Inequality in Household Adaptation to Schooling Shocks: Covid-Induced Online Learning Engagement in Real Time

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Abstract

We use high frequency internet search data to study in real time how US households sought out online learning resources as schools closed due to the Covid-19 pandemic. By April 2020, nationwide search intensity for both school- and parent-centered online learning resources had roughly doubled relative to pre-Covid levels. Areas of the country with higher income, better internet access and fewer rural schools saw substantially larger increases in search intensity. The pandemic will likely widen achievement gaps along these dimensions given schools' and parents' differing engagement with online resources to compensate for lost school-based learning time. Accounting for such differences and promoting more equitable access to online learning could improve the effectiveness of education policy responses to the pandemic. The public availability of internet search data allows our analyses to be updated as schools reopen and to be replicated in other countries.

1 Introduction

As schools across the United States closed in response to the Covid-19 pandemic, roughly 55 million K-12 students experienced a serious disruption to their school year. Though most schools quickly began offering some type of virtual education (Hamilton et al., 2020; Lake and Dusseault, 2020), there have been growing concerns about the effects of this unprecedented shift (Malkus, 2020; von Hippel, 2020). In particular, there were fears that low-income students would be unequally harmed by the shift to online learning, due to less access to online resources to compensate for lost in-person instruction (Horowitz, 2020). Such fears have largely been confirmed, as learning losses appear substantially higher for students in high-poverty schools than in low-poverty ones (Kuhfeld et al., 2022). As states and districts consider how to best educate students in the wake of the pandemic, it is critical to better understand the effect of pandemic-induced school closures on students' access to online learning resources, particularly for low-income students.

This paper uses high frequency, nationally representative Google search data to document in real time how parents and students sought out online resources as schools closed in response to the Covid-19 pandemic. Combining the online search measures with measures of demographic characteristics by geography, we estimate how Covid-induced demand for online resources varied by a range of geographic and socioeconomic factors, including income, internet access and school rurality.

We document three new findings. First, we show that pre-Covid search intensity for online learning resources can be usefully divided into two categories, which we call "school-centered resources" and "parent-centered resources". School-centered resources are platforms typically used by schools to provide instruction, assign work, or communicate with students (such as Google Classroom or Schoology). Parent-centered resources are more generic search terms likely indicating parents or students are seeking supplemental learning resources (such as home schooling or math worksheets). We show that search intensity for school-centered resources dwarfs that for parent-centered resources and that both follow the school calendar, peaking at the start of each school year and vanishing in the summer.

Second, we show that the onset of Covid dramatically disrupted this usual school calendar cycle of search intensity, as the pandemic triggered a very large increase in demand for online learning resources. By April 2020, nationwide search intensity for online learning resources had roughly doubled relative to pre-Covid levels. We find sharp increases in searches for both school- and parent-centered resources, suggesting that increased demand for online support came not only from schools shifting their mode of instruction but also from parents and students seeking additional support to fill learning gaps as schools closed.

Third, we show the pandemic substantially widened socioeconomic gaps in searches for online learning resources. Search intensity rose twice as much in areas with above median socioeconomic status (measured by household income, parental education, and computer and internet access) as in areas with below median socioeconomic status. Search intensity for school-centered resources, for example, increased by 15 percent for each additional $10,000 in mean household income and by roughly 5 percent for each percentage point increase in the fraction of households with broadband internet and a computer. Areas with more rural schools and Black students saw lower increases in search intensity. Socioeconomic gaps widened both between and within the country's four Census regions (Northeast, Midwest, South, and West). We also show that changes in search behavior correlate with changes in students' actual math progress, suggesting online search metrics may be a useful proxy for educational actions taken by parents and students.

Our work adds to three strands of the research literature. First, our paper shows that internet search behavior can provide useful, real-time information about education-related actions being taken by households. Prior work shows the utility of search data in predicting economic and social outcomes such as parents' preferences for schools (Schneider and Buckley, 2002), disease spread (Polgreen et al., 2008), consumer behavior (Choi and Varian, 2012), voting (Stephens-Davidowitz, 2014), and fertility decisions (Kearney and Levine, 2015). Most recently, Goldsmith-Pinkham and Sojourner (2020) use the volume of online search for unemployment benefits to predict post-Covid unemployment claims. Our results suggest that search data contain valuable information about how households react to educational shocks, both in terms of overall use of educational resources and in heterogeneity in such usage by socioeconomic characteristics.

Second, we measure a new aspect of the digital divide, namely the extent to which households seek out online learning resources either prompted by their schools or of their own accord. A large literature documents pre-Covid gaps in access to and proficiency in the use digital technologies by income, education, and family background (Bucy, 2000; Rice and Haythornthwaite, 2006; Jones et al., 2009; Vigdor et al., 2014). Multiple post-Covid surveys show consistent socioeconomic gaps in self-reported engagement with remote learning at a single point in time (Barnum and Bryan, 2020). We complement this evidence with the first nationally representative revealed preference measure of such engagement, based on households' actual behavior rather than self reports. Ours is also the first high frequency data brought to bear on this issue, allowing study of the evolution over time of engagement with online learning resources.

Third, we provide some of the clearest evidence on one channel through which the Covid-19 pandemic has likely widened socioeconomic educational gaps. Based on prior estimates of school closure effects from natural disasters and summer months, Kuhfeld et al. (2020) predict that Covid-induced closures will generate substantial learning losses, with the largest negative effects concentrated among low-achieving students. Aucejo et al. (2020) surveyed university students and find the pandemic lowered on-time graduation rates and job offers, with larger effects among low-income students. Using data from one online learning platform, Chetty et al. (2020) provide perhaps the only direct measure of Covid-induced learning loss, showing that low-income students experienced substantially larger and more persistent reductions in learning progress relative to high-income students. We show that socioeconomic gaps in engagement with online learning resources are not limited to a single platform or location but are a widespread and fundamental feature of the post-Covid landscape. Accounting for household responses to changing school inputs will be critical for predicting educational effects of the pandemic and policy responses to it, given evidence that parental and school investments are often substitutes, both in the US (Houtenville and Conway, 2008) and developing countries (Das et al., 2013; Pop-Eleches and Urquiola, 2013).

Our findings provide insight into the mechanisms underlying learning losses that have emerged following pandemic-induced school closures and can help inform future policy responses to schooling disruptions, whether related to the pandemic or not. That search for school-centered resources increases more in high income areas suggests either that those areas' schools are using online platforms more, that those areas' parents are more likely to engage with such platforms, or both. That search for parent-centered resources increases more in high income areas suggests that, separate from schools' actions, parents are differentially likely to seek out their own ways of compensating for their children's lost learning time.

