School Closure, Remote Work, and Parental Labor Supply

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Abstract. During the global pandemic of COVID-19 since 2020, most K-12 schools in the U.S. switched to remote or hybrid modes of instruction. This trend caused children to stay home, increasing childcare demand for parents. In this research, I employ a difference-in-differences methodology to investigate the impact of schools on the labor market outcomes of parents with children of school age, focusing on the intensive margin. Additionally, I utilize the work-from-home feasibility (teleworkability) dataset on occupations from Dingel and Neiman (2020) to explore their influence on the dynamic. Using CPS data from January 2020 to December 2021, I find that school closure significantly reduced parents' average weekly working hours compared to the rest the labor force; this effect diminished when the occupation was compatible with remote work. In addition, I find statistically significant evidence that school closures prompted parents to seek jobs more compatible with remote work.

1. Introduction

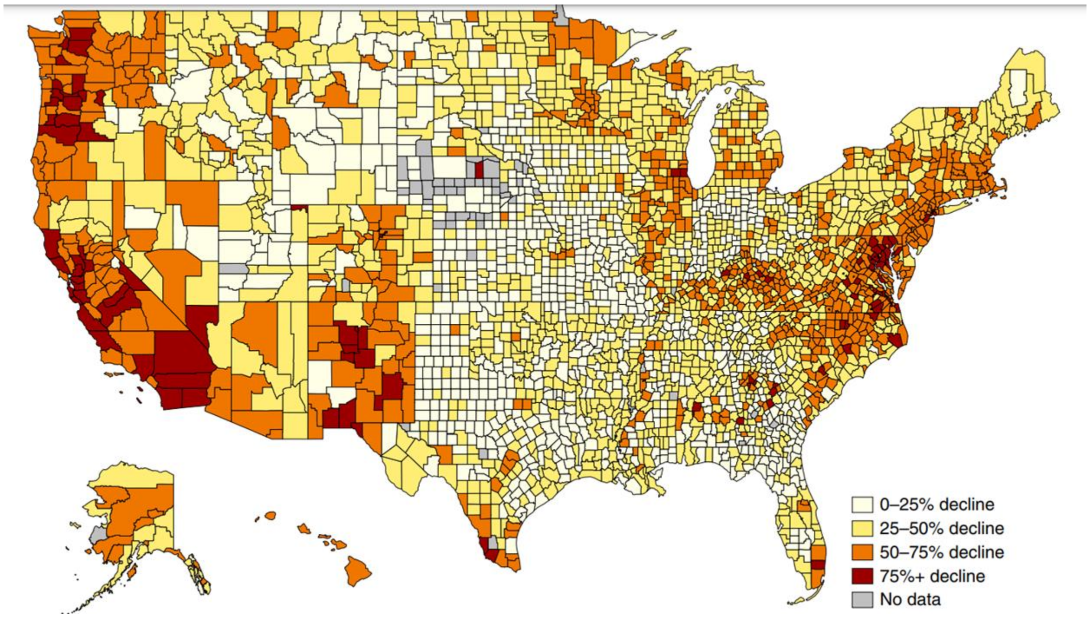
Amid the spread of COVID-19 in 2020, many local governments and school districts implemented policies that led to either the closure of schools and childcare institutions or a hybrid of in-person and remote instruction, leading to a nationwide decline in in-person attendance. Intuitively, the closure of k-12 schools would encourage parents to spend more time caring for their children who are now staying home, which can lead them to work less or even quit their jobs as a trade-off.

Moreover, the increased demand for staying home caused by school closures could potentially result in the labor force flowing across occupations and industries – as some jobs are more flexible, such as allowing remote work, than others for the parents to adapt to the new pattern of work-life balance. Thus, it is interesting to research whether working in an occupation that allows for remote work impacts this relationship; specifically, this paper will investigate whether compatibility with remote work prompted parents to switch between occupations. I will refer to this compatibility as “teleworkability” for the rest of the paper.

This study aims to empirically investigate the impact of k-12 school closures on parental labor supply concerning the intensive margins (weekly working hours) and structural changes (job compositions), with comparisons between different gender and age groups. Since the school closures were distributed unevenly across the country, as shown in Figure 1, I exploit county-level variations using a difference-in-difference approach (Garcia and Cowan, 2022).

This paper contributes to current literature in two ways. First, it investigates the role of teleworkability in one’s labor supply decisions. Second, it explores whether school closures caused a structural change in occupations concerning the composition of remote-work-compatible jobs. In Section 2, I review existing literature. In Section 3, I enumerate the data sources used in this paper. I introduce the models for employment status and occupation changes and discuss their limitations in Section 4. Then, in Section 5, I discuss the results.

Figure 1 - Mean Year-Over-Year Decline in In-person Attendance (Fall 2020)[1]



2. Literature Review

Amuedo-Dorantes et al. (2020) provide one of the earlier empirical studies on labor market implications of school closures. They utilize monthly CPS data from January 2019 to May 2020 at individual level to track labor market outcomes. By conducting difference-in-differences estimation with data aggregated at state-level, they find that school closures reduced weekly work hours of parents of school-age children by between 11 to 15 percent, with a large effect on women. While this study only exploits the variation at the state level, I do so at the county-level.

[1] Parolin, Zachary, and Emma K. Lee. "Large Socio-Economic, Geographic and Demographic Disparities Exist in Exposure to School Closures" (Nature Human Behavior, 2021), 525.

