# The Importance of Schools in Driving Children's Applications for Disability Benefits*

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We explore how schools affect children's applications to Supplemental Security Income (SSI). Because of the COVID-19 pandemic, schools varied in offering virtual or in-person learning during the 2020–21 school year. We use this variation to better understand the way schools, potentially through teacher referrals and informal networks, influence SSI applications. We find that applications were nearly 20 percent lower in counties with virtual learning relative to counties where all learning was in-person. Subgroup analysis suggests that school staff, likely through offering identification and referral services, and informal networks were mechanisms contributing to these differentials.

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## I. Introduction

Understanding the channels through which people learn about and ultimately access social benefit programs is important to maximize the programs' effectiveness. Many eligible people do not participate in social benefit programs (Currie 2006). Frequently cited reasons include factors such as administrative burden (e.g., Herd et al. 2013), stigma (e.g., Moffitt 1983), and limited knowledge (e.g., Chetty, Friedman, and Saez 2013). Knowing more about how recipients learn about benefits can lead to more effectively designing programs to directly address the barriers to participation that people face.

We explore the role that schools play in leading children to participate in the Supplemental Security Income (SSI) program. SSI offers monthly cash payments and, in most instances, Medicaid coverage to 1.0 million children. Schools may be an especially important channel through which families learn about SSI, leading them to ultimately apply for benefits. First, staff such as special education teachers may play an important role in identifying a disability that might lead students to qualify for benefits. Second, both formal and informal networking that occur within schools could lead to the spread of knowledge about the program. Critically, teacher reports play an integral role in the process that determines whether a child's disability makes him or her eligible.

The experience following the COVID-19 pandemic creates a natural experiment to assess the relationship between SSI and schools. At the beginning of the pandemic, all states in the United States had to close public schools and transition to virtual schooling. However, counties and states varied in the extent to which they returned to in-person learning in the school year following the start of the pandemic (2020–21 school year).

We use variation in school learning mode policies during the 2020-21 school year to examine the relationship between SSI and school closures.[1] Our primary approach classifies counties by the share of students subjected to school closures in September 2020, the beginning of the school year. We then use this variation in an event study specification with two-way fixed effects to estimate how applications evolved over the subsequent months in counties with more school closures. An array of checks—such as no significant pre-trends and several placebo tests—indicate that despite the nonrandom nature of school closures, our estimates are likely the causal effects. We also control for several time varying factors that might be correlated with both school closure decisions and child SSI applications. These include COVID-19 prevalence and deaths, and local economic activity as measured by foot traffic to bars and restaurants. Controlling for economic activity particularly captures the way the pandemic generally disrupted day-to-day life at the local level, allowing us to further separate the specific role that schools play.

We find that counties with more virtual schooling (that is, a higher percentage of students subject to closures) experienced immediate declines in child SSI applications following the school closure. Our event study findings indicate that applications were nearly 20 percent lower during the first several months of the 2020–21 school year in counties where all students were subject to school closures, compared to counties where no students were subject to school closures. These findings are entirely driven by children in households where no prior sibling had received an SSI award – families with children already on SSI may be more attuned to disability status and thus not need a referral from school staff, as well as are more generally aware of the

[1] School policies during this time were varied, including various types of hybrid models (for example, students coming in-person only in the morning or in the afternoon, or being open on different days for different groups of students). We abstract away from this by focusing only on school closures, which are defined in more detail below.

program. These differential patterns help reduce the likelihood that other confounders may be driving our main findings given such a confounder would presumably affect both types of households equally. Further supporting the results, we also found no corresponding decline in applications at birth or for application at ages 18 to 24. Both newborn children and young adults represent groups not likely to be enrolled in school and presumably would not be affected by school closings, thus representing a placebo test to our central hypothesis about school closing effects on SSI applications.

To further explore the mechanisms driving these patterns, we conduct subgroup analyses that characterize the county by factors such as presence of school psychologists. Our results suggest that school staff, and the identification and referral services they may offer, play an important role. The declines in child SSI applications were significantly larger in counties with relatively more school psychologists, where the switch to remote schooling led to a definitionally larger change in services available to students. In counties with relatively fewer school psychologists, school closures were not significantly associated with child SSI applications. Additionally, declines in child SSI applications from school closures were also significantly larger in counties that had low initial SSI participation before the pandemic. Counties with high SSI participation may have relatively more informal networks through which people learn about SSI, some of which may not have been disrupted during the pandemic. In low SSI participation counties, the school may be one of the only such networks, such that when schools close applications decline more.

School closures may have made it harder for parents to navigate the application process by leaving parents with additional childcare duties, potentially confounding our estimates on the role of schools. The parent or caregiver may have thus had less time to complete the application process, which would indicate something other than the school played a role in the application patterns. To assess this channel, we examine differential impacts on subgroups of those from two parent households and from households with earnings.[2] Households with two parents and without earnings may have more time available to go through the application process, and thus be less affected by school closures. However, the effect of school closures did not meaningfully differ for these groups.

The findings provide new evidence on the relationship between school processes and SSI participation and contribute to the broader literature on factors that influence SSI program participation. Deshpande and Li (2019) find that the closure of local SSA field offices (several years before the pandemic) led to a significant decline in disability benefit applications, suggesting that increasing the "cost" of applying for benefits dissuades some people from applying.[3] Several papers have explored the role of health insurance in influencing SSI participation, indicating that some apply for and participate in SSI primarily because it offers health insurance coverage (e.g., Burns and Dague 2017; Anand et al. 2018; Levere et al. 2019; Schmidt, Shore-Sheppard, and Watson 2020; Levere, Hock, and Early 2021). A recent paper finds that more generous housing vouchers lead to fewer SSI applications, indicating that housing programs and SSI are likely substitutes (Hembre and Urban 2023). By highlighting the role of schools, our paper provides evidence on another important channel that influences participation in SSI.

[2] The split is technically based on whether the household has countable income. Countable income for the purposes of SSI indicates whether a child's parent(s) have earnings above $85 in the month they applied. The $85 represents the amount of automatic exclusions for income that is disregarded in determining a child's benefit amount (if eligible).

[3] All Social Security Administration field offices temporarily closed at the beginning of the pandemic on March 17, 2020, and then offered substantial limited in-person services throughout the pandemic. No geographic variation in field office closures exist because all field offices closed at the same time, though our estimates control for distance to the nearest field office interacted with time.

More broadly, child SSI applications have been declining since 2010. Several other papers explore aspects of this decline. For example, Hemmeter, Levere, and Wittenburg (2024) estimate how much patterns in the frequency of continuing disability reviews contribute to changes over time in the child SSI caseload. Levere and Wittenburg (2024) use Medicaid data to estimate the number of children potentially eligible but not receiving SSI and summarize the health characteristics of those children. Our work complements those other papers, seeking to understand the narrower question of the role that schools play in children and families learning about SSI.

Additionally, our results contribute to a growing literature that demonstrates the consequences of remote learning during the COVID-19 pandemic. Several papers show that remote learning hindered children's learning both in the United States and abroad (e.g., Contini et al. 2021; Engzell, Frey, and Verhagen 2021; Jack et al. 2023; Kuhfeld, Soland, and Lewis 2022; Maldonado and De Witte 2022, Singh, Romero, and Muralidharan 2022). There is additional evidence that school learning mode choices had unintended consequences on an array of other outcomes. For example, many children left public schools, resulting in increases in both homeschooling and private school attendance (Musaddiq et al. 2022). Increased homeschooling might be particularly important for the context of our findings because it would lead to smaller networks for families and fewer opportunities for experienced teachers to refer students and families to SSI. Homeschooling could also lead to more specialized networks in cases where children with disabilities switch to homeschooling because desired services are not available in local schools. However, this option is not feasible for many low-income families: families that homeschool their children tend to be middle class.[4] Virtual learning was also associated with

[4] See https://nces.ed.gov/programs/digest/d17/tables/dt17_206.10.asp.

increased risks to children's mental health (Verlenden et al. 2021), which could affect the extent to which children are classified as having a disability, and thus could affect applications. Despite increased mental health risks, teen suicides declined with more virtual schooling (Hansen, Sabia, and Schaller 2023), and rates of ADHD diagnosis also fell (Freedman et al. 2023). Particularly related to the present analysis, Theobald, Goldhaber, and Katz (2024) show large declines in special education identification rates that continued through the 2020-21 school year. Finally, several papers show that remote learning led to reduced labor market activity for parents (Garcia and Cowan 2022; Hansen, Sabia, and Schaller 2022).

## II. Institutional Context

### *A. SSI*

Child SSI offers cash benefits and, in most cases, health insurance coverage to children with disabilities from low-income families. Families that qualify can receive a maximum monthly payment of $841 in 2022. Benefits are reduced by $1 for every $2 in earnings above a modest disregard amount. Benefits are also reduced by $1 for every $1 of unearned income deemed available to them from their parents (typically a fraction of parents' income). Most child SSI recipients are automatically enrolled in or eligible for Medicaid, though in some states a separate application must be filed for Medicaid coverage and SSI recipients will typically be accepted; in other states, eligibility criteria differ slightly. As of December 2019 (shortly before the COVID-19 pandemic), about 1.1 million children received SSI benefits.

To qualify for SSI, the potential recipient must apply for benefits and meet both asset and income criteria and a disability criterion. To apply for child SSI, a family must complete the necessary paperwork and provide details related to the health history of the child and the family's income and resources. The disability criterion requires a child to have a "marked and severe functional limitation." Additionally, based on parental deeming (or their own, if applicable), if a child has assets exceeding $2,000 or sufficiently high income that their SSI payment would be offset to $0, the child is not eligible. A state's Disability Determination Service (DDS) evaluates the medical aspect of the child's case.[5] The DDS relies on reports from doctors, therapists, and, importantly for our study, teachers.

Despite no statutory changes in eligibility requirements since 1997, child SSI applications have been declining since 2010, with an especially large drop in 2020, the first year of the COVID-19 pandemic (Figure 1). On average, applications declined by 4 percent annually between 2010 and 2019. This decline might partially be related to the improving economy after the Great Recession that might lead fewer people to meet asset and resource limits (Nichols, Schmidt, and Sevak 2017). However, these declines may also reflect the fact that some eligible children (or their caregivers) choose not to participate in the program or are not aware of the program. Prior research has found many locations where few children participate in SSI despite risk factors indicating higher expected levels of participation (Levere, Wittenburg, and Hemmeter 2022). The Social Security Administration (SSA) recently established vulnerable population liaisons to help reach families in areas with low child SSI participation. Despite these prior declines and a worsening economy in 2020, applications declined even further—by 17 percent—during 2020. Much of this decline was concentrated in the months immediately following the start of the COVID-19 pandemic in March 2020; between April and September 2020, total child SSI applications declined by roughly 30 percent relative to total applications between April and September 2019.

[5] A child found not eligible by the DDS may appeal for a reconsideration of the evidence within the DDS. If there is still a denial, the child may appeal to administrative law judges, an appeals council, and ultimately the federal courts.

The declines in child SSI applications during the 2020–21 school year, relative to the 2018–19 school year, varied substantially (Figure 2).[6] For each county, we compute the total number of applications during the two school years and then calculate the percentage difference. Most of the country experienced declines. Five percent of students lived in counties where the decline was at least 50 percent, whereas 16 percent of students lived in counties where applications increased.[7] In a separate paper (Levere, Hemmeter, and Wittenburg 2023), we highlight several area-level socioeconomic and demographic factors, such as field office closures and urbanicity, which are associated with the geographic variation in the decline in applications during the first few months of the pandemic (April to September 2020). In this paper, our primary focus is on total SSI applications from school-age children in a county during each month of the 2020–21 school year, focusing specifically on the extent to which school closures contribute to application patterns.

In contrast to SSI declines, other programs, such as the Supplemental Nutrition Assistance Program (SNAP), saw increases in participation during the pandemic, especially during the brief recession of 2020 (Figure 3). In Figure 3, participation in both SNAP and child SSI is benchmarked relative to participation in February 2020. In June 2020, SNAP participation was 18 percent higher than in February 2020.[8] In contrast, child SSI participation was the same. Part of these differences could relate to the application processes: applying for SSI requires medical information from an applicant that can take much longer to gather and process, whereas

[6] The 2018–19 school year was the last full school year before the pandemic. The pandemic had an immediate large effect on applications, making a comparison to the 2019–20 school year difficult to interpret.

[7] One percent lived in counties with no applications during the 2018–19 school year, so a percent change can thus not be calculated.

[8] Other programs such as Temporary Assistance to Needy Families (TANF) and Women, Infants and Children (WIC) also saw increases in participation at the outset of the pandemic.

SNAP relies on more limited information only related to income to make an eligibility determination. This leads the SSI application process to take substantially longer than the SNAP application process. Applications for SNAP can also be completed online, whereas SSI applications cannot. Additionally, the introduction of large macroeconomic stimulus programs may have led some families to avoid applying for SSI because they either exceeded SSI asset limits or did not have an immediate income need. Specifically, the supplemental unemployment insurance benefits available through the Coronavirus Aid, Relief, and Economic Security (CARES) Act and the economic impact payments were particularly effective in preventing declines in total income at the bottom of the income distribution (Larrimore, Mortenson, and Splinter 2022).[9]

*B. Connection between schools and SSI*

There is an important interaction between SSA and schools when a child applies for SSI. In reviewing a child's application, the state DDS can ask for school records such as academic performance, school-based therapies, and testing. The DDS can also request information about what a child can and cannot perform from teachers in a Teacher Questionnaire form. SSA maintains a guide for school professionals to help streamline the process of what teachers need to provide to facilitate the evaluation process. SSA staff have noted an influx of new applications at the start of a school year as teachers and school administrators refer new students (Tambornino, O'Day, and Burak 2015).

Additionally, though schools are not required to proactively identify SSI eligible children, school staff nonetheless may identify and refer students and families to SSI. For

[9] However, the supplemental unemployment benefits and economic impact payments did not count as income or resources for the purposes of SSI eligibility. Nonetheless, because of the fungibility of money, greater total resources available may have led some to at least expect they might not qualify.

children under 18, the primary source of supports for students with disabilities apart from families is through schools, whereas upon reaching adulthood programs become more fragmented (Honeycutt and Livermore 2018). Special education plays a particularly important role, with roughly 13 percent of school age children receiving special education services (Elder et al. 2021). As part of the Individuals with Disabilities Education Act, schools must identify and evaluate all children suspected to have a disability. Thus, through this identification process, teachers may become more attuned to students' disabilities.

Staff involved with children with disabilities, such as special education teachers and school psychologists, may also be likely to make a referral given their role in the SSI application process. As discussed earlier, when SSA evaluates an applicant's disability, it relies on reports from those in school who interact with the child to assess whether he or she has a "marked and severe functional limitation". Through this involvement in the application process, staff may be aware of the program and well equipped to know which students might be likely to qualify based on their disability. There is meaningful overlap between SSI and special education: about 22 percent of children in special education also receive SSI benefits (Lipscomb et al. 2017). Because of the means test associated with SSI, the number whose disabilities would make them eligible is presumably significantly higher. Additionally, it is in the school district's financial interest to identify SSI participants. In most states, SSI receipt is accompanied by Medicaid, which schools can bill for specific services related to special education.

Schools may also be an important network through which students and families learn about the program. Networks are known to be important for participation in government programs—for example, Chetty, Friedman, and Saez (2013) find that people who move to neighborhoods where many families self-report income near the Earned Income Tax Credit

(EITC) kink points become more likely to do the same and thus take maximum advantage of the EITC. Qualitative evidence on SSI specifically indicates that informal networks are critical for many people to learn about and ultimately apply for benefits (Tambornino, O'Day, and Burak 2015). Schools offer a potentially important network for children and families, with opportunities to develop connections formally and informally. These can include friendships made through the classroom and extracurricular activities as well as meeting people through events at the school.

### *C. The COVID-19 pandemic and schooling*

The COVID-19 pandemic completely upended public education in the United States with significant implications for students. By May 2020, public schools were closed in all states except Wyoming and Montana. Fear of spreading the virus, coupled with limited scientific understanding of how the virus spread, contributed to school closures. As discussed earlier, extensive evidence indicates that children suffered substantial losses in educational achievement (e.g., Contini et al. 2021; Engzell, Frey, and Verhagen 2021; Jack et al. 2023; Kuhfeld, Soland, and Lewis 2022; Maldonado and De Witte 2022).

