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Evidence From the COVID-19 Pandemic

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Schools, Job Flexibility, and Married Women's Labor Supply: Evidence From the COVID-19 Pandemic

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Abstract

This study explores the effect of school reopenings during the COVID-19 pandemic on married women's labor supply. We proxy for in-person attendance at US K-12 schools using smartphone data from Safegraph and measure female employment, hours, and remote work using the Current Population Survey. Difference-in-differences estimates show that K-12 reopenings are associated with significant increases in employment and hours among married women with school-aged children, with no measurable effects on labor supply in comparison groups. Employment effects of school reopenings are concentrated among mothers of older school-aged children, while remote work may mitigate effects for mothers of younger children.

JEL Codes: J11, J13, J22

Keywords: Labor Supply, Schools, School Closures, Labor Force Participation, Remote Work, Pandemic, COVID-19

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1 Introduction

The dramatic increase in employment among married women in the United States is among the most striking and transformational labor market trends of the past century. Bolstered by social change, wage gains, time-saving advancements in household technology, increasing control over fertility, and steep increases in college attendance, married women entered the labor force in droves during the 20th century. While only 10% of married women were employed in 1930, by 1990, that rate was 68%.[1] However, over the past 30 years married women's employment and earnings have stagnated far short of equality with those of men (Blau and Kahn, 2007; Eckstein et al., 2019).

Many explanations have been put forth for the stagnation of married women's relative labor supply, including rising expenses associated with childcare, lack of policy support for working parents, and the inflexibility of traditional jobs (Goldin, 2021). Research has also documented the persistence of women's primary role in household labor and parenting tasks. Indeed, even highly educated women and women who outearn their spouses contribute more to housework and are more likely to scale back their careers after having children than their male counterparts (Bertrand et al., 2010, 2015). Meanwhile, the time costs of raising children have increased over time (Dotti Sani and Treas, 2016). There is evidence that motherhood induces lower labor force participation (Lundborg et al., 2017; Jacobsen et al., 1999) and better female labor market opportunities lead to lower fertility (Schaller, 2016), suggesting women still face a strong push-and-pull trade-off between family and career.

Though there is a great deal of interest in understanding the determinants of married

[1] Authors' calculations using 5% decennial census samples.

women's labor supply, it is difficult to identify causal effects in this literature, particularly of supply-side factors (i.e., changes in the opportunity cost of employment). The COVID-19 pandemic provides a unique opportunity to gain insight into the competing factors underlying observed trends in married women's labor supply. Married women were, of course, impacted by the same forces that caused widespread uncertainty, fear, and reduced economic activity and led to layoffs and furloughs among millions of American workers. However, the pandemic also had unprecedented effects on the demands on maternal time at home as childcare facilities, in-home care and services, and K-12 schools shut down nationwide in March 2020 and, for the most part, did not begin to resume until the fall.[2]

Pandemic-related K-12 school closures have generated a rare chance to study a supply-side shock to married women's labor force participation and, more broadly, the labor market costs of changes in caregiving demands.[3] Changes in in-person instruction resulted first in a sudden and dramatic increase (when schools closed) and then decrease (when schools reopened) in the opportunity cost of women's time in the labor market. During school shutdown periods, tens of millions of American children were forced into remote schooling, putting them at risk of potential learning loss and mental health problems and placing unique demands on their parents. Rarely has there been an opportunity to study a near-universal, severe, and sudden

[2]While all custodial parents were impacted by school closures, we focus our discussion and analysis on married women, separately estimating effects for single mothers and custodial fathers. We do this because married women's labor supply has historically been the most responsive to family factors and because their labor supply behavior has largely driven overall patterns in women's labor supply (Blau and Kahn, 2007; Goldin, 2021). During the pandemic, Albanesi and Kim (2021) find that women accounted for two-thirds of the aggregate decline in employment in spring 2020, with especially large reductions in employment for married women with children, and Cortes and Forsythe (2020) find that these declines are not fully explained by gender differences in occupation or industry. Ultimately, the pandemic increased discrepancies in labor market outcomes and productivity both between women and men and between parents and non-parents (Adams-Prassl et al., 2020; Deryugina et al., 2021; Fairlie et al., 2021; Bansak et al., 2021).

[3]Previous research in this area has mostly examined changes in access to pre-K and kindergarten, finding substantial effects on maternal labor supply (Gelbach, 2002; Baker et al., 2008; Sall, 2014; Bauernschuster and Schlotter, 2015).

shock to children's needs—changes at the *intensive margin* of parenthood—on mothers' labor force outcomes.

One challenge in using pandemic school closures to identify the effects of children's school attendance (and, more broadly, changes in caregiving demands) on maternal labor supply is that the March 2020 shutdown of schools was near-universal and coincided with economic shutdown and widespread fear about the pandemic.[4] While geographic and temporal variation in school reopenings is a more promising source of identifying variation, a lack of comparable data (across school districts and over time) for identifying in-person attendance makes it difficult to consistently identify the timing of school reopenings across the nation. An important data source has been crowdsourced[5], but many states have not released administrative data, and the data are not easily comparable across localities. Furthermore, administrative data identify schools' reopening status over limited time windows and within three categories—virtual or remote, hybrid, and in person—that make it difficult to accurately determine how many students are attending school in person. In addition to these challenges in measuring school attendance, it is challenging to control for local economic activity and perceptions about the pandemic and the economy that are correlated with the timing of local school reopenings.

In this paper we use SafeGraph "point-of-interest" (POI) data documenting mobile phone foot traffic data at K-12 schools as a proxy for local school reopenings during the

[4]A common strategy for identification has been difference-in-differences. For example, Heggeness (2020) uses limited variation in the timing of school closures at the start of the pandemic to examine short-run effects on labor supply, finding increases in temporary employment leave among mothers only with no overall effects on employment. Heggeness and Suri (2021) study changes in custodial mothers' labor supply from before to after March 2020, relative to women with no children and custodial fathers, again finding a significant (relative) labor force withdrawal among mothers.

[5]COVID-19 School Data Hub: https://www.covidschooldatahub.com.

COVID-19 pandemic.[6] Our measure of high frequency (daily level) changes in the presence of smartphones on K-12 school property allows us to better capture district reopening policies throughout the entire US and over multiple waves of the COVID-19 pandemic than administrative sources of school reopening data. We construct a measure of relative foot traffic for K-12 schools in a set of localities (large counties, metropolitan areas, and rural areas) spanning the US, comparing monthly foot traffic to pre-pandemic levels. Our data span from September 2019 to October 2021, including three separate academic years affected by the pandemic. Rather than categorizing students discretely into remote learning, hybrid, and in-person learning, SafeGraph data allow us to roughly proxy for the *extent* of in-person instruction since our measure of reopening is continuous.

