School Closures and Effective In-Person Learning during COVID-19*

André Kurmann
Drexel University

Etienne Lalé
Université du Québec
à Montréal

July 23, 2022

Abstract

Social scientists have developed several schooling mode trackers to measure in-person, hybrid, and remote learning of students during the COVID-19 pandemic. In this paper, we compare eight of the most popular trackers for the U.S. and uncover substantial temporal and geographical differences, due in large part to how the trackers define the three schooling modes. We then estimate a new measure of effective in-person learning (EIPL) that combines information on school learning mode with cell phone data on school visits. The new measure provides a single number of the fraction of time that students spent learning in person and is made publicly available for a large, representative sample of both public and private schools. Consistent with other studies, we find that a school's share of non-white students and a school's prepandemic grades and size is associated with less in-person learning during the 2020-21 school year. Notably, we also find that schools in more affluent localities with higher pre-pandemic spending and schools receiving more federal emergency funding provided lower EIPL. These results are explained in large part by regional differences, reflecting political preferences, vaccination rates, teacher unionization rates, and local labor conditions.

JEL Classification: E24, I24
Keywords: COVID-19; School closures and reopenings; Effective in-person learning; Inequality

*Contact: Kurmann: Drexel University, LeBow College of Business, School of Economics, 3220 Market Street, Philadelphia, PA 19104 (email: kurmann.andre@drexel.edu); Lalé: Université du Québec à Montréal, Department of Economics, C.P. 8888, Succ. centre ville, Montréal (QC), H3C 3P8 Canada (email: lale.etienne@uqam.ca). Aseni Ariyaratne provided excellent research assistance. We thank Dennis Roche from Burbio, Nat Malkus from Return to Learn, and Safegraph for generously sharing their data. We also thank seminar participants at the 2nd joint IZA & Jacobs Center Workshop on "Consequences of COVID-19 for child and youth development" for their comments. The data constructed in this paper is available through the online repository of the Center for Open Science: http://doi.org/10.17605/osf.io/cghs2. All errors are our own.

1 Introduction

The COVID-19 pandemic led many schools in the U.S. to suspend or substantially reduce in-person learning. While available studies report conflicting results on the extent to which school closures helped prevent the spread of the virus,[1] evidence is emerging that remote instruction led to substantial learning losses and social-emotional harm with possibly large adverse long-term effects, especially for students from disadvantaged backgrounds.[2] Faced with the challenge of analyzing these consequences, different organizations have developed trackers to measure the amount of in-person, hybrid, and remote schooling that students obtained during the pandemic.

The objective of this paper is threefold. First, we compare existing schooling mode trackers and assess the extent to which they provide a consistent picture of in-person education during the pandemic. Second, we combine information from existing trackers with cell phone data on school visits to estimate a new measure of effective in-person learning (EIPL) for a large, representative sample of both public and private schools. Third, we study the association of EIPL with a host of school- and region-specific demographic and socio-economic indicators.

We compare eight of the most prominent trackers that collected information on schooling mode from school districts and state educational agencies or by directly surveying schools. We find large variations across the trackers in the percentages spent in the different schooling modes by region and time period. These variations, which are due to how each tracker defines the three schooling modes as well as coverage issues, also manifest themselves in differences in statistical associations of the trackers with regional, demographic, and socio-economic indicators. The variations pose an important challenge for researchers interested in documenting the extent and consequences of school closures across the U.S.

Motivated by these findings, we propose a new measure of the time that students effectively spent learning in person – EIPL. The measure maps anonymized cell phone data from Safegraph on visits to individual schools to information from schooling mode trackers. The mapping allows us to use school visits to estimate the fraction of hybrid learning that took place on an in-person basis and then select for each region the tracker information that provides the best fit with the visits data. The result is a single number of the relative importance of EIPL for the student population enrolled at a school. We estimate this number for a sample of more than 70,000 public and private schools that is highly representative of the universe of U.S. schools.

Compared to the existing schooling mode trackers, the EIPL measure has several advantages. It naturally addresses coverage issues with the different trackers; it is available for a large sample of both public and private schools at a weekly frequency for the entire 2020-21 school year; and the single number characteristic makes it more amenable to analyze the relationship with other variables than categorical indicators.[3] We make the EIPL dataset publicly available through the online repository of the Center for Open Science and hope it will be useful for other researchers.

[1] See Bravata et al. [2021], Chernozhukov et al. [2021a,b], Ertem et al. [2021], and the references therein, for systematic assessments of the effect of school closures on subsequent COVID-19 infections.

[2] See Dorn et al. [2021a], Halloran et al. [2021], Kogan and Lavertu [2021], Lewis et al. [2021], Goldhaber et al. [2022b] as well as Agostinelli et al. [2022], Jang and Yum [2020] or Fuchs-Schündeln et al. [2022] among others.

[3] As an example, consider two schools that experience the same increase in a tracker's in-person schooling mode but where one school was previously in remote mode and the other was previously in hybrid mode. The tracker's in-person measure would erroneously attribute the same increase in in-person learning to both schools, whereas our EIPL measure takes into account that hybrid schooling provides a certain amount of in-person learning. For further discussion and examples, see the main text.

In the last part, we investigate the extent to which pre-pandemic school and local characteristics correlate with EIPL during the 2020-21 school year. Naturally, these correlations should not be interpreted as causal, but they provide us with a set of stylized facts to understand the factors behind school closings and which segments of the student population were most affected. We find the following main results:

1. Public schools provided substantially less EIPL than private schools, with public charter schools ranking below public non-charter schools and private religious schools ranking above private nonreligious schools.

2. For both public and private schools, EIPL was lower in more affluent and more educated localities with a larger share of dual-headed households, and for schools with a larger share of non-white students.

3. For public schools, EIPL is negatively related to pre-pandemic school test scores, school size, and school spending per student as well as district Elementary and Secondary School Emergency Relief (ESSER) funding per student.

Finally, we show that a large part of these associations can be explained by a school's county share of Republican votes in the 2020 presidential election. COVID vaccination rates also predict higher EIPL while a state's teacher unionization rate and local labor conditions for teachers predict lower EIPL. In contrast, COVID case and death rates and whether a school is located in a dense, urban area do not have significant predictive power.

The relation of EIPL with race, school quality, size, spending per student, and Republican voting preferences validate results already documented in the literature (see, e.g., Gollwitzer et al. [2020]; Hartney and Finger [2020]; Parolin and Lee [2021]; Landivar et al. [2022]). This confirms that the proposed EIPL measure captures a component that is common across different school trackers. At the same time, our analysis establishes two results that, to the best of our knowledge, have not been highlighted before. First, we document a new nexus between income and public school closures: EIPL was on average lower – not higher – in more affluent localities; and this correlation is in large part accounted for by Republican voting preferences. Second, EIPL is negatively related to district ESSER funding per student, despite the fact that the program was advertised in Congress primarily as support for schools to reopen to in-person learning.

Taken together, the results suggest that at the national level, less affluent communities provided on average more EIPL. At the local level, however, schools that are on average associated with worse student outcomes provided less EIPL. These findings raise critical questions about education policy during the pandemic and the impact of in-person learning loss on future educational attainment as well as income inequality.

The paper is part of a growing literature that attempts to measure the extent and consequences of school closures during the pandemic. As reviewed below, several organizations and research teams have developed schooling mode trackers, among them Burbio, the Evidence Project, the COVID-19 School Data Hub, the Elementary School Operating Status team, and the American Enterprise Institute. In parallel, a number of studies have used school visits from anonymized cell phone data, in particular Safegraph, to proxy school closures during the pandemic: see Bravata et al. [2021], Chernozhukov et al. [2021a], Parolin and Lee [2021], Garcia and Cowan [2022], Hansen et al. [2022]. Our methodological contribution consists in combining these two data sources to develop a single number of the time effectively spent learning in person that we estimate for a large sample of schools. As described above, this number has clear merits over the existing

trackers, not just because of its granularity and coverage, but because categorical variables can provide a misleading measure of in-person learning as reflected by the large variations across trackers.[4] In turn, the use of cell-phone based school visits data alone is subject to issues of interpretation and measurement error. First, without additional information, it is not clear what a given decline in visits to a school during the pandemic represents in terms of lost in-person learning.[5] Second, attributing cell phones to a particular location is challenging, and our analysis reveals that this leads to very noisy data for a non-negligible number of schools. When building our EIPL measure, we therefore impose stringent quality checks and only retain schools for which the visits data is reliable.

Our EIPL measure can be used as an input for numerous analyses of the effects of pandemic school closures, such as on COVID infections and deaths (Auger et al. [2020]; Bravata et al. [2021]; Chernozhukov et al. [2021a]; Ertem et al. [2021]; Goldhaber et al. [2022a]); on local labor market (Garcia and Cowan [2022]; Hansen et al. [2022]; Landivar et al. [2022]; Prados et al. [2021]); on public school student enrollment (Dee et al. [2021]); on student learning achievement (Dorn et al. [2021b]; Halloran et al. [2021]; Engzell et al. [2021]; Kogan and Lavertu [2021]; Goldhaber et al. [2022b]), and on long-term income inequality and welfare (Agostinelli et al. [2022]; Jang and Yum [2020]; Fuchs-Schündeln et al. [2022]).[6] This literature is still at an early stage and rapidly expanding. In this respect, our regression results of EIPL against a rich set of local and regional indicators may serve as a useful guide for further analysis.