These results can help policymakers and school leaders formulate more effective responses to the educational disruptions caused by Covid-induced school closures. Students from lower income families and schools may require additional attention and resources given lower engagement with online learning resources during spring 2020. Moreover, because remote learning will likely remain a central piece of the public education system for the foreseeable future (Cleveland, 2020), preventing the widening of achievement gaps may require improving access to home computers and broadband internet for low income and rural students. Schools may also need to improve the deployment of remote learning platforms to more equitably engage students and parents in the use of those platforms.

Whether efforts to close gaps in online learning engagement succeed will only become clear as new data become available in subsequent school years. One advantage of using publicly available search data to measure household behavior is that our analyses can be easily updated in real time when the school year begins in the fall. This will help reveal whether socioeconomic gaps in engagement with online learning have narrowed since the initial shock of schools closing or if different remote learning strategies across regions were particularly successful. In addition, the set of search terms studied can be easily modified to accommodate new online learning resources as they emerge. Finally, our analyses can be replicated in other countries, particularly ones large enough to generate search data at sub-national levels such as provinces and cities. The flexibility of this approach shows promise for understanding the behavioral responses of households to school closures and developing policy responses in real time to address changing student needs.

2 Data and Empirical Strategy

2.1 Search Data

Our outcome measures of search intensity come from Google Trends, which makes publicly available weekly measures of internet search behavior both nationally and at finer levels of geography. The publicly available measure of search behavior for a given term or topic is "search intensity", which calculates the fraction of a given area's Google searches devoted to that term or topic. We scale the available measures so that our estimates can be interpreted as percent changes.

We focus on measuring search intensity for terms related to online learning. We first assembled a list of dozens of potential such keywords and then ranked the keywords by their nationwide popularity in the 5 years leading up to spring 2020. We then identified the 10 most popular keywords related to branded online learning resources (such as "Google Classroom" or "Khan Academy") and the ten most popular keywords for general online learning resources (such as "online learning", "home school", and "math worksheet"). Table 1 shows these top 10 lists and their popularity.[1] The most popular of these search terms by far is Google Classroom. Khan Academy, one of the next most popular terms, was roughly 13 percent as popular as Google Classroom. General (non-branded) learning resources saw substantially lower search intensity than that.

Table 1: Search Intensity of Top 10 Individual Keywords

School-Centered Resources			Parent-Centered Resources		
Keyword	Pre-Covid	Post-Covid	Keyword	Pre-Covid	Post-Covid
Google Classroom	1.00	1.95	Online school	0.04	0.06
Khan Academy	0.13	0.20	Online classes	0.03	0.05
Kahoot	0.33	0.19	Home school	0.03	0.03
Seesaw	0.02	0.15	Online class	0.00	0.02
Schoology	0.07	0.12	Math game	0.03	0.02
Class Dojo	0.01	0.06	Distance learning	0.00	0.02
Flipgrid	0.00	0.05	Math worksheets	0.00	0.02
D2L	0.05	0.05	Online math	0.00	0.01
Nearpod	0.02	0.02	Math problem	0.00	0.01
Edmodo	0.02	0.02	Online reading	0.00	0.00

Notes: Mean nationwide search intensity is shown for March-May 2019 (pre-Covid) and March-May 2020 (post-Covid). Search intensity of each term is measured relative to the pre-Covid search intensity for "Google Classroom".

We combine the ten items in each of these two lists to create two primary measures of search intensity for learning resources. Given the ten keywords in each list, we refer to branded learning resources as "school-centered resources" and general learning resources as "parent-centered

[1] For the full list of considered keywords, see Table A.1.

resources". The former list largely consists of educational platforms, such as Google Classroom and Schoology, that schools use to connect with students and are typically not used without the school's involvement. The latter list consists of general learning resources such as "math worksheets" and "home school", which we interpret as parents (or guardians or students themselves) searching for online learning resources on their own, without particular guidance from a school.[2]

2.2 Demographic Data

The finest geographic areas Google Trends allows us to study are called "Designated Market Areas" (DMAs), 210 groups of counties. We characterize the pre-Covid demographics of each DMA using data from the U.S. Census. This allows us to observe a variety of measures, including: mean household income; median household income; fraction of adults with a B.A.; fraction of households with broadband internet; and fraction of households with a computer. These five measures are so highly correlated that we combine them into a single measure that we call DMA-level socioeconomic status (SES). This allows us to do simple comparisons of search intensity across high and low SES areas of the country. We supplement this with data from the Stanford Education Data Archive (SEDA), which provides additional information such as the fraction of schools in rural areas and the racial composition of the school-age population. Table 2 shows that, as of 2016, 87 percent of households had a computer, 77 percent of households had broadband internet, and 25 percent of schools were in rural areas.

2.3 Empirical Strategy

We first estimate changes in nationwide search intensity for learning resources as a result of Covid-induced school closures, both week-by-week and averaged across the whole post- vs. pre-Covid period. To do so, we use pre-Covid data to control for how intense search for online learning resources usually is in a given calendar week. Deviations from that post-Covid can be interpreted as the pandemic school closure effect. In the week-by-week analysis, we use March 1, 2020 as the reference week to compare search intensity to because that was around the time families began hearing about Covid and schools began closing. When comparing the whole spring 2020 to prior springs, we exclude the ramp-up period of March 2020 because school closure discussions began in early March and nearly all schools were initially closed by states between March 16 and March 23.[3] In addition to studying how search for online learning resources changed nationwide, we also conduct the analysis separately by geographic SES. Our simplest analyses divide the nation into high (above median) and low (below median) SES areas, comparing how search behavior

[2]Khan Academy is perhaps the most ambiguous search term, in that many schools use it to deliver curriculum to students, but parents and students can also access it without the school's involvement. We place it in the list of school-centered resources but often show separate results for it and for Google Classroom, the two most popular search terms in the post-Covid period.

[3]See Table A.2 for a list of school closure dates by state.