For the 2020–21 school year, local education agencies made varying decisions as to whether to continue with virtual schooling or to resume in-person instruction (Figure 4). The figure shows the percentage of students in each county facing a school closure in September 2020 (as measured in SafeGraph data, discussed further below).[10] This decision was highly localized, with substantial variation in school learning mode choices even within counties (Kurmann and Lalé 2023). School closures may have exacerbated existing inequities, as students in schools with lower academic achievement and more minority students experienced more

[10] Appendix Figure 1 presents this information in a slightly different way, showing the distribution of students by school closure intensity. The buckets correspond to those with no students facing school closures (about 7 percent of students), those with more than 0 but less than 5 percent facing school closures, 5 to 10 percent, and so on.

school closures during the 2020–21 academic year (Parolin and Lee 2021). Like many other aspects of the pandemic, this decision was often politicized, with remote learning more common in areas with a higher Democratic vote share in the 2020 election (Jack et al. 2023); as is evident in Figure 4, remote learning was particularly prevalent in the Northeast and on the West Coast, whereas relatively few students faced school closures in the Midwest and the South.

Virtual schooling likely disrupted the key proposed drivers through which many students and families may learn about SSI. First, teachers may have found it more difficult to identify a student's disability remotely, particularly as the most common diagnoses for child SSI recipients are mental disorders such as autism spectrum disorder, developmental disabilities, and other mental disorders (these three categories account for 60 percent of current child SSI recipients' primary diagnoses). A reduction in teachers identifying disabilities would be consistent with evidence that teachers and other education providers also became less likely to report child abuse during the pandemic despite increases in parental neglect (Bullinger et al. 2023). It is also consistent with lower special education identification rates (Theobald, Goldhaber, and Katz 2024). Because the pandemic had such severe consequences on all aspects of life, even if a teacher were able to identify a student who was struggling or less engaged, it might have been challenging to determine that this was specifically because of a disability. Second, networking opportunities and connections to other families likely broke down, with fewer opportunities for interactions with events like afterschool activities cancelled. These problems might have been particularly exacerbated for the youngest school children, such as those in elementary school. Young children may have found it especially difficult to learn remotely given the need to remain concentrated in front of a screen for hours on end.

Taken together, school learning mode choices, and particularly the decision to use remote learning, might influence the way that students and families learn about and ultimately apply for SSI. In turn, local variation in learning mode therefore presents an opportunity to learn more about the role that schools play in children's participation in SSI.

## III. Data

Our primary data capture counts of child SSI applications at the county-month level. These data come from the Supplemental Security Record, which is SSA's primary system for tracking SSI applications, awards, and participation. These underlying data are at the individual level, and include key information like date of birth and parent Social Security number. This in turn allows us to identify other data associated with the child's application, such as whether the parent had any earnings or whether anyone else in the family receives SSI benefits. In turn, we aggregated these data by summing up applications within a county. We also measure awards, which we date by the date of initial application to link to the individual family's decision to apply.

We consider application and award counts for various age groups to track whether school closures have a differential impact by age; our primary specification uses school age children ages 5 to 17, but we also separately report outcomes for elementary school children (ages 5 to 10), middle school children (ages 11 to 13), and high school children (ages 14 to 17). One rationale for stratifying by age is that school connections to SSI might vary as students age. For example, mental impairments, which are the primary impairment for the majority of child SSI recipients, are likely to present at different ages (National Academies of Sciences, Engineering, and Medicine 2016). Additionally, the role of teachers might differ by age – children in elementary school typically only have a single teacher who see them for the full day and thus may get to know the student especially well, whereas older students may have multiple teachers. We also collect data on people who applied at age 0 (primarily low-birthweight applications),[11] as well as people who applied at ages 18 to 24. These groups represent placebo tests because both should likely be unaffected by decisions related to schooling. Appendix Figure 2 shows the count of child applications by age in the years 2019, 2020, and 2021. Across all years, the most common age to apply is age 0, representing about 13 percent of total child applications in all years. After about age 7, applications decline monotonically as children age.

We consider two alternative measures of remote learning that each capture a slightly different conceptual measure of student engagement (and hence, the interaction with SSI), though results are robust across both measures. Our primary measure comes from SafeGraph data compiled by Parolin and Lee (2021) that track foot traffic at schools based on cell phone presence.[12] The data indicate the percentage decline in visits to a school in each month relative to that same calendar month in 2019. A school is considered closed in a month if the decline in visits was larger than 50 percent.[13] These data are then aggregated to the county level, weighted by the number of students in each school. The closure variable captures the percentage of students in a county subject to a school closure in that month. We also collect data directly on

[11] Children with birthweight under 1200 grams or who have sufficiently low birthweight based on their gestational age can qualify for benefits if they are in a medical institution, such as neonatal intensive care unit. This is relevant only when the child is still age zero. Such children then have eligibility redetermined at 12 months old.

[12] The data come from an aggregated, anonymized sample of roughly 10 percent of mobile devices in the United States. The weighted sample of mobile devices has a high correlation with local population counts by state and county from the U.S. Census, as well as by race/ethnicity, education, and income (Parolin and Lee 2021). Though there are drawbacks associated with these data—particularly that people with low incomes are disproportionately less likely to have a cell phone (Vogels 2021)—these data are widely used in the economics literature because they are a powerful way to measure broader movement patterns, particularly during the pandemic and accompanying lockdowns (e.g., Allcott et al. 2020; Goolsbee and Syverson 2021; Freedman et al. 2023; Hansen, Sabia, Schaller 2023).

[13] To assess sensitivity to this 50 percent threshold, the data also consider closure thresholds of a 25 percent decline and a 75 percent decline. Our results are not sensitive to the choice of threshold to define closures. Alternative results using these other thresholds are available on request.

learning mode policies through the COVID-19 School Data Hub (Jack et al. 2023). These data indicate whether the public school offered virtual, hybrid, or in-person learning. We then aggregate to the county level, weighting by number of students in each school. Our primary measure of interest is the percentage of students in a county who were in virtual learning in a month. This measure is closely related to the measure of school closures from the SafeGraph data. Among counties that have both types of data, the correlation is fairly high at 0.64. Further, as discussed below, our results are not sensitive to the choice of metric.

Additionally, we collect data from several other sources to supplement these analyses, including those that serve as control variables in a regression and that characterize counties in subgroup analyses. COVID-19 data on new cases and deaths come from Johns Hopkins, which maintains a county-level database on COVID-19 outcomes. We also collect SafeGraph data on foot traffic to bars and restaurants during each month to control for the extent of economic disruptions in a county during the pandemic. Special education participation at the county level, along with the number of students attending public schools in each county, comes from Civil Rights Data Collection available through the Department of Education. School staff by district, which we aggregate to the county level, is available from the Common Core of Data (which the Department of Education also maintains). Finally, we use data from the Department of Labor on UI replacement rates and recipiency rates to classify states by the expected generosity of benefits.

## IV. Empirical strategy

We estimate the effect of school closures during the COVID-19 pandemic on child SSI applications using an event study model that characterizes counties by the percentage of students subjected to school closures in September 2020, the onset of the 2020–21 school year. A common estimation strategy would be to use a two-way fixed effects model, controlling for county and month fixed effects, and identifying changes based on within-county or within-month differences in virtual schooling. However, this approach to use time varying school closures does not work for several reasons. First, because applications may occur with a lag based on a school closure, it is not clear which month is the correct month of applications to consider. Second, recent literature on two-way fixed effects, such as Callaway and Sant'Anna (2021), highlight substantial econometric issues when the direction of treatment is non-monotonic. Here, periods of school closure can be followed by in-person instruction followed by subsequent school closures. These issues make it difficult to use a standard two-way fixed effects model. Thus, our primary specification includes county and month fixed effects to control for county time-invariant factors and general monthly patterns in application behavior. However, it only considers school closures as of a fixed point in time (September 2020). It therefore does not address the intensity of school closures (i.e., closure duration) or other time-based variation in school closures, though we estimate a robustness check accounting for closure intensity at the annual level. Crucially, this also means that the timing of the treatment is not staggered as the treatment we analyze occurs in every county at the same fixed point in calendar time in September 2020.

Equation (1) shows our primary estimating equation. The outcome, $SSI_{ct}$, measures the SSI application rate in county *c* in month *t*. Our main outcome measure considers applications among children ages 5 to 17, though we also consider alternative age group specifications. The application rate scales the number of applications by the population in that age range as of 2020, as measured by the Census. We control for both county and month fixed effects ($\gamma_c$ and $\theta_t$, respectively). $Onset\ Virtual_c$ characterizes the extent of the school closures in county *c* as of

September 2020, the onset of the 2020–21 school year (shown in Figure 4). Months *m* are measured relative to September 2020. All coefficients are estimated relative to the omitted month -2 (July 2020) because some schools started in August 2020. We cluster standard errors at the county level. We also weight the regression by child population in the county.

(1)

$$SSI_{ct} = \alpha + \gamma_c + \theta_t + \sum_{m=-44}^{9} \beta_m * Onset\ Virtual_c * 1(Month = m)_t + X_{ct} + \varepsilon_{ct}$$

The coefficients of interest are the $\beta_m$, which measure the relative difference in applications in a given month for a county with all students in virtual learning in September 2020 relative to a county that had no students in virtual learning at that time. The periods $m < 0$ test for differential pre-trends. If the primary factor driving a change in applications is the school closure, then there should be no differential application patterns in the months before the school closure took effect. The periods from $m = 0$ to $m = 9$ indicate the change in SSI applications in response to the school closure, where the month-by-month time dynamic allows us to estimate how long applications decline.

As part of the $X_{ct}$ variables, we also control for time varying measures related to the COVID-19 pandemic that might be correlated with both SSI applications and school closures. First, we control for the extent of the disruption to the local economy using a measure of visits to restaurants and bars in each county. Using SafeGraph data, we calculate monthly foot traffic to all bars and restaurants in a county. We then calculate the percentage change for a given calendar month relative to the same month in 2019, the year before the pandemic. This approach parallels the construction of our school closures measure, though it differs in that we use the raw percentage change rather than define a threshold for being “closed”. We also control for COVID-

19 cases and deaths, scaled by local population, as well as the county-level unemployment rate. Finally, we control for proximity to field office interacted with time. SSA offered limited in-person services at field offices in March 2020; in a separate paper, we show that applications at the start of the pandemic declined most in counties that had a field office, where the change In availability of services was greatest (Levere, Hemmeter, and Wittenburg 2023). We control for whether limited in-person services had differential effects over time by interacting proximity to nearest field office with month dummies.[14] A concern is that including time-varying controls in two-way fixed effects settings has strong identification requirements (Caetano and Callaway 2023). We show below that our results are mostly similar regardless of the controls included.

An overarching confounding factor that may influence applications was the way that school closures put greater demands on parents' time, leaving them with less time to complete the application process. Evidence suggests that the application process can entail costs that deter people from applying (Herd 2015; Deshpande and Li 2019); one such cost may be the amount of time it takes to complete the application. School closures may therefore have also influenced applications because of changes in time availability, rather than changes in anything specific that was occurring in schools. Our analysis of mechanisms teases out these different effects by dividing the number of applications in a county into those where there were two parents (who may have more time available) versus not two parents, or into those where parents had no income from work (who may have more time available) versus those who had income from work.

[14] All counties with a field office have a distance of 0, while in counties without a field office we measure the distance from the county centroid to the precise location of the nearest field office.

Another potential confounder is that if school closures are correlated with measures related to the economic and health disruptions associated with the pandemic, which can also be correlated with child SSI applications, then our analysis might capture the effects of pandemic severity rather than the school closures themselves. In supplemental findings, we explore the connection between school closures and our time varying control variables: foot traffic at bars and restaurants, cases, and deaths (see Appendix Table 1 and Appendix Figure 3).

Two key takeaways emerge that lend further credibility to our estimation strategy. First, even though school closures are significantly correlated with the measures of economic and health disruptions, substantial variation in school closures remains after controlling for these measures.[15] Second, political factors likely played an important role in the decision process around whether schools should offer in-person or virtual learning: cases and deaths followed presidential votes during this period (the Delta and then Omicron waves; Leonhardt 2022), and remote learning did not seem to meaningfully stop the spread of the virus (e.g., Bravata et al. 2021).[16] The inclusion of county fixed effects controls for these fixed political factors that do not vary within county. Additionally, by controlling for cases and deaths directly, our estimates should not be influenced by these time varying factors.

We also estimate difference-in-differences specifications that compare average monthly child SSI applications over the 2020–21 school year relative to a pre-period. Doing so modifies equation (1) by interacting the measure of school closures in September 2020 with an indicator

[15] In Appendix Table 1, we present results from a regression of the percentage of students in a county experiencing school closures in each month between September 2020 and June 2021 on the monthly change in foot traffic at bars and restaurants, cases, and deaths, controlling for both county and month fixed effects (the regression is weighted by county child population). In specifications with or without lags, the overall $R^2$ is approximately 0.19.

[16] Appendix Figure 3 shows event study estimates using equation (1), albeit using cases as an outcome. There are two primary takeaways from the figure. First, there are no significant pre-trends in cases in the months before September 2020, the month in which school closures are measured. Second, counties with more school closures had fewer cases in subsequent months.

for the month falling in a post-period relative to the pre-period (January 2017 to August 2020). In contrast, in our primary event study specification, we compare applications in each month to applications in July 2020, the omitted month. We define the post period in two ways, considering either the entire 2020-21 school year (September 2020 to June 2021), or dividing this into two semesters of five months each (the fall 2020 semester from September 2020 to January 2021 and the spring 2021 semester from February 2021 to June 2021). By offering a more succinct single estimated effect, these difference-in-differences specifications are particularly helpful in comparing differential impacts for different groups of SSI applicants (such as those ages 5 to 10 or age 0) or for subgroups by county characteristics (such as high versus low SSI participation).

To assess the mechanisms driving our main findings, we also conduct analyses by subgroup based on school characteristics and child SSI participation rates in 2019. We primarily consider two different subgroups based on whether the county is above or below the median in terms of (1) number of school psychologists per student and (2) SSI participation.[17] The specification for these subgroup impact estimates is given in equation (2). The coefficient $\beta_1$ gives the impact in the average month in the post-period in below median counties (where $County\_SG_c$ equals 0). We also report the coefficient $\beta_1 + \beta_2$, which gives the impact in the average month in the post-period in above median counties. Finally, we report the p-value on $\beta_2$, a test for whether the impacts are significantly different between above and below median counties.

(2)

[17] Appendix Figures 4 and 5 show maps indicating the county variation in each of these two measures, respectively. The correlation between the two measures is fairly low: when using the continuous input measure (e.g., the rate of child SSI participation), the correlation is approximately -0.05; the correlation between the subgroup indicators (above or below the median) is -0.11. We also consider special education participation as a subgroup in some specifications.

$$SSI_{ct} = \alpha + \gamma_c + \theta_t + \beta_1 * Onset\,Virtual_c * Post_t + \beta_2 * Onset\,Virtual_c * Post_t * County\_SG_c + X_{ct} + \varepsilon_{ct}$$

## V. Results

We show descriptive evidence in Table 1 that the decline in child SSI applications throughout the pandemic period and the 2020–21 school year was consistently the largest for elementary school (ages 5 to 10) and middle school aged children (ages 11 to 13). The table shows declines for cumulative applications across the given calendar months relative to applications during those same calendar months in 2019. For children ages 5 to 10, applications declined by about 36 percent in April to August 2020 (the pandemic period), 21 percent in September to December 2020 (the first half of the 2020–21 school year), and 30 percent in January to June 2021 (the second half of the 2020–21 school year). Relative to the decline in applications for the group that was age 0, these declines are substantively larger: 84 percent larger in the pandemic period, 25 percent larger in the first half of the 2020–21 school year, and 38 percent larger in the second half of the 2020–21 school year.[18] Patterns are similar for children ages 11 to 13. Though these trends are descriptive, they nonetheless illuminate the potential for schools to play a role in SSI applications; the youngest school age children would likely be the ones to be influenced most by remote learning given presumed difficulties using technology for many consecutive hours. Teachers in turn may have a hard time disentangling whether issues for young children are related to a behavioral issue associated with a disability or more general issues related to learning through technology.