We confirm that our proxy for K-12 reopenings is positively correlated with predicted school attendance derived from the most comprehensive administrative measures of school reopening policies, obtained from the COVID-19 School Data Hub (see Halloran et al., 2021). We also show that our proxy is associated with measurable increases in employment and work hours and substantial reductions in reported remote work within the K-12 education sector, using the Current Population Survey (CPS). Importantly, we document substantial geographic variation in the extent of K-12 reopenings, particularly during the 2020–2021 school year. We then link our measure of K-12 school reopenings to a set of (non-education sector) labor market measures for women with school-aged children from the CPS (Flood et al., 2021).

We employ difference-in-differences regressions, comparing the labor supply of married

[6] Other recent studies have used SafeGraph data to proxy for school reopenings to study the impacts of school attendance on disease spread and children's human capital accumulation (Bravata et al., 2021; Fuchs-Schündeln et al., 2021).

women with school-aged children within localities across periods of high and low school attendance during the pandemic, controlling for differential COVID-19 and macroeconomic shocks across jurisdictions. To account for geographic variation in general attitudes about the pandemic and the degree of economic reopening that was occurring separately from schools, we control for continuous measures of relative foot traffic at local restaurants and bars. We also estimate event studies and fully interacted triple-differences models, formally comparing the estimated effects of school reopenings for women in our treated group (married with school-aged children) to those for other women.

Our results show that K-12 school reopenings positively affect the labor supply of married women with school-aged children at the extensive and intensive margin, increasing both employment and (conditional) work hours in non-education sectors. In particular, we find that an increase in relative school foot traffic roughly equivalent to a full in-person "reopening" is associated with an increase in non-education employment of 3.3 percentage points and a small increase in (conditional) weekly work hours of 0.76. Other than responses within the education sector, we find *no* significant effects of school reopenings on the employment or hours of unmarried mothers, women without children, or married custodial fathers. Fully interacted triple-differences models confirm the magnitude and significance of these effects.

In addition to studying employment and work hours, we consider the effects of school reopenings on reported remote work using newly available data on job flexibility during COVID-19. Our ability to observe effects on remote work is important, as a long-standing argument for why women have been unable to balance work and family has been the inflexibility of traditional full-time in-person work arrangements, which do not lend themselves well to family-career balance.[7] Indeed, we find that school reopenings led to substantial reductions in remote work among married mothers, particularly those with a college education.

Estimating our model separately by child age, we show that mothers of 6- to 11-year-old children were more likely to switch away from remote work when schools reopened. Meanwhile, the employment effects of school reopenings were larger among mothers of 12- to 17-year-old children. This heterogeneity by child age may reflect several factors. For example, older children may require additional monitoring, may have more immediate mental health consequences, or may experience greater losses in human capital as a result of virtual schooling. It is also possible that mothers of older children work in less flexible jobs, or that employers are less likely to allow for remote work if children are old enough to be left home alone. This heterogeneity is a potential area for future study.

Taken together, our results imply additional costs of pandemic school closures beyond children's learning losses (Halloran et al., 2021) and suggest that school reopenings played an important role in helping mothers return to work in person during the COVID-19 pandemic. Returning to broader patterns in married women's labor supply, the changes that we document in mothers' employment in response to pandemic school closures are further convincing evidence of the competing forces of career and caregiving that women continue to face every day, even with older children, and even outside of the pandemic environment. Our study also highlights the potential role of remote work in helping women with children balance work and family going forward (Dettling, 2017).

[7] Job flexibility has also historically played a large role in the type of education women pursue, their occupations, and the earnings penalties they face when having children (Flabbi and Moro, 2012; Goldin, 2014).

2 Data and Methods

2.1 SafeGraph POI Data

Our proxy for in-person primary and secondary school attendance is a continuous monthly measure that spans the entire United States over more than two years. We construct this proxy using POI foot traffic data from SafeGraph, Inc. These data provide location-specific information collected from over 40 million anonymized smartphones that opted in to sharing geocoded data. Daily information is collected on mobile phone "pings" at over four million POIs in the United States and is aggregated by census block group and county. SafeGraph smartphone data have been used widely by economists studying mobility during the COVID-19 pandemic (see, e.g., Allcott et al. 2020; Cronin and Evans 2020; Dave et al. 2021; Goolsbee and Syverson 2021), including for studies focusing on schools (Bravata et al., 2021; Fuchs-Schündeln et al., 2021).

We aggregate daily county K-12 foot traffic to the month-by-locality level from September 2019 to October 2021 using the North American Industry Classification System (NAICS) code 611110: Elementary and Secondary Schools. For each county, we calculate weekday K-12 school foot traffic relative to weekday averages for January and February 2020 (before the pandemic) so that a county-month K-12 foot traffic value of 80 in the post-pandemic period would indicate that school foot traffic has returned to 80% of its pre-pandemic level.

As shown in our summary statistics table—Table A1—the mean value of our relative foot traffic measure in our estimation sample is about 52, with college-educated and non-white women living in areas with lower reopening shares. For ease of interpretation in our regression tables, we rescale our foot traffic variable so that a one-unit change reflects a move from the

5th to the 95th percentile of reopening, a change of around 58 points, to approximate the difference between a county where schools likely fully closed and a county where schools are likely fully reopen.

To ensure the patterns we observe are not merely capturing changes in foot traffic due to other state and local lockdown policies (i.e., stay-at-home advisories, nonessential business closures) or preferences of the local population (i.e., due to beliefs about contagion risk, severity of health consequences of contracting COVID-19), we also use SafeGraph data to measure foot traffic at restaurants (NAICS code: 7225) and drinking places (NAICS code: 7224). Analogous to our K-12 measure, our restaurant-bar foot traffic measures county-level foot traffic relative to winter 2020. As shown in Appendix Figure A1, while restaurant-bar foot traffic and K-12 foot traffic are correlated, there is substantial independent variation across these measures.

It is worth noting that while they allow us to pick up continuous variation in school visits, our SafeGraph data are intended to be a *proxy* for children's in-person school attendance. Many factors could affect foot traffic other than school closures and reopenings, and those will generate noise in our variable. For instance, while foot traffic drops on the weekends and during the summer, it does not drop to zero, potentially due to individuals passing by school grounds or families using school facilities for recreation when schools are not open for instruction. Moreover, even when schools were remote, staff were likely working on campus, and families may have stopped by to pick up lunches (which many districts still provided). In addition, there is some measurement error due to GPS drift.