Table 2: Demographic Characteristics of US Regions (DMAs)

	Mean	St.Dev.
(A) 2016 American Community Survey		
Mean household income (1,000s)	73.4	12.9
Median household income (1,000s)	54.9	10.2
Percent of adults with a B.A.	26.7	6.5
Percent of households with broadband internet	77.2	5.5
Percent of households with a computer	86.7	3.8
(B) 2016 Stanford Education Data Archive		
Percent of schools in rural areas	25.3	17.1
Percent of students who are Black	14.1	15.3
N	210	

Notes: Panels A and B respectively present population weighted averages from the 2016 American Community Survey (ACS) and Stanford Education Data Archive (SEDA).

evolved in those two sets of places. We can also compare areas by the extent to which they differ in individual components of SES, such as income or broadband penetration rates.

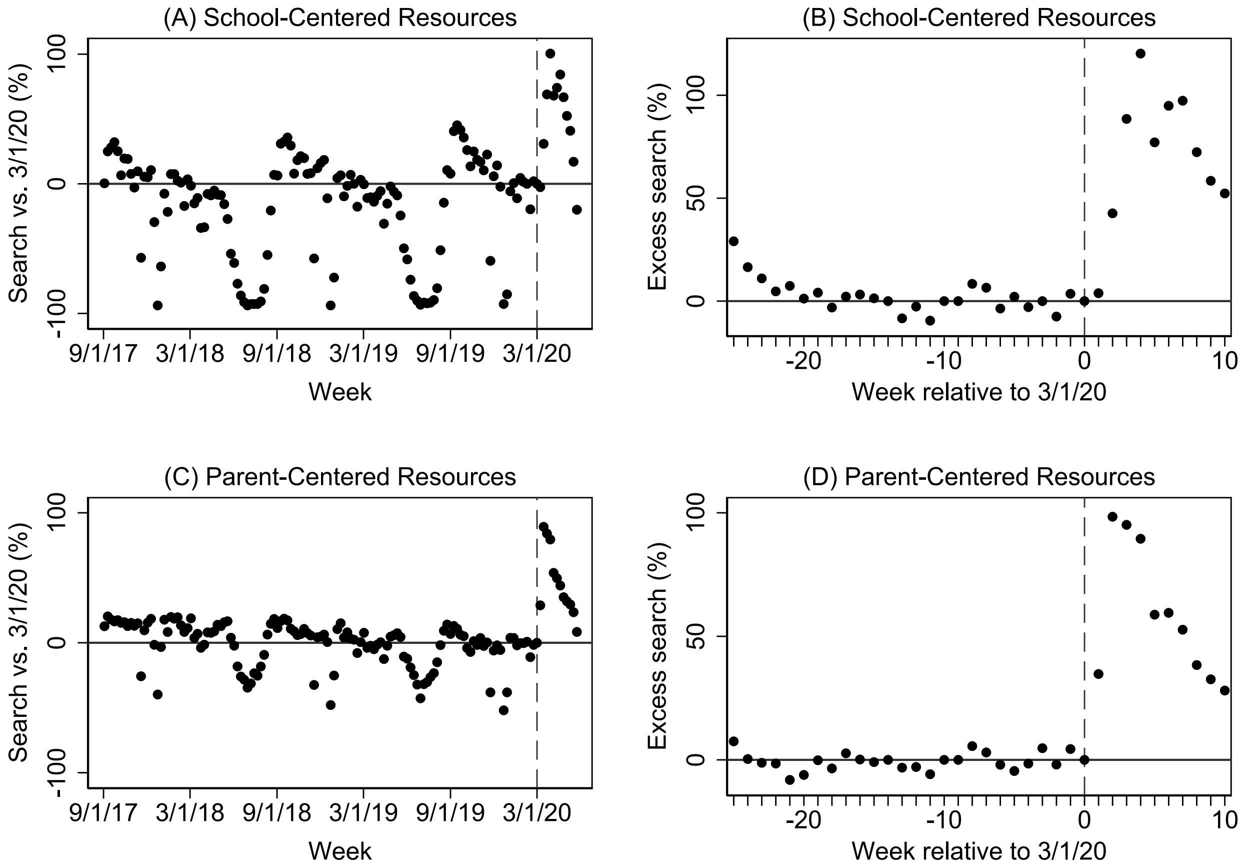
3 Results

Nationwide search intensity for learning resources followed regular annual patterns until March 2020, at which point search intensity dramatically increased relative to similar months in prior years. As seen in panel A of Figure 1, search intensity for school-centered resources typically peaks near the start of each school year and declines steadily until summer, when it largely vanishes. Panel C shows that search intensity for parent-centered resources is steadier throughout the school year but also declines substantially in summer. Covid-related school closures altered these patterns, with nationwide search intensity for both types of learning resources roughly doubling by late March. Search intensity then starts to decay, likely due to households successfully locating their desired online resources and to school years ending in May and June.

Panels B and D show "excess search" by removing typical pre-pandemic calendar patterns from the data. This shows even more clearly that there were no unusual pre-trends prior to March 2020 but then a large and statistically significant rise in search intensity that then starts to fade by May. At its peak in April, search for both sets of online learning resources was roughly 100 percent higher than typical for that time of year.

Growth in post-Covid search intensity varied substantially by geography and socioeconomic status. Figure 2 maps DMAs by quartiles of SES (panel A) and post-Covid changes in search inten-