[18] Relative to high school age children, the declines are also very large: 46 percent, 39 percent, and 55 percent larger, respectively.

In Figure 5, we show that applications declined significantly in counties with more school closures during the first few months of the 2020–21 school year. From October 2020 to January 2021, the estimated average monthly treatment effect was a decline of 0.007 percentage points, with the estimate in each month being statistically significant at the 1 percent level. Because our primary variable of interest captures the share of students in the county subject to school closures,[19] the decline can be interpreted as the difference in applications in a given month for a county in which all students faced school closures as compared to a county in which no students faced school closures, relative to the gap between such counties in July 2020. To put this number in perspective, the average monthly application rate during 2019 was 0.037 percent of children. The decline of 0.007 percentage points in these months thus represents a 19 percent decline in applications. Applications were also significantly lower in every month from February to May 2021.[20]

The coefficients in the pre-period mostly indicate small and statistically insignificant differences in applications across counties based on school closures in September 2020. One notable exception is May 2020, which is the only pre-period month from 2017 onward that has significantly higher applications (out of 42 total months). Five pre-period months have significantly lower applications at the 5 percent level, with some apparent seasonality to these

[19] As a reminder, a school is considered to be closed if there is at least a 50 percent decline in cell phones visiting the location in SafeGraph data in that month relative to the same month before the pandemic. The county-level metric then aggregates across all schools in the county to express a percentage of students subject to school closures.

[20] We explored the potential to extend the figure to also include the 2021-22 school year. Though the data are available, interpreting the findings are tricky. Because of the decline in applications that occurred during the pandemic, SSA devoted substantial resources and made agency priority goals to attempt to get more applications. This included establishing a position of vulnerable population liaison and setting agency priority goals to increase application rates. But these goals specifically targeted underserved areas that had experienced large declines (one of the criteria to define an underserved area was a decline in applications of at least 30 percent between 2019 and 2021). Thus, if we extend the data farther out, any patterns are likely no longer only the result of school closures but also reflect additional agency efforts.

patterns. Yet from visually inspecting the graph, it is clear that something substantially differs in the months following the school closures in September 2020.[21] While this may suggest potential endogeneity in the selection into remote schooling, particularly given the geographic patterns highlighted in Figure 4, we present several analyses below that reduce the likelihood of that interpretation: two placebo tests using applications at different ages as well as subdividing applications into those living in households where another child had or had not been previously awarded SSI.

As a whole, applications were almost 10 percent lower in each month of the 2020–21 school year than they were in the pre-period (from January 2017 through August 2020; Table 2). The point estimate of 0.0032 percentage points represents a 9 percent decline relative to the average monthly rate of applications throughout 2019. This table presents the difference-in-differences specification, considering the post-period to be all months from September 2020 onwards. Table 2 also shows a higher rate of decline when focusing on the months immediately following the school closure – the point estimate of 0.0048 percentage points in the Fall 2020 semester (defined as September 2020 to January 2021) represents a 13 percent decline.

Because these estimates stem from a continuous difference-in-differences model, the assumptions required to identify a causal dose response are fairly stringent (Callaway, Goodman-Bacon, and Sant'Anna 2024). Specifically, if there are heterogeneous treatment effects, the strategy must assume that the counties with more school closures would have had the same treatment effect from relatively rarer closures as do the counties that actually had fewer school

[21] In Appendix Figure 6, we also plot the raw rates of application in counties that were above and below the median in school closures, normalizing application rates to be relative to the July 2020 value (the omitted month from our event study specification). The patterns indicate no notable differential trends and the same seasonal patterns in the pre-period in both above and below median counties. They also indicate larger declines in applications in the above median school closure counties immediately following the school closure, which is especially notable given (if anything) slightly higher rates of application in the pre-period among above median counties.

closures, which may not be reasonable. To address this, Appendix Figure 7 indicates that there may be homogeneous treatment effects. For each county, we calculated the change in application rates for the 2020-21 school year as compared to the 2018-19 school year. The figure shows the average change in application rate as compared to county school closures.[22] There is a mostly monotonic and linear relationship between the change in child SSI applications and closure intensity. We also estimated a simple linear regression among all counties of the change in application rates (for the 2020-21 school year relative to the 2018-19 school year) on the share of students facing school closures in September 2020. This estimate is significantly negative, with a p-value less than 0.001, indicating that counties with more school closures saw bigger declines in child SSI applications. Additionally, we divide counties into closure quintiles based on the percentage of students facing school closures in the county in September 2020. We then estimate heterogeneous treatment effects by school closure quintile. Though not perfectly monotonic and imprecisely estimated, the results are broadly consistent with larger declines in applications as more students face school closures (Appendix Table 2).[23]

In the remaining columns of Table 2, we show that the aggregate declines in applications from school age children are largest among elementary school students (ages 5 to 10). The average monthly decline for children ages 5 to 10 is 0.0047 percentage points, representing a 10

[22] To simplify the presentation, we averaged the change in application rates across all counties based on 21 bins: one for counties that are not treated at all (no students facing a school closure in September 2020), and twenty equally sized bins (i.e., 0 to 5 percent, 5 to 10 percent, and so on). Because such a small share of students lived in counties where more than 95 percent of students faced school closures (only about 0.13 percent, see Appendix Figure 1), we do not include this point in the graph.

[23] Jakiela (2021) also points out that difference-in-differences estimates can be biased when there is a combination of heterogeneous treatment effects with negative weights. Our econometric approach likely ensures no negative weights for two reasons. First, Jakiela (2021) shows that negative weights typically emerge with a short pre-period – our pre-period is about three and a half years, versus only a nine-month follow-up period. Second, negative weights can also emerge when earlier treated areas have particularly long post-periods – our approach does not have a staggered treatment, meaning we have a balanced panel where the length of the post-period is identical in all counties.

percent decline relative to the average monthly rate of applications throughout 2019. Children ages 11 to 13 and 14 to 17 also experience somewhat smaller declines of about 6 to 7 percent. Inspecting the coefficients from the event study estimates across all three age groups in Appendix Figure 8 also indicates the effects are strongest at ages 5 to 10, though there are significant declines across all age groups.[24]

Declines in applications from school closures are entirely driven by households where no other child in the household had previously had an SSI award (Table 3). In households where a prior sibling had received an SSI award, the estimated decline in applications from school closures during both the 2020-21 school year and during the fall 2020 semester is small and not significant. In contrast, school closures led a large decline in applications specifically among children where no prior sibling had an SSI award. Families where a sibling or parent is already receiving SSI are likely to both (1) be more attuned to disability status and thus not need a referral from school staff, and (2) be more aware of SSI generally and thus not rely on a network to learn about the program. But the fact that we find a differential pattern across these two groups also reduces the chance that confounders associated with selection into school closures explain the results – that is, it seems unlikely that such a confounder would only exist for certain groups of families but not for others. Results are similar when we consider whether any child had previously applied for SSI (rather than been awarded), as well as when we broaden the definition of who had previously engaged with SSI to include parents (not pictured).

[24] Though we do not present the results, there is also a significant decline in applications associated with school closures for those ages 1 to 4, a group that is not directly subject to school closures. One possible explanation for this finding was the potential for a correlation between child care facility closures during the same period of school closings. Garcia and Cowan (2022) report a correlation between school and childcare facility closures of 0.82. Hence, our estimates might be picking up these relationships.

Though applications declined with school closures, awards were mostly unchanged (Table 4). For example, the first column shows that in an average month the decline in award rates was 0.0001, which was not statistically significant. Relative to the baseline award rate, this represents a 1 percent decline, which is substantively smaller than the analogous 10 percent decline in application rates from Table 2. Though focusing on the fall 2020 semester leads to a significant decline in awards at the 10 percent level, the relative decline of 7 percent represents a relatively smaller change than the decline in applications. The change in award rates at each age is also relatively smaller than the corresponding decline in applications. Thus, the people who did not apply because of the school closures were on the margin less likely to be awarded, indicating that these missed applications were among relatively less needy populations.

These findings potentially speak to increased targeting efficiency associated with the declines in child SSI applications during the COVID-19 pandemic. Introducing complexities and hassles in public programs can in theory increase targeting by ensuring that only those who most need benefits go through the burdensome process, though the merits of such a policy can be debated. Deshpande and Li (2019) point out ways that the burdensome SSI application process historically reduced targeting efficiency: when field offices closed, awards declined by more than applications. Here, the complexities associated with the pandemic seem to have increased targeting efficiency as awards declined by less than applications, with the biggest increase among middle school age applicants (where the point estimate on the change in awards is zero).

*Robustness checks*

We consider five primary robustness checks, each discussed below in turn. First, we consider an alternative measure of school closures—capturing school policies directly from the COVID-19 School Data Hub rather than cell phone movement from SafeGraph data. Second, we explore whether there were similar declines among applicants at different ages where school learning mode decisions should not influence applications: age 0, primarily those who are low-birthweight, and ages 18 to 24, young adults. Third, we consider a specification that accounts for the intensity of school closures, aggregating both school closures and applications to the school-year level. Fourth, we conduct a placebo test using applications from previous years to rule out that applications have different seasonal patterns in the counties where schools closed in September 2020. Fifth, we show the sensitivity of our results to the inclusion of various control measures.

Our primary findings are not sensitive to the choice of school closure metric (Figure 6). The figure uses a metric from the COVID-19 School Data Hub, which captures school policies directly, rather than the measure we use in our main estimates, which is based on cell phone visits to a given location. The primary drawback of the COVID-19 School Data Hub is that it does not capture the entire country. Nonetheless, the primary findings are mostly similar, with significantly lower applications in October to December 2020 in counties that had more students in virtual learning in September 2020, and consistently negative point estimates throughout the 2020-21 school year. We also find few significant differences in applications in the months before the school closures took effect. The regression-based estimates are slightly smaller than those presented in Table 2, though still significant at the 10 percent level when considering the change in the fall 2020 semester (point estimate = -0.0021).

Figure 7 shows placebo tests indicating that applications at several ages for non-school age children were similar regardless of the extent of school closures in the county. Panel A shows the results at age 0, which are primarily applications from children with low birth weight. School closures should likely not affect such applications, as such children are not directly affected by school learning mode decisions because they do not yet attend school. Panel B shows the results at ages 18 to 24, which are applications from young adults (and where the income and resource limits are importantly only based on the one's own income and resources, not a parent's). School closures also should not affect the applications of these young adults who are no longer of school age. That the event study patterns in both panels of Figure 7 do not show a similar pattern to the primary findings in Figure 5 lends further evidence that the primary estimates reflect the causal effect of school closures. The regression-based estimates in Table 2 at these ages are also small and not statistically significant.

We consider another specification that accounts for the duration of the school closing, finding mostly similar results. Specifically, we aggregate both school closures and applications across the entire school year and estimate a similar difference-in-differences specification.[25] The pre-period similarly includes school years back to 2017-2018. The coefficient (-0.0032) is similar to the main findings, and is almost significant ($p$-value = 0.106).

Appendix Table 3 shows a different type of placebo test, confirming that applications did not have similar seasonal patterns in the counties with school closures in September 2020 in the years before the pandemic. For this placebo test, we still characterize counties by the percentage of students facing school closures in September 2020. The outcomes measure student-age applications in calendar years before the pandemic. The first column shows our main estimate, repeating the first column in Table 2, using data from January 2017 to June 2021. In the second column, we use data from January 2016 to June 2020. Subsequent columns are fully before the

[25] One challenge with this approach is it may not reliably capture the extent of remote learning for specific students. For example, if half of students were in remote learning in September 2020 and half in October 2020, we could cumulate to get a treatment intensity of 1. An alternative county where all students were in remote learning in September 2020 would have the same treatment intensity of 1. Yet the total disruption to students, and thus the expected implications for SSI applications, would be very different from these two scenarios. This cumulative measure inherently cannot distinguish between them.

pandemic. The results generally pass this placebo test. Only one of the coefficients for the fall 2020 semesters is significantly different from zero (for 2016-2020 data). This coefficient is an order of magnitude smaller than our main estimate, and the triple difference remains significant even after we difference this placebo estimate off of our main findings (Appendix Table 4). This offers reassurance that our main results are not picking up seasonal patterns among the types of counties that closed schools in 2020, lending further evidence that our results reflect the causal estimate of school closures.

Our results are most not sensitive to the inclusion of time-varying covariates in the regressions (Appendix Table 5). The second column still indicates significant declines during the fall 2020 semester without the inclusion of covariates. Subsequent columns show the results when we include each set of covariates on its own. For the most part, results are similar and indicate significant declines associated with school closures regardless of which controls are included. The lone exception is the inclusion of distance to field office interacted with month, which leads to results no longer being significant.[26]

## VI. Mechanisms

Our primary results underscore that schools play an important role through which children and families learn about and apply for SSI, yet it is critical that we further understand exactly how schools influence this process. In this section, we use subgroup analyses to explore several potential channels for the impact of schools on children's SSI applications. As discussed earlier, our two main subgroups divide counties by those above and below the median in terms of

[26] We also test a specification that includes state-by-month fixed effects. Though this puts greater demands on the data, this approach identifies effects specifically using variation in school closures within states, and therefore is not subject to any state-level policy changes or responses to the pandemic unrelated to schools. The results continue to indicate significant declines in applications associated with school closures, both in the 2020-21 school year and during the Fall 2020 semester.

school psychologists per capita and in terms of child SSI participation rates. The former captures the extent to which school staff play an important role in potentially identifying a disability and in turn influencing SSI applications. The latter captures the extent to which local networks outside of schools might matter for families learning about the program. Importantly, the correlation between these two subgroups is quite low, indicating the two analyses capture separate results. We also consider several analyses that assess whether the way virtual learning affects parents, particularly through the additional burden associated with childcare, contributes to our findings – such a channel would confound our main interpretation on the role of schools.

School psychologists can offer early intervention services as well as mental and behavioral health services, services that would be difficult to offer during the pandemic. In counties with relatively more school psychologists, remote schooling led to a greater change in the availability of these services, which might include identification and referrals to SSI. In counties with relatively few school psychologists, those services were less widely available in the first place, leading to minimal change in their availability. Thus, we might expect to see larger changes in applications among counties with school closures that had relatively more school psychologists.

Consistent with this theory, the decline in child SSI applications in schools with greater virtual learning is larger in counties that have more school psychologists (Table 5). We divide counties by whether the number of school psychologists per student is above or below the median. As shown in Panel A of Table 5, in counties with above median school psychologists, the decline during the average month of the 2020–21 school year (or the fall 2020 semester) is approximately 0.007 percentage points and statistically significant. This represents a 23 percent decline relative to the average monthly application rate in 2019. In contrast, counties with below median school psychologists experienced no significant change from school closures. These impact estimates are also significantly different from each other. These findings highlight that school staff identifying and referring students potentially eligible for SSI is likely an important channel for our main results: the overall services offered directly through staff and special education are likely instrumental in connecting children and families to SSI.[27]

To further explore the potential role of networks, we assess whether the impacts of school closures on child SSI applications differ by the county's child SSI participation in 2019 (Table 6). We find a significant difference across counties by child SSI participation, with significantly larger declines in SSI applications from school closures in counties with low SSI participation. This provides suggestive evidence on the importance of networks more broadly. Though schools may be one type of network through which families learn about SSI, areas with high SSI participation may have other types of informal networks that were not disrupted during the pandemic, leading to no significant declines from school closures in high SSI counties. In contrast, in areas with low SSI participation, the school may be one of the only types of networks available. When schools only offered remote learning, this channel disappeared. All else equal, high SSI participation counties therefore still may have had other networks available to learn about SSI, while low SSI participation counties likely did not. In turn, this led to larger declines from school closures in these low SSI counties.

These results are consistent with other evidence suggesting informal networks play a role in driving child SSI participation. Tambornino, O'Day, and Burak (2015) conducted qualitative interviews with stakeholders to understand more about how children and families learn about

[27] We also estimate results considering a separate but similar subgroup for whether the county is above or below median in special education participation. This metric also captures the availability of in-school services before the pandemic. The findings are mostly similar (Appendix Table 6).

