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

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Abstract

We document large temporal and geographical discrepancies among prominent trackers that measure in-person, hybrid, and remote schooling in the U.S. during COVID-19. We then propose a new measure of effective in-person learning (EIPL) that combines information on schooling modes with cell phone data on school visits and estimate it for a large, representative sample of U.S. public and private schools. The EIPL measure, which we make publicly available, resolves the discrepancies across trackers and is more suitable for many quantitative questions. Consistent with other studies, we find that a school's share of non-white students and pre-pandemic grades and size are associated with less in-person learning during the 2020-21 school year. Notably, we also find that EIPL was lower for schools in more affluent and educated localities with higher pre-pandemic spending and more emergency funding per student. These results are in large part accounted for by systematic regional differences, in particular political preferences.

JEL Classification: I24, E24

Keywords: COVID-19; School closures and reopenings; Effective in-person learning; Inequality

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1 Introduction

The COVID-19 pandemic led many schools in the U.S. to suspend or substantially reduce in-person learning. Several organizations and research teams have developed schooling mode trackers to measure the extent of traditional, hybrid, and virtual schooling that students obtained during the pandemic. A rapidly growing literature uses these trackers to estimate the consequences of reduced in-person instruction on student enrollment and academic achievement (Dee et al., 2021; Dorn et al., 2021; Engzell et al., 2021; Jack et al., 2022; Kogan and Lavertu, 2021; Lewis et al., 2021; Goldhaber et al., 2022), COVID infection and death rates (Chernozhukov et al., 2021a; Ertem et al., 2021), as well as local labor market outcomes (Amuedo-Dorantes et al., 2023; Garcia and Cowan, 2022; Landivar et al., 2022; Prados et al., 2021).

While certainly indicative of school closures, these trackers have several drawbacks. First, as we document in this paper, the various trackers provide very different accounts of the fraction of students who spent the 2020-21 school year in either of the three schooling modes. The differences are due to how each tracker defines hybrid schooling as well as the sample of schools and source data that the trackers take into account. This poses an important challenge for researchers interested in analyzing the extent and consequences of school closures as the choice of tracker is not obvious but can substantially affect results.[1]

Second, even if one has good reason to prefer one tracker over the others, its usefulness for quantitative analysis is limited. This is because the trackers are qualitative – in particular, the category "hybrid" denotes an interval of possible in-person schooling days per week, reflecting the supply side of a school's reopening policy but not the students' take up of this option. While for some questions, one may prefer a measure of *potential* in-person learning (i.e. the supply side), for many other outcomes such as the ones studied in the above referenced papers, *effective* in-person learning (i.e. take up) is the more relevant metric. More generally, the treatments implied by the different schooling modes are not mutually exclusive. If a school is fully in-person (treatment 1), then it cannot be in hybrid mode (treatment 2). But if a school is not fully in-person, then it can be either in hybrid mode or in virtual mode. This makes it difficult to interpret regression results.[2]

Third, the quality and coverage of the different trackers varies by geography and time period, and the data is typically limited to county or district-level averages of public schools. This further limits the applicability of the trackers for empirical analysis.

Motivated by these issues, we propose a new measure of Effective In-Person Learning (EIPL) that we estimate by mapping anonymized cell phone data from Safegraph on visits to schools with information from schooling mode trackers. The Safegraph data is available weekly for a large, representative sample of both public and private schools. Our estimation allows for the possibility that student presence (in-person learning) and cell-phone presence (visits) at schools may not have varied 1:1 during the pandemic; that the trackers use different definitions of hybrid schooling; and that the trackers are subject to measurement error

[1] As shown in Appendix D, we find large differences across trackers in the statistical association of schooling mode with various local and school characteristics. More concerning still, we find that the effect of school closings on educational achievement, as estimated with a difference-in-difference design, varies importantly across trackers.

[2] Consider two schools that spent the same number of days during 2020-21 in traditional mode and the rest to varying degrees in hybrid mode. The average treatment effect of traditional mode on an outcome variable therefore depends on the covariation with hybrid mode in potentially non-trivial ways. Perhaps more importantly, if the treatment effect is heterogeneous across schools, then multiple-treatment regressions generally fail to identify the average treatment effect even if the research design is otherwise not subject to omitted variable bias (see Goldsmith-Pinkham et al., 2022).

that may vary by region.[3] For each school in the sample, we therefore select the estimate from the mapping between visits and tracker information with the smallest measurement error. The result is a database of weekly EIPL from March 2020 to June 2021 for more than 70,000 public and private schools. We make this database available through the online repository of the Center for Open Science at `https://osf.io/cghs2/`.

To illustrate the use of the data, we investigate the extent to which EIPL correlates with a host of school and local characteristics. 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. EIPL during the 2020-21 school year was substantially lower in public schools than in private schools, with public charter schools ranking below public non-charter schools and private religious schools ranking above private non-religious schools.

2. For both public and private schools, EIPL was lower in more affluent and more educated localities, 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 as well as Elementary and Secondary School Emergency Relief (ESSER) funding.

4. These correlations are in large part accounted for by the school county's share of Republican votes in the 2020 presidential election. COVID vaccination rates also predict higher EIPL, while mask requirements and teacher unionization rates predict lower EIPL.