Figure 1: Weekly Nationwide Search Intensity for Learning Resources



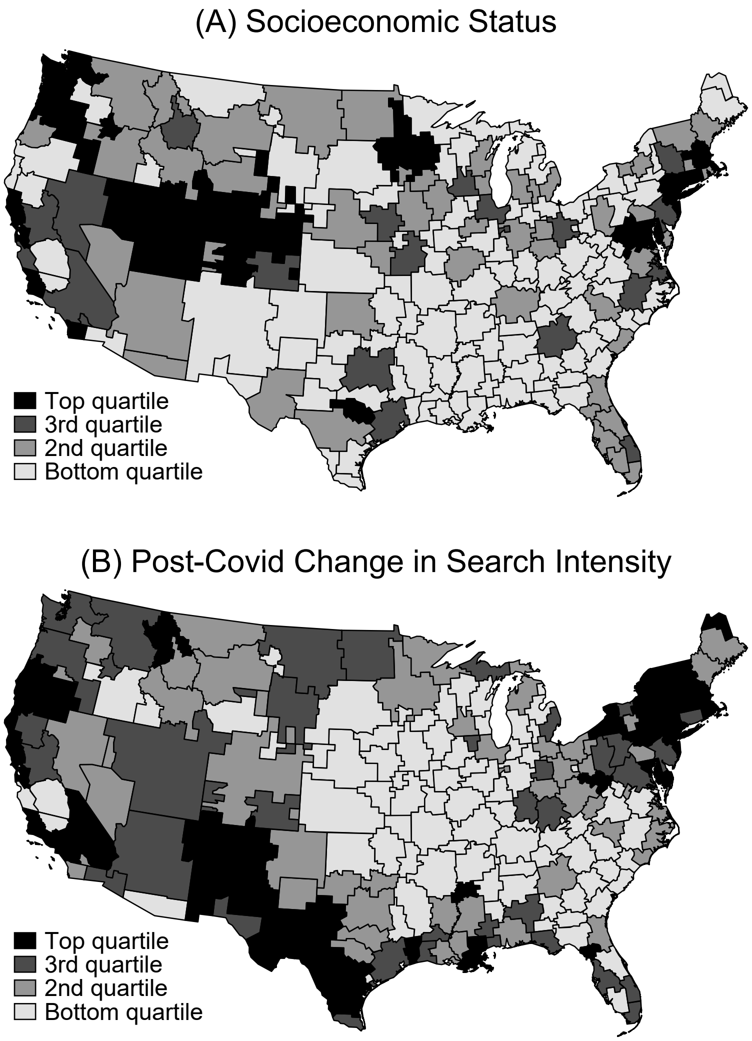
Notes: Panels A and C show raw weekly search intensity relative to March 1, 2020 for school- and parent-centered resources. Panels B and D show deviations from historical search levels during the weeks closest to March 1, 2020.

sity (panel B), defined as April-May search intensity differences between 2020 and prior years. Areas with high income, parental education and technological access are concentrated in the Northeast and West coast, as well as Utah and Colorado. Post-Covid search intensity also increases most noticeably, though not exclusively, in the Northeast and West coast, suggesting that high SES areas see larger spikes in search intensity for learning resources.

Weekly search intensity for learning resources increased significantly more in areas with higher income and better technological access. Figure 3 shows raw weekly search intensity in DMAs above and below median SES, in panels A and C. Both show that high SES areas of the country have substantially higher search than low SES areas once the pandemic begins, a pattern that was not evident in the data before.

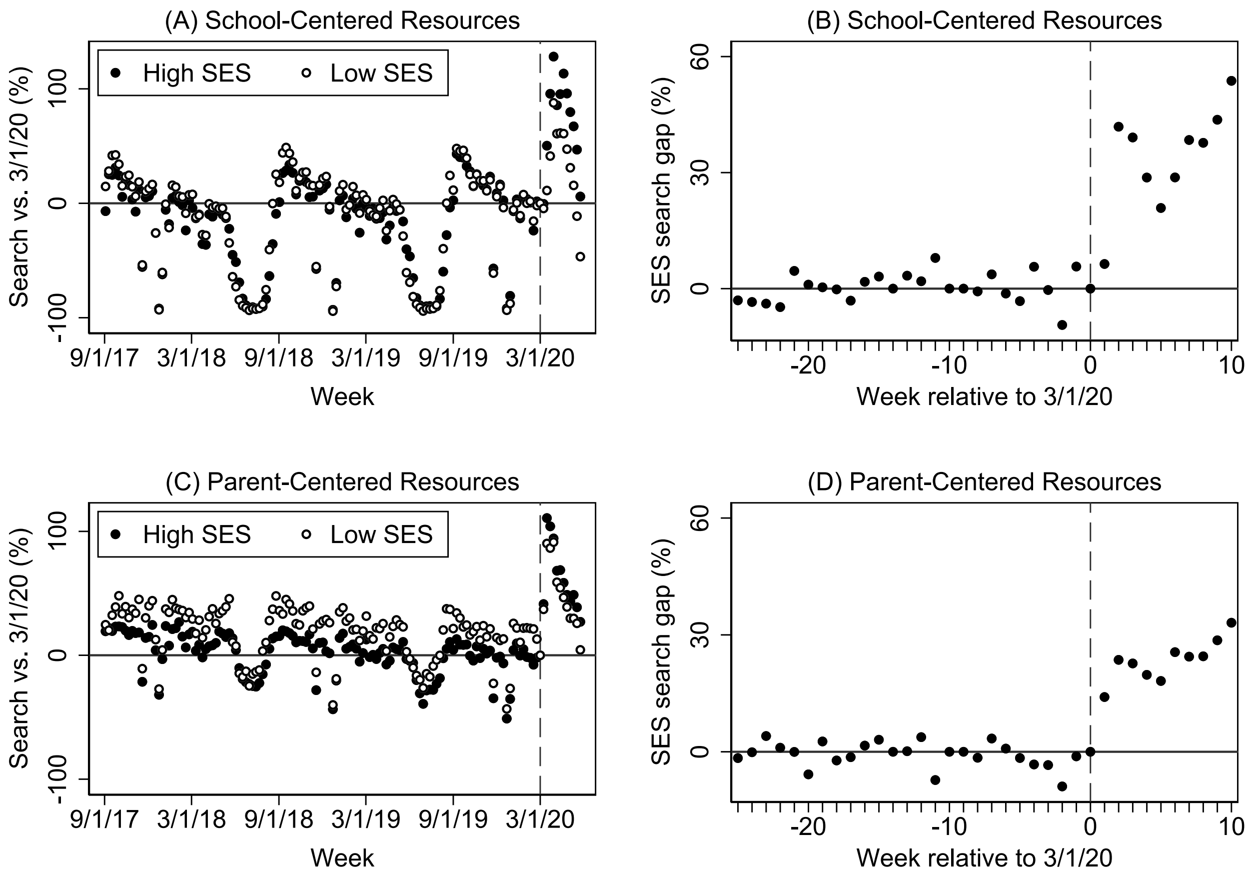
That inequality is made even starker in panels B and D, which take the difference between

Figure 2: Geography of Socioeconomic Status and Change in Search Intensity



Notes: The figure above maps Designated Market Areas (DMA) across the nation. Panel A sorts DMAs into quartiles of socioeconomic status. Panel B sorts DMAs into quartiles of post-Covid changes in search intensity for school-centered resources.