The paper proceeds as follows. Section 2 is our review and comparison of information provided by the schooling mode trackers. Section 3 explains our empirical approach for measuring EIPL based on learning mode data combined with school visits. The correlation study of EIPL with local population, school, and regional indicators is presented in Section 4. 5 concludes.

2 Comparison of schooling mode trackers

This section provides a comparison of what we consider to be some of the most prominent schooling mode trackers. To our knowledge, there exists no systematic review to help guide researchers interested in using these data to study pandemic school closures.

We consider schooling mode trackers that were constructed from guidelines and/or practices posted publicly by school districts and state educational agencies or by directly surveying schools. We do not impose any restriction on the mode of data collection, which may differ in terms of frequency, systematicity, and sampling methods. However, we do require that the primary data collected is from direct source of information about school learning modes. We require that the data are at a sub-national level.

We use several tools to conduct a wide search of available schooling mode trackers. We use Scopus's document search tools for the following keywords: "COVID-19", "School closure", "School reopening", and

[4] A blogpost by Camp and Zamarro [2022] also discusses issues of comparability for three of the schooling mode trackers reviewed below. Our work substantially expands over this discussion.

[5] Suppose cell phone usage is concentrated among school staff and parents. If school staff returned to school more quickly than students (e.g. to prepare the return of students or to teach only some students in person while others remained in remote-learning mode) or if students get dropped off and picked up by parents instead of using buses, then foot traffic data alone would overestimate in-person learning during the pandemic. Vice versa, consider a school that contains a playground or sports fields that are usually open to the public or used for games. If due to the pandemic, access to this playground or sports field is restricted even though the school has reopened, then cell phone traffic alone would underestimate in-person learning.

[6] Fuchs-Schündeln et al. [2022] represents a first application, using an earlier version of our EIPL. The version here is substantially expanded, exploiting additional information from schooling mode trackers across different regions and time periods.

"Schooling mode" (filtering on the date when they first appeared). We conduct a similar search on Mendeley, the Center for Open Science, and the open ICPSR data repository. We manually check the first 100 papers matching those keywords on Google scholar. Finally, we search on Google as well as on several education blogs to find data that may not have been used in academic research.

We end up with eight trackers that fit our definition: Burbio, the Center on Reinventing Public Education (CRPE), the COVID-19 School Data Hub (CSDH), Education Week (EdWeek), the Elementary School Operating Status (ESOS) database, the School Survey Dashboard of the Institute of Education Sciences (IES-SSD), MCH strategic data (MCH), and Return2Learn (R2L).

Table 1 overviews the trackers in terms of data structure and coverage, data source and collection methods, and available measures. There are a number of key differences across trackers. First, the time frequency, geographical coverage, and level of aggregation vary. On the one hand, CSDH offers the highest level of disaggregation, in the sense that it includes data at the school level, but only a subset of the CSDH schools have information available at the weekly frequency (about 10,000 schools). R2L, Burbio and EdWeek, on the other hand, provide data at the weekly frequency, but only at the district-, county-, and state-level, respectively. Second, the data collection methods are different, and as a result the degree of systematicity is not uniform across trackers. Some collected data at a lower cost (e.g. web scrapping) to increase coverage and hence representativeness; others, such as the CRPE, selected a smaller set of school districts and calculated sampling weights to extrapolate statistics from the selected districts. Third, with the exception of EdWeek, the trackers agree on the choice of the measured items – whether a school offers mostly in-person, hybrid, or remote learning – but there are important differences in how each tracker defines these indicators. In particular, depending on the tracker, hybrid learning may refer to part-day, part-week, rotating weeks, or alternating grades; and the fraction of part-day / part-week to qualify for hybrid learning varies (see Table 1 of the online appendix for details).

Table 1: Overview of schooling mode trackers

Data structure and coverage	Data source and collection method	Measures
Burbio		
• Balanced panel • Weekly data spanning the 2020-21 school year • 3,214 counties (aggregation of data collected from 1,200 school districts)	• Web scraping of school district websites, local news reports, social media, and other publicly available information. • Use the most in-person option available to the general student population to assign a learning mode to the school district.	% of school districts (weighted by student enrollment) within a county that operate in either In-Person, Hybrid, or Remote learning
CRPE (Center on Reinventing Public Education)		

• Panel data sampled at irregular time intervals • Three point-in-time data collection during the Summer and Fall term of 2020 (Jul.26 - Aug.1, Aug.16 - Aug.22, Nov.1 - Nov.7) • 477 school districts	• Web scraping of school district websites, local news reports, social media, and other publicly available information • CRPE data comes with assigned district weights created by the RAND corporation to create a representative sample	0/1 indicators of either In-Person, Hybrid, or Remote learning
COVID-19 School Data Hub (CSDH)		
Mixed levels and data frequencies: • Weekly: 10,121 sch. / 3,301 dist. • Bi-weekly: 4,725 sch. / 540 dist. • Monthly: 33,086 sch. / 1,380 dist. • Quarterly: 144 districts • Bi-annual: 11,928 sch.	• Data requests submitted to state education agencies for their record of learning models used during the 2020-21 school year. Data requested at either the school or district level, as available by the state, and at the most frequent reporting intervals available. • CSDH team communicated with the state for clarification when questions arose regarding data inconsistencies, missing information, etc.	0/1 indicators of either In-Person, Hybrid, or Remote learning
Education Week (EdWeek)		
• Balanced panel • Weekly data spanning the 2020-21 school year • 50 states, the District of Columbia and Puerto Rico	• Information gathered from orders or recommendations issued at the state level, and public statements or actions from governors and state officials. State order may be subject to waivers or overridden by other officials.	0/1 indicators for multiple categories: Full closure (and whether in effect or not), Partial closure, Ordered open, No order in effect, Some grades ordered open, Only hybrid or remote instruction
Elementary School Operating Status database (ESOS)		
• Panel data sampled at irregular time intervals • Two point-in-time data collection: Sep.20-30, 2020 and Apr.20-30, 2021 • 9,195 elementary school districts	• Information gathered from elementary school reopening plans broadly available to the public as parents and local communities.	0/1 indicators of either In-Person, Hybrid, or Remote learning, with several options for Hybrid learning (part day / part week / rotating weeks / other)
School Survey Dashboard of the Institute of Education Sciences (IES-SSD)		

• Unbalanced panel (some states or jurisdictions do not participate or do not meet the minimum participation guidelines for reporting in all waves) • Monthly frequency from January through May 2021 • 50 states, the District of Columbia and Puerto Rico	• Survey administered through a web-based data collection system in jurisdictions that have agreed to participate. Intended survey respondents are school or district test coordinators (State coordinators also invited to respond to individual school surveys or submit results for many schools at once).	% of student enrolled in either In-Person, Hybrid, or Remote learning
MCH strategic data		
Two cross-sectional datasets for the 2020-21 school year: • Fall 2020: 14,893 school districts • Spring 2021: 16,727 school districts	• Proprietary data compilation process and scoring method, with is continuous data updated throughout the school year.	0/1 indicators of either In-Person, Hybrid, or Remote learning, with several options for In-Person (full / on premises) and Hybrid learning (full / partial)
Return2Learn (R2L)		
• Balanced panel • Weekly data spanning the 2020-21 school year • 8,608 school districts	• Web scraping of school district websites, local news reports, social media, and other publicly available information. • Weekly updates of the data using a machine learning approach to analyze whether the new content indicates a change in operational status.	0/1 indicators of either In-Person, Hybrid, or Remote learning

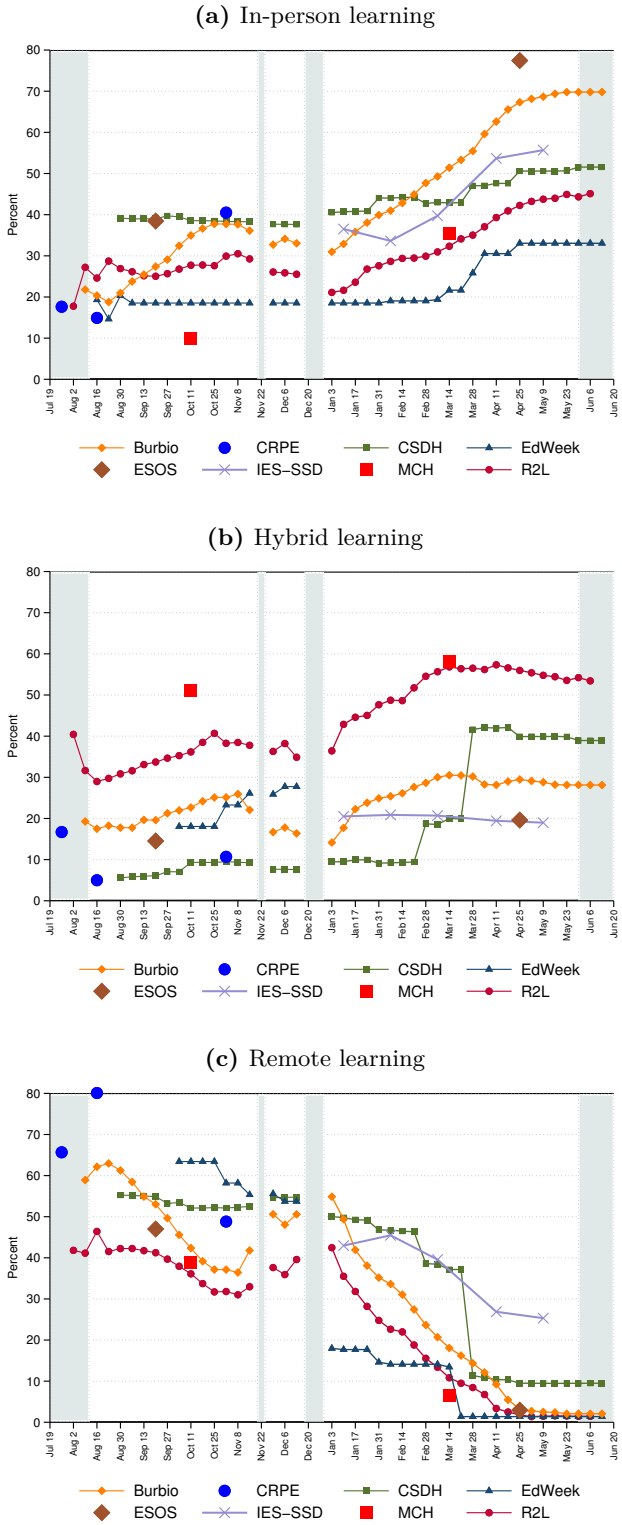
Notes: The table describes the structure, coverage, data source and collection methods, and measurements provided in eight publicly-available learning mode trackers.