SSI. Participants cited family, friends, and acquaintances as the most important source of information about the program. Keesler (2015) conducted focus groups and interviews with family members of child SSI recipients. Almost half mentioned learning about the program through family and friends, hospital social workers, school systems, pediatricians, or other support groups or networks. In a separate paper, we found that the largest overall declines in applications at the outset of the pandemic occurred in counties with higher initial child SSI participation and more people with disabilities (Levere, Hemmeter, and Wittenburg 2023). Such counties likely had the biggest changes in services during the first few months of the pandemic when shutdowns and stay-at-home orders were in place, pointing to the potential role that these informal networks may play in learning about SSI.

Another way that remote schooling may have influenced child SSI applications is if the additional demands on parents led them to have less time to complete the application process. Given our primary focus is on the role of schools, and in particular channels like staff referral and networks, this alternative channel would confound our main effect. We collected data dividing the number of child SSI applications by whether the child is from a household with two parents or not with two parents, as well as whether the child is from a household with countable earned income or no countable earned income. Households with two parents as well as households with no countable income may have more time available to go through the application process. Households with one parent or where parents have countable income might be especially burdened by the childcare duties associated with remote schooling.

The decline in applications is mostly similar for children in households that do and do not have two parents and in households with and without countable income (Table 7).[28] The estimates in Table 7 for the 2020-21 school year in Panel A are statistically indistinguishable from each other, both when dividing by number of parents and dividing by income. In Panel B, we find somewhat larger point estimates among households without two parents and among households with no countable income during the fall 2020 semester. Yet as a percentage, the coefficients are roughly equal – for example, the smaller point estimate of -0.0012 for households with two parents actually represents a larger relative decline (14.8 percent) than among households without two parents (12.1 percent). The results by income also work in the opposite direction as hypothesized. This suggests that the additional demands on parental time associated with remote learning may not have played an important role in our main effects.

We also found that remote learning had a differentially larger effect in states with low UI generosity as compared to states with high UI generosity (Appendix Table 7). We calculated an expected UI generosity by multiplying the UI recipiency rate (share of eligible people who get benefits) by the UI replacement rate (share of earnings replaced).[29] In states with high UI generosity, parents might be more willing to rely on UI during the pandemic, and thus have more time available to care for children and manage the application process. In such states, remote learning had no effect on applications. In contrast, in states with low UI generosity, remote learning led to significant reductions in child SSI applications. Remote learning may therefore

[28] Whereas our subgroup regressions shown in Tables 5 and 6 consider the same primary outcome as that in Table 2, these regressions use different outcomes (separating total child SSI applications into child SSI applications from different groups). Therefore, whereas the average of coefficients across columns in Tables 5 and 6 is roughly equal to the estimated impact in Table 2, it is instead the sum of coefficients across columns in Table 7 that is roughly equal to the estimated impact in Table 2.

[29] These data come from Department of Labor. We measure the recipiency rate as the average in 2020 and the replacement rate in the fourth quarter of 2020.

have influenced child SSI applications apart from its effect through schools. However, this should be considered as exploratory given the analyses by number of parents and parent earnings, which may more directly capture parent time available.

## VII. Conclusion

Our results highlight that schools play an important role in children and families learning about and ultimately applying for SSI benefits. We use the variation in school learning mode during the 2020–21 school year stemming from the COVID-19 pandemic to explore how schools influence child SSI applications. Virtual learning led to significant disruptions, including to several channels through which families might learn about SSI, particularly to the potential for school staff to identify and refer students to SSI and to formal and informal networks that exist through school.

Our primary results indicate that counties with more students in virtual schooling at the outset of the 2020–21 school year had fewer child SSI applications than counties with more in-person schooling. Additionally, our subgroup analyses highlight those effects differed by school characteristics and outside networks. The findings provide evidence that both staff identification and referral within schools, as well as networks outside of schools, can influence SSI applications.

We can use our findings to estimate the share of the decline in child SSI applications during the pandemic that can be explained by school closures. First, we used data on observed applications from January 2015 to February 2020 to predict monthly school-age child SSI applications in all months from March 2020 to June 2021 if not for the pandemic.[30] The

[30] To generate this predicted value, we run a regression of the number of child SSI applications on a linear time trend, a squared time trend, and calendar month dummies. The actual versus predicted values for these monthly application numbers are shown in Appendix Figure 9.

difference between this prediction and the actual value represents the decline stemming from the pandemic. In total during this time period, school-age child SSI applications declined by nearly 90,000, relative to the pre-pandemic trend; during the 2020-21 school year (the main focus of our study) the decline was about 50,000.

Next, we use our regression coefficients, which measure the monthly decline in the application rate if all students in a county are subject to school closures, to estimate the decline in applications stemming from school closures.[31] As a lower bound for this decline, we use our estimate of the average monthly decline in the application rate over the entire 2020-21 school year (-0.0032, Table 2, Panel A). As an upper bound, we use our estimate of the decline in the month immediately following school closures (-0.0100, Figure 5, estimate for October 2020). Using this approach, school closures led to a decline of between 8,000 and 21,000 child SSI applications, or between 14 and 43 percent of the total decline during the 2020-21 school year.

School closures can explain more of the decline during the earlier months of the 2020-21 school year, when the pandemic was still a larger factor – our estimates can explain 21 to 64 percent of the decline during the fall 2020 semester (from September 2020 to January 2021). We also use our approach to estimate how much school closures contributed to application declines from April to June 2020, when all public schools around the country were closed. During these months, when the decline in applications was largest, we can explain 20 to 64 percent of the

[31] Given our coefficient, we estimate the decline in applications in a given month as follows. We first use SafeGraph data to attribute the share of students in a county subject to school closures in that month. We multiply this share by the coefficient, which captures the decline in the application rate in that county given the actual level of school closures. We then aggregate to the national level to get the monthly decline in the child SSI application rate, weighting by county student-age population. We apply this monthly decline to the predicted level of applications in the absence of the pandemic to estimate the decline in applications stemming from school closures. One critical assumption is that the application rate in counties with no school closures would have been the predicted application rate in the absence of the pandemic. Though numerous other factors during the pandemic influenced patterns in the application rate (Levere, Hemmeter, and Wittenburg 2023), the goal of this back-of-the-envelope calculation is to isolate how much of the total decline can be explained just by the school channel.

decline in applications. This estimate is similar to the estimate from the fall 2020 semester, despite covering a different time period with differing prevalence of school closures, offering further reassurance that this approach is reliable.

These results can help inform ways that policymakers might consider conducting outreach to facilitate access to child SSI among those eligible as the pandemic wanes. SSI participation has declined for the past decade, with especially large declines in applications during the first few months of the pandemic. SSA recently created vulnerable population liaisons to help encourage those eligible for SSI to participate in the program. Our findings indicate that deploying resources through schools might be especially effective. Educating teachers, school psychologists, and other school staff about SSI to ensure that they know about it and can identify students likely to be eligible (at least from a disability perspective) might help promote greater access. SSA already has information pamphlets for educators about the program; expanding their use, especially in schools and districts with few school psychologists, may be a low-cost effort to ensure all eligible children are receiving benefits. Other efforts that can help spread knowledge about SSI through existing school networks might also be productive uses of resources.

Our findings also contribute to the growing conversation around the spillover effects of school closures during the COVID-19 pandemic. Research has found that children's learning suffered (e.g., Jack et al. 2023; Maldonado and De Witte 2022), indicating the primary challenges associated with virtual learning. Much other research has explored the other consequences of the school closure decision. School closures may have improved students' mental health—perhaps because of reduced bullying, resulting in lower teen suicide rates (Hansen, Sabia, and Schaller 2023). Rates of ADHD diagnoses also fell (Freedman et al. 2023), though it is unclear whether that is because the prevalence of ADHD declined. However, other research indicates that virtual learning presented greater mental health risks (Verlenden et al. 2021). We find that losing access to the informal networks associated with schools and the important services offered through school psychologists led to lower rates of child SSI applications.

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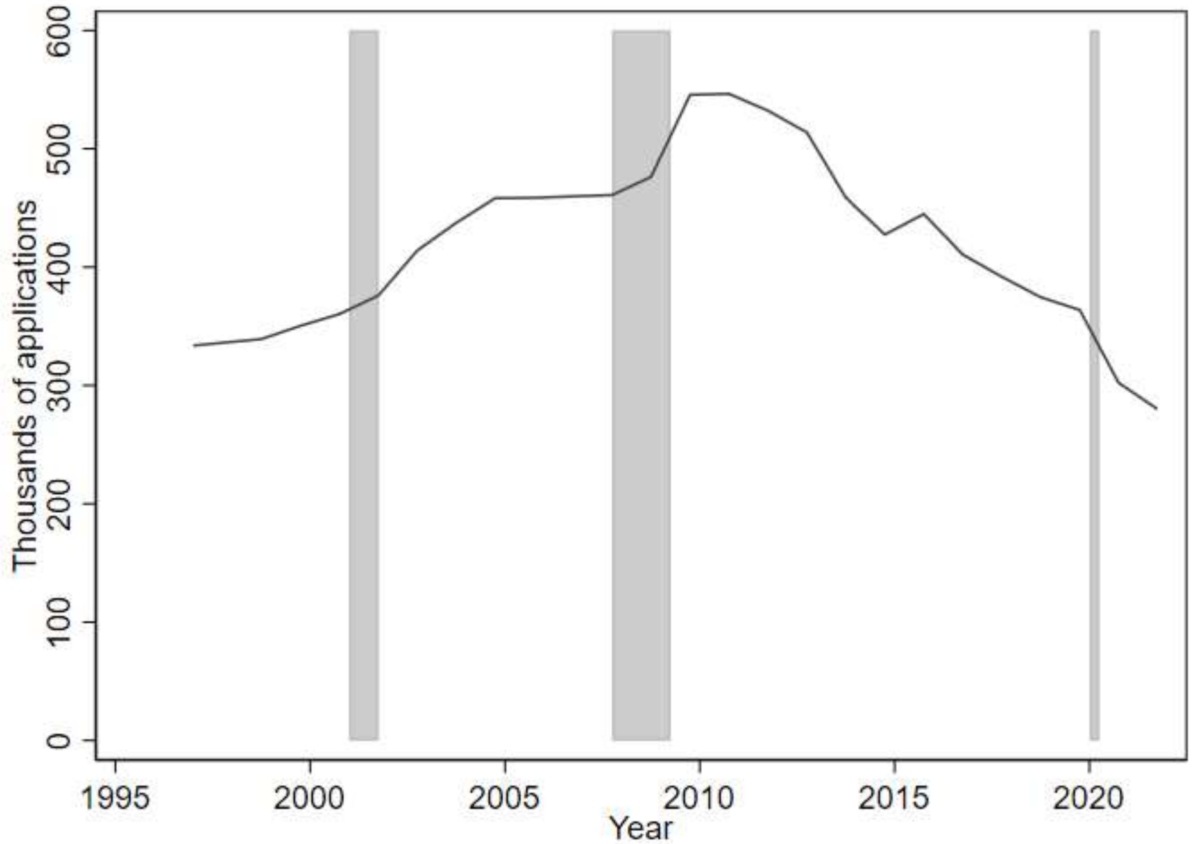
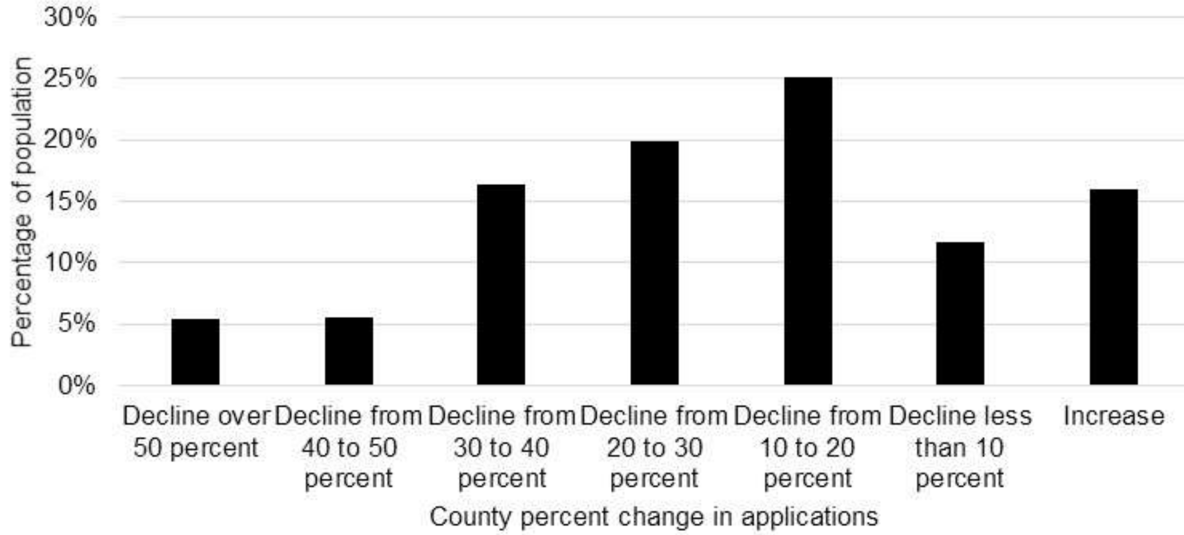
Figure 1. Child SSI applications, 1997 to 2021



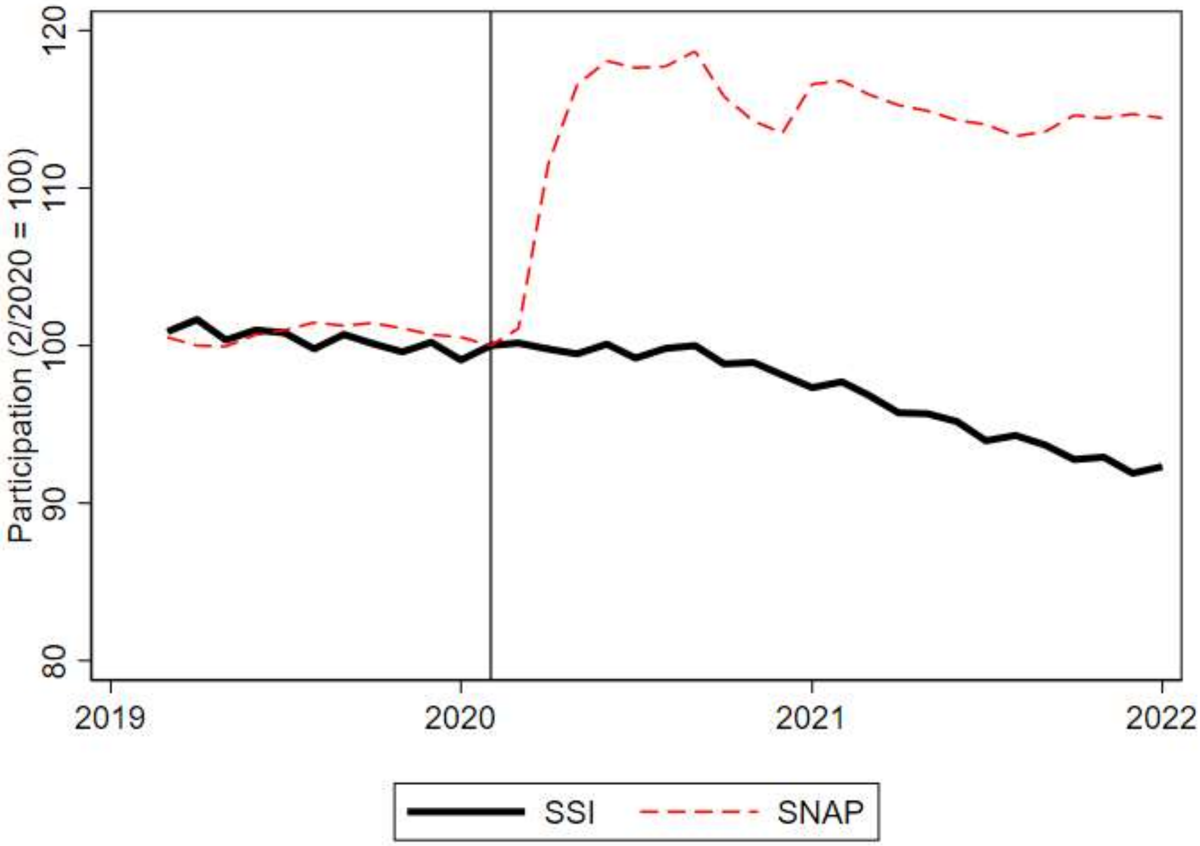

Source: SSI Annual Statistical report.
Note: Gray bars indicate recessions.