Figure 3: Search Gap by Socioeconomic Status



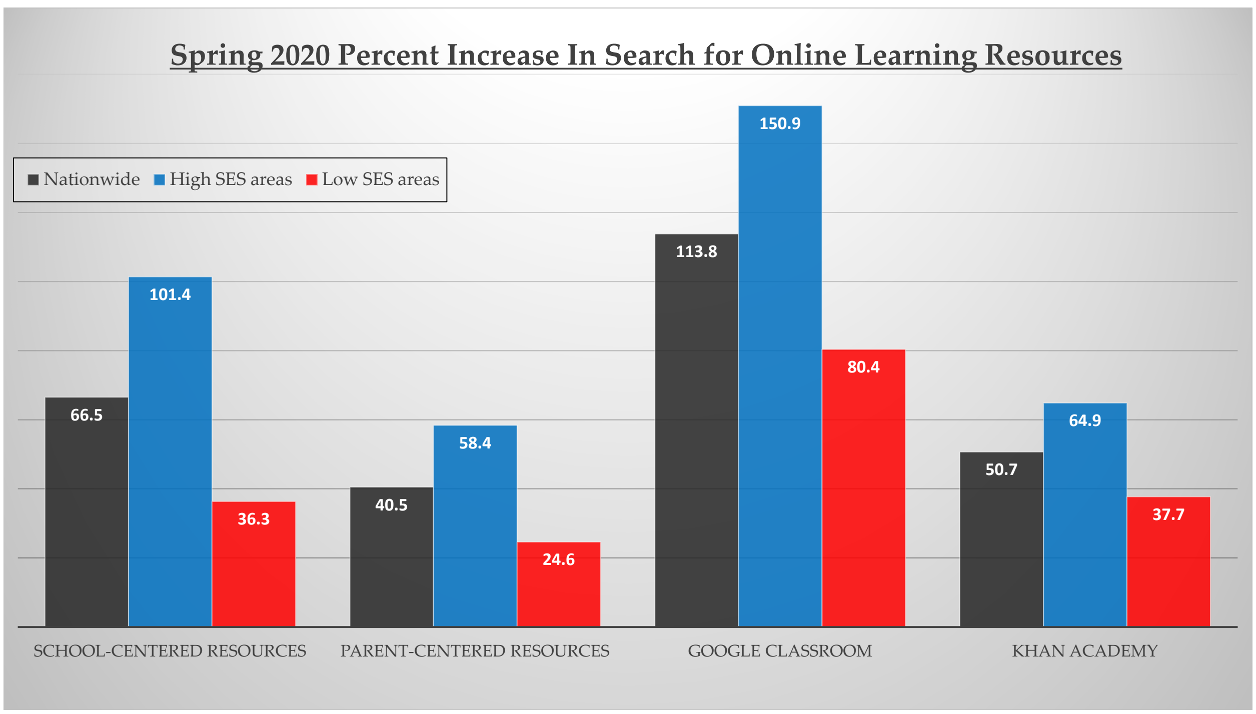
Notes: Panels A and C show raw weekly search intensity relative to March 1, 2020 for school- and parent-centered resources, dividing the nation into Designated Market Areas (DMAs) of above and below median socioeconomic status. Panels B and D estimate differences between high and low SES areas, controlling for historical search levels.

the two sets of points at the panels to their left (and control for historical calendar effects). Panel B shows that, by mid-March, high SES areas saw 30-50 percentage point higher jumps than low SES areas in search intensity for school-centered learning resources. Similarly, high SES areas saw roughly 30 percentage point higher jumps in search intensity for parent-centered resources. These weekly differences between high and low SES areas are statistically significant and do not decay with time.

Figure 4 averages the change in search intensity across all the weeks in April and May 2020, both nationwide and for low and high SES areas separately. In spring 2020, nationwide search for school-centered learning resources was 67 percent higher than normal. This average masks, however, large differences by SES. High SES areas saw search for school-centered resources increase 101 percent (i.e. double), while search in low SES areas for such resources rose only by 36 percent. Search for one specific school-centered resource, Google Classroom, rose by 151 percent in high SES areas but only 80 percent in low SES areas. Search for Khan Academy also rises and unequally by area SES, though all of the increases are smaller than for Google Classroom. Such differences may reflect differences in parental resources, preferences, or information, or may reflect differences by SES in the extent to which schools were transitioning to such online learning platforms.

Search for parent-center resources reflects a similar pattern, if smaller in magnitude. Nationwide, spring 2020 search for such resources was 41 percent higher than normal. This was an average of 58 percent higher search in high SES areas and only 25 percent higher search in low SES areas. Unlike with school-centered resources, these differences likely have little to do with actions taken by schools. Instead, they more likely reflect difference solely in parental resources, preferences, or information.

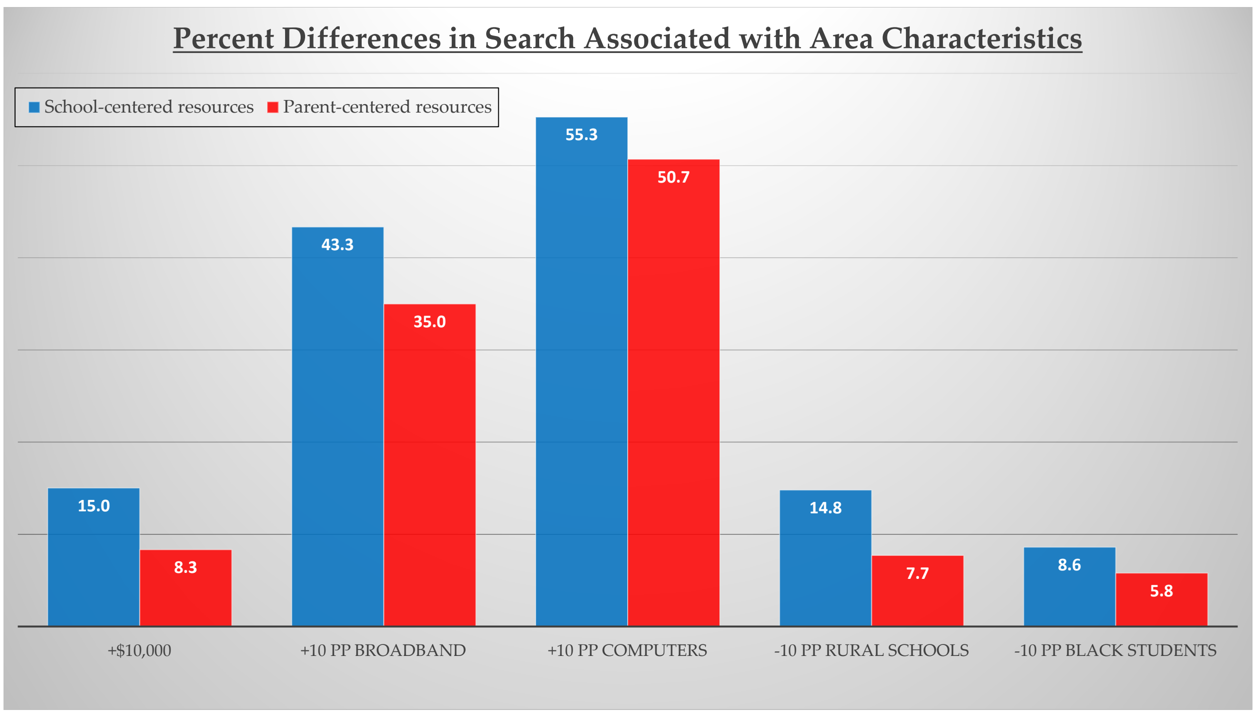
Figure 4: Search Gap by Socioeconomic Status



Notes: Each bar represents the average change in search intensity relative to historical norms for April-May 2020. High and low SES areas each represent half the country by population.