Figure 1 compares the schooling modes of 2020-21 according to the different trackers.[7] While they generally evolve in the same direction, there are also large differences in both magnitude and timing. In particular, there is substantial disagreement about the extent to which schools returned to in-person learning, and whether this return was mainly due to a shift away from hybrid or remote learning. Moreover, while Burbio, R2L, and IES-SSD predict a relatively smooth transition out of remote learning during the Spring term, the CSDH and EdWeek report more abrupt changes, likely due to the frequency of the data collection process. In sum, the eight trackers paint a qualitatively similar but quantitatively different picture of school closures and the provision of in-person learning during the pandemic.

Aside from the large variations in average schooling mode over time, there are also large geographic

[7] Figure 1 presents the student-weighted average of each learning mode from each tracker. For CSDH, we average data using school-level and district-level student enrollment data. For schools districts that also have school-level data available in CSDH, we first aggregate data to the district level by taking the (student-weighted) average of the district-level and school-level indicators. For EdWeek, data for hybrid and remote learning is discontinued over the sample period (panels (b) and (c) of Figure 1). For MCH, the data is collected at various, potentially irregular, point in time within each semester (making it difficult to assess whether MCH data match the timing of changes across learning modes); the MCH data in Figure 1 are plotted at the midpoint of the Autumn and Spring semesters.

Figure 1: Comparison of Schooling Mode Trackers



Notes: The figures show the percentage share of each learning mode according to the different trackers, aggregated using public school student enrollment at either the school, district, county, or state level. The learning mode trackers are: Burbio, the Center on reinventing public education (CRPE), the COVID-19 school data hub (CSDH), EducationWeek (EdWeek), the Elementary school operating status (ESOS) database, the School survey dashboard of the Institute of Education Sciences (IES-SSD), MCH strategic data (MCH), and Return2Learn (R2L). The shaded regions denote the Summer, Winter, and Thanksgiving breaks.

variations between the trackers. Consider for instance Burbio and R2L, which according to 1 appear to be fairly well correlated with each other. Yet, across all counties and weeks of the 2020-21 school year, the correlation between Burbio's and R2L's share of in-person learning is 0.59, and the correlation for hybrid learning is 0.45. Digging deeper, the county-level correlation over time of the two trackers' share of in-person learning is *negative* for about 20% of all counties, with an interquartile range of correlations of 0.78 (similar results obtain for the share of hybrid learning). For the other trackers, the regional disparities in schooling mode are even larger.

While a detailed analysis is beyond the scope of this paper, our assessment of the data suggests the definition of the three schooling modes and in particular hybrid learning is the main reason for the differences between school trackers. In addition, the trackers vary substantially in terms of coverage across regions, which leads to both geographic and average variations over time. These differences pose an important challenge for the study of school closures across the U.S. and how the resulting loss of in-person learning affects school enrollment and learning outcomes of students from different backgrounds. Indeed, as we explain below, the variations in schooling mode trackers lead to large differences in the statistical association of each tracker with local school and socio-economic indicators as well as regional characteristics.

3 From changes in school visits to effective in-person learning

This section describes how we use school visits data together with information from different schooling mode trackers to construct our EIPL measure. Details and additional analysis are provided in the online appendix.

3.1 Data, sample restrictions, and measurement of changes in school visits

A key input for our EIPL measure comes from Safegraph, a private company which provides data on over 7 million Places of Interest (POIs) for the U.S., including visits derived from over 40 million anonymized cell phones. We retain all POIs with North American Industry Classification System code 611110 ("Elementary and Secondary Schools") that have weekly visit data. We match these POIs by school name and geo-location or address to the universe of public and private schools from the NCES's Common Core of Data and the Private School Universe Survey, which results in about 110,000 high-quality matches. Relative to the universe of schools, we lose about 12,000 schools. The matched sample remains highly representative in terms of demographic and geographic makeup.

The weekly visit count for each school is organized in seven dwell time intervals, ranging from less than 5 minutes to more than 240 minutes. Visits decline during major holidays and summer break; drop precipitously on March 13, 2020 and remain substantially lower on average thereafter. At the same time, due to the increase in cell phones covered by Safegraph, visits generally trend upward prior to the pandemic; and visits to individual schools can be subject to substantial variation, both from one week to another and across dwell time intervals. While some of these variations reflect school characteristics and idiosyncratic events, others are due to the inherent difficulty of attributing cell phones to a particular location.

To address these measurement issues, we proceed in three steps. First, we construct a dwell-time weighted average of weekly visits for each school that is normalized by the weekly count of cell phones covered by

Safegraph at the state level:

$$\widetilde{v}_{j,t} = \frac{1}{n_{s(j),t}} \sum_{d=1}^{7} \omega_j(d) v_{j,t}(d), \tag{1}$$

where $v_{j,t}(d)$ denotes raw visits of dwell time d for school j in week t; $\omega_j(d) = \frac{\sum_{t=t_{-1}}^{t_0} v_{j,t}(d)}{\sum_{t=t_{-1}}^{t_0} v_{j,t}}$ measures the importance of visits of dwell time d for school j during reference period $t = t_{-1}, \ldots, t_0$ beginning in November 2019 through the end of February 2020 (excluding the weeks of Thanksgiving, Christmas and New Year); and $n_{s(j),t}$ is the normalization by the count of devices in state $s(j)$ in which school j is located.

Second, we drop about 37,000 schools with sparse or noisy visit data – an issue that seems to be overlooked by existing analyses of the Safegraph data. This step is important in terms of sample construction. For the approximately 73,000 schools that remain, we construct sample weights that keep the dataset representative of the universe of schools. We estimate these weights using a Probit model where the dependent variable is an indicator taking the value of 1 for schools that are included in the dataset and is 0 for schools not matched to Safegraph or with sparse or noisy visit data; and the regressors are county-level measures of family structure and education, population density, geographic locale of a school, and Census region dummies. The estimated school-level sample weights are included in the public release of our dataset.

In the final step, we construct the change in school visits as the percent difference in dwell-time weighted, normalized visits relative to the average $\widetilde{v}_{j,0} = \frac{1}{t_0 - t_{-1} + 1} \sum_{t=t_{-1}}^{t_0} \widetilde{v}_{j,t}$ over the reference period:

$$\Delta\widetilde{v}_{j,t} = 100 \times \frac{\widetilde{v}_{j,t} - \widetilde{v}_{j,0}}{\widetilde{v}_{j,0}}. \tag{2}$$

3.2 Estimating effective in-person learning

To estimate EIPL, we map changes in Safegraph school visits, $\Delta\widetilde{v}_{j,t}$, to changes in learning mode from Burbio and R2L. The reason we select the Burbio and R2L schooling mode data is that they provide high-frequency (i.e. weekly) variations that enable us to measure the substitution across learning modes and thereby extract the component of hybrid learning that is effectively done in person.[8] Our approach proceeds in two steps. First, we aggregate changes in weekly visits to the county level for Burbio, respectively the district level for R2L, and estimate the mapping. Second, we use the estimates to predict EIPL at the individual school level.

For expositional purposes, we focus on the county-level aggregation; the steps for the district-level aggregation are analogous. Denote by $\Delta\widetilde{v}_{c,t} = \sum_{j \in c} \kappa_j \Delta\widetilde{v}_{j,t}$ the average change in school visits in county c in week t relative to the reference period, where κ_j is the share of county c's students enrolled in school j. Next, define the fraction of total school time that is EIPL by students in county c during week t as

$$EIPL_{c,t} = T_{c,t} + \gamma H_{c,t}, \tag{3}$$

where $T_{c,t}$ is the share of school time in traditional in-person learning mode, $H_{c,t}$ is the share in hybrid learning mode, and γ defines the fraction of hybrid learning spent in person.

Since both $\Delta\widetilde{v}_{c,t}$ and $EIPL_{c,t}$ measure percent deviations from the pre-pandemic baseline, we can

[8] See Table 1. Weekly data are also available from CSDH and EdWeek. However, the weekly CSDH data covers about 10,000 schools (most schools in CSDH are observed at the monthly frequency), and the EdWeek data is at the state level.

formulate the relationship between the two variables as $EIPL_{c,t} = \alpha + \beta\Delta\widetilde{v}_{c,t} + \varepsilon_{c,t}$, or equivalently

$$T_{c,t} = \alpha + \beta\Delta\widetilde{v}_{c,t} - \gamma H_{c,t} + \varepsilon_{c,t}. \tag{4}$$

The regression tells us not only how a given change in school visits maps into EIPL, but also the proportion γ of hybrid learning spent in person.