The relation of EIPL with race, test scores, school size, and school spending confirm results previously documented by, e.g., Parolin and Lee [2021] or Landivar et al. [2022], while the relation with Republican voting preferences is consistent with Hartney and Finger [2020], Gollwitzer et al. [2020] and Valant [2020]. Our contribution is to analyze these relations in a multivariate context, which reveals that systematic regional variations more so than local or school characteristics account for the large observed regional differences in public school closures. Indeed, our analysis uncovers a new nexus between income, voting preferences, and access to in-person learning: EIPL was on average lower – not higher – in more affluent localities, and this is in large part accounted for by their lower Republican vote share. Equally striking, we find that ESSER funding is on average not associated with higher EIPL even though the program was advertised primarily as support for schools to reopen for in-person learning. These findings raise critical questions about education policy during the pandemic and have potentially important implications for the impact of in-person learning loss on future educational attainment as well as income inequality.[4]

Besides the above mentioned studies based on schooling mode trackers, several other studies have used school visits from cell phone data, in particular Safegraph, to proxy directly for school closures during the pandemic (Bravata et al., 2021; Chernozhukov et al., 2021b; Parolin and Lee, 2021; Garcia and Cowan, 2022; Hansen et al., 2022). The proposed EIPL measure advances over these proxies by taking into account information from schooling mode trackers and by allowing for the relationship between school visits and in-person learning during the pandemic to be different from 1:1, which our estimates suggest is important for

[3] For instance, if a school includes a playground that is frequented during school closure, then visits may decline less during the pandemic than EIPL. Vice versa, cell phones may be erroneously attributed to schools, especially in an urban environment. If cell phone traffic around the school declined during the pandemic, then visits may decline more than EIPL.

[4] See Agostinelli et al. [2022], Fuchs-Schündeln et al. [2022] or Jang and Yum [2023] for examples of work on this issue.

many cases. Furthermore, attributing cell phones to a particular location is subject to inherent measurement issues, and our analysis reveals that this leads to sparse or noisy data for a non-negligible number of schools. Accordingly, we estimate EIPL only for schools with reliable visits data.

The paper proceeds as follows. Section 2 compares the different schooling mode trackers. Section 3 describes our empirical approach for measuring EIPL. Section 4 studies the relation of EIPL with school-specific and local indicators. Section 5 concludes.

2 Comparison of schooling mode trackers

This section compares prominent schooling mode trackers for the U.S. We limit the comparison to trackers that are constructed from a direct source of information about schooling mode; e.g., school district websites or social media, public guidelines by school districts and state educational agencies, or direct surveys of schools. However, we do not impose any restrictions on geographical coverage, frequency, or granularity of the data.

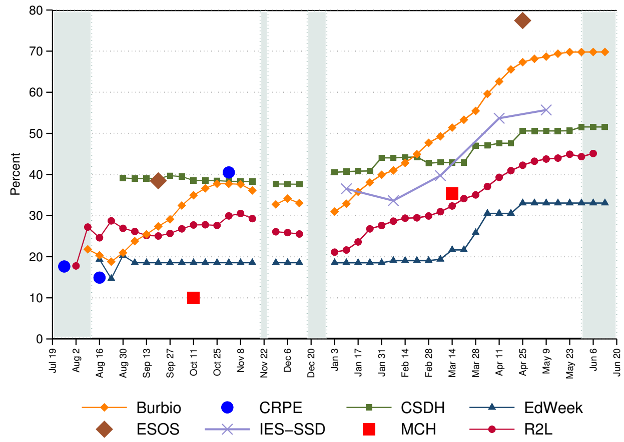
In total, eight trackers fit our criteria: the State-by-State Building Reopening Data from EducationWeek (EdWeek) and the School Survey Dashboard of the Institute of Education Sciences (IES-SSD) for state-level data; Burbio's School Opening Tracker (Burbio) for county-level data; the Nationally Representative District Database from the Center on Reinventing Public Education (CRPE), the Elementary School Operating Status (ESOS) database, School District Covid Operating Plans from MCH strategic data (MCH), and the Return2Learn (R2L) tracker of the American Enterprise Institute for school district-level data; and the COVID-19 School Data Hub (CSDH) for school districts and school-level data. Each of the trackers reports schooling modes as the percent of students in either traditional (fully in-person), hybrid (partially in-person), or virtual (fully remote) mode.

Figure 1 reports student-weighted averages of schooling modes for the 2020-21 school year from each trackers. There are large differences in both magnitude and timing of the extent of hybrid schooling and, therefore, the extent of traditional and virtual schooling. Consider for instance Burbio and R2L, the trackers with the largest geographical coverage. Burbio reports an average share of students in hybrid mode that is consistently below the share reported by R2L, and vice versa for traditional and virtual mode. In turn, while the Burbio and R2L predict a relatively smooth transition out of remote learning during Spring of 2021, other trackers such as the ones from CSDH and EdWeek report large, abrupt changes.