We begin our analysis by confirming that our foot traffic measure is correlated with other variables that might pick up school reopenings: employment, work hours, remote work in the education sector in the CPS, and an alternative proxy constructed from the most extensive administrative database of school reopening policies, the COVID-19 School Data Hub. In the CPS, we identify individuals working in the education sector. Using the School Data Hub, we construct a predicted share of students attending school in person by identifying the stated learning model ("in person," "hybrid," or "virtual") for each set of grades, summing the number of students enrolled in grades reported to be in person plus 0.5 times the number in "hybrid" mode, and dividing by total enrollment.[8]

Table 1 presents the results demonstrating a "first-stage" association between our measure of reopenings and other variables that should be associated with reopening. The analysis focuses on all prime-age individuals (ages 25 to 54) and prime-aged individuals with a college education. The table shows that our proxy is highly correlated with employment, hours, and remote work in the CPS. In particular, an increase in our SafeGraph measure that is approximately equivalent to a full reopening is associated with a 1.4 percentage point increase in the likelihood that college-educated workers are employed in the education sector and a 2.5-hour increase in weekly work hours, as well as a full 20 percentage point decrease in remote work within the education sector. Our measure is also strongly and positively correlated with the predicted share of students attending in person from the Data Hub. Scatter plots in Appendix Figure A2 show these correlations at the area level.[9]

Next, we illustrate the geographic variation in the timing of school reopenings. In the left-

[8]This measure is admittedly rough as the administrative data are only available for some states and the detail in the data as well as the frequency of data reporting varied widely across states. It is also impossible to determine the share of time spent on in person learning for students in hybrid formats.

[9]In Appendix Table A3, we also explore what happens when we replace our main proxy with the Data Hub predicted attendance rate. Though that measure is correlated with ours, we do not find any effects of changes in that measure, even on outcomes within the education sector, leading us to prefer the SafeGraph measure.

hand side of Panel A in Figure 1, we show trends in state-level school foot traffic for three states that represent the minimum (California), median (Florida), and maximum (South Dakota) levels of fall 2020 school foot traffic relative to January–February 2020. At the onset of the COVID-19 pandemic in the US in mid-March 2020, schools across the country closed simultaneously and remained closed throughout the end of the school year and the subsequent summer. However, there is substantial variation in the degree of reopening in the 2020–21 academic year. Among the three states shown, K-12 schools in California largely remained closed in the fall, while Florida schools partially reopened and South Dakota schools reopened almost entirely.

In Panel B, we provide a map showing county variation in K-12 foot traffic in fall 2020 relative to pre-pandemic levels. It shows that a large share of counties in the South and Midwest were returning in-person while counties in the West and the Northeast were not. In addition to these broad patterns, the map shows that school reopening rates significantly varied within regions and even within some states.

2.2 Labor Market Data

For the analysis in Table 1, and to generate locality-specific measures of employment, work hours, and remote work for married women with school-aged children and for comparison groups, we use monthly labor market data from the CPS, downloaded from IPUMS (Flood et al., 2021). Due to limited sample sizes, the CPS masks county of residence for a large number of observations. We thus match geographic areas as follows. If a county identifier is available, we match labor market data to SafeGraph data based on county. If a county is unavailable but the Metropolitan Statistical Area (MSA) is identified, we match at that level. If neither county nor MSA is identified, we combine individuals into "unincorporated geographic areas" within each state and aggregate foot traffic for that region. This gives us a total of 313 areas for our analysis.

Our CPS sample includes men and women 25–54 years old. We focus on married women who have at least one child in the household and for whom either the youngest or oldest child is between the ages of 6 and 17.[10] We also construct a handful of comparison groups, including unmarried women with school-aged children, women with no children, and married men with custodial school-aged children. As measures of labor supply, we generate an indicator variable for employment ("employed, at work") and a variable that reflects reported actual hours worked last week at all jobs. Both measures include self-employed workers. We identify remote work using a new CPS question asking whether a respondent worked from home for pay at any time during the past four weeks due to the COVID-19 pandemic. Our remote work variable is available starting in May 2020 and ends in September 2021.

The upper right-hand panel of Figure 1 shows variation during the pandemic in aggregate employment rates for married women with school-aged children versus other women as well as for married men with school-aged children and other men (gray lines). The figure shows that married women with school-aged children were similarly impacted by the COVID-19 pandemic in spring 2020 overall. Other than having generally lower employment during the summer months[11], married women with children do not appear to have had a slower return to the labor market than the other groups. The map in Panel B2 shows geographic variation in

[10] We cannot identify women who have a school-aged middle child.

[11] A recent paper by Price and Wasserman (2021) shows that the relative drop in labor supply for women during summer months is present even within sectors and reflects in part a labor supply response to increased childcare responsibilities.

labor market reentry for women with school-aged children in fall 2020, with counties grouped into metropolitan areas, and "unincorporated" areas based on data availability. While the map shows a range in the relative employment measure, it is difficult to discern a clear geographic pattern in labor market reentry, and it does not clearly match or mirror the map of relative foot traffic to the left.

2.3 Methods

For our main analyses, we estimate panel data models that measure the association between changes in relative K-12 foot traffic and changes in maternal employment outcomes within geographic areas over time, controlling for individual demographics, area factors, and common regional shocks. Our model is represented by the following equation:

$$LS_{irdt} = \beta_r + \gamma * \text{Reopen}_{rdt} + \tau_{dt} + X'_{it}\delta + Z'_{rt}\Phi + u_{irdt}, \tag{1}$$

where LS_{irdt} is a labor supply measure for individual i in area r in census division d at time t, and Reopen_{rdt} is our proxy for school reopenings that varies at the area-year-month level. β_r represents local area fixed effects and τ_{dt} represents division-specific time (year-by-month) effects. X_{it} represents a set of individual demographic controls for age, race/ethnicity, and education, and Z_{rt} is a set of time-varying local area controls including foot traffic to restaurants and bars (our proxy for "general" reopening policy and sentiment) and the cumulative COVID-19 death rate. Our estimates are weighted using individual CPS sample weights, and we cluster our standard errors at the area (r) level.

Our main coefficient, γ, identifies the effects of local changes in relative school foot traffic on maternal labor supply. Our goal is to determine whether mothers in localities in which in-person school attendance increased most dramatically (e.g., in fall 2020) expanded their labor supply at a higher rate. Given that our treatment variable range is scaled to the base period at 100, an untransformed coefficient would indicate how a 1 percentage point change in school attendance affects employment. For ease of interpretation, we adjust our coefficients by a factor of 58.6—the difference between the relative foot traffic at the 5th and 95th percentiles—to capture the effect of fully opening schools versus fully closing them.