While (4) can be estimated as a panel across all counties, respectively school districts, one important concern is that the mapping between changes in school visits and learning modes may not always be the same; e.g. because of differences in hybrid learning arrangements across districts. A second concern is that the quality of the Burbio and the R2L data differs across region and time period. To address these concerns, we estimate (4) separately for Burbio and R2L at both the Core-Based Statistical Areas (CBSA) level and the state level. For each regression, we restrict $\alpha = 100$ as implied by the pre-pandemic baseline when schools were fully in person (i.e. $T_{c,0} = 100$, $\Delta\widetilde{v}_{c,0} = 0$, and $H_{c,0} = 0$), and find the regression time window with the highest R-squared. This provides us with four sets (Burbio-CBSA, R2L-CBSA, Burbio-state, R2L-state) of estimates $\left\{\hat{\beta}, \hat{\gamma}\right\}$ and associated R-squared for every school j. To predict $EIPL_{j,t}$, we then use the regression coefficients associated with the highest R-squared subject to the restrictions that the proportion of hybrid learning spent in person is within its theoretical bounds, $0 < \hat{\gamma} < 1$, and the R-squared is over 0.25.[9] Using the coefficient $\hat{\beta}$ obtained in this way, we compute EIPL at school j during week t as: $\hat{EIPL}_{j,t} = 100 + \hat{\beta}\Delta\widetilde{v}_{j,t}$. Observe that the algorithm effectively trades off geographic variation in regression coefficients with regression fit and does so by using either the Burbio or the R2L data that is of higher quality.[10]

Table 2: Mapping school visits to Effective In-Person Learning

(a) Source of regression coefficients to map school visits to EIPL

	Burbio (CBSA)	R2L (CBSA)	Burbio (State)	R2L (State)
Number of schools	21,615	17,098	16,166	18,348
Percent of schools	29.5	23.3	22.1	25.1

(b) Distribution of regression coefficients to map school visits to EIPL

	Mean	Percentile				
		5th	25th	50th	75th	95th
$\hat{\beta}$	1.18	0.72	1.13	1.20	1.27	1.43
$\hat{\gamma}$	0.29	0.04	0.17	0.27	0.37	0.63
R squared	0.81	0.45	0.68	0.88	0.96	0.99

Notes: Panel (a) shows the distribution of schools by type of regression coefficient retained for the OLS estimation of (4). Panel (b) shows the distribution of retained regression coefficients and R-squared, weighted by the different school weights.

Table 2 reports summary statistics for the estimated coefficients retained to predict $EIPL_{j,t}$. As shown

[9] The restrictions on $\hat{\gamma}$ applies only in a few cases. R-squared is lower than 0.25 for all four regressions in Arkansas and Maine, where both the Burbio and R2L data appear to be of low quality. For those, we use regression coefficients from neighboring states.

[10] We could apply the same algorithm at the county level. In many cases, however, this would result in R-squared that are lower than at the CBSA level. More generally, we have experimented with several modifications of the algorithm, and the results reported below remain very robust.

in panel (a), across the approximately 73,000 schools, the retained estimates are evenly distributed between Burbio and R2L and between the CBSA and state level, indicating that both Burbio and R2L data are useful and that allowing for finer geographic variation would in about half the cases produce a worse fit.[11]

Panel (b) shows the school-weighted distribution of the retained estimates and R-squared across schools. The regressions are generally tightly estimated with a median R-squared of 0.88. The estimated mapping between changes in school visits and EIPL, $\hat{\beta}$, ranges from about 0.7 to 1.4 while the estimated proportion of hybrid learning spent in person, $\hat{\gamma}$, ranges from 0.04 to 0.6. As confirmed in further analysis, these distributions reflect large regional variations in the mapping from school visits to EIPL. Focusing on means, a one percentage point decline in school visits predicts an average reduction in EIPL by 1.2 percentage points, and the predicted fraction of hybrid learning spent in person is 0.3 or the equivalent of 1.5 days out of a 5 day school week.

3.3 Relation of schooling mode trackers with EIPL

It is instructive to compare EIPL with the schooling mode trackers. In Table 3, we merge each tracker with our EIPL data (aggregated to either the district, county, or state level i, depending on the tracker) and calculate the bivariate correlation between average EIPL and the average share of in-person (T_i), hybrid (H_i) and remote (R_i) learning, respectively, for the time period covered by each of the schooling mode trackers.

Table 3: Effective In-Person Learning compared to schooling mode trackers

	Burbio	CRPE	CSDH school	CSDH district	EdWeek	ESOS	IES-SSD	MCH	R2L
	(1)	(2)	(3a)	(3b)	(4)	(5)	(6)	(7)	(8)
T_i	73.3	78.8	58.9	73.1	92.6	72.8	89.3	66.6	63.3
	(1.25)	(2.95)	(0.41)	(1.27)	(8.03)	(0.75)	(8.07)	(0.93)	(0.87)
H_i	-20.2	0.50	-14.2	2.4	-27.3	-28.9	-11.0	-15.3	-11.2
	(1.80)	(4.79)	(0.50)	(1.86)	(20.5)	(1.04)	(15.9)	(0.96)	(1.11)
R_i	-73.6	-69.6	-61.7	-74.8	-80.7	-72.1	-82.0	-60.7	-70.6
	(1.25)	(3.44)	(0.40)	(1.24)	(12.6)	(0.75)	(10.06)	(0.88)	(0.79)
# of geo. units	2,953 counties	438 districts	39,629 schools	10,275 districts	51 states	8,497 districts	51 states	11,991 districts	7,953 districts
# of weeks	45	3	49	49	43	2	5	2	45
% of data covered	94.0	91.8	66.2	73.3	100	92.4	100	71.5	92.4

Notes: The table reports the correlation between EIPL and the average share of in-person (T_i), hybrid (H_i) and remote (R_i) learning provided in the schooling mode trackers from: Burbio, the Center on reinventing public education (CRPE), the COVID-19 school data hub (CSDH), the Elementary school operating status (ESOS) database, the School survey dashboard of the Institute of Education Sciences (IES-SSD), MCH strategic data (MCH), and Return2Learn (R2L). EIPL, in-person, hybrid and remote learning are averaged over the weeks covered by the school tracker in each column of the table. Standard errors are in parentheses. The lower panel reports the number of overlapping geographic units and weeks, and fraction of the school tracker data that are covered by the EIPL database.

Across all trackers, the EIPL measure is strongly positively (negatively) correlated with the share of in-person (remote) learning. It is also remarkable that, despite the weak correlations across pairs of trackers evidenced in Figure 1, the correlations with EIPL are similar, suggesting that EIPL captures a common

[11] One may be concerned that the Safegraph data is more noisy in some parts of the country, but the pre-pandemic variance of visit changes is evenly distributed across CBSAs.

component. In contrast, the correlation with the share of hybrid learning is small and in some cases insignificantly different from zero. This reflects a fundamental characteristic of hybrid learning, that its relation with EIPL is non-linear. For regions that chose to keep schools closed for much of the 2020-21 school year, hybrid learning is low and so is EIPL. For regions that chose to reopen schools for most of the year, hybrid learning is also low but, naturally, EIPL is high. For regions in-between, hybrid learning is high while EIPL is moderate. This inverse hump-shaped pattern of hybrid learning with respect to EIPL represents an important, though perhaps underappreciated challenge for empirical analyses that use the share of hybrid learning as a regression variable. By combining in-person and hybrid learning, our estimation of EIPL circumvents this issue.

A final interesting result from Table 3 is that the EIPL dataset includes a large fraction of the schools covered across the different trackers. Two thirds of the schools in CSDH are present in our dataset; 70 to 90 percent of the school districts covered in other trackers are included in ours; and almost 95 percent of the counties from Burbio cover schools that are in our dataset. While the overlap is important, the EIPL dataset has clear advantages through its granularity: it allows to study schools separately by type (public charter/public non-charter/private religious/private nonreligious) and grade (elementary/middle/high), with each school equipped with a sampling weight to ensure representativeness. The school-level EIPL measure aggregates up in a way that is consistent with the categorical indicators of the three learning modes available from other, more aggregated data, while being easier to work with as it is a continuous variable.