Also, since only data up to May 2020 are studied (only three months into the pandemic), this paper may fail to adjust for the annual trend of labor market fluctuations; my paper will solve this issue by extending the time frame to the end of 2021.

On the other hand, many other empirical studies do not find negative correlation between school closures and parental labor supply. Koppa and West (2021) find that employment was unaffected by school closures. They find that reopening did not increase employment, either, due to "policy uncertainty." Barkowski et al (2021) conclude that childcare needs did not reduce the parental labor supply in terms of both employment and weekly work hours, due to the availability of teleworking. In addition, they find no systematic difference between men and women's responses to the pandemic.

Garcia and Cowan (2022) have the paper that most closely links to my study. They collect the monthly data from CPS from January 2020 to June 2021 for labor market outcomes. They introduce closure rate of childcare institutions as another dependent variable in difference-in-differences analysis, with parents of children aging 5-18 as the experiment group and find that school closure did not impact employment but reduced the weekly working hours by around 2 hours, and women and people without college education are affected disproportionately.

My paper builds on Garcia's model by considering if an occupation is feasible for remote work. I investigate if a remote-work-amendable job negates the effect of school closure for parents. My paper also exploits the panel identifiers in the CPS data to discern the relationship between school closure and change in occupations and inspects if the direction of change correlates to teleworkability, which can have significant implications to the research of labor flow during the pandemic. Moreover, greater timespan allows me to explore the aftermath of those effects after schools resumed in-person instruction.

3. Data

I utilize monthly labor-related statistics of people who were employed and aged 21 or above from Current Population Survey (CPS) from January 2020 to December 2021. To exploit the county-level variation, I only use the observations that have county identifiers, which is around 41 percent of all observations and from top 9% populous counties in the US.

I also employ share of schools closed in each county from U.S. School Closure & Distance Learning Database (Parolin et al, 2022a). The database tracks in-person visits to 94% of school districts of public K-12 schools across 98% of counties in the U.S. It uses 50% year-to-year drop in in-person participation rate as the threshold to determine whether a school is "closed." 25% and 75% cutoffs are available as well for robustness checks. To identify the periods in which a county has its schools closed, I use the share of schools closed, weighted by number of students. I define that a county "has its schools closed" when the share reaches 75% and "has its schools reopened" when the share falls below 50%.

As a control option, I extract the percentages of closure childcare institutions closure in a county from U.S. Database of Childcare Closures during COVID-19 (Parolin et al, 2022b). The database tracks visits to about 78 percent of all licensed childcare institutions in the nation. It defines childcare institutions with above 50% year-to-year in-person participation rate drop as "closed" and below 50% as "open." I define analogously the county-level "childcare institutions closed" and "childcare institutions reopened" identifiers to those for school closures.

Additionally, to introduce remote work as an alternate option to change in employment status in response to school closures, I use the teleworkability dataset by Dingel and Neiman (2020) to quantify how well an occupation allows one to work remotely. From zero to one, the teleworkability index indicates how compatible an occupation is with remote work. I crosswalk this dataset from SOC codes to the OCC2010 code used by CPS with some manual work. I also employ COVID-19 statistics from Center for Systems Science and Engineering (CSSE, 2022) at Johns Hopkins University to control Covid-related impact at county-level.

4. Models

To estimate the effects of school closure, I employ the difference-in-differences method that treats adults with school-age (5-17 years old) children in their households as the experiment group. To justify this approach, I regress the interaction terms between the predictors and time on the CPS data from 2018 to 2019. The difference in working hours between the control group and the experimental group is statistically significant ($p < 0.1$) in only two out of 24 months. There is no statistically significant difference in the teleworkability trends. As shown in Figures 1 and 2, the difference in working hours and teleworkability between the groups stayed consistent before early 2020, when pandemic spread across the nation and schools started to close. Both statistical and graphical evidence point to the existence of parallel trends before school closures.

Moreover, both parents and workers without children experienced a decline in working hours and rise in average teleworkability in early 2020, suggesting that people pursued occupations that are more compatible with remote work during the pandemic. More interestingly, Figure 3 depicts a larger spike in teleworkability among parents than the rest of the population. This implies that school closure might be correlated with a higher demand of remote work for parents, assuming that the supply of teleworkable jobs is homogenous between the two groups, This section is organized as follows. In Section 4.1, I present the baseline model for labor market outcomes. In Section 4.2, I introduce the closure of childcare institutions as a control factor. I model occupation changes in Section 4.3. In Section 4.4, I explore the limitations of my research design.