The pandemic widened gaps in search intensity for learning resources not only by broad measures of SES, but also by specific measures such as income, technological access, rurality and race. Figure 5 shows our estimates of the extent to which differences in such characteristics are related to differences in search intensity changes for online learning resources. For example, search intensity for school-centered resources increases by an additional 15 percent with every additional $10,000 in an area's mean household income. Areas with 10 percentage point higher rates of broadband access or computer ownership saw jumps in search 35-55 percent larger than areas with less technological access. Search for online learning resources was higher in areas with fewer rural schools, and in areas with smaller proportions of Black students. Parent-based resources show similar patterns, though with somewhat smaller magnitudes. Measures of SES (such as income or broadband access), school rurality and race are independently associated with search behavior even when controlling for each other.

Figure 5: Search Gap by Area Characteristics

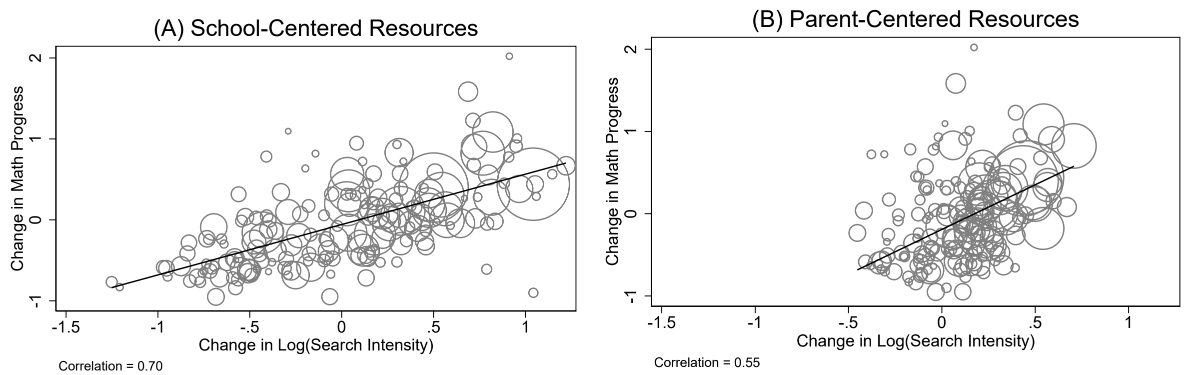


Notes: Each bar represents the association between the average spring 2020 change in search intensity and the listed characteristic of a given area.

Finally, we note three additional analyses that further illuminate or strengthen the prior results. First, the observed post-Covid widening of search intensity gaps is fairly linear in SES and not just driven by the most and least disadvantaged areas. Second, the widening of gaps by SES is not only the result of SES gaps between regions of the country but gaps within regions. SES-based search intensity gaps appear even when making comparisons of areas within Census regions (Northeast, Midwest, South, West).

Third, we show that changes in search intensity for educational resources are correlated with changes in actual math progress made by students, suggesting a relationship between online search and actual student and parent behaviors that impact educational outcomes. Figure 6 plots the DMA-level relationship between post-Covid changes in math progress, as measured by badges earned in the popular math app Zearn, and post-Covid changes in search intensity for school- and parent-centered resources. For both types of search, we observe a high correlation (0.70 and 0.55) between changes in search behavior and changes in math progress. Areas where households began searching much more for educational resources are also those where students made the most progress in math. This makes more plausible the idea that online search metrics serve as useful proxies for households' educational behaviors and investments.

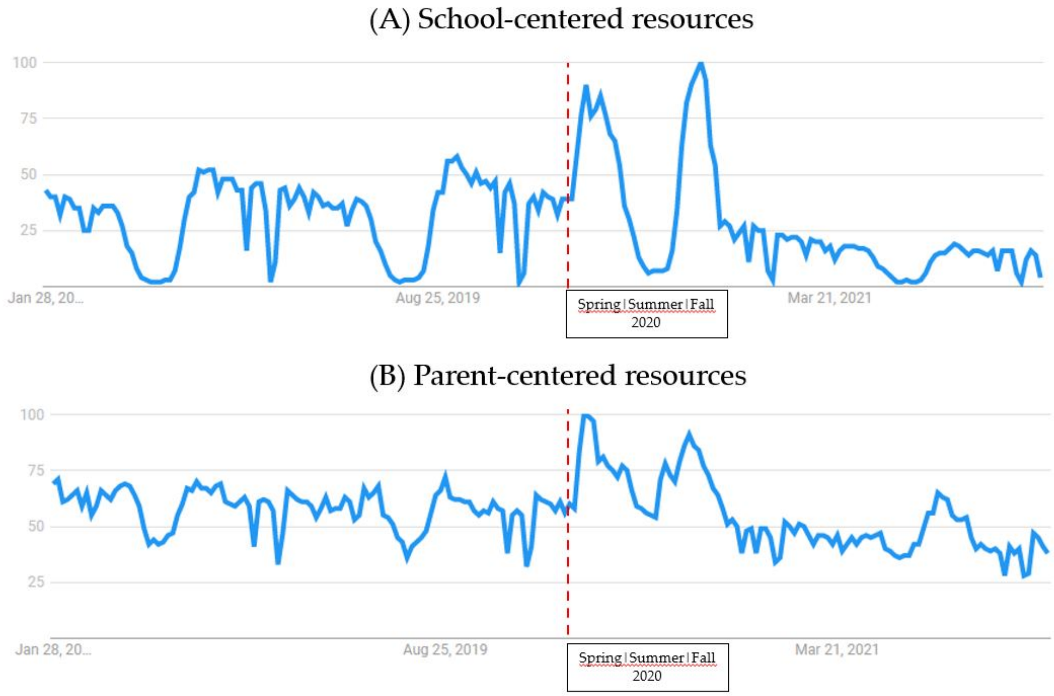
Figure 6: Search Intensity and Math Progress



Notes: The figures above show the correlation between DMA-level changes in math progress (as measured by Zearn) and changes in search intensity for school- and parent-centered resources.