4 EIPL during the pandemic: when, where, and for whom?

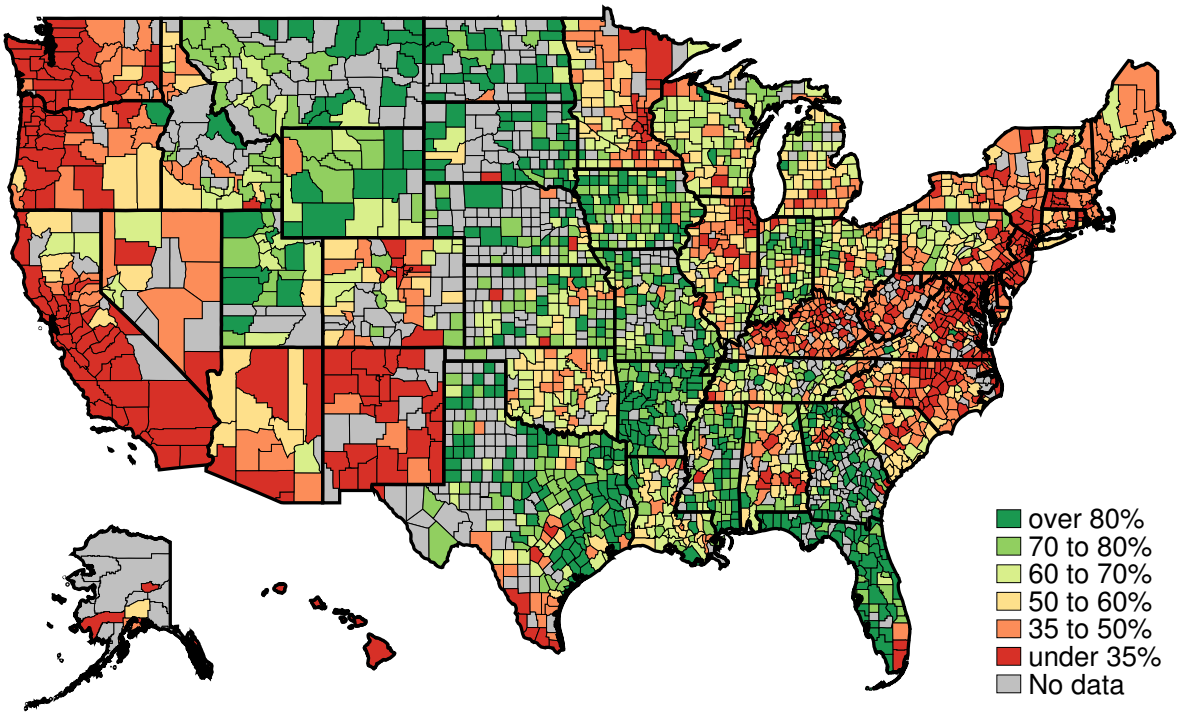
To illustrate the properties of our EIPL measure, we document differences in EIPL over time and across regions, and then turn to a host of characteristics that may account for those differences. Several results in this section have been established in prior studies, suggesting that the EIPL measure captures a component that is common across many schooling mode and schools' cell phone traffic databases. We clearly indicate those results and explain which of the findings are novel.

Panel (a) of Figure 2 describes the regional disparities in EIPL. After dropping to between 0% and 20% for almost all counties from March to May 2020 (see the appendix), EIPL recovered to 60% or higher in many counties in the South and Central North, while in counties in the North and Mid-Atlantic and the West it remained stuck in the 0% to 35% range. Panel (b) provides further information by reporting the top 10 and bottom 10 cities in terms of average EIPL from September 2020 through May 2021 among the 50 biggest U.S. cities by population. In cities in Florida such as Jacksonville, Tampa or Orlando, EIPL averaged over 75%, whereas in cities in California, Oregon and Washington such as Los Angeles, Portland or Seattle, EIPL averaged 20% or less.

Why did some schools return to in-person learning more quickly than others and what explains the large regional disparities? To answer this question, we analyze how various observable school and local characteristics surrounding the school correlate with EIPL. Then we return to geography and examine the extent to which these are driven by systematic regional differences. This correlational study highlights a set of facts that can help us understand the "for whom" in order to quantify the consequences of pandemic-induced learning losses for different segments of the student population and formulate appropriate policies going forward.

Figure 2: Regional Disparities in Effective In-Person Learning

(a) Effective in-person learning across U.S. counties during the 2020-21 school year



(b) The top 10 and bottom 10 U.S. cities in terms of effective in-person learning

Rank	CBSA name	EIPL	Rank	CBSA name	EIPL
1	Jacksonville, FL	87.6%	41	Sacramento-Arden-Arcade-Roseville, CA	22.9%
2	Tampa-St. Petersburg-Clearwater, FL	81.3%	42	Washington-Arlington-Alexandria DC-VA	22.9%
3	Orlando, FL	77.1%	43	Baltimore-Towson, MD	22.4%
4	Houston-Baytown-Sugar Land, TX	61.9%	44	Seattle-Bellevue-Everett, WA	20.3%
5	Fort Worth-Arlington, TX	61.8%	45	Portland-Vancouver-Beaverton, OR-WA	20.2%
6	Cincinnati-Middletown, OH-KY-IN	61.3%	46	San Jose-Sunnyvale-Santa Clara, CA	17.0%
7	Dallas-Plano-Irving, TX	60.7%	47	Las Vegas-Paradise, NV	16.5%
8	Detroit-Livonia-Dearborn, MI	58.3%	48	Los Angeles-Long Beach-Santa Ana, CA	16.4%
9	Nassau-Suffolk, NY	57.6%	49	Oakland-Fremont-Hayward, CA	15.9%
10	Nashville-Davidson--Murfreesboro, TN	57.4%	50	Riverside-San Bernardino-Ontario, CA	14.5%

Notes: The top panel shows the student-weighted average county EIPL from September 2020 to May 2021 by different percentile ranges for all counties for which we have reliable data on at least three schools. The bottom panel shows the top-10 and bottom-10 Core-Based Statistical Areas (CBSAs) in terms of average EIPL among the 50 largest CBSAs by population. EIPL for each CBSA is computed as the student-weighted average across schools with reliable data.

4.1 School type and grade

Perhaps the most obvious observable school characteristics are type (public non-charter, public charter, private non-religious, or private religious school) and grade (elementary school, middle school, high school, or a combination thereof) as designated by the NCES. From March to May 2020, all school type and grade combinations averaged less than 20% of EIPL. For the 2020-21 school year, however, there are substantial differences. EIPL is lowest for public charter schools (averaging 36%), followed by public non-charter schools (44%), private non-religious schools (51%), and private religious schools (57%). In turn, EIPL is lower for middle and high-schools (averaging 39%) than for elementary schools (56%), and these differences are more pronounced for public than for private schools.

The EIPL ranking by school type, which to our knowledge has not been analyzed in prior research, may come as a surprise for two reasons. First, public charter schools are typically independent and not unionized whereas public non-charter schools belong to school districts that, for some urban areas, are comprised of several hundred schools and often unionized. One could have expected that these features would have made it easier for charter schools to reopen to in-person learning. Second, according to Hanson [2021], tuition for non-religious private schools is on average more than twice as high as tuition for religious private schools. The additional resources and resulting smaller class sizes could have made it easier for non-religious private schools to reopen to in-person learning. Yet, in both cases, exactly the opposite occurred.

The EIPL ranking by school grade is not a new finding; see Parolin and Lee [2021], Musaddiq et al. [2021], or Burbio's dashboard. Given the importance of the early stages of schooling for human capital accumulation, it likely contributed to shielding younger children from some of the adverse effects of school closures, compared to their older peers. Indeed, Fuchs-Schündeln et al. [2022] structurally estimate that it is children just starting secondary school during the 2019-20 school year that endure the largest losses in their earnings capacity in the long run.

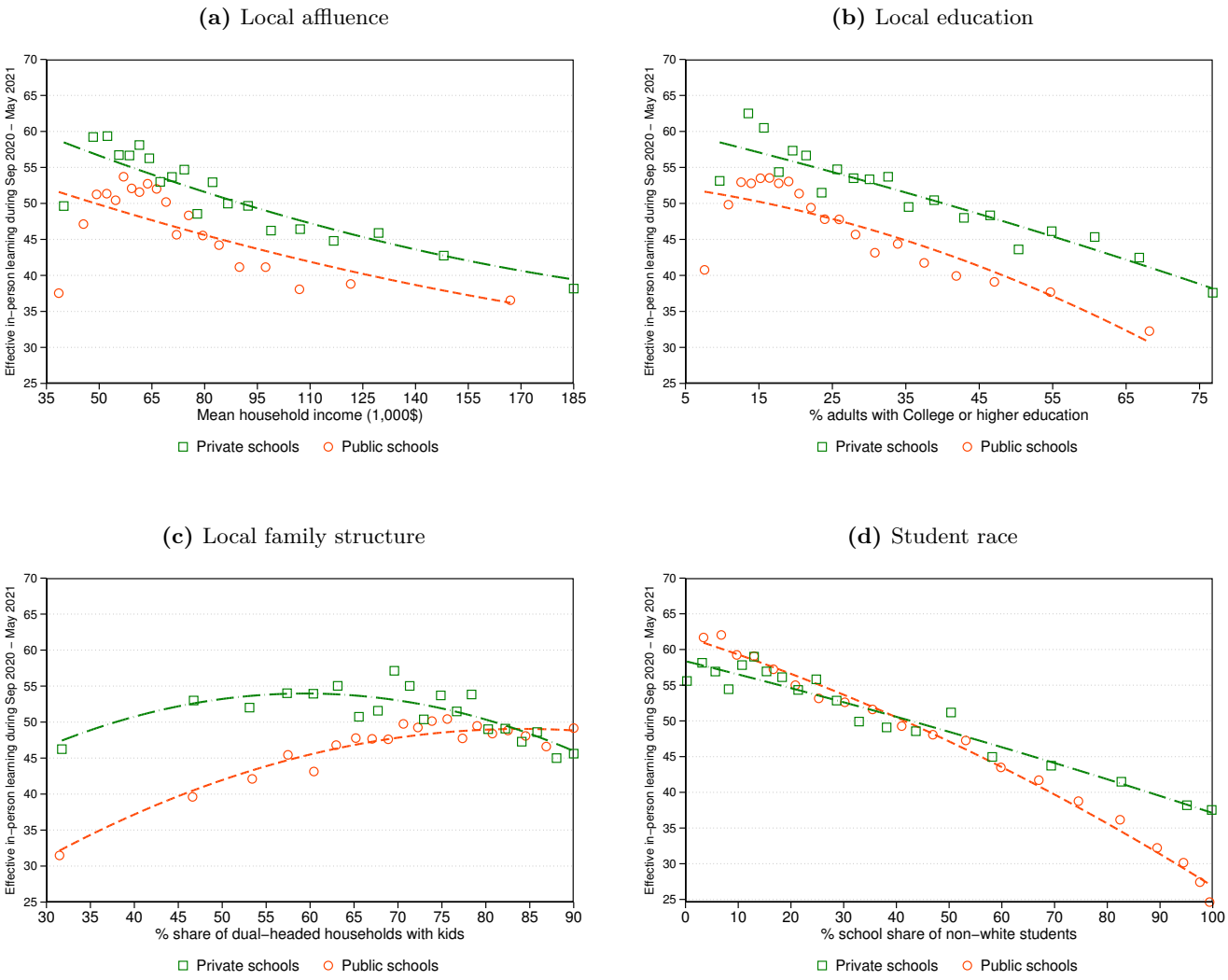
4.2 Local affluence and education, family structure, and student race

