

$$TNP_{st} = \sum_{k \in K}^{K} NPI_{st}^{k}. \tag{3}$$

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 re-opened in some states.

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:

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

where Y_{ist} captures the ith respondent labor supply outcome, that is, 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.[9] The variable SC_{st} is the school closure index, which captures the extent of school closures at the state and 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 status, race, the number of children in the household, the presence of children younger than 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.

[9]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 A.4, our main findings remain qualitatively the same.

Parental Labor Supply during Early School Closures

Main Findings

Table 2 provides a preliminary assessment of the impact of school closures on the parental labor supply of two-parent households. As noted earlier, our focus is on two-parent households with young school-age children. Approximately 88% of children 6 to 12 years old reside in such households. In addition, given our interest in 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% and 12%, 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.[10] Nonetheless, school closures do not appear to have significantly altered the propensity of not being at work during the prior week for either fathers or mothers. Heggeness (2020) looked at labor supply impacts at the beginning of the pandemic using a similar difference-in-differences 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 through a significant reduction of their employment likelihood.[11] The asymmetric response of men and women shown in Table 2 is consistent with findings from the parental time investments literature, which has documented how parental child care responsibilities fell primarily on mothers shortly after the onset of the pandemic, with the additional child care provided by women being less sensitive to their employment than the child care provided by men (Adams-Prassl,

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

[11]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 A.5 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 significant level.

Table 2. Labor Supply Response to School Closures of Two-Parent 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*
School closure (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 younger than 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-parent households between 16 and 64 years old who have at least one child between 6 and 12 years old. The sample in columns (3) and (4) is made up of individuals currently employed. Columns (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 (reference category: white), the presence of children younger than 6 years old in the household (HH), cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) to (6). Refer to Table A.1 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. CPS, Current Population Survey; FE, fixed effects.
***Significant at the 1% level; ** at the 5% level; * at the 10% level.

Boneva, Golin, and Rauh 2020; Alon, Doepke, Olmstead-Rumsey, and Tertilt 2020; Sevilla and Smith 2020; Zamarro and Prados 2021).[12]

The models in Table 2 control for the adoption of other social distancing 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 used daily Google searches to disentangle the impacts of various policy changes.[13] In contrast to school closures, which negatively affected 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 because of 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.

Identification

A reasonable concern with the results in Table 2 is the possibility that the estimated impacts are biased because of the non-random closure of schools. While no policy is ever arbitrarily adopted (Allcott et al. 2020), our concern should be focused on factors associated with school closures potentially correlated to 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 parental labor supply trend. Because our identification relies on changes brought on by 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, Lewis, and Postel 2018; Goodman-Bacon 2018). Specifically, the event study takes the following form:

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

[13]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 A.6, 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 A.7.

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

where Y_{ist} is the outcome for individual i in state s and month t. The indicator function $\mathbf{1}(SC_{st}>0)$ represents the tth month before or after the SC_{st} index first turned positive in state s. We examine the existence of pre-trends during the 15 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% 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, no clear breaks appear in the employment trends, albeit a small decline among women. By contrast, evidence shows a break in the trend of hours worked by mothers and fathers following school closures (see estimates in Table A.8), with the impact remaining statistically different from zero during one to two months after school closures.

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 A.9, 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.