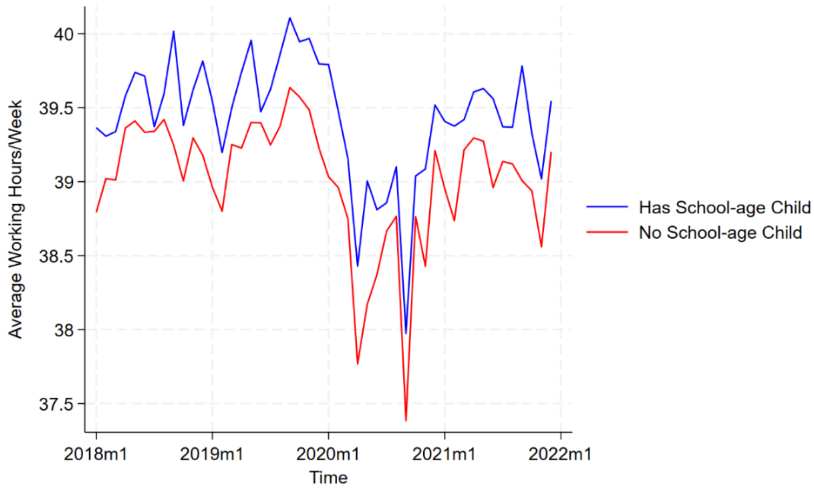


Figure 2 - Trend in Working Hours

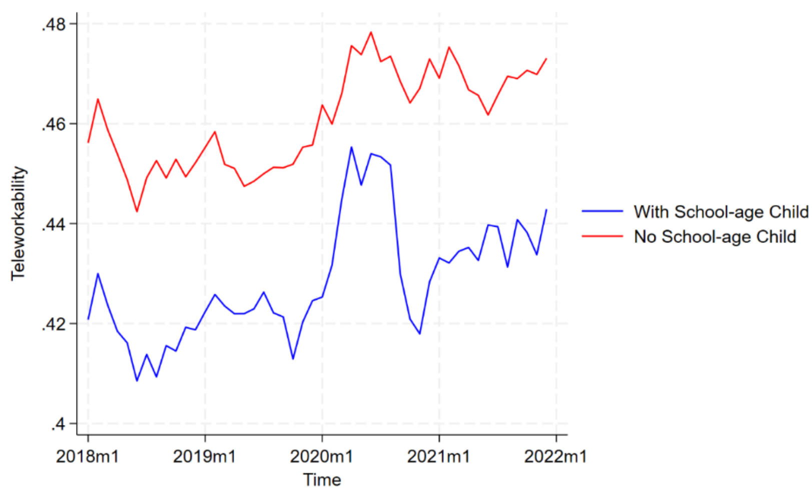


Figure 3 - Trend in Teleworkability

4.1 Baseline Models

Our baseline regression model is shown in Equation (1):

$$Y_{ict} = \boldsymbol{X}_{ict}\boldsymbol{\alpha} + \boldsymbol{Z}_{ict}\boldsymbol{\gamma} + \beta_1(S_{ct} \times K_{ict}) + \beta_2(S_{ct} \times K_{ict} \times T_{ict}) + w_t + v_c + \xi_{ict} + \varepsilon_{ict} \quad (1)$$

Y_{ict} refers to the labor market outcomes (in my study, hours worked last week) for individual i in county c and month t. $\boldsymbol{X}_{ict}$ denotes a horizontal vector of both individual and county characteristics in month t, including COVID-19 related variables in each county (the cumulative number of COVID-19 cases and deaths per 100,000 people) and a set of individual characteristics (age, gender, race and ethnicity, occupation and industry, number of children in household, etc.). S_{ct} refers to the share of schools closed in county c month t. K_{ict} indicates whether an individual has at least one child who is 5-17 years old (the school age) in their household. $\mathrm{T}_{\mathrm{ict}}$ refers to the teleworkability of an individual's occupation. $\mathbf{Z}_{ict}$ contains the interaction terms between K_{ict}, S_{ct}, and $\mathrm{T}_{\mathrm{ict}}$ that are not explicitly listed. w_t represents the time fixed effect, with January 2020 as the baseline period, and v_c represents the county fixed effect. ξ_{ict} represents the unobserved variables, including county-level policy dummy variables (e.g., stay-at-home orders, non-essential business closures, public space restrictions), several other county-level COVID-19 related statistics (monthly changes in Covid cases and deaths, and vaccination rates) and personal traits such as education attainment. ε_{ict} is the error term.

My key hypothesis is that school closures have a disproportionate impact on labor supply of parents who have school-age children. In addition, working in an occupation that is compatible with remote work might mitigate this impact, as it provides parents more flexibility to balance between work and parenthood. Thus, β_1 and β_2 are my coefficients of interest with hypothesis that $\beta_1 < 0$ and $\beta_2 > 0$. To identify the coefficients of interest, I exploit withincounty variation of school closures as well as control for other individual characteristics like gender, age, race, and ethnicity.

This model also makes several assumptions. First, since the school closures data only tracks visits to the public schools, I must assume that school closure and reopening rates are homogeneous across the public and private sectors. This assumption makes sense because as stated in the Motivation section, schools closed mostly because of the spread of COVID-19 and related policies, whose effects should strike private and public schools similarly. Many private schools also take the COVID-19 policies of the local school district as a guideline. Thus, even if discrepancy exists between the two sectors, it should not be very significant, and the generally small share of private schools further reduces its influence.