Next we consider EIPL by local affluence, education and family structure, which are prominent inputs for models of human capital accumulation (e.g. Cunha et al., 2010), as well as student race. We proxy local affluence by household income, education by the share of households with a college degree or higher, and family structure by the share dual-headed households with children, all measured at the zip-code level of the school and based on 2016-2019 estimates from the American Community Survey. For race, we use the school's share of non-white students as provided by the NCES. Results are robust to using the variables at the census block group or tract of the school, or at the school district level.[12]

Figure 3 reports binned scatterplots of the unconditional relationship between average school EIPL from September 2020 to May 2021 and the different variables. As shown in panel (a), there is an inverse relationship between EIPL and household income: schools in zip-codes with *high* household income provided on average *lower* EIPL. Panel (b) shows a similar result for education: schools in zip-codes with a *high* share of college-educated people provided on average *lower* EIPL. Consistent with the above results, EIPL is on average about 10% higher for private schools than for public schools but the relationship of EIPL with

[12] We have also considered several alternative socio-economic indicators describing the neighborhood of the school, including Chetty et al. [2020]'s indicators of Income Mobility and many of the other variables available from their Opportunity Atlas database. While these variables are correlated with EIPL, they are also highly correlated with the above measures of local affluence and education and do not add significant explanatory power to the below regressions.

Figure 3: Effective In-Person Learning by Local Affluence, Education, Family Structure, and Race



Notes: The figures show binned scatterplots of average EIPL from September 2020 to May 2021 for public schools and private schools, respectively, by (a) zip-code average household income, (b) zip-code average share of household with a college degree or higher, (c) zip-code share of dual-headed households, and (d) school share of non-white students. Observations are weighted by the school-specific sampling weight described in the appendix.

household income and education is otherwise very similar. Panel (c) shows that there is positive relationship between EIPL and local share of dual-headed households for public schools but no systematic relationship for private schools. As we will see below, the positive relationship for public schools changes once we control for other observable school characteristics. Finally, as shown in panel (d), there is also a clear inverse relationship between EIPL and the share of non-white students. For schools with close to 0% of non-white students, EIPL averaged over 60%, independent of whether the school is public or private. For schools with close to 100% of non-white students, in contrast, EIPL averaged only about 25% for public schools and just below 40% for private schools.

Given the general association of poverty with race, the inverse relationship of EIPL with both affluence and race may come as a surprise.[13] We further investigate this result through OLS regressions of average 2020-21 school EIPL on the different measures. Figure 4 reports the results. To save on space, we show only results for public schools, but the results for private schools are very similar. The brown square-shaped plots show the point estimates and 95% confidence intervals from regressing EIPL separately on zip-level household income, education, and share of dual-headed households together with the share of non-white students and controls for school type and school grade. The yellow and red plots are discussed further below. The coefficients are scaled so that they show the implied change in EIPL of going from the 25th to the 75th percentile of the distribution of a variable.[14]

All three indicators of affluence are negatively related to EIPL in a significant and quantitatively important manner. EIPL for a school located in a zip-code at the 75th percentile of the income and education distribution was on average 5%, respectively 7-8% lower than for a school at the 25th percentile. The relationship between and the share of dual-headed households with children is also negative, due to the fact that schools in zip codes with a larger share dual-headed households have on average a smaller share of non-white students. This highlights the importance of analyzing the relation between EIPL and different school characteristics in a multivariate setting. To our knowledge, these results have not been highlighted by other studies. They indicate that at the national level less affluent communities provided on average more – not less – EIPL.

The negative relationship between EIPL and a school's share of non-white students, on the other hand, is not a new finding. Even after conditioning on local income, education, and parental structure, EIPL for a school with a student body at the 75th percentile of the non-white distribution was on average 15-22% lower during the 2020-21 school year than for a school at the 25th percentile of the distribution. Further analysis shows that this negative relationship is in large part driven by the share of Hispanic students and less by the share of black students. These findings are consistent with Camp and Zamarro [2022], Landivar et al. [2022], and Parolin and Lee [2021], among others.

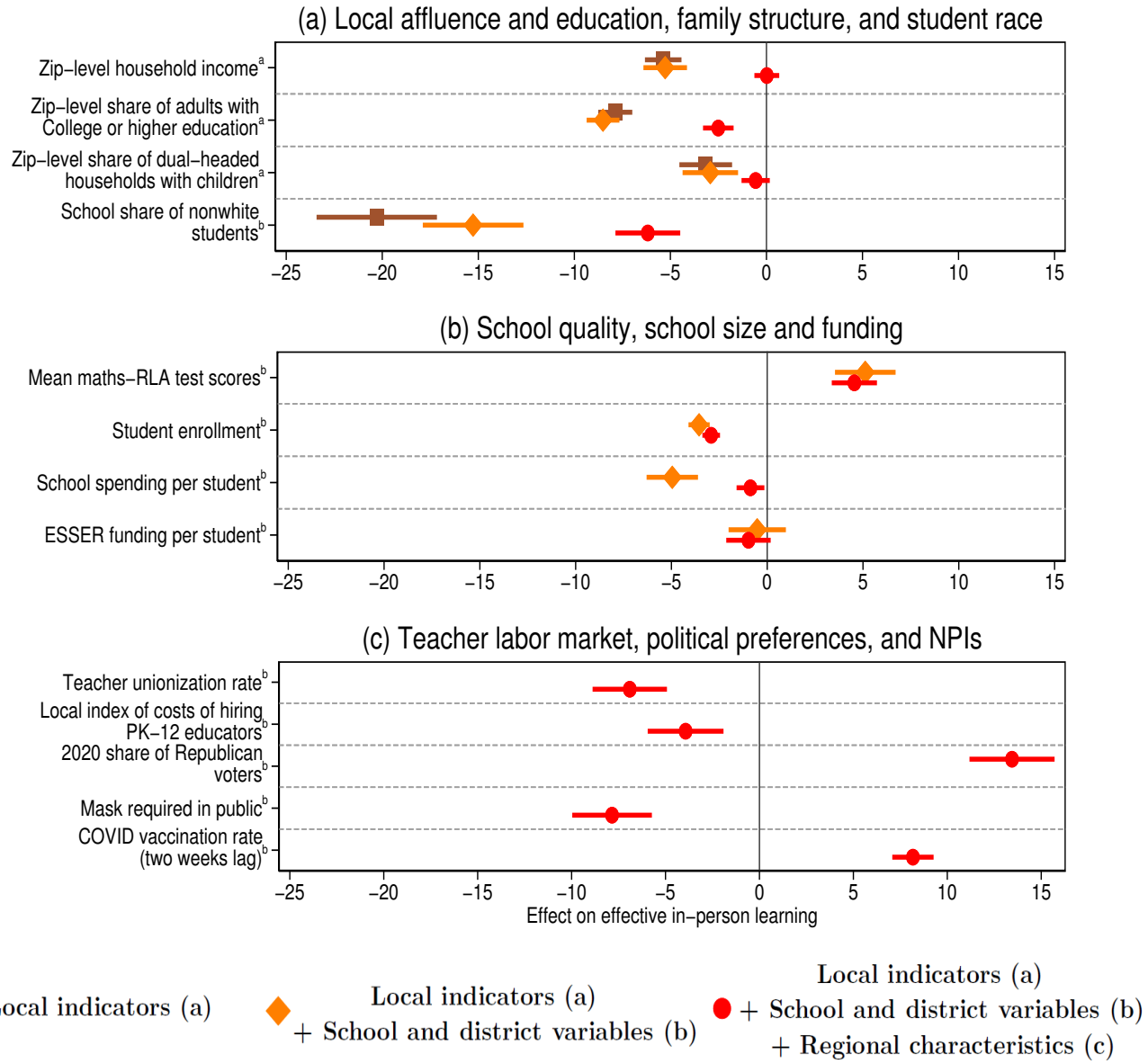
4.3 Public school tests scores, school size, and school funding

We extend the analysis by considering the relation between EIPL and school quality, school size, and school funding. We proxy school quality with pre-pandemic average tests scores, based on data from Fahle et al.

[13] As shown in the appendix, the share of a school's non-white students is essentially uncorrelated with local affluence, education, and parental structure.