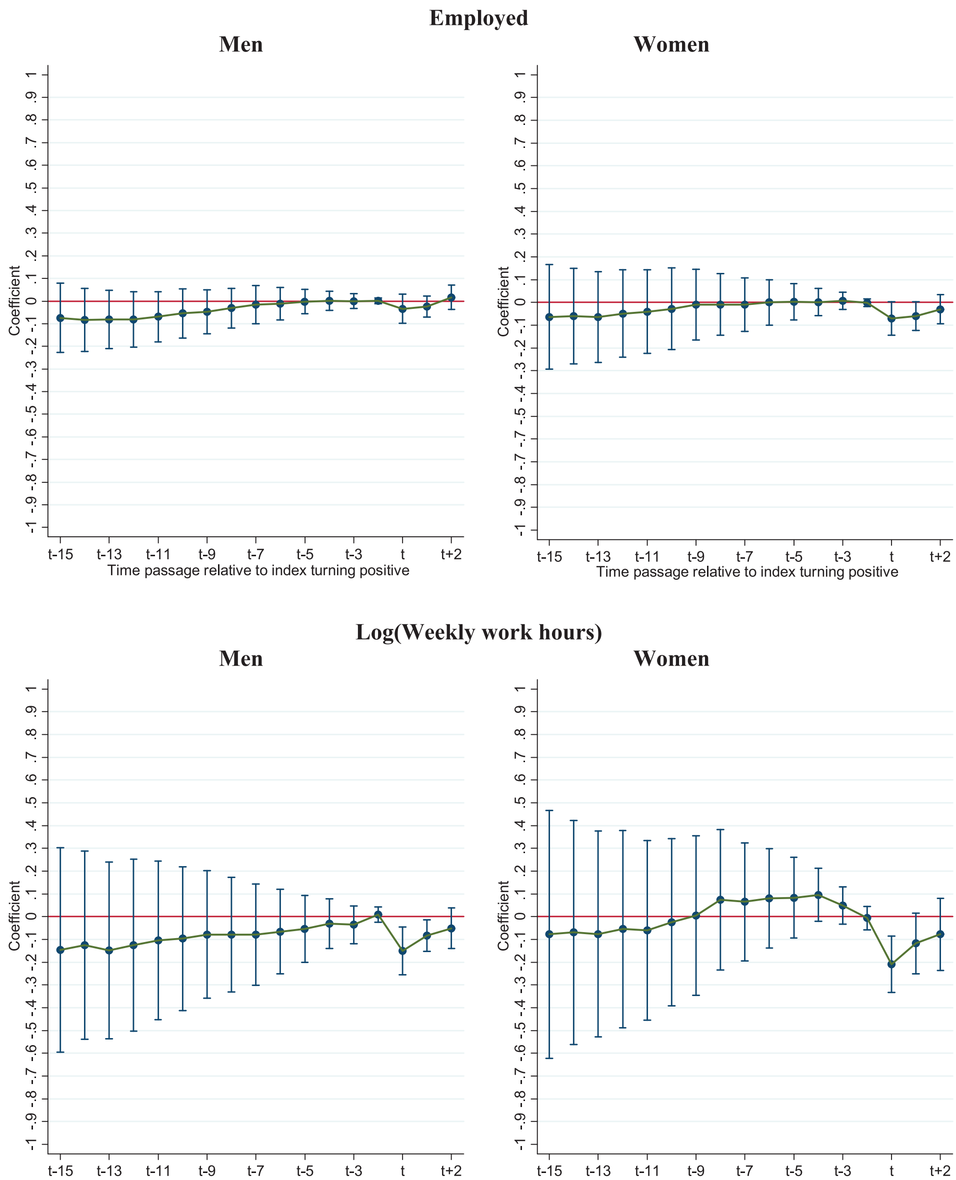
Assessing Mechanisms: Competing Work and Child Care Responsibilities

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 suggest that parents experienced a drop in employment as they assumed greater child care responsibilities (e.g., Adams-Prassl et al. 2020; Andrew et al. 2020b; and Sevilla and Smith 2020 for the United Kingdom; Del Boca, Oggero, Profeta, and Rossi 2020 and Biroli et al. 2021 for Italy; and Farré, Fawaz, González, and Graves 2021 for Spain). 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.

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

Figure 5. Event Study



Notes: These figures display the coefficients from the event study for our main sample of two-parent households, along with 95% confidence intervals. Estimates are provided in Table A.8.

child care and work responsibilities. We merge the Standard Occupational Classification (SOC) system 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.[14] In our sample, 40% of fathers and 55% of mothers 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 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. Two findings are worth noting here.

First, school closures had a much less 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. By 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% as schools closed, whereas their counterparts able to work remotely did so by 12%.

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 compared to 10 percentage points in the case of mothers able to work remotely. Furthermore, work hours of mothers able to telework dropped by 17% as schools closed, relative to the 23% reduction in work hours experienced by mothers unable to work remotely. Overall, these results are consistent with Kalenkoski and Pabilonia (2021), who found 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, fathers with non-essential

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

Table 3. Heterogeneous Responses Based on Respondents' Ability to Telework or Classification as Essential

	(1)	(2)	(3)	(4)
	Employed		*Log (Weekly work hours)*	
	Men	*Women*	*Men*	*Women*
School closure (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 × 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 × 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 × 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	
An essential worker (SC + essential × 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-parent households between 16 and 64 years old who have at least one child between 6 and 12 years old. The sample in columns (3) and (4) is made up of 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 (reference category: white), the presence of children younger than 6 years old in the household (HH), cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). Refer to Table A.1 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. CPS, Current Population Survey; FE, fixed effects.
***Significant at the 1% level; ** at the 5% level; * at the 10% level.

jobs reduced their weekly work hours by 15%, compared to 11% for 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 mothers 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% whereas mothers with non-essential jobs decreased their weekly work hours by 23%.