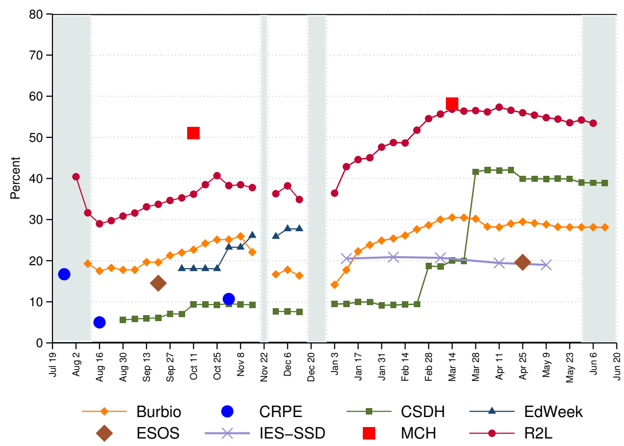
The discrepancies in schooling mode across trackers are even more important at the regional level. Consider again Burbio and R2L which, despite the sizable level differences, evolve similarly over time on average. At the county level, the mean correlation coefficient between the two trackers' share of traditional learning during the 2020-21 school year is only 0.59, with an interquartile range of 0.78 and 20% of counties showing a *negative* correlation coefficient. Similar discrepancies arise across the other trackers. Further analysis in Appendix B suggests that these discrepancies are due in large part to how each tracker defines hybrid schooling mode as well as differences in the data source used to build the trackers.

Figure 1: Comparison of Schooling Mode Trackers

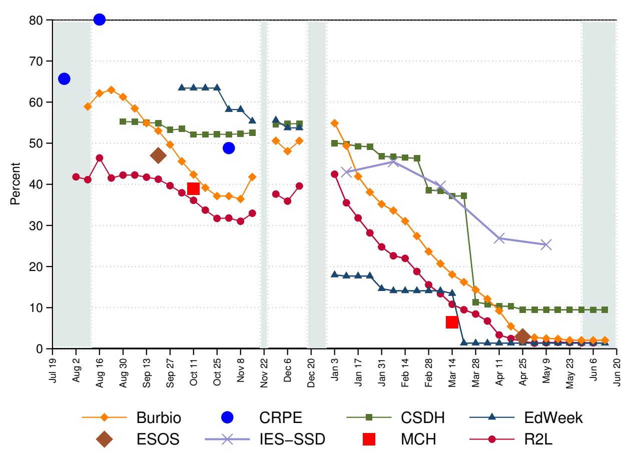
(a) Traditional



(b) Hybrid learning



(c) Virtual



Notes: The figures show the average share of each schooling mode according to each of the trackers, weighted by public school student enrollment at either the school, district, county, or state level. The schooling mode trackers are: 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). The shaded regions denote the Summer, Winter, and Thanksgiving breaks.

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

In this section, we first describe the construction of our sample of school visit changes from Safegraph data. Then, we explain how we estimate EIPL by mapping school visit changes to information from schooling mode trackers. Since in practice, the mapping relies on having sufficient temporal variation, we prioritize trackers with data at weekly frequency; i.e., Burbio, CSDH, EdWeek, and R2L. However, the weekly CSDH data is limited to about 10,000 schools, with the other schools observed only at monthly frequency, and the EdWeek data is at the state level. We therefore implement the estimation using tracker information from Burbio and R2L only.

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

The key input for our EIPL measure comes from Safegraph, which provides data on over 7 million Places of Interest (POIs) for the U.S., including visits from geolocating over 40 million anonymized cell phones to places. We retain all POIs with North American Industry Classification System (NAICS) code 611110 ("Elementary and Secondary Schools"). As detailed in Appendix C, we match these POIs by school name and geolocation 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 POI is organized in seven dwell time intervals, ranging from less than 5 minutes to more than 240 minutes. Raw visit counts decline during major holidays and summer break; drop precipitously on March 13, 2020 when the U.S. declared a national health emergency; and remain substantially lower on average thereafter. At the same time, due to the increase in cell phones covered by Safegraph, visits display a general upward trend prior to the pandemic. Moreover, visit counts to POIs can vary substantially from one week to another as well as across dwell time intervals. While some of these variations reflect school characteristics and idiosyncratic events, others are due to the inherent difficulty of geolocating cell phones to a particular place.

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:

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

where $v_{j,t}\left(d\right)$ denotes raw visits of dwell time d for school j in week t; $\omega_j\left(d\right) = \frac{\sum_{t=t_{-1}}^{t_0} v_{j,t}(d)}{\sum_{t=t_{-1}}^{t_0} v_{j,t}}$ 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 $s\left(j\right)$ 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 studies with Safegraph data. For the approximately 73,000 schools that remain, we estimate sample weights that keep the dataset representative of the universe of schools. The weights are included in the public release of the 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

As discussed in the introduction, the main issue with using school visit changes as a direct proxy of in-person learning is that the relationship between cell-phone presence (visits) and student presence (in-person learning) during the pandemic may not be 1:1. Our methodological contribution consists of deriving an expression for true (unobserved) EIPL and use school visits together with information from schooling mode trackers to estimate EIPL.

Formally, consider EIPL of students attending schools in county (or school district) c in week t. A given tracker measures the percent of students in traditional, hybrid, and virtual schooling mode, denoted respectively as $T_{c,t}$, $H_{c,t}$ and $V_{c,t}$. As shown in Appendix A, EIPL can be related to $T_{c,t}$ and $H_{c,t}$ through

$$EIPL_{c,t} = \left(T_{c,t} - \mu_c^T + \eta_{c,t}^T\right) + \left(\gamma_c H_{c,t} + \eta_{c,t}^H\right) + \left(\mu_c^V + \eta_{c,t}^V\right), \tag{3}$$

where $\mu_c^T \geq 0$ denotes the average deviation from 100% in-person learning when the tracker classifies schooling mode as traditional; γ_c the average fraction of in-person learning when the tracker classifies schooling mode as hybrid; $\mu_c^V \geq 0$ the average deviation from 0% in-person learning when the tracker classifies schooling mode as virtual; and $\eta_{c,t}^T$, $\eta_{c,t}^H$, $\eta_{c,t}^V$ measurement errors associated with each of the schooling modes.