Figure 2. Distribution of the change in child SSI applications during the 2020–21 school year



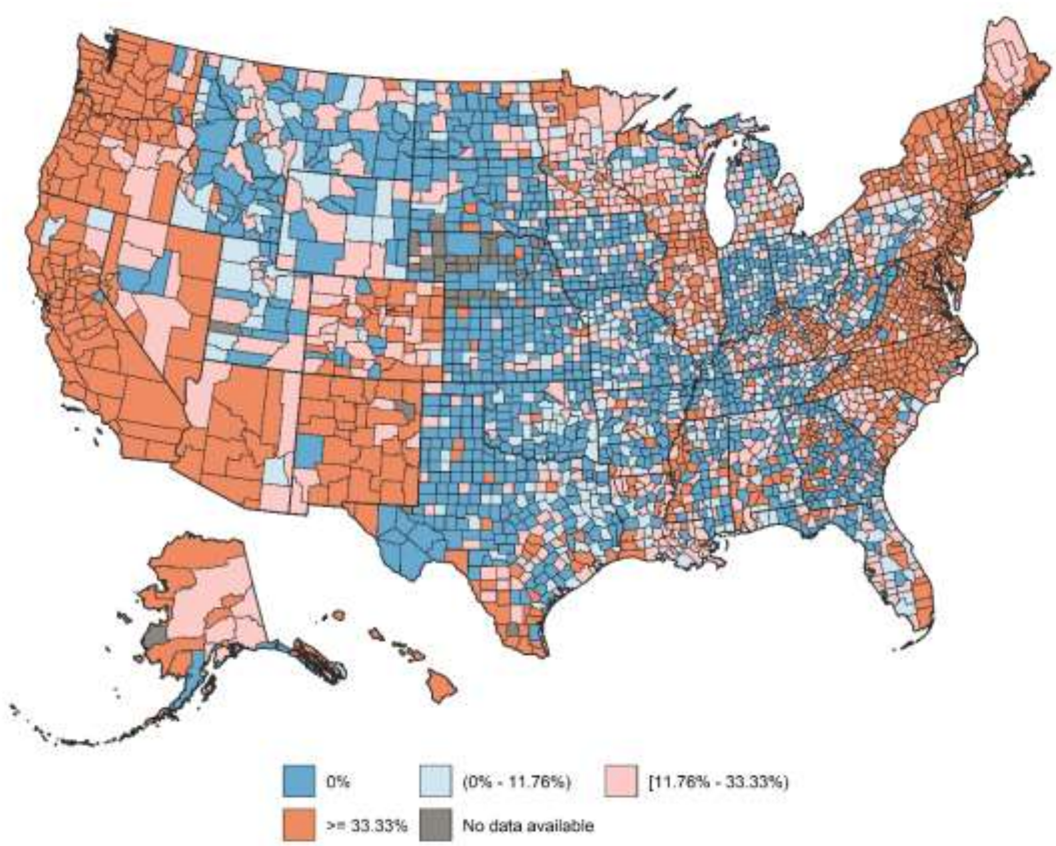

Source: Authors' calculations using SSA administrative data.
Note: For each county, calculates the percentage change in total applications between the 2018–19 school year and the 2020–21 school year. Reports the percent of the population living in counties with each range of percent change. About one percent of the population lives in counties that had no child SSI applications in 2018–19, for whom a percent change cannot be calculated.

Figure 3. Program participation trends, February 2019 to December 2021



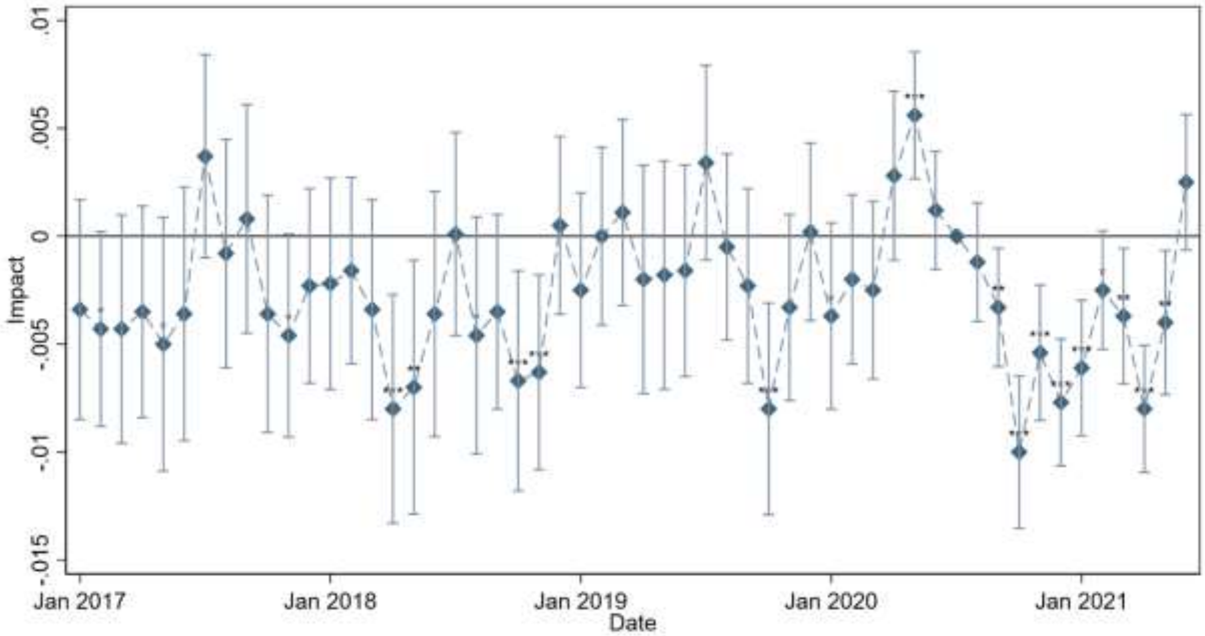

Source: SSI monthly statistics; Food and Nutrition Service SNAP and WIC data tables; Department of Health and Human Services TANF caseload data.
Note: Numbers for SSI consider only children's SSI participation. Participation is scaled so that it is equal to 100 in February 2020, leading all values to indicate a percentage difference in that period relative to February 2020.

Figure 4. Percentage of students facing school closures, September 2020



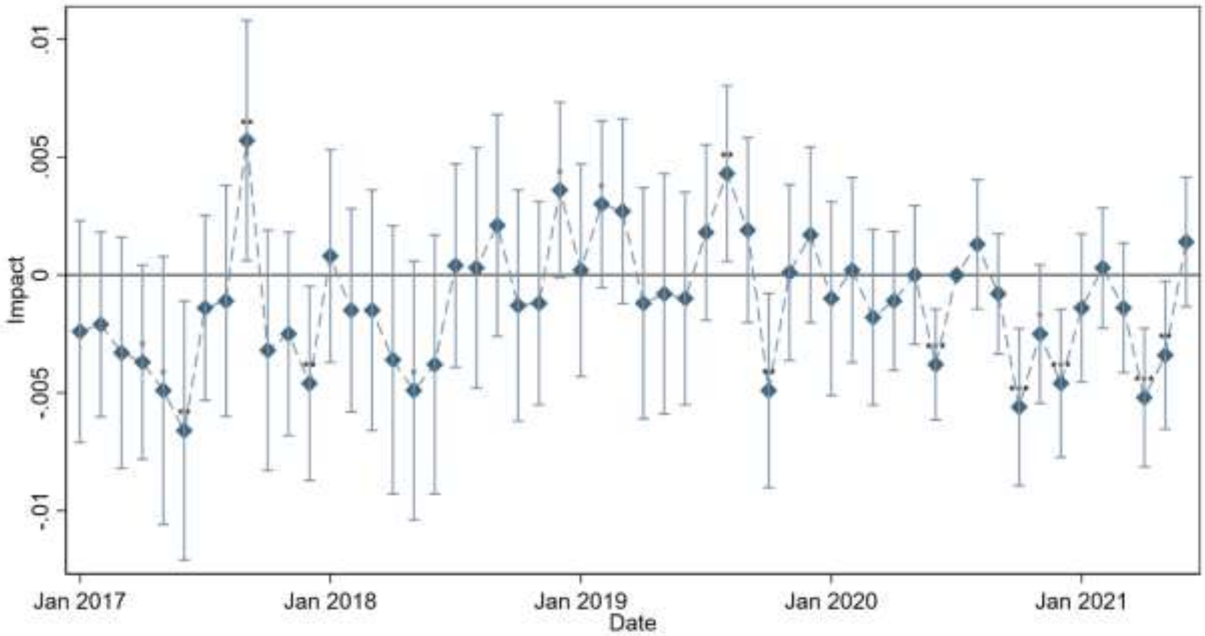

Source: SafeGraph data.
Note: Shows the percentage of students in each county subjected to a school closure in September 2020, the onset of the 2020–21 school year. School closure is defined as a decline in cell phone activity at the school of at least 50 percent relative to September 2019.

Figure 5. Event study estimates for school-age SSI applications (ages 5 to 17) using school closures measured with SafeGraph cell phone data




Note: Presents coefficients of $\beta_k$ from equation (1), using an outcome of applications among school age children (ages 5 to 17) scaled by the school-age child population. The regression is weighted by school-age child population in the county. The omitted month is July 2020. School closures are measured in September 2020 and are based on SafeGraph data (Parolin and Lee 2021).
***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

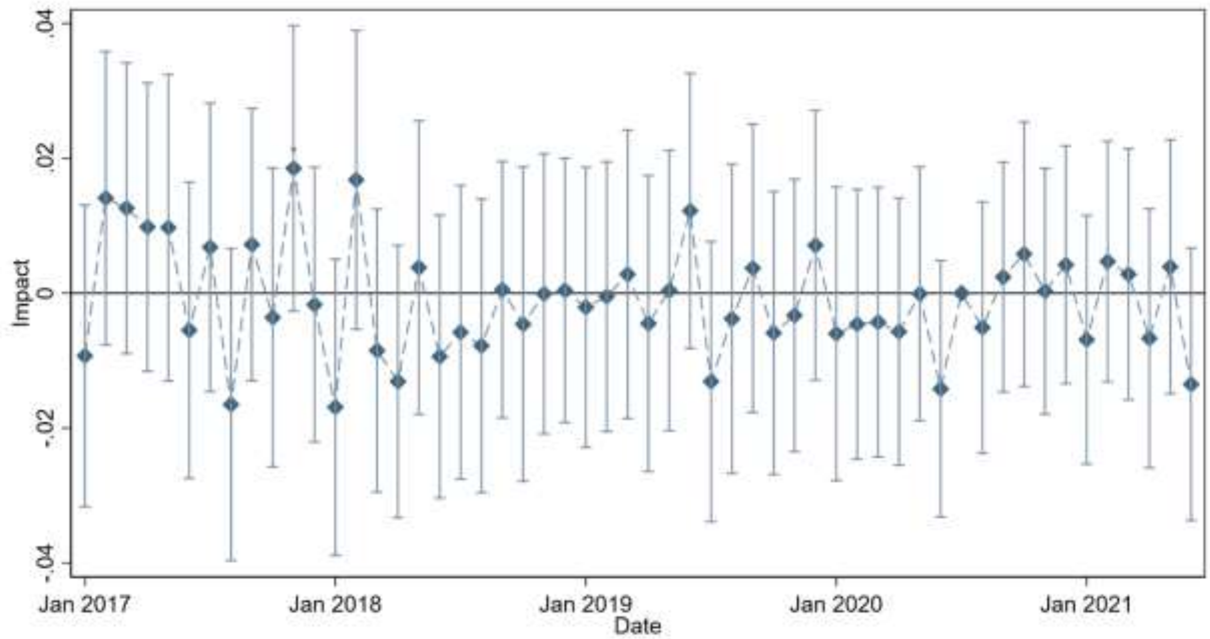
Figure 6. Event study estimates for school-age SSI applications (ages 5 to 17) using school closures measured with COVID-19 School Data Hub policy data



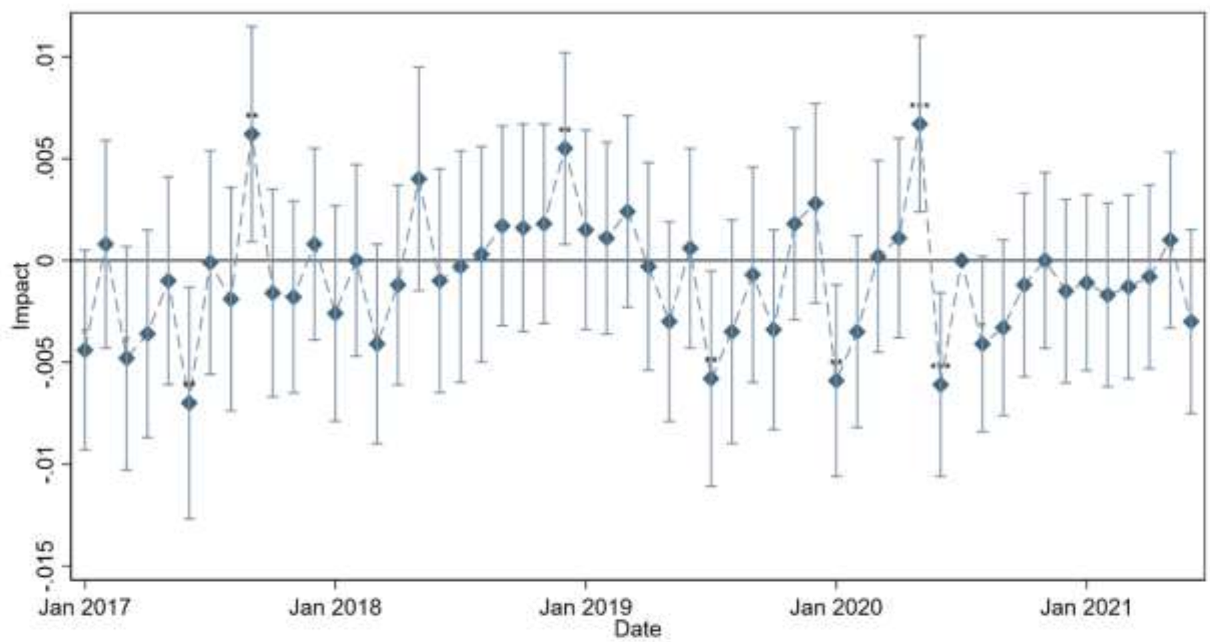

Note: Presents coefficients of $\beta_k$ from equation (1), using an outcome of applications among school age children (ages 5 to 17) scaled by the school-age child population. The regression is weighted by school-age child population in the county. The omitted month is July 2020. School closures are measured in September 2020 and are based on data from the COVID-19 School Data Hub (Jack et al. 2023).
***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Figure 7. Placebo event study estimates

Panel A. Age 0 applications




Panel B. Age 18 to 24 applications (young adults)




Note: Presents coefficients of $\beta_k$ from equation (1), using an outcome of applications among children age 0 or ages 18 to 24 scaled by the county population for people of that age. The regression is weighted by population of children in the county. The omitted month is July 2020. School closures are measured in September 2020 and are based on SafeGraph data (Parolin and Lee 2021).

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Table 1. Declines in child SSI applications during the COVID-19 pandemic

| Age group | April–August 2020 (Pandemic period) | September–December 2020 (First half of 2020–21 school year) | January–June 2021 (Second half of 2020–21 school year) |
|---|---|---|---|
| Age 0 | -19.3% | -17.0% | -21.5% |
| Ages 1–4 | -26.6% | -12.7% | -13.3% |
| Ages 5–10 | -35.5% | -21.2% | -29.7% |
| Ages 11–13 | -36.6% | -22.9% | -30.6% |
| Ages 14–17 | -24.3% | -15.2% | -19.1% |

Source: Authors' calculations from Supplemental Security Record

Note: All numbers expressed as the decline in total applications in those months relative to the total over the same calendar months in 2019.