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 as compared to fathers' employment, hinting at the mothers' prominent role as child caretakers as a possible explanation. In what follows, we investigate this hypothesis further by assessing the compounded impact of personal job traits and having a partner at home—defined as having a spouse or partner at home because she or he is able to telework, was not at work during the week prior to the interview, was unemployed, or was out of the workforce.

Differences by Households' Ability to Care for Children

The fact that responses to school closures had a much less disruptive impact on parental labor supply when mothers and fathers were able to *telework* further suggests that child care 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* who is hypothetically able to supervise the children to make a significant difference.

The estimates in Table 3 document the importance of respondents' ability to telework and the essential job classification in taming parental labor supply reductions as schools closed. 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.[15]

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

[15]As noted by Wooldridge (2003), the coefficients on the interaction terms should not be interpreted in isolation but instead jointly with other relevant coefficients in the model. One unexpected finding in Table 4 refers to the negative coefficient for *Partner at home* × *SC* which, interpreted jointly with the coefficients on *Partner at home* and *SC*, yields a negative and statistically significant estimate. A closer inspection according to the labor force status of the partner at home (see Tables A.10 to A.13) 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 attributable 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 when schools closed.

Table 4. Heterogeneous 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*
School closure (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 × SC	–0.045**	–0.070**	–0.038*	0.016
	(0.019)	(0.031)	(0.021)	(0.045)
Respondent able to telework	–0.001	–0.005	–0.028**	0.008
	(0.004)	(0.005)	(0.012)	(0.018)
Respondent able to telework × SC	0.040*	0.000	–0.033	0.036
	(0.021)	(0.030)	(0.037)	(0.042)
Partner at home × Respondent able to telework	0.006	0.032***	0.003	0.033
	(0.004)	(0.008)	(0.012)	(0.021)
Partner at home × Respondent able to telework × SC	0.043*	0.101**	0.080*	–0.012
	(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 + Respondent able to telework × SC + Partner at home × SC)	0.0006	–0.050	–0.096***	–0.126**
p value	(0.8081)	(0.1713)	(0.0020)	(0.0181)
p value (1)=(2)	0.0044			
p value (3)=(4)			0.5528	
Partner NOT at home (SC + Respondent able to telework × 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-parent households between 16 and 64 years old who have at least one child between 6 and 12 years old. The sample in columns (3) and (4) is made up of 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 (reference category: white), the presence of children younger than 6 years old in the household (HH), cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). Refer to Table A.1 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. CPS, Current Population Survey; FE, fixed effects.
***Significant at the 1% level; ** at the 5% level; * at the 10% level.

at home, whereas their teleworking 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. Heterogeneous Responses among Essential Workers Based on Having a Partner at Home

	(1)	(2)	(3)	(4)
	Employed		*Log (Weekly work hours)*	
	Men	*Women*	*Men*	*Women*
School closures (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 × SC	0.009	0.057**	0.008	0.085*
	(0.020)	(0.022)	(0.026)	(0.050)
Respondent essential	0.006	0.009*	0.022***	0.033*
	(0.003)	(0.006)	(0.007)	(0.017)
Respondent essential × SC	0.063***	0.121***	0.037	0.108**
	(0.020)	(0.020)	(0.029)	(0.050)
Partner at home × Respondent essential	–0.007**	–0.004	–0.010	0.031*
	(0.003)	(0.005)	(0.008)	(0.016)
Partner at home × Respondent essential × SC	–0.016	–0.059***	–0.013	–0.079
	(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 + Respondent essential × SC + Partner at home × 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 + Respondent essential × 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-parent households between 16 and 64 years old who have at least one child between 6 and 12 years old. The sample in columns (3) and (4) is made up of 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 (reference category: white), the presence of children younger than 6 years old in the household (HH), cohabitation status, and the presence of the partner at home. We also control for the type of occupation in columns (3) and (4). Refer to Table A.1 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. CPS, Current Population Survey; FE, fixed effects.
***Significant at the 1% level; ** at the 5% level; * at the 10% level.

Table 5 repeats the same exercise but focuses 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 versus fathers with essential jobs. This finding is true even though the work hours of fathers with essential jobs dropped by 10%, as opposed to 14%, when having a partner at home; by 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 closely intertwined nature of parental labor supply decisions and household composition inhibits 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.

Parental Labor Supply Responses When Children Are Older

To conclude, with the purpose of further gauging the relevance of *child care 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 older than age 13. 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 because of 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 driven mainly 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-parent households without children (see Table A.14).