Since both EIPL and visit changes measure percent deviations from the pre-pandemic baseline, the relationship between the two variables should satisfy $EIPL_{c,t} = 100 + \beta_c \Delta \widetilde{v}_{c,t} + \varepsilon_{c,t}$, where $\Delta \widetilde{v}_{c,t}$ is the average (student-weighted) school visits change in county c in week t; and $\varepsilon_{c,t}$ is the measurement error implied by the Safegraph data. By leaving β_c unrestricted, we allow the relationship between in-person learning and visits during the pandemic to be different from 1:1. Replacing $EIPL_{c,t}$ with the expression in (3) and rearranging, we obtain

$$T_{c,t} = (100 + \mu_c) + \beta_c \Delta \widetilde{v}_{c,t} - \gamma_c H_{c,t} + (\varepsilon_{c,t} - \eta_{c,t}), \tag{4}$$

where $\mu_c = \mu_c^T - \mu_c^V$ and $\eta_{c,t} = \eta_{c,t}^T + \eta_{c,t}^H + \eta_{c,t}^V$. Linear regression of this equation provides us not only with an estimate of how a given change in school visits maps into EIPL, $\hat{\beta}_c$, but also with an estimate of the fraction of in-person learning that students spent on average in person when in hybrid mode, $\hat{\gamma}_c$.

Seen through equation (3), the large discrepancies in schooling modes across trackers documented in Section 2 manifest themselves through differences in the average fraction of in-person learning γ_c implied by a tracker's definition of hybrid mode and differences in the various measurement errors. This suggests that we estimate (4) for each of the trackers and retain the estimates that, conditional on visit changes, imply the smallest error or equivalently the largest R-squared.

While (4) can in principle be estimated at the county level, this runs into the practical problem that for some counties and trackers, there is little time variation in $T_{c,t}$ and $H_{c,t}$, or $T_{c,t}$ and $H_{c,t}$ are almost perfectly negatively related (this occurs when $V_{c,t} = 0$ for most weeks and thus $T_{c,t} \approx 100 - H_{c,t}$). For these cases,

$\hat{\gamma}_c \to 1$ and $\hat{\beta}_c \to 0$ since $\Delta\widetilde{v}_{c,t}$ is subject to idiosyncratic variation. We therefore estimate (4) separately at the CBSA and the state level for different sample periods of the 2020-21 school year. Moreover, to avoid overfitting, we restrict $\mu_c = 0$ and retain the $\hat{\beta}_c$ associated with the highest R-squared subject to $0 < \hat{\gamma}_c < 1$, where c now indicates the CBSA or state.[5] The estimate of EIPL at school j during week t is then given by $E\hat{IPL}_{j,t} = 100 + \hat{\beta}_{c(j)}\Delta\widetilde{v}_{j,t}$, where $\hat{\beta}_{c(j)}$ is the regression coefficient from the tracker that implies the highest R-squared for the CBSA or state in which school j is located.

Table 1: 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
$\hat{\beta}_c$	1.18	0.72	1.13	1.20	1.27	1.43
$\hat{\gamma}_c$	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 1 reports summary statistics of the resulting estimates. Across the approximately 73,000 schools, the retained estimates are evenly distributed between CBSA and state level regressions obtained from Burbio and R2L data (panel (a)). This indicates that, given the parameter constraints, allowing for within-state variation would in about half the cases produce a worse fit, and that the quality of the two trackers relative to observed visit changes varies across regions. The regressions are generally tightly estimated with a median R-squared of 0.88 and an interquartile range of 0.68 to 0.96 (panel (b)).[6] The median $\hat{\beta}_c$ is 1.2, with an interquartile range of 1.13 to 1.27, implying that EIPL generally varied by a larger proportion than visits during the 2020-21 school year. In turn, the median $\hat{\gamma}_c$ is 0.27, suggesting that the fraction of hybrid learning spent in person was about 30% or 1.5 days out of a 5-day school week on average. However, there is considerable variation across regions and trackers, as indicated by the interquartile range of 0.17 to 0.37, reflecting both variations in school policies with regards to hybrid in-person learning (i.e. the supply side) and students' take up of this option.

[5] The restriction $\mu_c = 0$ assumes that the average deviation of traditional mode from 100% learning, μ_c^T, equals the average deviation of virtual mode from 0% learning, μ_c^V – an assumption that we generally cannot reject. The restriction $0 < \hat{\gamma}_c < 1$ imposes that the fraction of hybrid learning spent in person is within its theoretical bounds – a restriction that binds in only very few cases. Given these restrictions, estimating (4) at the county level would in many cases result in a R-squared that is lower than at the CBSA or state level.

[6] For most CBSAs in Arkansas and Maine, the R-squared is lower than 0.25 for both trackers. For those schools, we use regression coefficients from neighboring states. See Appendix A for details.

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

Given the estimates of β, we construct EIPL for each school in our Safegraph sample and investigate the extent to which EIPL varied during the pandemic and across regions. As shown in the Appendix, EIPL dropped to between 0% and 20% for almost all counties from March to May 2020. During the 2020-21 school year, however, there are large disparities in EIPL. As illustrated in Figure 2, EIPL recovered to 60% or higher in the South and Central North, while in the North and Mid-Atlantic and the West EIPL remained stuck in the 0% to 35% range. Focusing on the 50 biggest U.S. cities by population, we see that in cities in Florida such as Jacksonville, Tampa or Orlando, EIPL averaged over 75% for the 2020-21 school year, whereas in cities in California, Oregon and Washington such as Los Angeles, Portland or Seattle, EIPL averaged 20% or less.