Table 2. Difference-in-differences estimates of the effect of school closures on application rates, by age

| Period | Ages 5–17 | Ages 5–10 | Ages 11–13 | Ages 14–17 | Age 0 | Ages 18–24 |
|---|---|---|---|---|---|---|
| **Panel A** | | | | | | |
| 2020–21 * | -0.0032** | -0.0047** | -0.0021* | -0.0018** | 0.0019 | -0.0003 |
| Onset virtual | (0.0013) | (0.0019) | (0.0013) | 0.0008 | (0.0033) | 0.0010 |
| **Panel B** | | | | | | |
| Fall 2020 * | -0.0048*** | -0.0070*** | -0.0026* | -0.0033*** | 0.0032 | -0.0005 |
| Onset virtual | (0.0013) | (0.0019) | (0.0014) | 0.0009 | (0.0037) | 0.0011 |
| Spring 2021 * | -0.0015 | -0.0024 | -0.0015 | -0.0002 | 0.0005 | -0.0002 |
| Onset virtual | (0.0015) | (0.0022) | (0.0015) | 0.0010 | (0.0040) | 0.0012 |
| 2019 average | 0.0369 | 0.0472 | 0.0339 | 0.0241 | 0.1068 | 0.0462 |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Table 3. Difference-in-differences estimates of the effect of school closures on student-age SSI applications, by whether another child in household previously received SSI

| Period | Prior sibling award | No prior sibling award | *p*-value of difference |
|---|---|---|---|
| **Panel A** | | | |
| 2020–21 * Onset virtual | -0.0000 | -0.0032*** | 0.003 |
| | (0.0004) | (0.0010) | |
| **Panel B** | | | |
| Fall 2020 * Onset virtual | -0.0003 | -0.0044*** | 0.000 |
| | (0.0004) | (0.0010) | |
| Spring 2021 * Onset virtual | 0.0003 | -0.0018 | 0.097 |
| | (0.0004) | (0.0012) | |
| 2019 average | 0.0077 | 0.0292 | |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. We used the parents identified on a child's application to identify whether another child in the household had previously had an SSI award, and then calculate divide the total number of applications into those where a prior sibling had an award and those where a prior sibling did not have an award. We then estimate separate regressions, one for each outcome measure, where each regression model is the same as that used in Table 2.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Table 4. Difference-in-differences estimates of the effect of school closures on award rates, by age

| Period | Ages 5–17 | Ages 5–10 | Ages 11–13 | Ages 14–17 | Age 0 | Ages 18–24 |
|---|---|---|---|---|---|---|
| **Panel A** | | | | | | |
| 2020–21 * | -0.0001 | -0.0002 | 0.0002 | -0.0002 | 0.0006 | 0.0000 |
| Onset virtual | (0.0005) | (0.0008) | (0.0006) | 0.0004 | (0.0022) | 0.0004 |
| **Panel B** | | | | | | |
| Fall 2020 * | -0.0009* | -0.0014* | 0.0000 | -0.0010** | 0.0003 | 0.0000 |
| Onset virtual | (0.0005) | (0.0008) | (0.0007) | 0.0004 | (0.0027) | 0.0005 |
| Spring 2021 * | 0.0007 | 0.0010 | 0.0004 | 0.0005 | 0.0009 | 0.0000 |
| Onset virtual | (0.0006) | (0.0009) | (0.0006) | 0.0004 | (0.0027) | 0.0005 |
| 2019 average | 0.0134 | 0.0184 | 0.0110 | 0.0077 | 0.0630 | 0.0164 |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Table 5. Difference-in-differences estimates of the effect of school closures on student-age SSI applications, by county school psychologist prevalence

| Period | Low school psychologists (below median) | High school psychologists (above median) | *p*-value of difference |
|---|---|---|---|
| **Panel A** | | | |
| 2020–21 * Onset virtual | 0.0001<br>(0.0016) | -0.0074***<br>(0.0020) | 0.004 |
| **Panel B** | | | |
| Fall 2020 * Onset virtual | -0.0024<br>(0.0016) | -0.0077***<br>(0.0022) | 0.063 |
| Spring 2021 * Onset virtual | 0.0027<br>(0.0018) | -0.0071***<br>(0.0021) | 0.000 |
| 2019 average | 0.0414 | 0.0327 | |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. Data on school psychologists are available for local education agencies from the Common Core of Data. We then aggregate both the number of school psychologists and number of enrolled students across local education agencies in the county. Counties are then divided by whether they fall above or below the weighted median in terms of school psychologists per student.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Table 6. Difference-in-differences estimates of the effect of school closures on student-age SSI applications, by county child SSI participation

| Period | Low child SSI participation (below median) | High child SSI participation (above median) | *p*-value of difference |
|---|---|---|---|
| **Panel A** | | | |
| 2020–21 * Onset virtual | -0.0055***<br>(0.0013) | -0.0009<br>(0.0016) | 0.024 |
| **Panel B** | | | |
| Fall 2020 * Onset virtual | -0.0065***<br>(0.0014) | -0.0028*<br>(0.0016) | 0.095 |
| Spring 2021 * Onset virtual | -0.0044***<br>(0.0014) | 0.0011<br>(0.0020) | 0.014 |
| 2019 average | 0.0204 | 0.0534 | |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. Child SSI participation is measured as of 2019. We convert this number to a rate by scaling by the population of children under 18 in 2019. Counties are then divided by whether they fall above or below the weighted median in terms of child SSI participation rate.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Table 7. Difference-in-differences estimates of the effect of school closures on student-age SSI applications, by number of parents and countable income

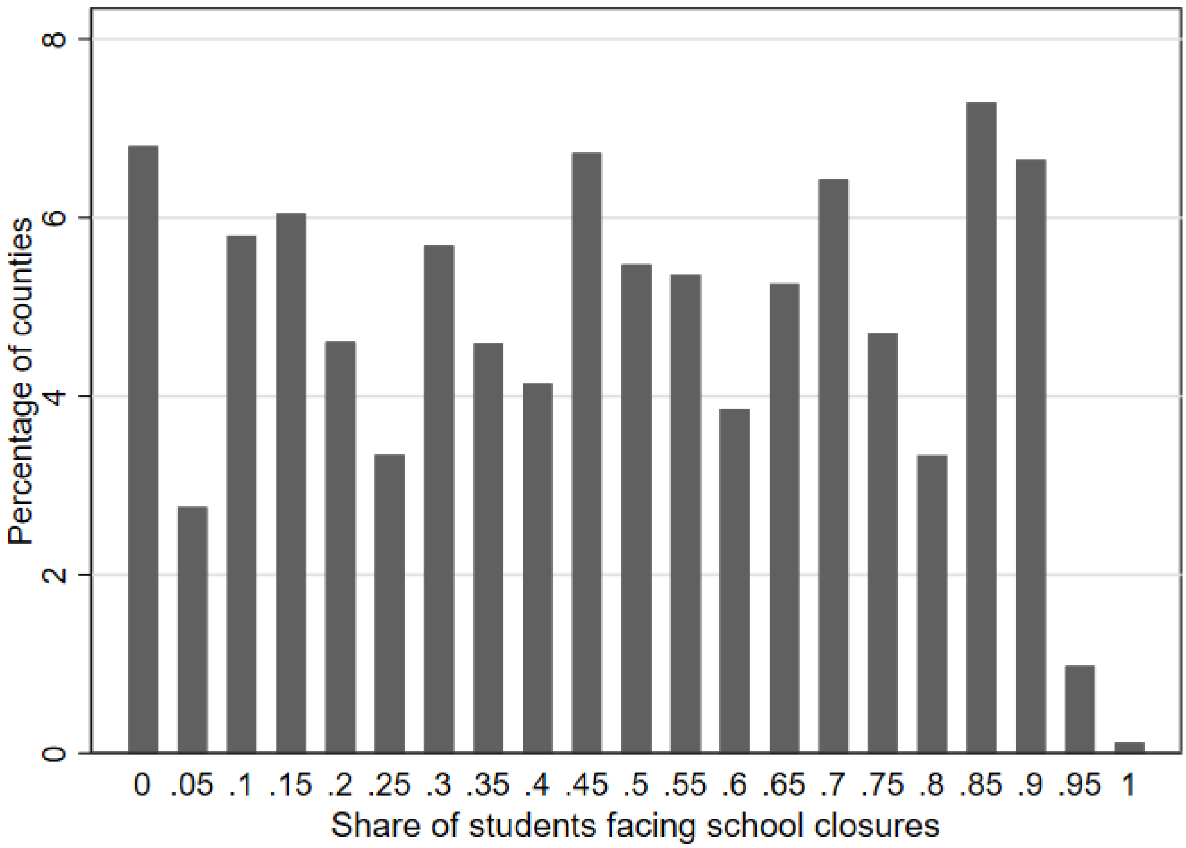
| Period | Two parents | Not two parents | *p*-value of difference | Parents have countable income | Parents have no countable income | *p*-value of difference |
|---|---|---|---|---|---|---|
| **Panel A** | | | | | | |
| 2020–21 * | -0.0009 | -0.0023*** | 0.162 | -0.0009*** | -0.0023** | 0.219 |
| Onset virtual | (0.0006) | (0.0008) | | (0.0003) | (0.0011) | |
| **Panel B** | | | | | | |
| Fall 2020 * | -0.0012** | -0.0035*** | 0.021 | -0.0012*** | -0.0036*** | 0.040 |
| Onset virtual | (0.0006) | (0.0008) | | (0.0004) | (0.0011) | |
| Spring 2021 * | -0.0006 | -0.0009 | 0.792 | -0.0005 | -0.0010 | 0.708 |
| Onset virtual | (0.0007) | (0.0009) | | (0.0003) | (0.0013) | |
| 2019 average | 0.0081 | 0.0288 | | 0.0152 | 0.0217 | |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. On the left, for each county, the number of applications is divided into those from children with two parents listed on the application or with either zero or one parent listed on the application. On the right, for each county, the number of applications is divided into those from children where parents have countable income or where parents have no countable income. Countable income is an amount of earnings sufficient to lead SSI benefits to be offset if awarded, so captures earnings slightly above a nominal disregard amount. We then estimate separate regressions, one for each outcome measure, where each regression model is the same as that used in Table 2.

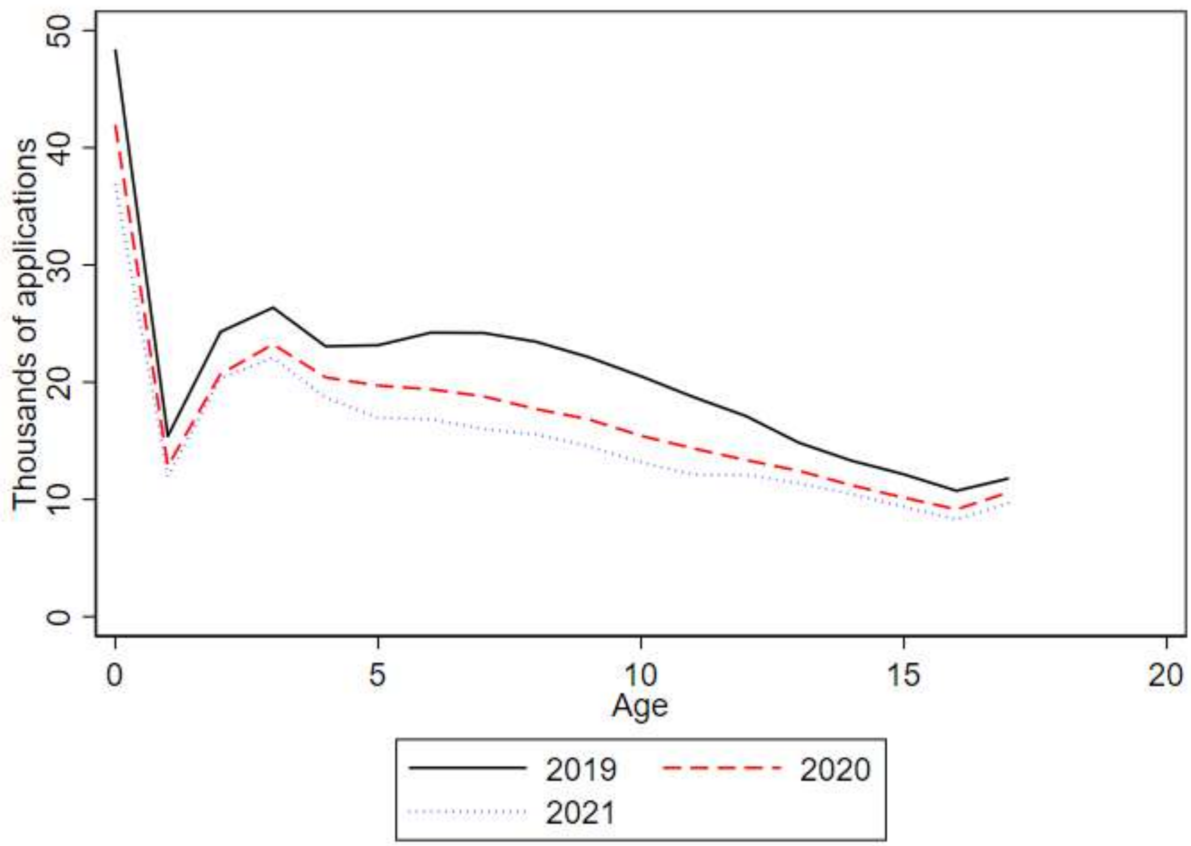
***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Figure 1. Histogram of school closure intensity distribution



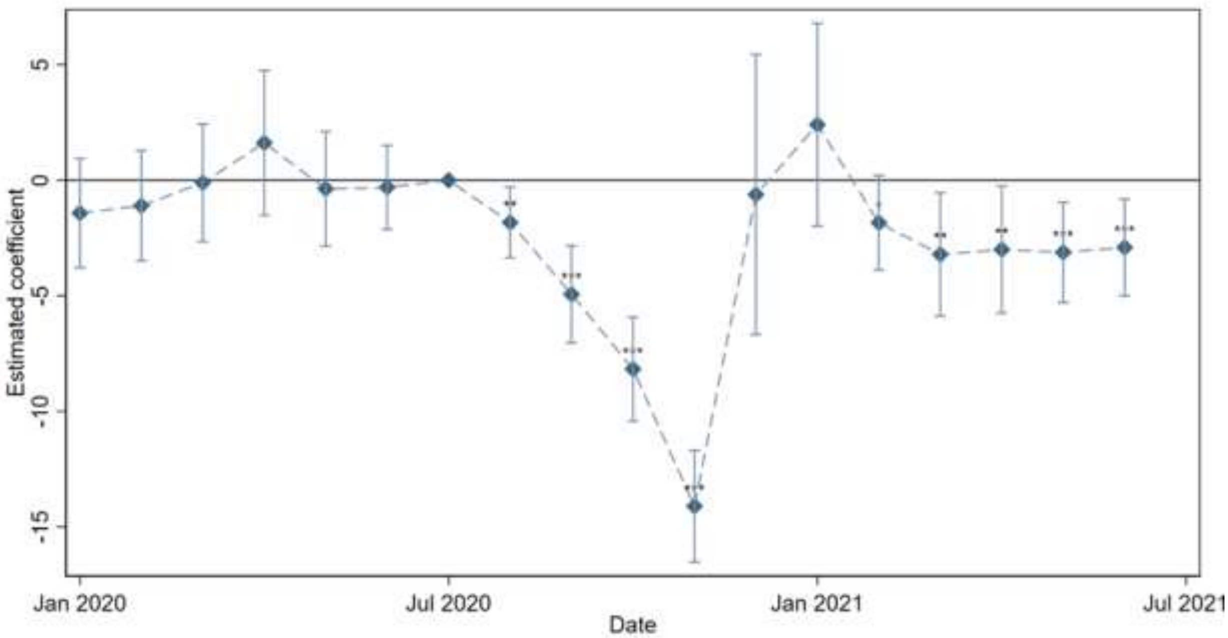

Source: SafeGraph data.
Note: Groups counties by the percentage of students in each county subjected to a school closure in September 2020, the onset of the 2020–21 school year. School closure is defined as a decline in cell phone activity at the school of at least 50 percent relative to September 2019. The first bar corresponds to exactly zero students facing school closures, while each subsequent bar corresponds to the amount above the prior bar and less than or equal to the amount shown (i.e., less than or equal to 5 percent, more than 5 but less than or equal to 10 percent, and so on). The averages are weighted by county child population to mirror our estimation strategy.