An Exploration of Longer-Term Implications of Early School Closures

Our focus thus far has been on the impact of school closures on parental labor supply during the 2019–2020 academic year, exploiting the unanticipated closing of schools during the final months of the academic year. As noted earlier, descriptive data from around the world during the early days

Table 6. Two-Parent Households with Children Only 13+ Years Old

	(1)	(2)	(3)	(4)
	Employed		*Log (Weekly work hours)*	
	Men	*Women*	*Men*	*Women*
School closure (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-parent households between 16 and 64 years old who have at least one child older than 13 years of age and no child between 6 and 12 years old. The sample in columns (3) and (4) is made up of 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 (reference 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). Refer to Table A.1 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. CPS, Current Population Survey; FE, fixed effects.
***Significant at the 1% level; ** at the 5% level; * at the 10% level.

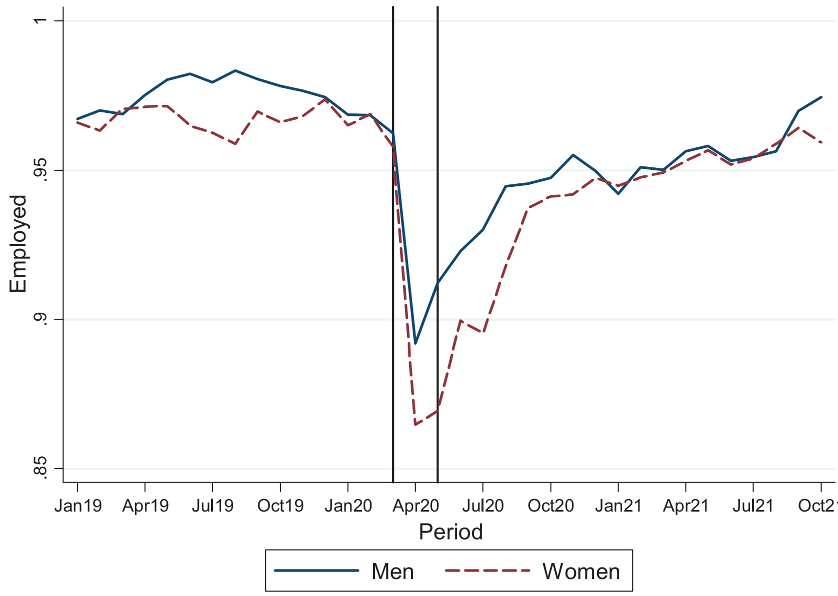
of the pandemic suggest that parents reduced their work hours as they assumed greater child care responsibilities after school closures.[16] In this final section, we link long-run employment outcomes to early school closures to assess longer-term adjustments of parental employment to the shock.

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 (with respect to their February 2019 levels). While the probability of being employed declined by 8% for men and 11% for women from the pre-COVID period to April 2020, it rose by 9% and 11%, respectively, between April 2020 and October 2021. Similarly, we see a 2.5% and a 5% 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 have no long-run labor market effects. To address that inquiry, we examine how parental employment in recent months appears to have been

[16]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 United Kingdom; 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.

Figure 6. Employment for Two-Parent Households by Gender (Jan 2019–Oct 2021)



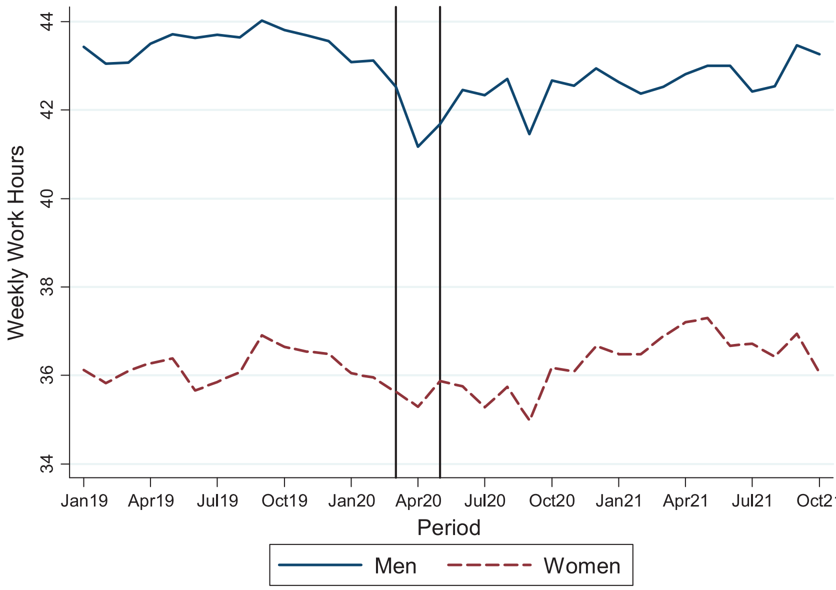
Notes: This figure plots the evolution of the mean of our labor outcome variable from January 2019 to October 2021. The sample includes individuals between 16 and 64 years old from two-parent households with at least one child between 6 and 12 years old.