While these regional disparities are striking, there are also large differences in EIPL within counties. For instance, the within-county interquartile range of EIPL averages 16% for the 2020-21 school year, and the extent of this dispersion is similar across counties with different levels of average EIPL. This suggests that regional disparities in EIPL may in part be driven by differences in school and local characteristics that apply similarly across the country.

To investigate further, we analyze how observable school and local characteristics correlate with EIPL. Then we return to geography and examine the extent to which these correlations are accounted for by systematic regional differences. The result is a set of facts that can help us understand the "for whom", which hopefully provides guidance for other studies that analyze pandemic-induced learning losses.

4.1 School type and grade

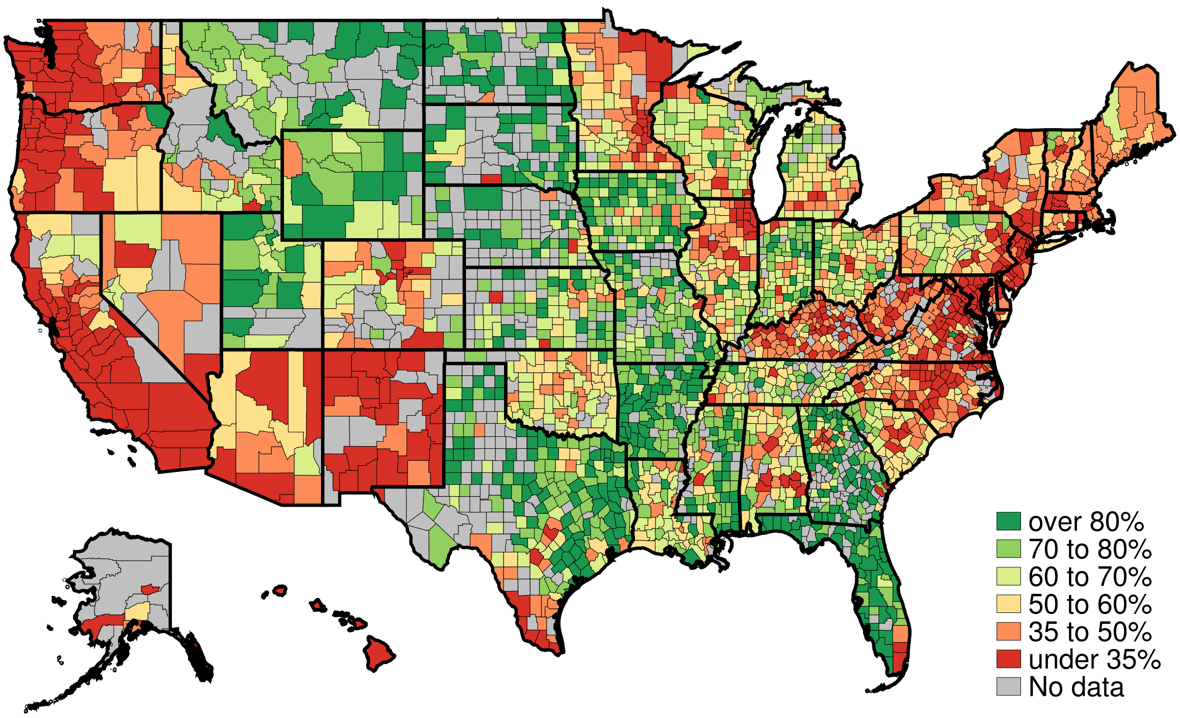
We start by comparing EIPL by school type and grade. As reported in the Appendix, for the 2020-21 school year, EIPL is lowest for public charter schools (averaging 36%), followed by public non-charter schools (44%), private non-religious schools (51%), and private religious schools (57%). In turn, EIPL 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 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, comprise several hundred schools and are 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 confirms results by Parolin and Lee [2021], Musaddiq et al. [2022], 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, in Fuchs-Schündeln et al. [2022] we project that children just starting secondary school during 2019-20 will endure the largest losses in their earnings capacity in the long run.

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 during the 2020-21 school year