The second assumption is that school closures do not correlate with the parental market outcomes specifically. I.e., School closure is not adversely affected by the labor market outcomes of parents. Garcia et al. (2022) test this assumption by comparing the labor market outcomes between parents of children ages 0-5 and those of children ages 5-17[2]. Borrowing their method, I can hence add a “having young (0-4 years old) child” (J_{ict}) dummy and its interactive terms with school closures and teleworkability to our baseline model:

$$Y_{\mathrm{ict}} = \boldsymbol{X}_{ict}\boldsymbol{\alpha} + \mathbf{Z}_{ict}\boldsymbol{\gamma} + \beta_1(S_{ct} \times K_{ict}) + \beta_2(S_{ct} \times K_{ict} \times \mathrm{T}_{\mathrm{ict}}) + \beta_3(S_{ct} \times J_{ict})$$
$$+\beta_4(S_{ct} \times J_{ict} \times \mathrm{T}_{\mathrm{ict}}) + w_t + v_c + \xi_{ict} + \varepsilon_{ict} \qquad (2)$$

In this equation, my null hypothesis is that $\beta_1 \geq 0$, $\beta_2 \leq 0$, and $\beta_3, \beta_4 \neq 0$, when the dependent variable is hours worked last week, for example.

[2] Garcia et al., “The Impact of School and Childcare Closures on Labor Market Outcomes during the COVID-19 Pandemic” (NBER, 2022), 8.

4.2 Childcare Institutions

The baseline model has one major limitation by disregarding the closure of childcare institutions and preschools, which could cause similar labor market outcomes to those of school closure. As shown in Figure 4c, there exists a strong and positive correlation between the closures of schools and childcare institutions ($\rho = 0.8872$). Thus, if the closure of childcare institutions influences the labor market outcomes of parents of school age children, it would cause a positive omitted variable bias for school closure. There exists a plausible scenario when some parents send their school age children to part time childcare programs to reduce the childcare burden. Even if their impact on the labor market is limited to parents of very young children (0-4 years old), this variable can contaminate the control group and skew the regression results.

Therefore, to eliminate the omitted variable bias and the potential contamination of sample, as well as to see if the effects of childcare closures take place only on parents of very young children, I incorporate childcare-institutions-related statistics and their interactive terms with the "having school-age children" dummy into Equation 3:

$$\begin{aligned} Y_{\mathrm{ict}} = \boldsymbol{X}_{ict}\boldsymbol{\alpha} + \mathbf{Z}_{ict}\boldsymbol{\gamma} + \beta_1(S_{ct} \times K_{ict}) + \beta_2(S_{ct} \times K_{ict} \times \mathrm{T}_{\mathrm{ict}}) + \beta_3(S_{ct} \times J_{ict}) \\ +\beta_4(S_{ct} \times J_{ict} \times \mathrm{T}_{\mathrm{ict}}) + \beta_5(C_{ct} \times K_{ict}) + \beta_6(C_{ct} \times K_{ict} \times \mathrm{T}_{\mathrm{ict}}) \\ +\beta_7(C_{ct} \times J_{ict}) + \beta_8(C_{ct} \times J_{ict} \times \mathrm{T}_{\mathrm{ict}}) + w_t + v_c + \xi_{ict} + \varepsilon_{ict} \end{aligned} \quad (3)$$

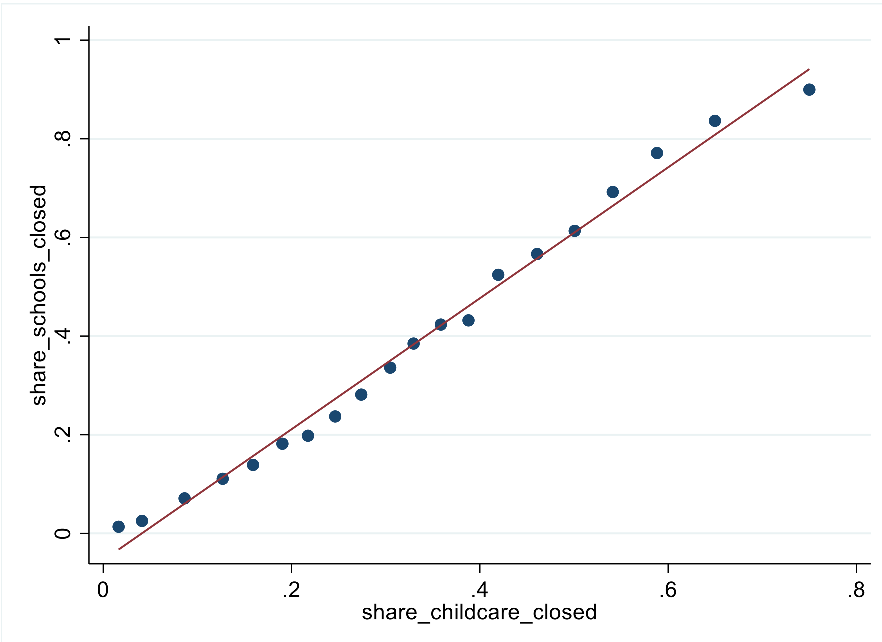
In this equation, C_{ct} and D_{ct} are county-level "having childcare closed" and "having childcare reopened" dummies, respectively. I define them analogously to the county-level school status. My null hypothesis is that $\beta_1 \geq 0$, $\beta_2 \leq 0$, $\beta_3, \beta_4, \beta_5, \beta_6 \neq 0$, $\beta_7 \geq 0$, and $\beta_8 \leq 0$, when the dependent variable is hours worked last week, for example.