[14] More precisely, all right-hand side variables are expressed as deviations from the mean, normalized by the interquartile range. Here and below, all estimates are weighted by the school-specific sampling weights to ensure representativeness; standard errors are clustered at the county level.

Figure 4: The Relationship of Effective In-Person Learning with School and Local Characteristics



(*) All regressions include School type and grade controls

Notes: The figure shows the estimated effects on EIPL from weighted OLS regressions with standard errors clustered at the county level and school weights calculated as explained in the appendix. The sample consists of approximately 60,000 public schools. The regressions are estimated for weekly school EIPL from September 2020 to May 2021. The estimates for the first three variables, denoted by ^{a}, are the result of separate regressions for each of the three variables in combination with the other variables listed below. The coefficient estimates for the other variables denoted by ^{b} are the result of regressions where all the variables are included jointly. The brown square-shaped estimates show the effects of regressing EIPL on the variables in the top box only. The yellow diamond-shaped estimates show the effects of regressing EIPL on the variables in the top and middle box. The red round-shaped estimates show the effects of regressing EIPL on the variables in all three boxes. All regressions control for school type (charter vs. non-charter school) and school grade (elementary vs. middle vs. high. vs. combined school). In addition, the regressions for the red round-shaped estimates control for pre-pandemic ICU bed capacity, two-week lagged county COVID case and death rates, dummies for various other non-pharmaceutical interventions, maximum weekly temperature in the county, county population density, and dummies for rural-urban continuum codes. All estimates except for the "Mask required in public" dummy are scaled so that they show the implied change in EIPL of going from the 25th percentile to the 75th percentile of the distribution of a variable. See the appendix for details.

[2021].[15] For school funding, we consider both pre-pandemic school spending per student obtained from EdunomicsLab [2021] as well as district-level ESSER funding by student compiled by Malkus [2021b]

As above, we estimate OLS regressions of EIPL on local income, education, parental structure, and student race and then add the different variables.[16] As shown by the yellow diamond-shaped coefficient plots in Figure 4, EIPL is estimated to be higher for schools in districts with higher pre-pandemic test scores. Parolin and Lee [2021] obtain the same result based on pre-COVID third grade math test scores from Chetty et al. [2014]'s Opportunity Atlas database. EIPL is lower for larger schools, and interestingly, is also inversely related to school spending and ESSER funding per student, although not significantly so in the latter case. Note that these estimates control for local income, education, parental structure, and race, suggesting that school quality, school size, and school funding are independent predictors of EIPL.

The negative association between EIPL and school spending is a new finding, as far as we know, but it may have been expected given the positive correlation between school spending and local affluence. The absence of a positive association of EIPL with ESSER funding per student, in turn, is remarkable because ESSER, which was appropriated by Congress in three waves totaling $190 billion or almost five times the annual federal K-12 spending prior to the pandemic, was advertised primarily as support for school reopening. We return to this point below. Also note that controlling for test scores, school size, and school funding barely changes the negative relation of EIPL with local affluence, education, and parental structure, but reduces the effect of share of non-white students by roughly one third. This is because the share of non-white students is negatively correlated with test scores and positively correlated with school size. Even so, the share of non-white students remains a strong predictor of lower EIPL.

4.4 Geography

For the last part of the analysis, we ask how much of the relation of EIPL with school and local characteristics is driven by systematic regional differences that are not directly related to the school. From Figure 2 we know that schools with higher EIPL are generally located in the central and southern parts of the U.S. – regions that in general were more favorable towards reopening the economy despite potential health risks and at the same time have seen lower COVID vaccination rates. To assess the relative importance of these factors for EIPL, we re-estimate the above regressions and add county-level vote shares in the 2020 presidential election as a proxy for the general stance towards reopening the economy and two-week lagged vaccination rates. Furthermore, we add teacher unionization rates, a comparable wage index for PK-12 educators in the local labor market, controls for a county's COVID health situation as measured by pre-pandemic ICU bed capacity, lagged COVID case and death rates and various non-pharmaceutical interventions (NPIs), as well maximum weekly temperature and indicators of urban density.

The red round-shaped coefficient plots in Figure 4 report the results. First, schools in areas with higher teacher unionization rates and a higher comparable wage index provided on average lower EIPL. At the same time, a large share of Republican votes in the 2020 presidential election is a strong predictor of higher EIPL during the 2020-21 school year.[17] These results are not new. Hartney and Finger [2020] report similar

[15] We use district-level average test scores for 2018-19, which are available for almost all districts. School-level test scores are available for only a subset of schools and yield very similar results.

[16] As above, we include local income, education, and parental structure one-by-one together with race and the other variables. Since the estimates for race and the other variables barely change across regressions, we report these estimates controlling for local income, education, and parental structure jointly.

[17] Partisan vote shares are highly persistent at the county level. Hence, results are virtually identical when using vote shares

correlations between teachers' union strength and the presidential vote shares of the Republican candidate on the one hand and a district's propensity to reopen schools to in-person learning on the other. Valant [2020] and Gollwitzer et al. [2020] show that areas with a larger share of Republican-leaning voters exhibit less physical distancing, weaker support for stay-at-home orders and more school reopenings. Interestingly, the estimates show that higher vaccination rates are also a strong predictor of higher EIPL.

Second, and importantly, the addition of the different regional attributes increases the predictive power of the regression substantially while reducing the relationship of EIPL with local affluence, education, and parental structure to almost zero. In other words, the negative predictive effect of local affluence, education, and parental structure on EIPL in the above regressions arises primarily because these variables proxy for voter preferences and to a lesser extent vaccination rates, teacher unionization rates and the local wage comparison index. These results offer a new perspective on the nexus between income at the national vs. at the local level and the provision of EIPL.

Third, the inverse relation between EIPL and the share of non-white students is also reduced. Yet, even after controlling for all the state and county-specific attributes, a school with a student body at the 75th percentile of the non-white distribution is predicted to average 3-7% lower EIPL during the 2020-21 school year than a school at the 25th percentile of the distribution.

Fourth, the negative coefficient estimate on test scores and school size remain largely unaffected, indicating that even after controlling all the other school characteristics and regional attributes, school quality and size played an important role for EIPL. By contrast, the regional variables completely absorb the negative association of EIPL with pre-pandemic school spending per student, indicating that school spending did not play a decisive role for EIPL overall but instead picked up systematic differences across regions. Finally, the inverse relation between EIPL and ESSER funding per student becomes somewhat more negative. Hence, even within counties, schools in districts with more ESSER funding per student provided on average not more but slightly less EIPL.

4.5 EIPL for whom? The view from schooling mode trackers

To conclude this section, we assess whether we would reach similar conclusions if we had used the different schooling mode trackers instead of EIPL. We run the same regression as above on school trackers data, focusing on the district or county level to maximize comparability across the results.[18] We summarize here the results and present the full details in the online appendix.

First, the statistical associations between the in-person learning mode of the different trackers and local affluence, education, family structure and race are similar in terms of (most) coefficient signs but are substantially weaker than for our EIPL measure. The weaker association may be explained by the higher level of geography in these data, which removes part of the local variations in those variables. One important exception is that the Burbio coefficient suggests a positive relation between the share of non-white students and in-person learning, while the other trackers indicate a negative correlation (consistent with our findings and those in prior studies).

Second, the schooling mode trackers indicate that ESSER funding per student is associated with addi-

in the 2016 presidential election.

[18] We cannot run the same analysis for EdWeek and exclude the IES-SSD data which is only at the state level. For CSDH, we use the district instead of the school-level data. To control for school characteristics (i.e., grades and school type), we aggregate data to the district or county level, i.e. we measure the share of the student population enrolled in elementary schools, etc.

tional remote learning, except for Burbio and CRPE where ESSER funding per student is associated with fewer weeks of remote learning. The granularity of the EIPL database allows for more precise estimates that help decide between the conflicting results.

Third, the schooling mode trackers also point to a positive association between in-person learning and Republican vote shares during the 2020 election. But once again, there are sizable differences in terms of magnitude across trackers. The schooling mode trackers also show, consistent with our school-level regression, that the mask mandates were negatively related (hence, a substitute policy) to EIPL while the vaccination campaign acted as a complement to school reopenings.

5 Conclusion

We review several school trackers of the options – in-person, hybrid, remote learning – that were more frequently in place during the COVID-19 pandemic, and document a number of systematic differences between them regarding the extent of school closures and reopenings. We then propose a measure of effective in-person learning (EIPL) which we argue allows for a better assessment of the exposure of students in-person learning and its relation to a host of population, school, and regional characteristics. We make the EIPL dataset publicly available for future research on the COVID-19 school disruptions. To conclude, we highlight three questions raised by these data:

1. Why did schools in more affluent and more educated areas with higher funding per student provide less EIPL? We show that this inverse relationship is in large part about political preferences. But why would more Democratic-leaning areas have been more reluctant to let students return to in-person learning? One potential explanation is that independent of political preferences, more affluent and educated parents were on average more likely to be able to work from home and therefore considered the cost of supervising students' virtual learning from home (either in person or by hiring help) more manageable. It might also be that parents had a different perception of the risk of sending students back to in-person school, for instance due to different news and social-media exposure. Both of these explanations contrast, however, with the observation that even within counties, private schools (which generally attract students from wealthier backgrounds) provided more EIPL than public schools. No matter the explanation, it remains that students in more affluent and more educated areas of the U.S. received on average less EIPL.