3 Results

The results from estimating Equation 1 are presented in Table 2. Recall that our model controls for division-specific time effects and time-varying local factors including COVID-19 death rates and reopening policies. In Panel A, we present the estimated effects for women with school-aged children (ages 6 to 17). The first two columns contain estimates for employment in the K-12 sector and employment in other sectors. Columns 3 and 4 report effects on weekly work hours, separately for K-12 and other sectors. Columns 5 and 6 report estimated effects on remote work shares in K-12 and other sectors.

Our results suggest that married women with school-aged children changed both *whether* and *how* they worked based on whether schools reopen in person. In columns 1, 3, and 5 of Table 2, we see changes in the education sector employment among married women with kids similar to those seen for the full sample in Table 1. More importantly, however, we find that school reopenings are associated with a 3.3 percentage point increase in employment *outside* the education sector for married women with school-aged kids. We also find a 0.760 increase in weekly (conditional) work hours outside of the education sector and a 3.3 percentage point reduction in reported remote work.

In Panel B, we report effects for three comparison groups: unmarried women with school-aged children (a group affected by school reopenings that likely did not have as much flexibility to change their employment in response), women without children, and married custodial fathers (again, a group affected by school reopenings but with a lower labor supply elasticity). Where school reopenings likely had direct demand-side effects, we see similarities across the groups. For instance, the estimated effect on K-12 employment is 1.8 percentage points for married women with school-aged children versus 1.3 percentage points for married men with school-aged kids, and 1.4 percentage points for women without children. Likewise, we consistently find that school reopenings are associated with a large and precise drop in remote work for those in the K-12 sector. On the other hand, *only* married women with school-aged children show increases in employment and reductions in remote work in sectors outside the K-12 sector when schools reopen for in-person instruction.

In Table 3, we focus exclusively on mothers of school-aged children and explore heterogeneity within that category. In Panel A, we stratify by education and find that in-person school reopenings increase non-education employment by similar margins (3.6 versus 3.5 percentage points) among mothers with and without any college education. On the other hand, school reopenings lead to a 4.4 percentage decline in remote work for college-educated mothers as opposed to a statistically insignificant 1.4 percentage point decline for those with no bachelor's degree. We also note that within the education sector, there is an even larger decline in remote work among college-educated married women (23.9 percentage points) than for the full sample (Table 1), and those without a bachelor's degree show no decline in remote work with school reopenings.[12]

In Panel B of Table 3, we split by the age of children, focusing on married mothers with children ages 6 to 11 versus those with children ages 12 to 17. We find that in-person school reopenings have a *larger* and more precise effect on employment (3.8 percentage points versus 2.5 percentage points) for women with older children. At the same time, it appears that nearly all of the decline in remote work is driven by women with younger children, who see a 5.4 percentage point decline versus a 0.3 percentage point drop for women with older school-aged kids.

In summary, we find that in-person K-12 schooling is associated with gains in employment for married women with school-aged kids but not for any other group, including single mothers and married custodial fathers. Interestingly, this pattern of findings contrasts with earlier research on kindergarten and pre-K expansions, which finds larger effects for single and non-college-educated women (Gelbach, 2002; Sall, 2014) or no effects at all (Fitzpatrick, 2010). How large are these impacts? At the peak of the COVID-19 recession, married women with school-aged kids saw their employment drop by 15 percentage points. Therefore a 3.2 percentage point increase would represent 21% of the gains in employment seen by those women since the pandemic began.

Some key questions emerge when considering our findings. Remote work appears to be a key source of job flexibility during the pandemic that mothers used when schools were taught remotely, and that effect is concentrated among mothers of young children. However, we find that the extensive margin labor force impacts are principally driven by women with older

[12] This is reassuring with regard to our proxy's validity as those without college degrees working in K-12 schools likely work in occupations where remote work is difficult or impossible (food service, transportation, etc.).

children. Is this because married mothers left the labor force when schools were remote in an attempt to invest in their children's human capital? Are the effects on women with older children larger because their children were in grades where worse academic performance could have more severe consequences with college shortly on the horizon (Halloran et al., 2021; Kofoed et al., 2021)? While children have shown some degree of resilience to educational interruptions (Pischke, 2007), women with older children may be rationally forecasting that their children will have less time to make up for disruptions to their human capital. It is also possible women with younger children choose more flexible jobs, which they move out of as their children age, or that employers are less lenient with mothers of older children.

3.1 Extensions

To explore the credibility of the parallel trends assumption underlying our difference-in-differences estimator, we present findings from two event study analyses. The first event studies use the full distribution of (relative) foot traffic at schools, accounting for the fact that the volume of school foot traffic varies over time both within and across states. This event study approach aligns with the continuous school foot traffic measure used in equation (1) and most resembles a distributed lag-type model. Schmidheiny and Siegloch (2019), we estimate

$$\gamma_{iat} = \gamma_0 + \sum_{j \neq -1} \gamma_j D^j_{ist} + X'_{ist}\alpha + \tau_t + \mu_s + \epsilon_{ist}, \tag{2}$$

where j denotes event time and D^j_{iat} is a set of variables that measure the difference between area-specific school foot traffic in month-by-year t and t-1 occurred j periods from t. Each

γ_j can be interpreted as an estimated effect of school foot traffic across event time relative to $j(i, s, t) = -1$. Results from this approach are in Figure 2. These events studies provide evidence supporting the common trends assumption in our primary model.

The second event study approach focuses on prominent increases in school foot traffic (foot traffic that reaches at least 90% of what foot traffic levels were in January–February 2020) and uses the estimator developed by Callaway and Sant'Anna (2021) to account for heterogeneous and dynamic treatment effects (Goodman-Bacon, 2021). Sun and Abraham (2021) note that in the presence of heterogeneous treatment effects over time, event study coefficients generated from two-way fixed effects estimators may be biased. In applying the Callaway and Sant'Anna estimator for our event studies, we restrict the counterfactuals in each period to jurisdictions that had not yet (or never) experienced a prominent increase in school foot traffic. This avoids potentially problematic comparisons of mothers' labor market outcomes in areas that were "later school openers" versus "earlier school openers."