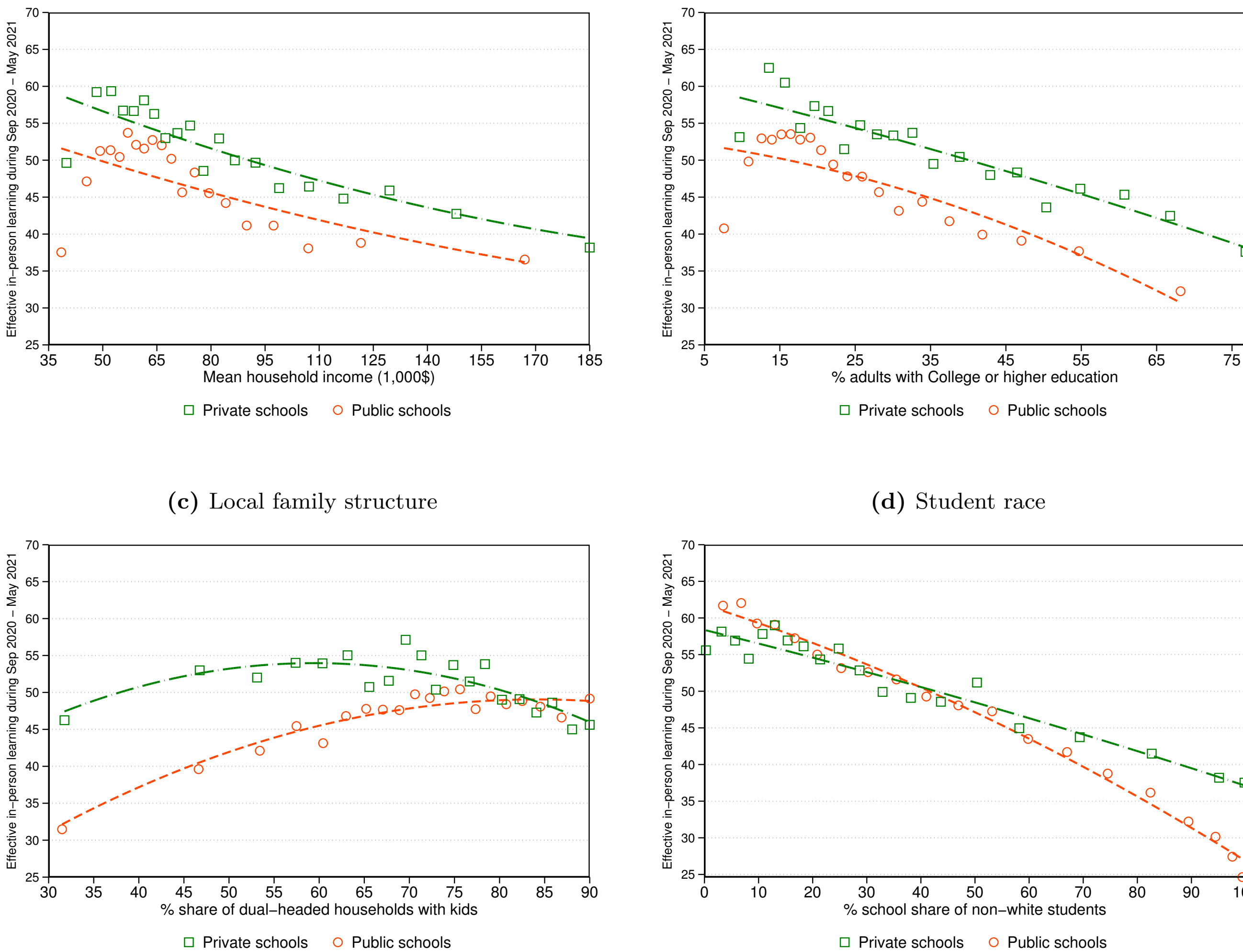
Rank	CBSA name	EIPL	Rank	CBSA name	EIPL
1	Jacksonville, FL	87.6%	41	Sacramento-Arden-Arcade-Roseville, CA	22.9%
2	Tampa-St. Petersburg-Clearwater, FL	81.3%	42	Washington-Arlington-Alexandria DC-VA	22.9%
3	Orlando, FL	77.1%	43	Baltimore-Towson, MD	22.4%
4	Houston-Baytown-Sugar Land, TX	61.9%	44	Seattle-Bellevue-Everett, 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.

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

Next we consider EIPL by local affluence and education as well as family structure and 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 of dual-headed households with children, all measured at the zip-code level of the school.[7] For race, we use the school's share of non-white students as provided by the NCES.

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



(a) Local affluence **(b)** Local education **(c)** Local family structure **(d)** Student 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.

Figure 3 shows that EIPL during the 2020-21 school year was on average *lower* in zip codes with *high*

[7] Results are robust to using the variables at the census block group or tract of the school, or at the school district level. Results are also robust to using alternative indicators of affluence from Chetty et al. [2020]'s Opportunity Atlas and the NCES's school neighborhood poverty index.

household income. A similar negative relation holds between education and EIPL. Consistent with the above results, EIPL is on average about 10% higher for private than for public schools, but the association of EIPL with household income and education is otherwise similar. In turn, there is a positive relationship between average EIPL and local share of dual-headed households for public schools but no systematic relationship for private schools. Finally, EIPL is inversely related to 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.

To provide a sense of the quantitative importance of these results, we estimate univariate linear regressions of average 2020-21 EIPL on each of the variables. We then scale the estimated coefficients to show the implied change in EIPL of going from the 25th to the 75th percentile of the distribution of a variable. For comparison with results that follow, we limit the analysis to public schools. The Appendix provides equivalent results for private schools.

The brown square-shaped estimates in panel (a) of Figure 4 reports the results. The other estimates in the figure are explained below. EIPL for a school located in a zip-code at the 75th percentile of the income distribution is on average 3-5% lower than for a school at the 25th percentile. The same interquartile difference is associated with 7-8% lower EIPL for education and 3-5% higher EIPL for share of dual-headed households. In comparison, the difference in EIPL by race is much larger: a school with a share of non-white students at the 75th percentile has on average 18-23% lower EIPL than a school at the 25th percentile.

Given the general association of poverty with race, the inverse relationship of EIPL with both affluence and race may come as a surprise. As shown in the Appendix, however, household income and share of non-white students are essentially uncorrelated *across* zip-codes. It is only *within* local areas (e.g., CBSAs or counties) that the two variables are negatively correlated. This suggests that the results in Figure 3 are in large part driven by systematic regional differences. Also, the R-squared for all the regression is lower than 0.1, which means that differences in local affluence, education, composition and race account by themselves for only a relatively small share of the variation in EIPL across schools.