Appendix Figure 2. SSI applications in 2019–2021, by age



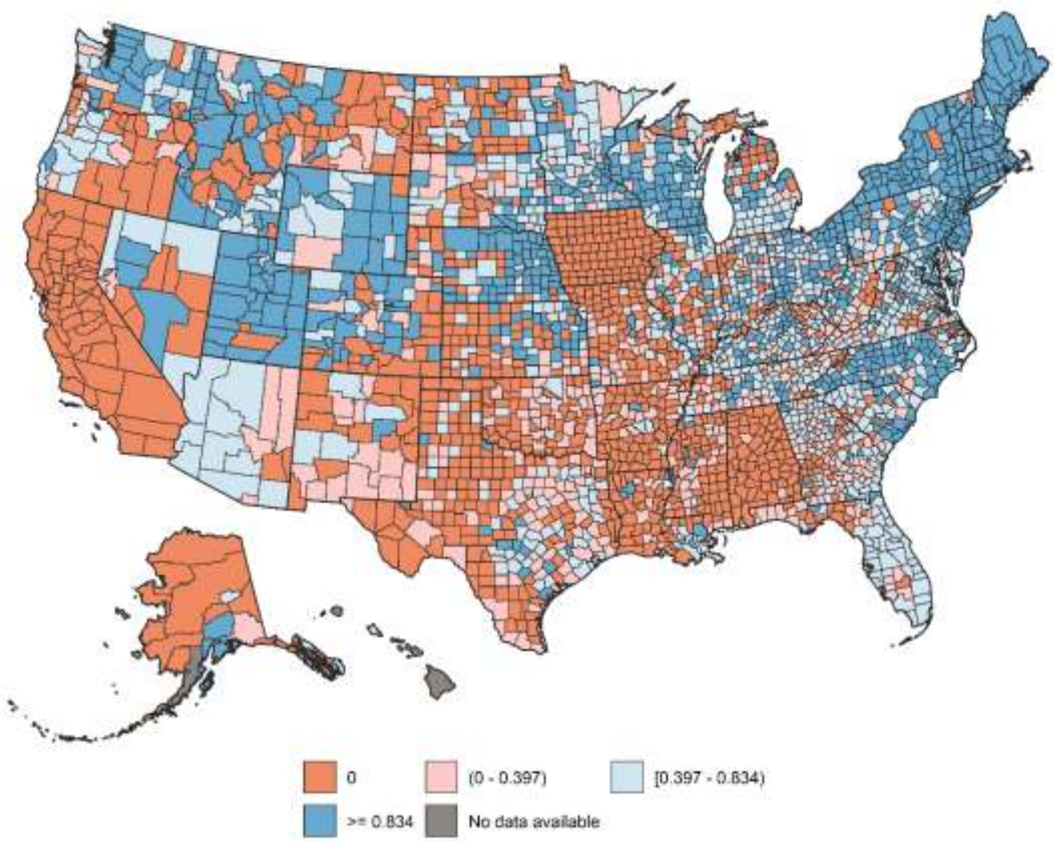

Source: Authors calculations using Supplemental Security Record

Appendix Figure 3. Event study estimates for local COVID-19 cases




Source: Authors' calculations.
Note: Presents coefficients of $\beta_k$ from equation (1), using an outcome of monthly COVID-19 cases per 1,000 residents. The regression is weighted by county population. The omitted month is July 2020. School closures are measured in September 2020 and are based on SafeGraph data (Parolin and Lee 2021).
***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

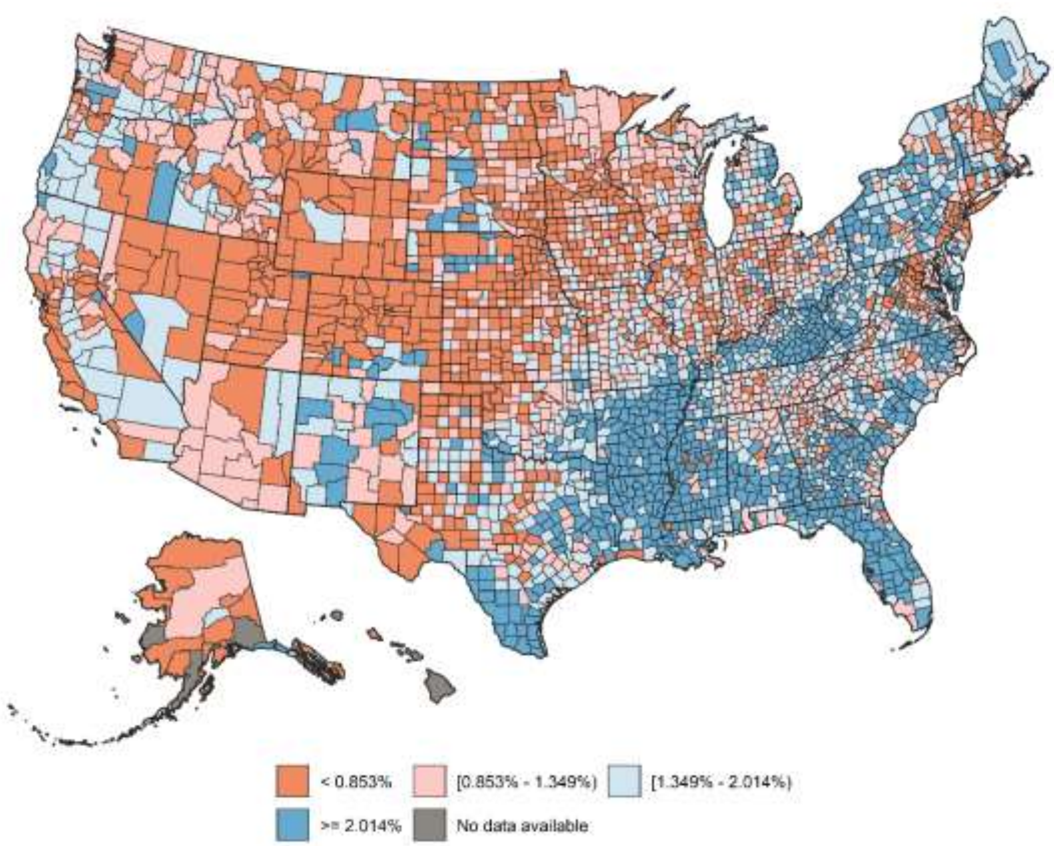
Appendix Figure 4. School psychologists per 1,000 students




Source: Department of Education Common Core of Data

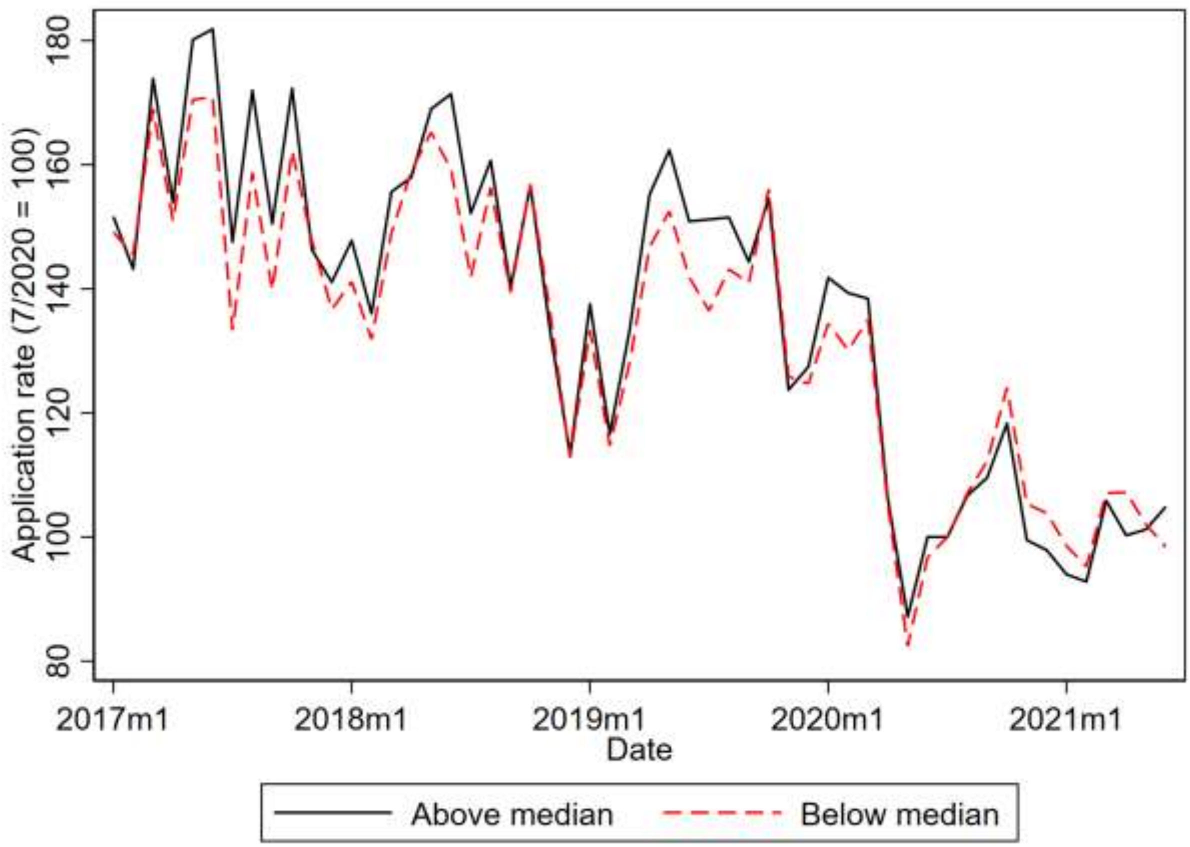
Note: Aggregates data by summing both the number of school psychologists and the total number of students across all local education agencies within a county.

Appendix Figure 5. Child SSI participation



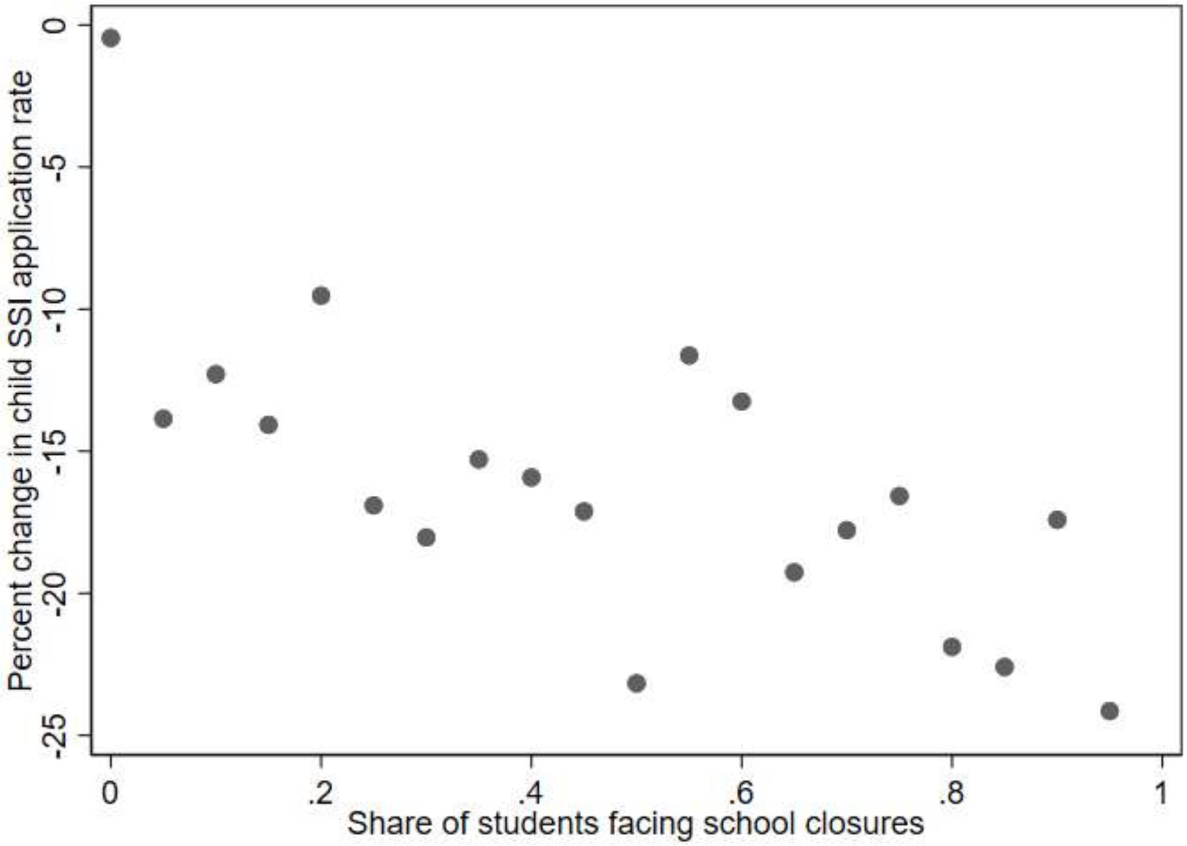

Source: Supplemental Security Record
Note: Calculates the percentage of children receiving SSI in December 2019.

Appendix Figure 6. SSI applications by county school closure status



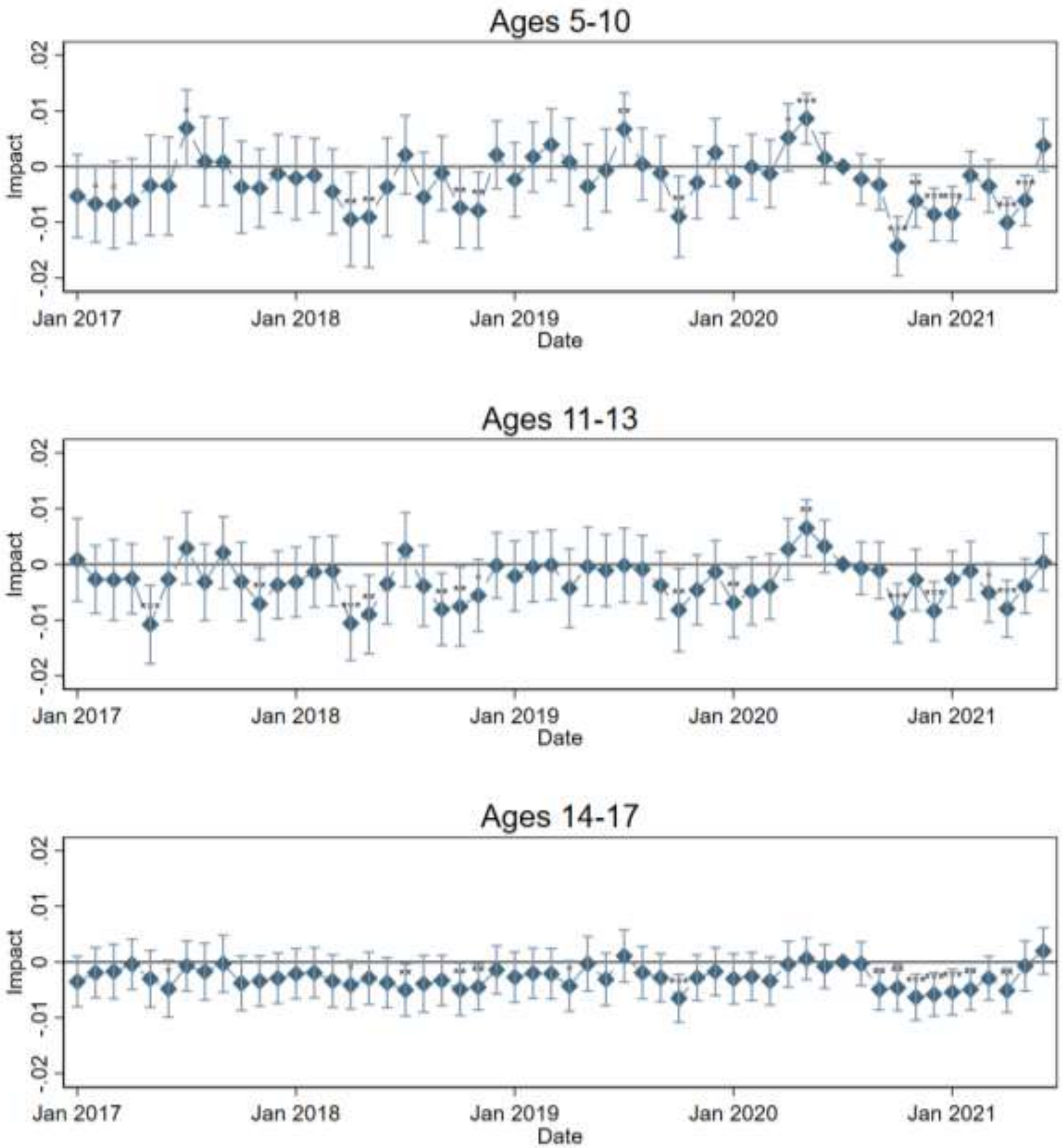

Note: We divide counties by whether the rate of school closures is above or below the median school closure rate in September 2020 (using the weighted average school closures). We then calculate the weighted average application rate in each month across the set of counties that are above and below the median, and scale this rate such that it is normalized to be equal to 100 in July 2020. The lines therefore represent the change in application rates relative to July 2020 in each type of county.