We also control for smaller increases in school foot traffic that could capture hybrid learning (50% to 89.9% of the foot traffic level in January–February 2020) and for prominent increases in restaurant and bar foot traffic (foot traffic at least 90% of its January–February 2020 levels). Together, the event study approaches described above will help us assess the credibility of parallel trends and ensure our estimated treatment effect is not contaminated by heterogeneous and dynamic treatment effects (Rees et al., 2021). The results from our event-study analysis using Callaway and Sant'Anna (2021) estimates are shown in Appendix Figure A3. They provide additional evidence in support of the common trends assumption as well as show an increase in non-education employment among married women with school-aged children following a prominent K-12 school reopening.

In Appendix Table A2, we present estimates for fully interacted triple difference (DDD) models with married women with school-aged kids versus women with no kids. DDD models have been a standard approach used in the literature to study the labor market effects of the pandemic (see, e.g., Fairlie et al. (2021); Heggeness and Suri (2021). Not surprisingly, given the null effects for the comparison groups in Table 2, the effects in the DDD are similar to our main difference-in-differences estimates. In fact, this is true regardless of the control group we use and even when we estimate a DDD for "treated" (married with school-aged kids) versus everyone else in the CPS sample.

4 Conclusions

In this paper, we provide evidence on the role of school reopenings during the COVID-19 pandemic in facilitating mothers' return to the labor market. Our use of SafeGraph data to proxy for school reopenings allows us better coverage across time and geography than administrative measures of school reopenings and allows us to exploit continuous variation in in-person attendance even within administrative categories of school policy. We find evidence that school foot traffic was associated with increased employment and work hours and reductions in remote work among married women with school-aged children.

While the nature of the school closures and reopenings that we study is unique to the COVID-19 pandemic, our results provide important insights into longer-run trends in married women's labor force participation and in particular into the stagnation of their labor market standing relative to single women and to men. The labor supply effects of school reopenings that we find for married women and the stark *lack* of any effects for other groups underscore the importance of caregiving in creating the gender-wage gap—a story recently highlighted by Goldin (2021).

Our findings imply that despite decades of labor market progress, married mothers still bear the brunt of shocks to the value of home production and thus are likely to also carry the burden of smaller, more common shocks such as those to children's health and mental health. Further, we show that the competing demands of career and parenting are not unique to mothers of young children and are perhaps even stronger for mothers of older school-aged children, who may have less job flexibility to accommodate any shocks. Finally, our remote work findings corroborate recent research by Dettling (2017), suggesting remote work may be a key component to facilitating work-family balance for married women in particular and that job flexibility likely mitigated employment losses for mothers during the pandemic.

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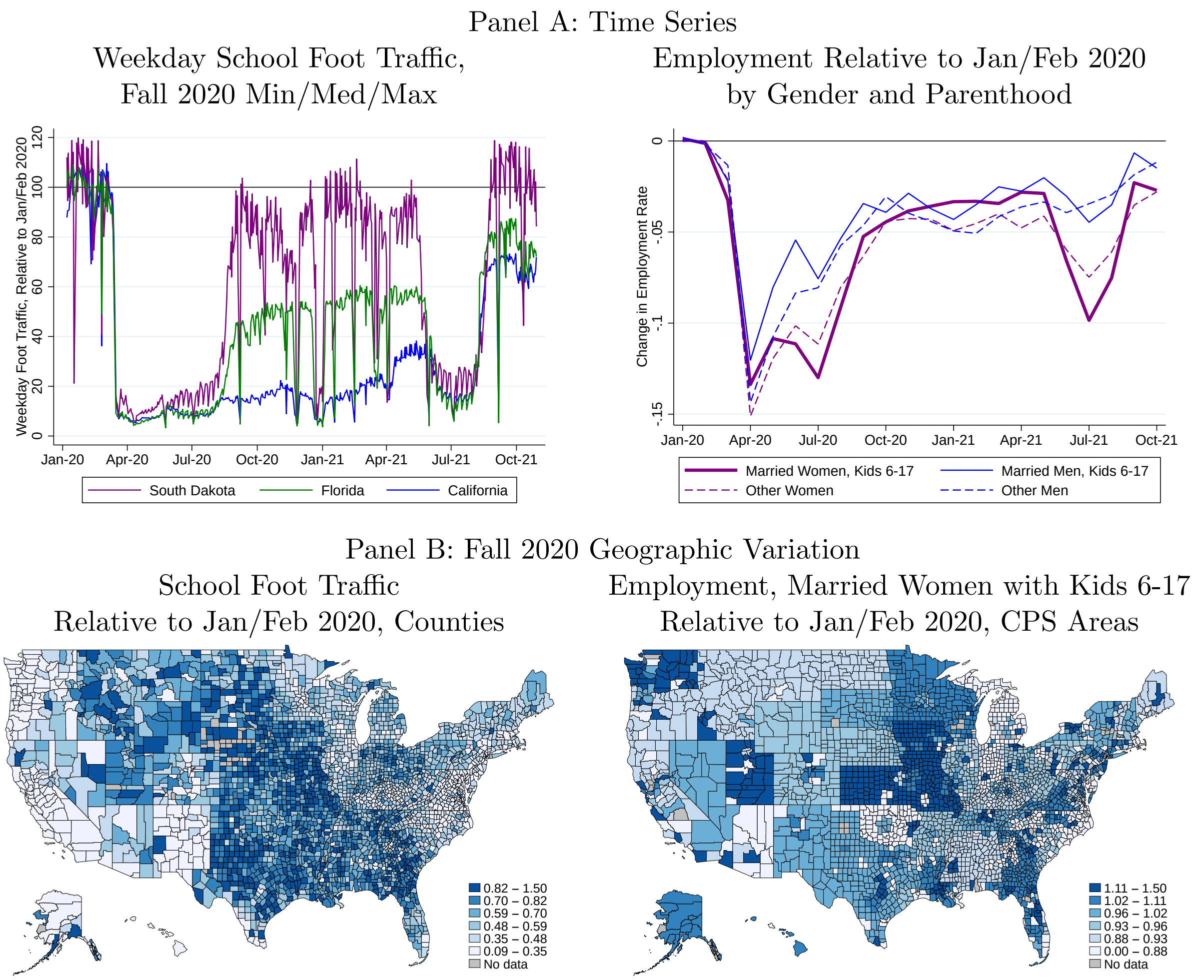
5 Exhibits