Figure 7 shows nationwide search intensity for school- and parent-centered resources after the spring 2020 perior that has been the focus of this paper. As in prior years, search for both types of resources plunges during the summer, when schools are not in session. Interestingly, search for parent-centered resources does not drop in summer as much as in prior years, suggesting that at least some parents are using the summer to supplement their child's missed learning opportunities. Search for these resources then spikes again in fall 2020 as schools reopen, some in person but many remotely. Then, from January 2021 through January 2022, search for both types of resources drops to low levels in a sustained fashion that is historically unusual. One explanation may be that parents have by this point found all the resources they need, so that searching through Google has become less important. Another explanation is that the pandemic has had a longer-term impact on the way that households and schools function, and that this sustained drop is a reflection of that.

Figure 7: Updated Search Data Through January 2022



Notes: The figures above show nationwide search intensity from January 2017 through January 2022.

4 Discussion

We document a sharp increase in searches for learning resources as schools closed in response to the Covid-19 pandemic. By April 2020, nationwide search intensity for online learning resources had roughly doubled relative to baseline. The shock of school closures increased demand both for the specific online platforms schools shifted instruction to (such as Google Classroom) and for the supplemental resources that households sought out to fill gaps in their learning (such as math worksheets). The likelihood of future school closures or partial reopenings implies these supplemental online resources are likely to become important drivers of student learning.

Though demand for online resources increased in both high and low SES areas, the increase was substantially larger in high SES areas. Areas of the country with higher income, greater internet access, and fewer rural schools had substantially larger increases than less advantaged areas. Along with results from several contemporaneous studies, these results suggest that academic gaps across students will be wider than normal in future school years, a result strengthened by our finding that changes in search behavior correlate with changes in students' math progress.

Our results suggest the potential value of policy responses that directly address these documented inequalities in engagement with online learning resources. Students in low SES areas and rural communities are likely to need additional support to overcome the educational challenges created by Covid-19. Because online learning will likely remain a key component of school systems in the near future, school leaders and policymakers may want to prioritize access to home computers and broadband internet. Improving access to and engagement with online learning platforms will likely be an important step to equalizing learning opportunities and preventing a widening of achievement gaps.

Publicly available, high frequency internet search data helps illuminate the evolution of educational choices made by households, as well as socioeconomic inequalities in those choices. Our analyses can be updated in real time to study future changes in engagement with online learning, can be modified to study different search terms, and can be replicated in other countries. Household adaptation to schooling shocks is an understudied phenomenon that can be readily observed in internet search data. Understanding and accounting for such behavioral responses by parents and students will be critical to predicting the long-term effects of the pandemic.

References

Aucejo, E. M., J. F. French, M. P. U. Araya, and B. Zafar (2020). The impact of COVID-19 on student experiences and expectations: Evidence from a survey. *NBER Working Paper 27392*.

Barnum, M. and C. Bryan (2020, June 26). America's great remote-learning experiment: What surveys of teachers and parents tell us about how it went. *Chalkbeat*.

Bucy, E. P. (2000). Social access to the internet. *Harvard International Journal of Press/Politics 5*(1), 50–61.

Chetty, R., J. N. Friedman, N. Hendren, and M. Stepner (2020). Real-time economics: A new platform to track the impacts of COVID-19 on people, businesses, and communities using private sector data. *NBER Working Paper 27431*.

Choi, H. and H. Varian (2012). Predicting the present with Google Trends. *Economic Record 88*, 2–9.

Cleveland, C. (2020, June 29). Toward reopening: What will school look like this fall? *Education-Next*.

Das, J., S. Dercon, J. Habyarimana, P. Krishnan, K. Muralidharan, and V. Sundararaman (2013). School inputs, household substitution, and test scores. *American Economic Journal: Applied Economics 5*(2), 29–57.

Goldsmith-Pinkham, P. and A. Sojourner (2020). Predicting initial unemployment insurance claims using Google Trends. *Working Paper*.

Hamilton, L. S., D. Grant, J. H. Kaufman, M. Diliberti, H. L. Schwartz, G. P. Hunter, C. Messan Setodji, and C. J. Young (2020). COVID-19 and the state of K–12 schools: Results and technical documentation from the spring 2020 American educator panels COVID-19 surveys. *RAND Research Report*.

Horowitz, J. (2020, April 15). Lower-income parents most concerned about their children falling behind amid COVID-19 school closures. *Pew Research Center*.

Houtenville, A. J. and K. S. Conway (2008). Parental effort, school resources, and student achievement. *Journal of Human Resources 43*(2), 437–453.

Jones, S., C. Johnson-Yale, S. Millermaier, and F. S. Pérez (2009). US college students' internet use: Race, gender and digital divides. *Journal of Computer-Mediated Communication 14*(2), 244–264.

Kearney, M. S. and P. B. Levine (2015). Media influences on social outcomes: The impact of MTV's 16 and Pregnant on teen childbearing. *American Economic Review 105*(12), 3597–3632.

Kuhfeld, M., J. Soland, and K. Lewis (2022). Test score patterns across three COVID-19-impacted school years. *Annenberg Institute Working Paper 22-521*.

Kuhfeld, M., J. Soland, B. Tarasawa, A. Johnson, E. Ruzek, and J. Liu (2020). Projecting the potential impacts of COVID-19 school closures on academic achievement. *Annenberg Institute Working Paper 20-226*.

Lake, R. and B. Dusseault (2020, April 27). Remote classes are in session for more school districts, but attendance plans are still absent. *Center on Reinventing Public Education*.

Malkus, N. (2020, June 16). School districts' remote-learning plans may widen student achievement gap. *EducationNext*.

Polgreen, P. M., Y. Chen, D. M. Pennock, F. D. Nelson, and R. A. Weinstein (2008). Using internet searches for influenza surveillance. *Clinical Infectious Diseases 47*(11), 1443–1448.

Pop-Eleches, C. and M. Urquiola (2013). Going to a better school: Effects and behavioral responses. *American Economic Review 103*(4), 1289–1324.