Appendix Figure 7. Relationship between decline in child SSI applications and school closures in September 2020.



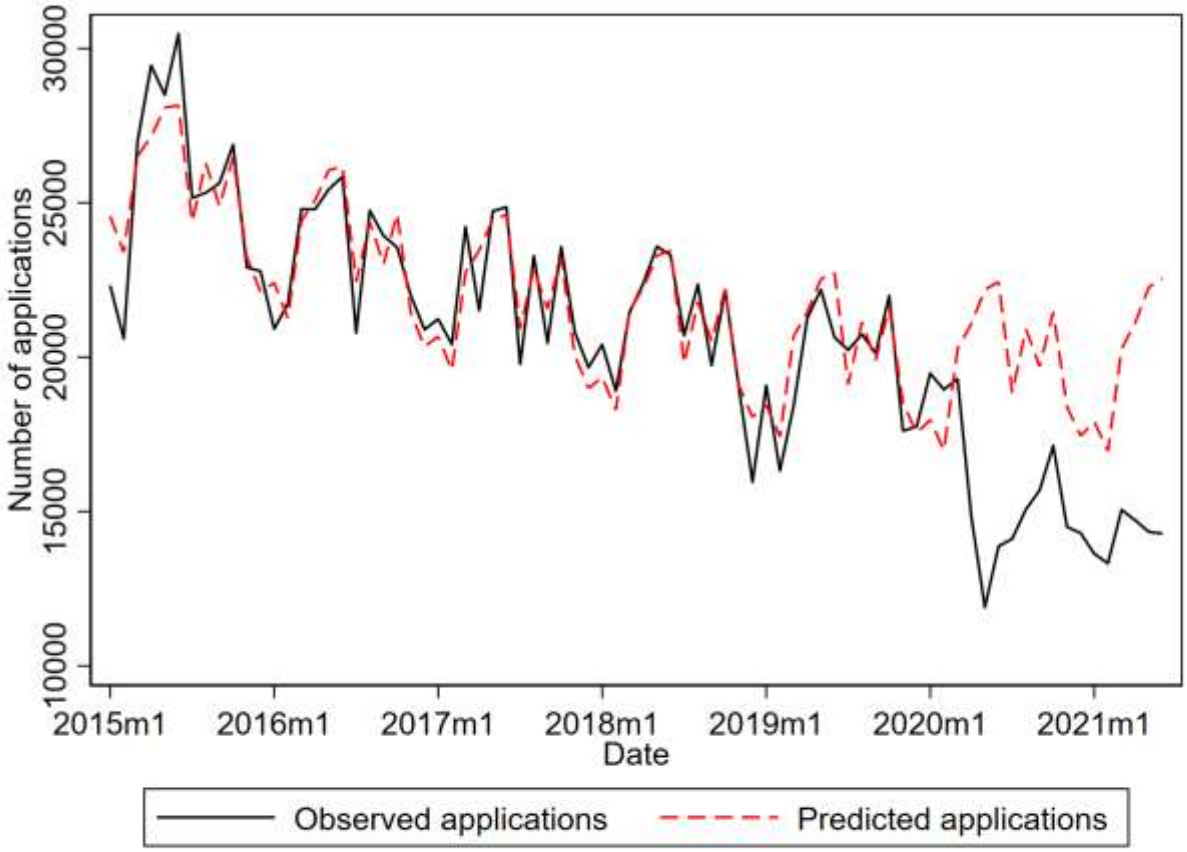

Note: The percent change in child SSI application rate is calculated for the entire 2020-21 school year relative to the 2018-19 school year. The figure shows the average percent change across all counties in a given bin of school closures. These bins include those counties where no students faced school closures, and twenty equally sized bins (i.e., 0 to 5 percent, 5 to 10 percent, and so on). Because such a small share of students lived in counties where more than 95 percent of students faced school closures (only about 0.12 percent, see Appendix Figure 1), we do not include this point in the graph. The share of students facing school closures are measured in September 2020 and are based on SafeGraph data (Parolin and Lee 2021).

Appendix Figure 8. Event study estimates for school-age SSI applications by age group using school closures measured with SafeGraph cell phone data




Note: Each panel presents coefficients of $\beta_k$ from equation (1), using an outcome of applications among children of that age group scaled by the relevant child population. The regression is weighted by school-age child population in the county. The omitted month is July 2020. School closures are measured in September 2020 and are based on SafeGraph data (Parolin and Lee 2021).
***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Figure 9. Observed and predicted student-age SSI applications




Note: Observed applications are based on author calculations from the Supplemental Security Record. Predicted applications are generated with a regression of monthly total applications on both a linear and quadratic time trend and calendar month dummies from January 2015 through February 2020. We then use the coefficients to generate estimates for the period from March 2020 to June 2021. Student-age applications are those from children ages 5 to 17.

Appendix Table 1. Relationship between COVID-19 severity and school closures.

| COVID-19 Severity Metric | (1) | (2) |
|---|---|---|
| **Foot traffic at bars and restaurants** | | |
| Contemporaneous | -0.3560*** | -0.3733*** |
| | (0.0198) | (0.0179) |
| One month lag | -- | 0.0413*** |
| | | (0.0151) |
| **Cases** | | |
| Contemporaneous | -0.0008** | -0.0009*** |
| | (0.0004) | (0.0003) |
| One month lag | -- | 0.0009*** |
| | | (0.0003) |
| **Deaths** | | |
| Contemporaneous | 0.0855*** | 0.0665*** |
| | (0.0114) | (0.0119) |
| One month lag | -- | 0.0122 |
| | | (0.0096) |
| $R^2$ | 0.191 | 0.187 |

Source: Authors' calculations using data from Parolin and Lee (2021), SafeGraph, and Johns Hopkins

Note: The outcome captures the share of students in a county experiencing a school closure in a given month from Parolin and Lee (2021). Foot traffic at bars and restaurants captures the percent change in total visits to all bars and restaurants in a county in that month relative to the same calendar month in 2019 using SafeGraph data. Cases and deaths capture new cases and deaths per 1,000 people in the county over each month. The table shows the coefficients and standard errors (clustered by county) from a regression of school closures on the specified COVID-19 metrics including both county and month fixed effects.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 2. Difference-in-differences estimates of the effect of school closures on application rates, by school closure quintile

| Period | Quintile 1 | Quintile 2 | Quintile 3 | Quintile 4 | Quintile 5 |
|---|---|---|---|---|---|
| **Panel A** | | | | | |
| 2020–21 * Onset | 0.0015 | -0.0015 | -0.0032** | -0.0022 | -0.0013 |
| virtual | (0.0013) | (0.0013) | (0.0015) | (0.0016) | (0.0014) |
| **Panel B** | | | | | |
| Fall 2020 * | 0.0028** | -0.0007 | -0.0020 | -0.0012 | -0.0016 |
| Onset virtual | (0.0013) | (0.0013) | (0.0014) | (0.0015) | (0.0013) |
| Spring 2021 * | 0.0013 | -0.0012 | -0.0033** | -0.0020 | 0.0001 |
| Onset virtual | (0.0013) | (0.0014) | (0.0015) | (0.0016) | (0.0015) |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 3. Placebo estimates for the effects of school closure on application rates using data from different years

| Period | Main estimate (2017-2021) | 2016-2020 | 2015-2019 | 2014-2018 | 2013-2017 |
|---|---|---|---|---|---|
| **Panel A** | | | | | |
| 2020–21 * | -0.0032** | 0.0005 | 0.0001 | -0.0016* | -0.0012 |
| Onset virtual | (0.0013) | (0.0011) | (0.0011) | (0.0009) | (0.0009) |
| **Panel B** | | | | | |
| Fall 2020 * | -0.0048*** | -0.0021** | -0.0013 | -0.0005 | -0.0011 |
| Onset virtual | (0.0013) | (0.0010) | (0.0012) | (0.0011) | (0.0010) |
| Spring 2021 * | -0.0015 | 0.0032** | 0.0015 | -0.0029*** | -0.0012 |
| Onset virtual | (0.0015) | (0.0015) | (0.0011) | (0.0009) | (0.0010) |

Source: Authors' calculations

Note: Uses data on school closures in September 2020, but considers outcomes of student age applications measured in previous years. The estimates in the first column show the same information from Table 2, using data from January 2017 through June 2021. All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). In other columns, the outcomes are measured over the same calendar months, but 1, 2, 3, and 4 years earlier. Onset virtual captures the percentage of students in virtual schooling as of September 2020 in all columns. Thus, the columns besides the main estimate represent a placebo test for if applications dropped in the counties that closed schools during the same calendar months before the pandemic.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 4. Triple difference estimates for the effects of school closures on application rates, differencing off data from prior years

| Period | Main estimate (2019-2021) | 2018-2020 | 2017-2019 | 2016-2018 | 2015-2017 |
|---|---|---|---|---|---|
| **Panel A** | | | | | |
| 2020–21 * | -0.0032** | -0.0033*** | -0.0022 | -0.0004 | -0.0009 |
| Onset virtual | (0.0013) | (0.0010) | (0.0014) | (0.0016) | (0.0017) |
| **Panel B** | | | | | |
| Fall 2020 * | -0.0048*** | -0.0021* | -0.0021 | -0.0029* | -0.0023 |
| Onset virtual | (0.0013) | (0.0012) | (0.0015) | (0.0015) | (0.0017) |
| Spring 2021 * | -0.0015 | -0.0044*** | -0.0022 | 0.0021 | 0.0004 |
| Onset virtual | (0.0015) | (0.0014) | (0.0016) | (0.0019) | (0.0019) |

Source: Authors' calculations

Note: Uses data on school closures in September 2020, but estimates a triple difference specification, where the third difference is for student age applications measured in previous years. The estimates in the first column show the same information from Table 2, using data from January 2017 through June 2021. All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). In other columns, the outcomes are measured both during the main time period and over the same calendar months, but 1, 2, 3, and 4 years earlier. Onset virtual captures the percentage of students in virtual schooling as of September 2020 in all columns. These are also interacted with an indicator for data coming from the 2019 to 2021 period. Thus, the columns besides the main estimate represent a triple difference specification that differences off the extent to which applications dropped in the counties that closed schools during the same calendar months before the pandemic.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 5. Sensitivity of estimates for application rates to including time-varying controls

| Period | Main estimate (all controls) | No controls | COVID-19 cases and deaths | Foot traffic to restaurants and bars | County UE rate | Distance to SSI field office X month |
|---|---|---|---|---|---|---|
| **Panel A** | | | | | | |
| 2020–21 * | -0.0032** | -0.0008 | -0.0012 | -0.0035*** | -0.0004 | 0.0013 |
| Onset virtual | (0.0013) | (0.0012) | (0.0012) | (0.0011) | (0.0011) | (0.0013) |
| **Panel B** | | | | | | |
| Fall 2020 * | -0.0048*** | -0.0024* | -0.0034*** | -0.0047*** | -0.0020* | -0.0003 |
| Onset virtual | (0.0013) | (0.0012) | (0.0013) | (0.0011) | (0.0011) | (0.0013) |
| Spring 2021 * | -0.0015 | 0.0008 | 0.0009 | -0.0021 | 0.0011 | 0.0028** |
| Onset virtual | (0.0015) | (0.0013) | (0.0013) | (0.0014) | (0.0012) | (0.0014) |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. The first column shows the main specification (from Table 2), which includes all the time-varying controls. The second column shows the results if no controls are included. Each subsequent column shows the results if only that specific time-varying control is included. UE rate refers to unemployment rate.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 6. Estimates for the effects of school closure on application rates using different months to define school closures

| Period | Main estimate (9/20) | 10/20 | 11/20 | 12/20 | 1/21 | 2/21 | 3/21 | 4/21 | 5/21 |
|---|---|---|---|---|---|---|---|---|---|
| Pandemic * Onset virtual | 0.0034** | 0.0045*** | 0.0042*** | 0.0037*** | -0.0010 | -0.0021 | -0.0010 | -0.0018 | -0.0024 |
| | (0.0015) | (0.0015) | (0.0014) | (0.0013) | (0.0016) | (0.0018) | (0.0021) | (0.0027) | (0.0029) |
| Post * Onset virtual | -0.0026* | -0.0009 | 0.0005 | 0.0010 | -0.0022 | -0.0037** | -0.0019 | -0.0019 | 0.0002 |
| | (0.0014) | (0.0014) | (0.0016) | (0.0014) | (0.0016) | (0.0018) | (0.0020) | (0.0026) | (0.0027) |

Source: Authors' calculations

Note: Varies the months in which onset virtual is measured, which captures the percentage of students in virtual schooling as of the month specified in the column title. All estimates are relative to the pre-period. The pre-period includes all months from January 2019 to March 2020. The pandemic period captures April 2020 through the month immediately preceding the month of school closure. The post-period refers to the month of school closure through June 2021.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 7. Difference-in-differences estimates of the effect of school closures on application rates, by county special education prevalence

| Period | Low special education (below median) | High special education (above median) | *p*-value of difference |
|---|---|---|---|
| **Panel A** | | | |
| 2020–21 * Onset virtual | -0.0021 | -0.0069*** | 0.075 |
| | (0.0016) | (0.0022) | |
| **Panel B** | | | |
| Fall 2020 * Onset virtual | -0.0034** | -0.0089*** | 0.059 |
| | (0.0017) | (0.0023) | |
| Spring 2021 * Onset virtual | -0.0007 | -0.0050** | 0.135 |
| | (0.0018) | (0.0024) | |
| 2019 average | 0.0337 | 0.0401 | |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. The number of special education students are available for local education agencies from the Civil Rights Data Collection. We then aggregate both the number of special education students and number of enrolled students across local education agencies in the county. Counties are then divided by whether they fall above or below the weighted median in terms of the share of students in special education.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.

Appendix Table 8. Difference-in-differences estimates of the effect of school closures on application rates, by state UI generosity

| Period | Low UI generosity (below median) | High UI generosity (above median) | *p*-value of difference |
|---|---|---|---|
| **Panel A** | | | |
| 2020–21 * Onset virtual | -0.0069*** | -0.0002 | 0.003 |
| | (0.0020) | (0.0015) | |
| **Panel B** | | | |
| Fall 2020 * Onset virtual | -0.0086*** | -0.0016 | 0.003 |
| | (0.0020) | (0.0015) | |
| Spring 2021 * Onset virtual | -0.0052** | 0.0013 | 0.010 |
| | (0.0022) | (0.0018) | |
| 2019 average | 0.0390 | 0.0355 | |

Source: Authors' calculations

Note: All estimates are relative to the pre-period of January 2017 to August 2020. In Panel A, the post-period refers to September 2020 to June 2021, the 2020–21 school year. In Panel B, the post-period is divided into the fall 2020 semester (September 2020 to January 2021) and the spring 2021 semester (February 2021 to June 2021). Onset virtual captures the percentage of students in virtual schooling as of September 2020. To calculate UI generosity, we calculated expected UI benefits by multiplying the average replacement rate for those who get UI benefits by the recipiency rate among those eligible. Both measures are available from the Department of Labor. States are then divided by whether they fall above or below the weighted median for UI generosity.

***/**/* indicate estimate is significantly different from 0 at the 1/5/10 percent level.