An alternative approach to avoiding the contamination of the sample by the closure status of childcare institutions is simply to exclude parents of young children (0-4 years old) from our control group. Still, the variables about childcare intuitions need to be controlled because of their potential effect on parents of school-age children. Thus, I modify the baseline model by adding the county-level closure and reopening status of childcare institutions and restricting the control group to parents without children below the age of 18:

$$Y_{\mathrm{ict}} = \boldsymbol{X}_{ict}\boldsymbol{\alpha} + \mathbf{Z}_{ict}\boldsymbol{\gamma} + \beta_1(S_{ct} \times K_{ict}) + \beta_2(S_{ct} \times K_{ict} \times \mathrm{T}_{\mathrm{ict}}) + \beta_3(C_{ct} \times K_{ict})$$
$$+\beta_4(C_{ct} \times K_{ict} \times \mathrm{T}_{\mathrm{ict}}) + w_t + v_c + \xi_{ict} + \varepsilon_{ict} \qquad (4)$$

In Equation 4, when the dependent variable is at work hours last week, for example, my hypothesis is $\beta_1, \beta_2 < 0$ and $\beta_3 \geq 0, \beta_4 \geq 0$.

*Figure 4 - **School vs Childcare Closure Share by County***[3]



[3] Both school and childcare institutions closure share use the 50% cutoff in drop of year-to-year in-person attendance.

4.3 Occupational Changes

To determine whether school closures drive parents to change occupations, especially if they choose to work remotely to take care of their children, I exploit the longitudinal identifiers of the CPS data. Moreover, to determine the starting and ending months of the *de facto* school closure policies, I employ the county-level “school closed” and “school reopened” identifiers, defined in Section 3. Here I present my model:

$$Y_{\mathrm{ict}} = \boldsymbol{X}_{ict}\boldsymbol{\alpha} + \mathbf{Z}_{ict}\boldsymbol{\gamma} + \beta_1(S_{ct} \times K_{ict}) + \beta_2(R_{ct} \times K_{ict}) + w_t + v_c + \xi_{ict} + \varepsilon_{ict} \tag{5}$$

where Y_{ict} is the individual-level occupation change identifier or the change in teleworkability of one’s occupation, ΔT_{ict}. S_{ct} is a dummy variable that identifies the month when the county has its schools closed. R_{ct} refers to the school-reopened date identifier. This setting allows us to determine the shift in labor market structure before and after school closure.

To identify the effect of school closure on parents’ preferences for occupations, I assume that their exposure to jobs by teleworkability has similar trends as the rest of the population. I assume no forward-looking behaviors exist to school closure or reopening. That is, people only react after the policy changes take effect. To take account of frictions in the labor market, I check the outcomes with lags of one, two, or three months. When the dependent variable is occupation changes, my hypothesis is $\beta_1, \beta_2 \neq 0$. When the dependent variable is the change in teleworkability of the occupation, my null hypothesis is $\beta_1 \leq 0$, $\beta_2 \geq 0$.

4.4 Limitations

In this section I explore several unmentioned limitations of my research design.

First, to include teleworkability, my sample contains only those employed. It precludes me from exploring the extensive margins of labor supply. This may also introduce biased selections, as people who become unemployed may have different characteristics from those employed. For example, if one must stop working because of school closures, my data only capture those who keep their employment; thus, I assume those workers share similar characteristics with those who quit their jobs.

Similarly, dropping the 59% who do not have a county identifier from my CPS sample and excluding 91% of the counties will likely skew the result of the regression, due to the biased selection of the counties – only counties with large enough numbers of households are selected, which generally are urban or suburban areas, and counties from less populous rural areas are missing. Observations who miss the county identifier may also be caused by the lack of permanent address, which is correlated to labor outcome, income, and many other individual characteristics in my model. Nonetheless, this should only be a tiny percentage of the population, and the sample still has a good representation for the big cities.

The assumption that the supply of teleworkable occupation for parents follows a similar trend as that for the rest of the population might be hard to verify. Most job postings do not explicitly discriminate against applicants based on their parenthood; however, there might exist discrete discriminations. Also, parents could have different exposures to occupations due to their childcare responsibilities. Comparing parents of school age children to parents of young children might solve part of the problem, but those two groups still exhibit different characteristics due to the difference in age of their children.

Another issue is I include observations in summer (from June to August) when most schools were not in session and had limited student participation. Because schools across the nation have varying opening and ending dates as well as different summer programs, it is difficult to determine which periods should be included in the sample. This may lead to less significant results from the OLS regressions, as for those having school age children, school closures due to COVID-19 would not mean much increased burden in childcare – the children were not going to school anyway.

5. Results

The COVID-19 pandemic has caused a decline in employment, as the at work rate and average weekly working hours dropped by 2.7% and 1.27 hours, respectively, from March 2020 to September 2020. The summary statistics (see link at the end for details) also show that, despite the difference in timing, all the counties closed at least 75 percent of their schools by Fall 2020. In this section, I will examine the results from the regression models discussed in the previous section. In Section 5.1, I will interpret regression results on weekly working hours. Then, I will do the same to regression results on occupation changes and average teleworkability in Section 5.2.