Rice, R. E. and C. Haythornthwaite (2006). Perspectives on internet use: Access, involvement and interaction. *The Handbook of New Media*, 92–113.

Schneider, M. and J. Buckley (2002). What do parents want from schools? evidence from the internet. *Educational evaluation and policy analysis 24*(2), 133–144.

Stephens-Davidowitz, S. (2014). The cost of racial animus on a black candidate: Evidence using Google search data. *Journal of Public Economics 118*, 26–40.

Vigdor, J. L., H. F. Ladd, and E. Martinez (2014). Scaling the digital divide: Home computer technology and student achievement. *Economic Inquiry 52*(3), 1103–1119.

von Hippel, P. (2020, April 9). How will the coronavirus crisis affect children's learning? Unequally. *EducationNext*.

Table A.1: Search Intensity of Individual Keywords

Branded Learning Resources			General Learning Resources		
Keyword	Pre-Covid	Post-Covid	Keyword	Pre-Covid	Post-Covid
Google Classroom	1.00	1.95	Online school	0.04	0.06
Khan Academy	0.13	0.20	Online classes	0.03	0.05
Kahoot	0.33	0.19	Home school	0.03	0.03
Seesaw	0.02	0.15	Online class	0.00	0.02
Schoology	0.07	0.12	Math game	0.03	0.02
Class Dojo	0.01	0.06	Distance learning	0.00	0.02
Flipgrid	0.00	0.05	Math worksheets	0.00	0.02
D2L	0.05	0.05	Online math	0.00	0.01
Nearpod	0.02	0.02	Math problem	0.00	0.01
Edmodo	0.02	0.02	Online reading	0.00	0.00
Flocabulary	0.02	0.02	Educational game	0.00	0.00
Starfall	0.03	0.02	Education game	0.00	0.00
GoNoodle	0.00	0.02	Online lessons	0.00	0.00
ClassDojo	0.00	0.02	Free preschool worksheets	0.00	0.00
Socrative	0.02	0.00	Educational apps	0.00	0.00
			Education apps	0.00	0.00
			Educational games	0.00	0.00
			Vocabulary game	0.00	0.00
			School worksheets	0.00	0.00
			Reading game	0.00	0.00
			Online tutoring	0.00	0.00
			Virtual education	0.00	0.00
			Online lesson	0.00	0.00
			Virtual school	0.00	0.00
			Educational videos	0.00	0.00
			Educational app	0.00	0.00
			Free school worksheets	0.00	0.00
			Education app	0.00	0.00
			Online science	0.00	0.00
			Online social studies	0.00	0.00
			Education games	0.00	0.00

Notes: The pre-Covid sample contains search data from March 2019 through May 2019 in the United States. The post-Covid sample contains search data from March 2020 through May 2020 in the United States. Magnitudes are interpreted as search popularity relative to the popularity of ”Google Classroom” in the pre-Covid time period. Search terms are not case sensitive, so ”Google Classroom” is equivalent to ”google classroom.” The focus of this paper is K-12 online learning resources, so we do not include keywords related to professional services (e.g., Webex), textbooks (e.g., Pearson), or postsecondary (e.g., Canvas), or adult learning (e.g., Masterclass).

Table A.2: School Closure Dates by State

State	Legal status	State closure start date	Date closed for the year	Public school enrollment
Alabama	Ordered	March 19	April 6	744,930
Alaska	Ordered	March 16	April 9	132,737
Arizona	Ordered	March 16	March 30	1,123,137
Arkansas	Ordered	March 17	April 6	493,447
California	Recommended	March 19	April 1	6,309,138
Colorado	Ordered	March 23	April 20	905,019
Connecticut	Ordered	March 17	May 5	535,118
Delaware	Ordered	March 16	April 24	136,264
District of Columbia	Ordered	March 16	April 17	85,850
Florida	Recommended	March 16	April 18	2,816,791
Georgia	Ordered	March 18	April 1	1,764,346
Hawaii	Ordered	March 23	April 17	181,550
Idaho	Recommended	March 24	April 6	297,200
Illinois	Ordered	March 17	April 17	2,026,718
Indiana	Ordered	March 20	April 2	1,049,547
Iowa	Ordered	March 16	April 17	509,831
Kansas	Ordered	March 18	March 17	494,347
Kentucky	Recommended	March 16	April 20	684,017
Louisiana	Ordered	March 16	April 15	716,293
Maine	Recommended	March 16	March 31	180,512
Maryland	Ordered	March 16	May 6	886,221
Massachusetts	Ordered	March 17	April 21	964,514
Michigan	Ordered	March 16	April 2	1,528,666
Minnesota	Ordered	March 18	April 23	875,021
Mississippi	Ordered	March 20	April 14	483,150
Missouri	Ordered	March 23	April 9	915,040
Montana	Closure expired	March 16	n/a	146,375
Nebraska	Ordered	March 23	April 3	319,194
Nevada	Ordered	March 16	April 21	473,744
New Hampshire	Ordered	March 16	April 16	180,888
New Jersey	Ordered	March 18	May 4	1,410,421
New Mexico	Ordered	March 16	March 26	336,263
New York	Ordered	March 18	May 1	2,729,776
North Carolina	Ordered	March 16	April 24	1,550,062
North Dakota	Ordered	March 16	May 1	109,706
Ohio	Ordered	March 17	April 20	1,710,143
Oklahoma	Ordered	March 17	March 25	693,903
Oregon	Ordered	March 16	April 8	606,277
Pennsylvania	Ordered	March 16	April 9	1,727,497
Puerto Rico	Ordered	March 16	April 24	365,181
Rhode Island	Ordered	March 23	April 23	142,150
South Carolina	Ordered	March 16	April 22	771,250
South Dakota	Recommended	March 16	April 6	136,302
Tennessee	Recommended	March 20	April 15	1,001,562
Texas	Ordered	March 23	April 17	5,360,849
Utah	Ordered	March 16	April 14	659,801
Vermont	Ordered	March 18	March 26	88,428
Virginia	Ordered	March 16	March 23	1,287,026
Washington	Ordered	March 17	April 6	1,101,711
West Virginia	Ordered	March 16	April 21	273,855
Wisconsin	Ordered	March 18	April 16	864,432
Wyoming	Closure expired	March 16	n/a	94,170

Notes: Data come from Education Week's "Coronavirus and School Closures" website, last updated on May 15, 2020. All closure dates refer to 2020.