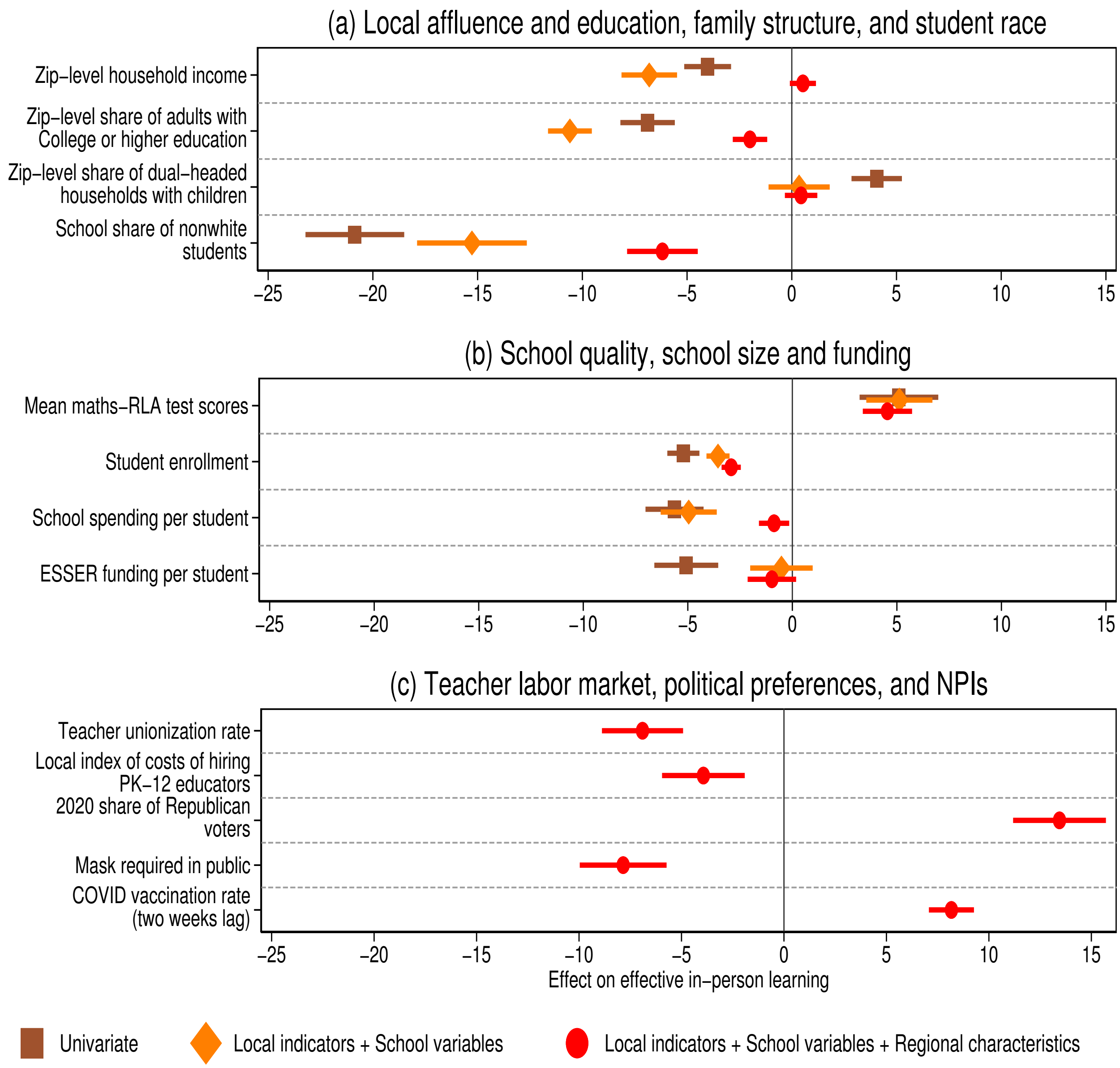
4.3 Public school tests scores, school size, and school funding

We extend the analysis by considering the relation between EIPL and school test scores, school size, and funding. We obtain pre-pandemic test scores from Fahle et al. [2021], and we measure school size by student enrollment per school from the NCES.[8] For 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 begin with univariate regressions of average 2020-21 EIPL on each of the variables. The brown square-shaped estimates in panel (b) of Figure 4 show the results. EIPL is higher in schools with higher pre-pandemic test scores but lower for larger schools. EIPL is also lower for schools with higher pre-pandemic spending per student and for schools in districts that received more ESSER funding per student. This 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

[8]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 similar results.

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



Notes: The figure shows the estimated coefficients and 95% confidence intervals of regressing weekly school EIPL from September 2020 to May 2021 on the different variables. The sample consists of approximately 60,000 public schools. The brown square-shaped estimates show the results of univariate regressions of EIPL on the listed variable only, controlling for school type (charter vs. non-charter school) and school grade (elementary vs. middle vs. high. vs. combined school). The yellow diamond-shaped estimates show the results of multivariate regressions of EIPL, controlling for the other variables in panel (a) and panel (b). The red round-shaped estimates show the result of adding the variables in panel (c) to the multivariate regressions together with 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 rural / urban area indicators. All variables except for the "Mask required in public" indicator are scaled so that the estimates show the implied change in EIPL of going from the 25th percentile to the 75th percentile of the distribution of a variable. All regressions are weighted with standard errors clustered at the county level and school weights calculated as explained in the appendix.

support for school reopening.