Table 1 - Hours Worked Last Week, All Population (Shortened)

VARIABLES	Equation (1)	Equation (2)	Equation (3)	Equation (4)
School closure x	-0.867***	-0.881***	-1.100**	-0.917
Presence of school age children	(0.299)	(0.286)	(0.472)	(0.594)
School closure x	0.865**	0.893**	2.386***	2.344**
Presence of school age children x	(0.338)	(0.334)	(0.724)	(0.867)
Teleworkability				
Observations	416,504	416,504	416,504	363,792
R-squared	0.041	0.041	0.041	0.040

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.1 Intensive Margins of Labor Supply

Table 1 displays the results of the regression on weekly working hours. Columns 1-4 display the results from Equations (1)-(4), respectively. In Table 1, the interaction of school closure and presence of school age children has a consistently negative effect on parents' weekly working hours, ranging from 0.87 to 1.1 hours. All but Equation (4) are statistically significant at conventional levels. As speculated, having a fully teleworkable job causes parents to work longer compared to those with jobs that are not compatible with remote work. The effect ranges from 0.87 to 2.39 hours per week.

In columns (2) and (3), the interaction between having children aged 0-4 and school closure, as expected, do not have a significantly negative effect on parental labor supply. In column (3), having young children while school closed cause parents to reduce their hours of working by 2.6 hours. Again, this effect diminishes when the parent's occupation is amendable to remote work. Thus, we reject the hypothesis that the closures of schools or childcare institutions do not have a negative impact on parents' working time. School closures have a significant negative impact on parental labor supply.

Moreover, in Table 5 (the complete version of Table 2), in column (2), the interaction between the presence of young children and school closure does not have significant effects on parental working hours. This supports the assumption that reverse causality does not exist between school closure and parental labor supply.

Table 2 - Occupation Changes, All Population (Shortened)

VARIABLES	1 Month Gap	2 Months Gap	3 Months Gap
School closed today x	-0.00293	0.0118**	-0.00642**
Presence of school age children	(0.00462)	(0.00442)	(0.00299)
School reopened today x	-0.0133	-0.00700	-0.0111**
Presence of school age children	(0.0172)	(0.0159)	(0.00532)
Observations	470,482	470,482	470,482
R-squared	0.013	0.014	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3 - Change in Teleworkability (Shortened)

VARIABLES	1-Month Gap	2-Months Gap	3-Months Gap
School closed today x	-0.00434***	0.00553***	0.0119**
Presence of school age children	(0.000739)	(0.00157)	(0.00472)
School reopened today x	-0.00344**	-0.0146***	-0.0205***
Presence of school age children	(0.00142)	(0.00218)	(0.00567)
Observations	289,705	173,969	79,052
R-squared	0.004	0.007	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.2 Occupation Changes

Table 2 presents the regression results on the existence of occupation changes from certain time periods from the beginning and the end of school closures, on all individuals from the sample. In columns (1)-(3), results are based on gaps of one, two, and three months, respectively. Both columns (2) and (3) show significantly positive effect of the interaction of school closure and having school age children on parents' likelihood to switch to a new job. In all columns, the interaction of school reopening and having school age children has negative effects on parents' likelihood of job changes. Thus, I reject the hypothesis that school closure and reopening have no effect on parents' occupation changes.

Table 3 displays the results of regression on the change in teleworkability of the occupations of the individuals. In columns (1)-(3), results are based on gaps of one, two, and three months, respectively. In columns (2)-(3), the interaction between school closure and having school age children has a significantly positive effect on the parent's occupation's teleworkability, ranging 0.004 to 0.012. Across all columns, the interaction between school reopens and having school age children has a significantly negative effect on the teleworkability of the parent's occupation. Thus, I reject the null hypothesis that school closure and reopening have no effect on parents' preferences on remote work.

Due to the friction of the labor market, the ascending order of the magnitude and statistical significance of the effects in both tables are expected. Therefore, I conclude that parents actively pursue jobs that are compatible with remote work once schools close; they behave the opposite way when schools reopen.

6. Conclusion

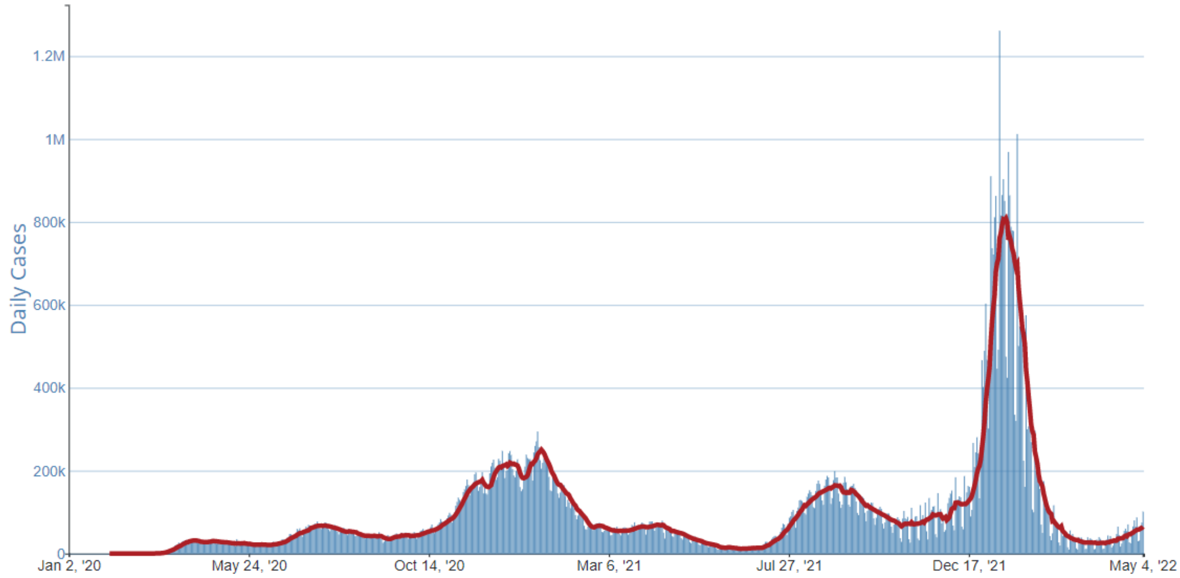
In this research, I find that School closure and reopening from January 2020 to December 2021 had significant effects on labor market outcomes. Consistent to previous literature done by Amuedo-Dorantes et al (2020) and Garcia et al (2022), I find that school closure had a significantly negative impact on the working hours of the parents of school age children, but the magnitude of this impact is much smaller compared to findings in previous research. Moreover, I find that working in a job that is compatible with remote work eliminates this impact. This further supports the narrative that increased childcare responsibility caused the decline in parental labor, as parents who worked from home would have more flexibility to take care of their children at home, mitigating the impact from school closures.