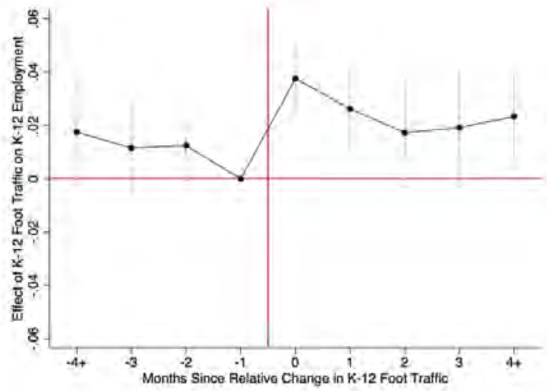
Figure 1: Variation in School Reopenings and Women's Labor Supply



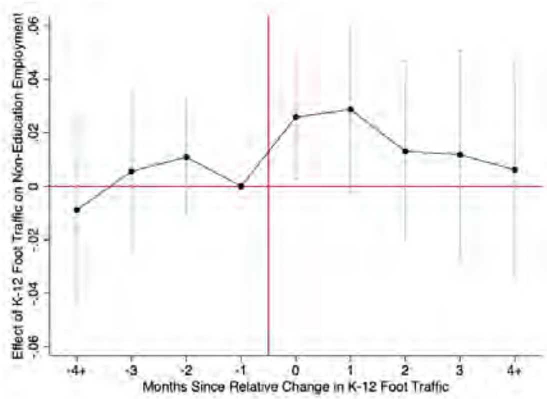
Notes: School foot traffic data are from SafeGraph. Employment rates are calculated using a sample of individuals aged 25–54 in the Current Population Survey.

Figure 2: Dynamic Effects of K-12 School Reopenings on Labor Supply of Married Women with School-Aged Children: Event Study Estimates

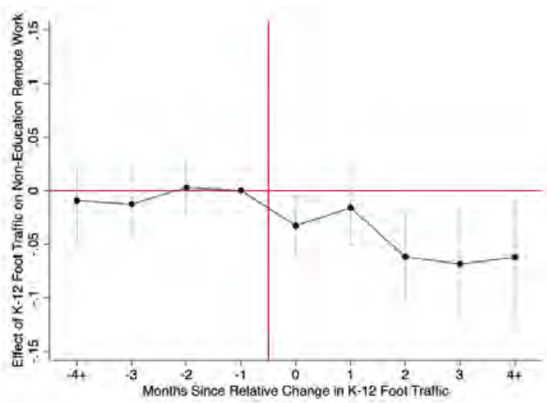
Education Employment



Non-Education Employment



Non-Education Remote Work



Notes: Vertical bars represent 95% confidence intervals around estimated treatment effects over time obtained from regression described in equation (2).

Table 1: Estimated Associations Between SafeGraph Data and Alternative School Reopening Proxies

	Education Sector Employment Rate		Hours Last Week, Education Sector		Remote Work, Education Sector		Predicted Attendance, COVID-19 Data Hub
	All	College	All	College	All	College	
K12 Foot Traffic	0.009***	0.014***	2.126***	2.507***	-0.191***	-0.202***	33.216***
	(0.002)	(0.003)	(0.524)	(0.549)	(0.021)	(0.022)	(4.185)

Notes: Individual-level data are from the Current Population Survey and include individuals aged 25–54. COVID-19 Data Hub prediction is constructed with administrative data from https://www.covidschooldatahub.com (see text). All regressions include area fixed effects and census division-specific year-month fixed effects. Individual control variables include age, race (fractions Black Non-Hispanic, other Non-Hispanic, and Hispanic), education (less than high school, high school graduate, some college, bachelor's degree, advanced degree), and marital status. COVID-19 controls include an indicator for positive cumulative deaths per capita and a continuous measure of cumulative deaths per capita. Observations are weighted using CPS individual sample weights. Robust standard errors, which allow for clustering at the area level, are shown in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 2: Estimated Effects of K-12 Reopenings on Labor Market Outcomes

	Employment		Work Hours		Remote Work	
	K12	Other	K12	Other	K12	Other
	Panel A: Primary Treated Group					
	Married Women with School-Aged Children					
K12 Foot Traffic	0.018***	0.033***	0.050	0.760**	-0.191***	-0.032**
	(0.007)	(0.012)	(0.903)	(0.369)	(0.035)	(0.016)
	Panel B: Comparison Groups					
	Unmarried Women with School-Aged Children					
K12 Foot Traffic	0.014*	0.003	1.243	-0.133	-0.100	0.014
	(0.008)	(0.019)	(1.882)	(0.541)	(0.083)	(0.018)
	Women without Children					
K12 Foot Traffic	0.000	0.008	3.789***	-0.059	-0.213***	0.002
	(0.005)	(0.009)	(0.871)	(0.236)	(0.036)	(0.012)
	Men with Children Ages 6-17					
K12 Foot Traffic	0.013***	0.001	3.905***	0.255	-0.191***	0.002
	(0.003)	(0.008)	(1.300)	(0.291)	(0.065)	(0.009)

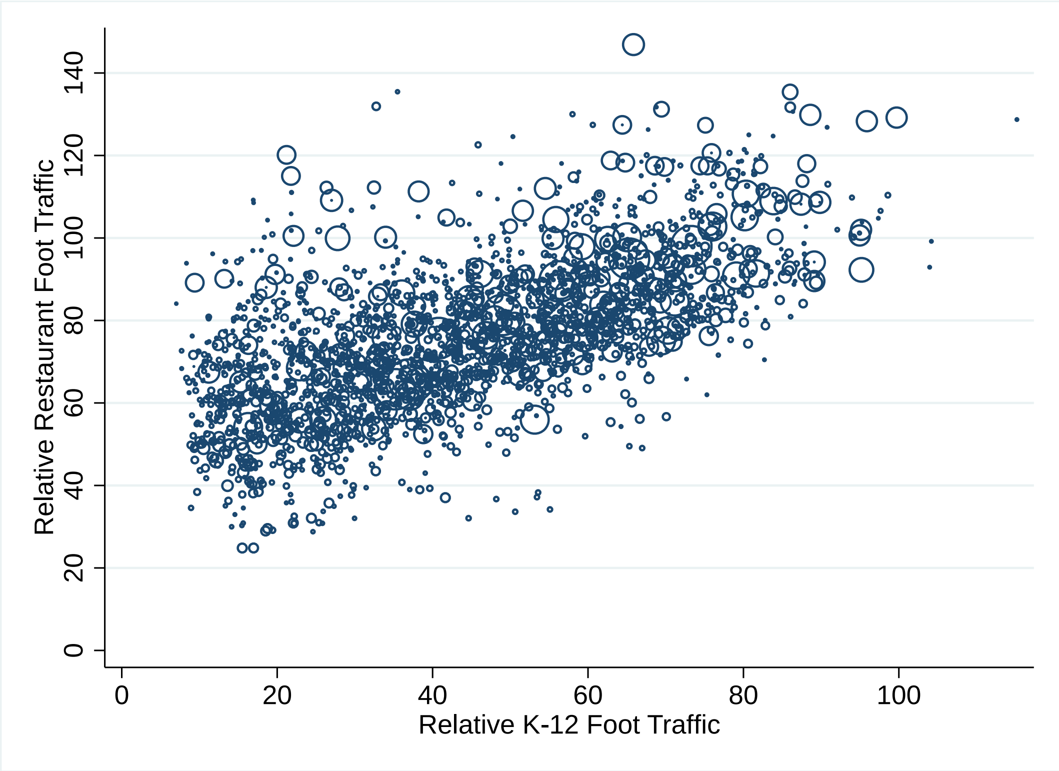
Notes: The treatment variable is K-12 weekday foot traffic relative to an area's average K-12 weekday foot traffic in Jan/Feb 2020. All coefficients are scaled up by 58.6—the difference between the 5th and 95th percentile of area reopening shares. All regressions include area fixed effects and census-division-specific year-month fixed effects. Individual control variables include age, race (Black Non-Hispanic, other Non-Hispanic, and Hispanic), education (less than high school, some college, bachelor's degree, advanced degree), and marital status. Area COVID-19 controls include an indicator for positive cumulative deaths per capita and a continuous measure of cumulative deaths per capita. Observations are weighted using CPS sample weights. Robust standard errors, which allow for clustering at the area level, are shown in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table 3: Heterogeneity in the Estimated Effects of K-12 Reopenings on Labor Market Outcomes, Married Females with School-Aged Children