While these results are interesting, it is important to keep in mind that the different regressors are not independent of each other. For instance, as shown in the Appendix, ESSER funding is strongly negatively correlated with school test scores. The negative univariate association of ESSER funding with EIPL may therefore simply reflect that more ESSER funding was allocated to schools with low test scores and low initial EIPL and that once one controls for this difference, ESSER funding may become positively associated with EIPL (perhaps because it did support at least partially the reopening of schools).

To assess this possibility, we run multivariate regressions with the variables listed in panel (a) and (b) of Figure 4. The yellow diamond-shaped estimates show the results. First, when controlling for race and school characteristics, the negative association of EIPL with local income and education becomes larger while the positive association with local share of dual-headed households disappears.[9] Second, the association of EIPL with race is reduced but remains the quantitatively most important predictor of EIPL. Further analysis in the Appendix reveals that this result is mostly driven by the share of Hispanic students and less by the share of Black students. Third, the association of EIPL with test scores, enrollment, and spending per student remains similar while the negative association of EIPL with ESSER funding is reduced to zero but fails to become positive.

It is instructive to compare our findings with results reported elsewhere in the literature. The finding that even after controlling for a host of school characteristics, EIPL in more affluent and less educated communities was on average lower – not higher – during the 2020-21 school year has not been highlighted by other studies. The negative relationship between EIPL and a school's share of non-white students, on the other hand, is not a new finding (see e.g. Camp and Zamarro, 2022, Landivar et al., 2022, and Parolin and Lee, 2021). What is new, however, is that this relationship remains even after conditioning on local affluence and education as well as school characteristics. Similarly, while the positive association of EIPL with school test scores is not new (see e.g., Parolin and Lee [2021]), we show that it remains after taking into account many other local and school characteristics. Finally, the absence of a positive relation of EIPL with ESSER funding, even after controlling for many other variables, is a new and in our view striking result.

4.4 Geography

Given the large disparities in EIPL across regions documented in Figure 2, it is natural to ask to what extent the association of EIPL with local and school characteristics is just reflections of systematic geographic differences. To address this question, we add several geographic markers to the above multivariate regressions and investigate their impact. Specifically, we add CBSA-level teacher unionization rates and a county-level comparable wage index for PK-12 educators computed by the NCES as proxies for the bargaining power of teachers; the county-level Republican vote share in the 2020 presidential election as a measure for the general stance towards reopening the economy, including schools; as well as county-level local mask mandates and two-week lagged vaccination rates as indicators of the perceived aversion towards COVID infections. Furthermore, we include controls for a county's COVID health situation as measured by pre-pandemic ICU bed capacity, lagged COVID case and death rates, and indicators of non-pharmaceutical interventions (NPIs); as well as controls for the maximum weekly temperature and urban density.

[9] Due to the high collinearity of household income, share of college educated, and share of dual-headed households, we include each of these variables separately when estimating their marginal association with EIPL. For the other multivariate regressions, we include these variables jointly.

The red round-shaped coefficient estimates in Figure 4 report the results. Consistent with Hartney and Finger [2020], Gollwitzer et al. [2020] and Valant [2020], schools in areas with a larger share of Republican votes in the 2020 presidential election had on average substantially higher EIPL during the 2020-21 school year. Interestingly, higher local vaccination rates also predict higher EIPL. In contrast, mask requirements, teacher unionization and the local wage index for PK-12 educators are associated with lower EIPL.

Adding Republican vote shares and to a lesser extent vaccination rates, teacher unionization rates, and the local wage index also substantially increases the predictive power of the regression while reducing the association of EIPL with local affluence, education, and school spending per student close to zero. In other words, the negative relationship of these variables in the above regressions arises primarily because they proxy for political preferences and other systematic geographic differences. Our results therefore offer a new nexus between affluence, voting preferences, and public school closures. At the same time, even though the inverse relation between EIPL and the share of non-white students is reduced, it remains significant: a school with a student body at the 75th percentile of the non-white distribution is predicted to average 4-8% lower EIPL during the 2020-21 school year than a school at the 25th percentile of the distribution. Finally, the addition of Republican vote share and other regional characteristics implies a small negative relation between EIPL and district ESSER funding per student. Hence, even after controlling for all these covariates, EIPL was not higher in school districts with more ESSER funding.

5 Conclusion

This paper starts by highlighting important discrepancies between popular pandemic schooling mode trackers. We then propose a new measure of effective in-person learning (EIPL) that we estimate by mapping school visits data from Safegraph with tracker information from Burbio and Return2Learn. This new measure not only resolves the discrepancies across trackers, but is also more suitable for many quantitative questions about the extent and consequences of pandemic school closures We make the EIPL dataset publicly available and hope it is useful for future research. As an application, we analyze the relation of EIPL to various school and local characteristics. The analysis uncovers several new results that raise important questions:

1. Why was EIPL lower for schools in more affluent and more educated areas with higher funding per student? 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, EIPL was higher in private schools (which generally attract students from wealthier backgrounds) than in 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 was EIPL lower in schools with a higher share of non-white students, even within a given county and controlling for neighborhood and school characteristics? This 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 more ESSER funding per student not lead to higher 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.

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.

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