Meanwhile, I find that school closures significantly increased the likelihood of parents of school age children changing their occupation. In addition, I find that parents change their occupations mostly to those with higher compatibility to remote work, suggesting school closures created an increase in demand for working from home for the parents.

Note: If you are interested in replication of the paper or future updated versions, please go to my GitHub repository: https://github.com/theout/School_Closure.

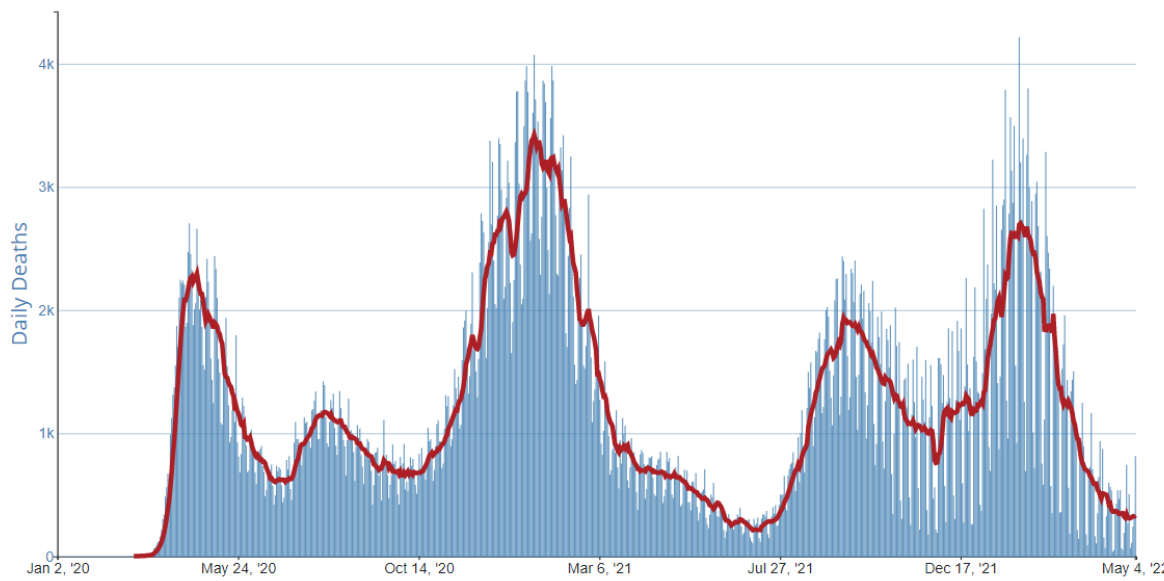
7. Appendix

Figure 5 - Daily Trends in COVID-19 Cases in the United States Reported to CDC[4]



*The red bar represents the 7-day moving average

Figure 6 - Daily Trends in Number of COVID-19 Deaths in the United States Reported to CDC[5]



*The red bar represents the 7-day moving average

[4] CDC, data retrieved on May 10, 2022.

[5] CDC, see above

Table 4 – Summary Statistics by Survey Month, All Population

VARIABLES	(1) Mar 2020	(2) Sept 2020	(3) Mar 2021	(4) Sept 2021
In labor force	0.646	0.638	0.635	0.640
At work	0.591	0.564	0.571	0.589
Not at work	0.0251	0.0213	0.0193	0.0195
Unemployed	0.0267	0.0507	0.0409	0.0295
Work hours last week	38.86	37.59	39.22	39.22
Age	49.62	49.62	49.65	49.65
Female	0.523	0.523	0.523	0.523
White race	0.753	0.750	0.755	0.751
Black race	0.129	0.130	0.131	0.130
Asian race	0.086	0.091	0.084	0.087
Other race	0.032	0.029	0.030	0.032
Married, spouse present	0.534	0.521	0.521	0.515
Observations	32668	33817	33060	32218

(1) All numbers displayed are means weighted with final basic CPS person weights.
(2) Only observations kept in the cleaned sample are represented here.
(3) The average work hours last week only represent those who report working hours