2. Why did schools with a higher share of non-white students provide less EIPL, even within a given county and controlling for neighborhood poverty and other school characteristics? This striking result defies a simple explanation and yet seems key given the large and persistent educational achievement gaps between students of different races that existed already before the pandemic.

3. Why did schools in districts with more ESSER funding per student not provide more EIPL? One possible reaction is that without ESSER funding, schools would have been closed for even longer. Yet, the absence of a positive relationship arises even within counties and despite controlling for many other school characteristics, which makes this an unlikely explanation. Another potential explanation is that Congress imposed few constraints on how ESSER funding could be used, and according to estimates by Malkus [2021a], less than 20% had been spent by August 2021. If these funds were spent

primarily to improve students' remote learning capacities (e.g. providing students with computers and wireless connections) instead of upgrades to the school buildings and personal protection equipment, then ESSER funding would have primarily facilitated remote learning instead of a return to in-person learning; i.e. its main advertised purpose.[19]

Exploring these questions goes beyond the scope of the paper but they are clearly important to understand the causes and consequences of school closings during the pandemic.

References

Francesco Agostinelli, Matthias Doepke, Giuseppe Sorrenti, and Fabrizio Zilibotti. When the great equalizer shuts down: Schools, peers, and parents in pandemic times. *Journal of Public Economics*, 206:104574, 2022.

Katherine A Auger, Samir S Shah, Troy Richardson, David Hartley, Matthew Hall, Amanda Warniment, Kristen Timmons, Dianna Bosse, Sarah A Ferris, Patrick W Brady, Amanda Schondelmeyer, and Joanna Thomson. Association between statewide school closure and COVID-19 incidence and mortality in the US. *JAMA*, 324(9):859–870, 2020.

Dena Bravata, Jonathan H Cantor, Neeraj Sood, and Christopher M Whaley. Back to school: The effect of school visits during COVID-19 on COVID-19 transmission. *NBER Working Paper 28645*, 2021.

Andrew M Camp and Gema Zamarro. Determinants of ethnic differences in school modality choices during the COVID-19 crisis. *Educational Researcher*, 51(1):6–16, 2022.

Victor Chernozhukov, Hiroyuki Kasahara, and Paul Schrimpf. The association of opening K-12 schools and colleges with the spread of COVID-19 in the United States: County-level panel data analysis. *Proceedings of the National Academy of Sciences*, 118(42), 2021a.

Victor Chernozhukov, Hiroyuki Kasahara, and Paul Schrimpf. Causal impact of masks, policies, behavior on early covid-19 pandemic in the U.S. *Journal of Econometrics*, 220(1):23–62, 2021b.

Raj Chetty, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. Where is the Land of Opportunity? The geography of intergenerational mobility in the United States. *Quarterly Journal of Economics*, 129 (4):1553–1662, 2014.

Raj Chetty, John N Friedman, Nathaniel Hendren, Maggie R. Jones, and Sonya S. Porter. The Opportunity Atlas: Mapping the Childhood Roots of Social Mobility. *NBER Working Paper 25147*, 2020.

COVID-19 School Data Hub. School Learning Model Database, 2021. URL https://www.covidschooldatahub.com/for_researchers.

[19]The remaining unspent ESSER funds could still be put to good use, for instance by providing summer learning programs for students, especially since ESSER funds were allocated to school districts according to pre-pandemic Title I spending and thus benefited disproportionally schools with students from poorer backgrounds. As pointed out by Malkus [2021a], however, ESSER funding comes with very few constraints and it is unclear to what extent school districts will use the funds for their intended purpose.

Flavio Cunha, James J. Heckman, and Susanne M. Schennach. Estimating the technology of cognitive and noncognitive skill formation. *Econometrica*, 78(3):883–931, 2010.

Thomas Dee, Elizabeth Huffaker, Cheryl Phillips, and Eric Sagara. The revealed preferences for school reopening: Evidence from public-school disenrollment. *NBER Working Paper 29156*, August 2021.

Emma Dorn, Bryan Hancock, Jimmy Sarakatsannis, and Ellen Viruleg. Covid-19 and education: The lingering effects of unfinished learning. Technical report, McKinsey & Company, 2021a.

Emma Dorn, Bryan Hancock, Jimmy Sarakatsannis, and Ellen Viruleg. Covid-19 and education: The lingering effects of unfinished learning. *Technical report, McKinsey & Company*, 27, 2021b.

EdunomicsLab. National education resource database on schools, November 2021. URL www.edunomics.org/nerds.

Per Engzell, Arun Frey, and Mark D Verhagen. Learning loss due to school closures during the COVID-19 pandemic. *Proceedings of the National Academy of Sciences*, 118(17), 2021.

Zeynep Ertem, Elissa M Schechter-Perkins, Emily Oster, Polly van den Berg, Isabella Epshtein, Nathorn Chaiyakunapruk, Fernando A Wilson, Eli Perencevich, Warren BP Pettey, Westyn Branch-Elliman, et al. The impact of school opening model on SARS-CoV-2 community incidence and mortality. *Nature Medicine*, pages 1–7, 2021.

Erin M Fahle, Benjamin R Shear, Demetra Kalogrides, Sean F Reardon, Richard DiSalvo, and Andrew D Ho. Stanford Education Data Archive (Version 4.1), 2021. URL http://purl.stanford.edu/db586ns4974.

Nicola Fuchs-Schündeln, Dirk Krueger, Andre Kurmann, Etienne Lale, Alexander Ludwig, and Irina Popova. The fiscal and welfare effects of policy responses to the COVID-19 school closures. *IMF Economic Review*, (forthcoming), June 2022.

Kairon Shayne D Garcia and Benjamin W Cowan. The impact of school and childcare closures on labor market outcomes during the COVID-19 pandemic. *NBER Working Paper 29641*, 2022.

Dan Goldhaber, Scott A Imberman, Katharine O Strunk, Bryant G Hopkins, Nate Brown, Erica Harbatkin, and Tara Kilbride. To what extent does in-person schooling contribute to the spread of Covid-19? Evidence from Michigan and Washington. *Journal of Policy Analysis and Management*, 41(1):318–349, 2022a.

Dan Goldhaber, Thomas J Kane, Andrew McEachin, Emily Morton, Tyler Patterson, and Douglas O Staiger. The consequences of remote and hybrid instruction during the pandemic. *NBER Working Paper 30010*, 2022b.

Anton Gollwitzer, Cameron Martel, William J Brady, Philip Pärnamets, Isaac G Freedman, Eric D Knowles, and Jay J Van Bavel. Partisan differences in physical distancing are linked to health outcomes during the COVID-19 pandemic. *Nature Human Behaviour*, 4(11):1186–1197, 2020.

Clare Halloran, Rebecca Jack, James Okun, and Emily Oster. Pandemic Schooling Mode and Student Test Scores: Evidence from US States. *NBER Working Paper 29497*, November 2021.

Benjamin Hansen, Joseph J Sabia, and Jessamyn Schaller. Schools, job flexibility, and married women's labor supply: Evidence from the COVID-19 pandemic. *NBER Working Paper 29660*, 2022.

Melanie Hanson. Average Cost of Private School. Technical report, EducationData.org, 2021. URL https://educationdata.org/average-cost-of-private-school.

Michael T Hartney and Leslie K Finger. Politics, markets, and pandemics: Public education's response to COVID-19. *Perspectives on Politics*, pages 1–17, 2020.

Youngsoo Jang and Minchul Yum. Aggregate and intergenerational implications of school closures: A quantitative assessment. *Covid Economics, Vetted and Real-Time Papers*, 57:46–93, 2020.

Vladmir Kogan and Stéphane Lavertu. How the COVID-19 pandemic affected student learning in Ohio: Analysis of Spring 2021 Ohio state tests. Technical report, 2021.

Liana Christin Landivar, Leah Ruppanner, Lloyd Rouse, William J Scarborough, and Caitlyn Collins. Research note: School reopenings during the COVID-19 pandemic and implications for gender and racial equity. *Demography*, 59(1):1–12, 2022.

Karyn Lewis, Megan Kuhfeld, Erik Ruzek, and Andrew McEachin. Learning during COVID-19: Reading and math achievement in the 2020-21 school year. Technical report, NWEA Center for School and Student Progress, 2021.

Nat Malkus. How much of federal COVID-19 relief funding for schools will go to COVID-19 relief? Technical report, American Enterprise Institute, 2021a.

Nat Malkus. Federal COVID Elementary and Secondary School Emergency Relief funding district-level data compilation. Technical report, Return to Learn Tracker, American Enterprise Institute, 2021b. URL http://www.returntolearntracker.net/esser/.

Tareena Musaddiq, Kevin M Stange, Andrew Bacher-Hicks, and Joshua Goodman. The pandemic's effect on demand for public schools, homeschooling, and private schools. *NBER Working Paper 29262*, 2021.

Zachary Parolin and Emma K Lee. Large socio-economic, geographic and demographic disparities exist in exposure to school closures. *Nature Human Behaviour*, 5(4):522–528, 2021.

Maria J Prados, Gema Zamarro, and Andrew Camp. School reopenings, childcare and labor outcomes during COVID-19. *Unpublished manuscript*, 2021.

Jon Valant. School reopening plans linked to politics rather than public health. *Brown Center Chalkboard, Brookings Institution*, 2020. URL https://www.brookings.edu/blog/brown-center-chalkboard/2020/07/29/school-reopening-plans-linked-to-politics-rather-than-public-health/.