	Employment		Hours Last Week		Remote Work	
	K12 Sector	Other Sectors	K12 Sector	Other Sectors	K12 Sector	Other Sectors
Panel A: By Education						
Bachelor's or Advanced Degree						
K12 Foot Traffic	0.030**	0.036**	0.357	0.840	-0.239***	-0.044*
	(0.013)	(0.017)	(1.081)	(0.625)	(0.042)	(0.025)
No Bachelor's Degree						
K12 Foot Traffic	0.012*	0.035**	-0.965	0.700	-0.031	-0.014
	(0.006)	(0.016)	(1.807)	(0.478)	(0.082)	(0.019)
Panel B: By Child Age						
Kids Ages 5-11						
K12 Foot Traffic	0.036***	0.025	0.184	0.655	-0.242***	-0.054***
	(0.009)	(0.016)	(1.208)	(0.497)	(0.050)	(0.019)
Kid Ages 12-17						
K12 Foot Traffic	0.008	0.038**	0.106	0.287	-0.183***	-0.003
	(0.009)	(0.015)	(1.226)	(0.470)	(0.046)	(0.020)

Notes: The treatment variable is K-12 weekday foot traffic relative to an area's average K-12 weekday foot traffic in Jan/Feb 2020. All coefficients are scaled up by 58.6—the difference between the 5th and 95th percentile of area reopening shares. All regressions include area fixed effects and census division-specific year-month fixed effects. Individual control variables include age, race (fractions Black Non-Hispanic, other Non-Hispanic, and Hispanic), education when applicable (less than high school, high school graduate, some college, bachelor's degree, advanced degree), and marital status. COVID-19 controls include an indicator for positive cumulative deaths per capita and a continuous measure of cumulative deaths per capita. Observations are weighted using CPS individual sample weights. Robust standard errors, which allow for clustering at the area level, are shown in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

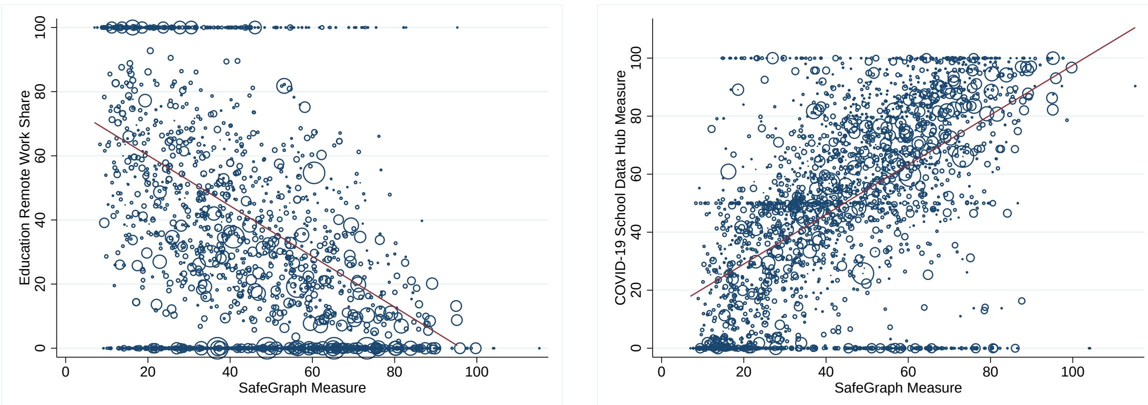
Figure A1: Variation in Restaurant and School Foot Traffic



Notes: Data are from SafeGraph. The scatter plot shows variation in the pooled sample of area-month observations. Markers are weighted by area population.

Figure A2: Scatter Plots: SafeGraph School Reopenings vs. Other Reopenings Proxies

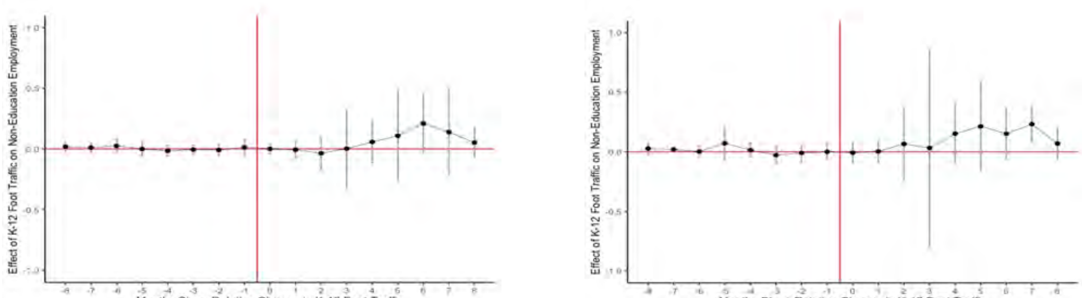
Education Sector Remote Work Share | Predicted Attendance, COVID-19 Data Hub



Notes: Data sources are SafeGraph, the Current Population Survey, and https://www.covidschooldatahub.com. The scatter plots show variation in the pooled sample of area-month observations. Markers are weighted by area population.