Table 5 - OLS Regression on Weekly Working Hours, all population

VARIABLES	Equation (1)	Equation (2)	Equation (3)	Equation (4)
Presence of school age child	-0.0885	-0.249	-0.286	-0.346*
	(0.154)	(0.151)	(0.168)	(0.196)
School closure	-0.608	-0.620*	-0.387	-0.465
	(0.359)	(0.353)	(0.473)	(0.499)
Presence of school age child x School closure	-0.867***	-0.881***	-1.100**	-0.917
	(0.299)	(0.286)	(0.472)	(0.594)
Teleworkability	1.330***	1.419***	1.271***	1.281***
	(0.193)	(0.201)	(0.240)	(0.238)
Presence of school age child x Teleworkability	-0.00483	0.0524	0.314	0.206
	(0.183)	(0.183)	(0.209)	(0.258)
School closure x Teleworkability	1.113***	1.103***	0.259	0.267
	(0.386)	(0.381)	(0.651)	(0.678)
Presence of school age child x School closure x Teleworkability	0.865**	0.893**	2.386***	2.344**
	(0.338)	(0.334)	(0.724)	(0.867)
Presence of young child		-0.614***	-0.352	
		(0.170)	(0.208)	
Presence of young child x School closure		0.172	1.707**	
		(0.302)	(0.628)	
Presence of young child x Teleworkability		-0.931***	-1.455***	
		(0.254)	(0.277)	
Presence of young child x School closure x Teleworkability		0.0391	-3.028***	
		(0.472)	(0.914)	
Childcare closure			-0.434	-0.245
			(0.546)	(0.614)
Presence of school age child x Childcare closure			0.366	-0.0811
			(0.739)	(0.995)
Childcare closure x Teleworkability			1.408	1.348
			(0.922)	(0.957)
Presence of school age child x Childcare closure x Teleworkability			-2.488**	-2.184
			(1.133)	(1.513)
Presence of young child x			-2.614**	

Childcare closure				
			(1.089)	
Presence of young child x Childcare closure x Teleworkability			5.156***	
			(1.267)	
Constant	47.53***	47.90***	47.94***	48.02***
	(0.459)	(0.474)	(0.498)	(0.553)
Observations	416,504	416,504	416,504	363,792
R-squared	0.041	0.041	0.041	0.040

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6 - OLS Regression on Occupation Changes, All Population

VARIABLES	(1) 1-month gap	(2) 2-month gap	(3) 3-month gap
Presence of school age child	0.00906***	0.00536*	0.00309
	(0.00284)	(0.00305)	(0.00183)
School closure start	0.0344**	0.0456***	0.0422***
	(0.0161)	(0.0117)	(0.00563)
Presence of school age child x School closure start	-0.00293	0.0118**	-0.00642**
	(0.00462)	(0.00442)	(0.00299)
School reopen start	0.0324	0.0296*	0.0183**
	(0.0222)	(0.0162)	(0.00757)
School reopen start x Presence of school age child	-0.0133	-0.00700	-0.0111**
	(0.0172)	(0.0159)	(0.00532)
Presence of young child	0.00496	0.00309	0.00122
	(0.00414)	(0.00367)	(0.00165)
Presence of young child x School closure start	0.00663	-0.00114	-0.00546
	(0.00625)	(0.00493)	(0.00418)
School reopen start x Presence of young child	-0.0220*	-0.0319**	-0.0107
	(0.0124)	(0.0150)	(0.00628)
covid_confirmed_ratio	1.34e-05	1.53e-05*	1.01e-05***
	(1.24e-05)	(7.99e-06)	(3.32e-06)
covid_deaths_ratio	-0.000425	-0.000465**	-0.000295***
	(0.000353)	(0.000209)	(8.76e-05)
age	-0.000181**	-0.000341***	-0.000276***
	(7.70e-05)	(7.18e-05)	(5.02e-05)
Number of children	-0.00315**	-0.00288**	-0.00165**
	(0.00130)	(0.00130)	(0.000766)
Constant	0.370***	0.624***	0.829***
	(0.0182)	(0.0134)	(0.00687)
Observations	470,482	470,482	470,482
R-squared	0.013	0.014	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7 - OLS Regression on Teleworkability Changes, All Population

VARIABLES	(1) 1-month gap	(2) 2-month gap	(3) 3-month gap
Presence of school age child	-4.41e-06	-0.000212	0.000188
	(0.000756)	(0.00172)	(0.00257)
School closure start	0.00344***	-0.00255**	-0.00197
	(0.000583)	(0.00120)	(0.00231)
Presence of school age child x School closure start	-0.00434***	0.00553***	0.0119**
	(0.000739)	(0.00157)	(0.00472)
School reopen start	-0.00155*	0.00479***	0.00116
	(0.000845)	(0.000873)	(0.00205)
School reopen start x Presence of school age child	-0.00344**	-0.0146***	-0.0205***
	(0.00142)	(0.00218)	(0.00567)
covid_confirmed_ratio	-8.53e-08	-5.32e-08	-1.59e-07
	(1.24e-07)	(2.09e-07)	(5.23e-07)
covid_deaths_ratio	6.67e-06	9.43e-06	2.94e-05
	(6.48e-06)	(1.16e-05)	(2.53e-05)
age	1.31e-05	4.16e-05	4.30e-05
	(2.40e-05)	(3.95e-05)	(5.17e-05)
Number of children	-0.000254	-0.000635	-0.000541
	(0.000302)	(0.000688)	(0.00118)
Constant	0.000210	-0.00105	-0.00321
	(0.00153)	(0.00255)	(0.00416)
Observations	289,705	173,969	79,052
R-squared	0.004	0.007	0.011

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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