shaped by early school closures adopted more than 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. Less fortunate parents who lacked such options, however, 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 earlier in the section labeled Identification) with the latest available labor supply outcomes in October 2021 (employment and work hours) in the spirit of Correia, Luck, and Verner (2020).[17]

[17]Specifically, we estimate the following model: (6) $Y_{is}^{Oct\ 2021} = \alpha + \beta SC_s^{April\ 2020} + \varepsilon_{ist}$ where Y_{is}^{2021} captures if the *i*th respondent is employed during the week prior in October 2021. For those who report being at work 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.

Figure 7. Weekly Work Hours for Two-Parent 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-parent households with at least one child between 6 and 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."

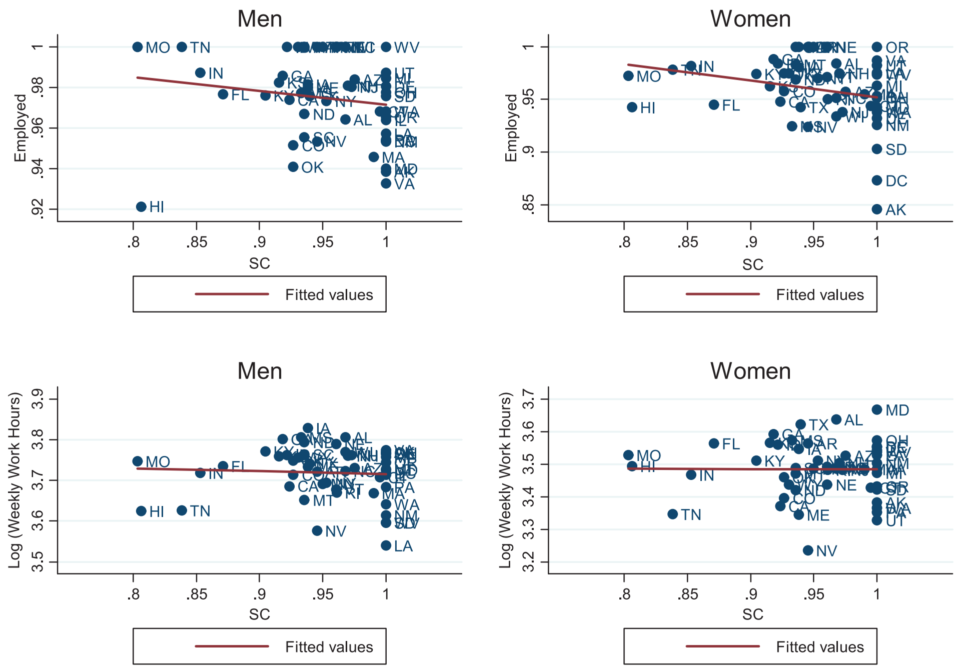
Figure 8 presents the relationship between labor market outcomes in October 2021 and the SC index. States that closed earlier and for a longer period at the beginning of the pandemic lagged in terms of employment in October 2021. While these estimates need to be interpreted with caution because of omitted 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.[18] While purely descriptive, this evidence underscores the vital role of schools in explaining parental labor supply, as confirmed by the disproportionate increase in child care responsibilities borne by mothers during the pandemic (e.g., Zamarro and Prados 2021).

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

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

Figure 8. Long-Term Implications of Early School Closures



Notes: These figures display the coefficients from estimating Equation (6) in footnote 17 for our main sample of two-parent households. The p values for hours worked by men and women equal 0.000 and 0.064, respectively.

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 various model specifications confirm the reliability of our estimates.

We also document how parental labor supply responded in different ways 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 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 were fathers, even if the mothers 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 child care responsibilities. Placebo tests focusing on parents with children older than age 13, as well as placebo tests on men and women without children, provide suggestive evidence of the reduction in parental work hours following school closures being primarily led by increased child care responsibilities at home.

The data used in the main analysis include 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, which highlights the urgency to re-integrate them into the workforce and expand child care programs and telework opportunities.

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