Figure A3: Dynamic Effects of Prominent Increase in K-12 School Foot Traffic: Event Studies Using Callaway-Sant'Anna Estimates

Employment for Mothers with Any School Aged Children | Employment for Mothers with Older School Aged Children



Notes: Vertical bars represent 95% confidence intervals from Callaway-Sant'Anna (2021) estimates. The treatment is defined as a jurisdiction attaining at least 90 percent of school foot traffic relative to the January/February 2020 period. Control jurisdictions are defined as those areas that had not yet (or never) attained the 90 percent threshold. Estimates include controls for school foot traffic of 50 to 89.9 percent relative to the January/February 2020 period and restaurant/bar foot traffic of at least 50 percent relative to the January/February 2020 period.

Table A1: Sample Means

	Women			Men	Married Women with School-Aged Kids					
	Married Kids 6-17	Unmarried Kids 6-17	No Kids	Kids 6-17	College Degree	No Degree	Kids 6-11	Kids 12-17	White	Non-White
Employed, Education Sector	0.09	0.05	0.06	0.03	0.13	0.04	0.09	0.10	0.12	0.06
Employed, Other Sector	0.55	0.64	0.65	0.84	0.69	0.52	0.54	0.56	0.57	0.52
Hours Last Week, Education Sector	37.15	38.16	39.60	41.47	39.89	33.23	36.49	37.55	37.18	37.06
Hours Last Week, Other Sector	36.70	37.33	38.85	42.87	40.64	36.10	36.22	37.08	36.41	37.17
Worked Remotely, Education Sector	0.32	0.31	0.36	0.32	0.39	0.20	0.33	0.29	0.31	0.36
Worked Remotely, Other Sector	0.27	0.18	0.28	0.21	0.47	0.14	0.29	0.25	0.28	0.26
K12 Relative to Winter 2020	51.94	53.02	51.34	52.19	49.93	52.89	51.89	52.15	53.61	49.50
Restaurants Relative to Winter 2020	77.88	78.34	76.39	78.09	74.45	79.23	77.72	78.17	80.24	74.45
White	0.59	0.42	0.59	0.57	0.65	0.51	0.59	0.60	1.00	0.00
Black	0.08	0.27	0.15	0.10	0.10	0.08	0.08	0.08	0.00	0.19
Other Race	0.11	0.05	0.10	0.09	0.17	0.08	0.12	0.11	0.00	0.28
Hispanic	0.22	0.26	0.17	0.24	0.09	0.32	0.21	0.22	0.00	0.53
Less the High School	0.08	0.12	0.06	0.11	0.00	0.16	0.07	0.09	0.03	0.16
High School Grad	0.20	0.30	0.23	0.27	0.00	0.38	0.18	0.20	0.16	0.25
Some College	0.24	0.34	0.26	0.24	0.00	0.46	0.23	0.25	0.26	0.21
Bachelor's Degree	0.29	0.15	0.30	0.23	0.21	0.00	0.30	0.28	0.33	0.22
Advanced Degree	0.20	0.08	0.16	0.15	0.79	0.00	0.21	0.18	0.22	0.16
Married	1.00	0.00	0.41	0.84	0.74	1.00	1.00	1.00	1.00	1.00
Age	40.90	38.32	39.41	41.81	40.40	39.64	38.76	43.14	41.21	40.45
Observations	150016	63605	258233	163027	199515	77446	87986	86495	99227	50789

Notes: The CPS sample includes all individuals between the ages of 25 and 54. Observations are weighted using CPS individual sample weights. Hours and rates of remote work are estimated conditional on employment. K-12 and restaurant foot traffic are shown relative to a baseline value of 100 and can be interpreted as (proxies for) "percent reopen relative to pre-pandemic levels".

Table A2: Triple-Differences (Fully Interacted) Model: Married Women with School-Aged Kids vs. Women with No Kids

	Employment		Hours Last Week		Remote Work	
	K12 Sector	Other Sectors	K12 Sector	Other Sectors	K12 Sector	Other Sectors
K12 Foot Traffic	0.000	0.008	3.789***	-0.059	-0.213***	0.002
	(0.005)	(0.010)	(0.872)	(0.236)	(0.036)	(0.012)
K12 Traffic x Schoolkids	0.017**	0.025*	-3.739***	0.820*	0.022	-0.034*
	(0.008)	(0.015)	(1.236)	(0.439)	(0.050)	(0.019)

Notes: The treatment variable is K-12 weekday foot traffic relative to an area's average K-12 weekday foot traffic in Jan/Feb 2020. All coefficients are scaled up by 58.6—the difference between the 5th and 95th percentile of area reopening shares. All regressions include area fixed effects and census division-specific year-month fixed effects. Individual control variables include age, race (fractions Black Non-Hispanic, other Non-Hispanic, and Hispanic), education (less than high school, high school graduate, some college, bachelor's degree, advanced degree), and marital status. COVID-19 controls include an indicator for positive cumulative deaths per capita and a continuous measure of cumulative deaths per capita. Observations are weighted using CPS individual sample weights. Robust standard errors, which allow for clustering at the area level, are shown in parentheses. Significance at 1%, 5%, and 10% levels are indicated by ***, **, and *, respectively.

Table A3: Regressions with the COVID-19 School Data Hub Measure, Married Women with School-Aged Children

	SafeGraph	Employment		Hours Last Week		Remote Work	
	K-12 Foot Traffic	K12	Other	K12	Other	K12	Other
	(Baseline=100)	Sector	Sectors	Sector	Sectors	Sector	Sectors
COVID-19 Hub Measure	0.106**	0.000	-0.000	0.002	-0.008	-0.001	0.000
	(0.017)	(0.000)	(0.000)	(0.016)	(0.008)	(0.001)	(0.000)

Notes: The data source is https://www.covidschooldatahub.com (see notes on Figure A1). All regressions include area fixed effects and census division-specific year-month fixed effects. Individual control variables include age, race (fractions Black Non-Hispanic, other Non-Hispanic, and Hispanic), education (less than high school, high school graduate, some college, bachelor's degree, advanced degree), and marital status. COVID-19 controls include an indicator for positive cumulative deaths per capita and a continuous measure of cumulative deaths per capita. Observations are weighted using CPS individual sample weights. Robust standard errors, which allow for clustering at the area level, are shown in parentheses. Significance at 1% and 5% levels are indicated by **, and *, respectively.