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How America's Schools Responded to the COVID Crisis

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Abstract: COVID-19 has forced essentially all schools in the country to close their doors to in-person activities. In this study, we provide new evidence about variation in school responses across school types. We focus on five main constructs of school activity during COVID-19: personalization and engagement in instruction, personalization and engagement in other school communication with students, progress monitoring (especially assignment grading), breadth of services (e.g., counseling and meals), and equitable access (to technology and services for students with special needs). We find that the strongest predictor of the extent of school activities was the education level of parents and other adults in schools' neighborhoods. Internet access also predicts school responses. Race, parent/adult income, and school spending do not predict school responses. Private schools shifted to remote learning several days faster than traditional public schools, though others eventually caught up. On some measures, charter schools exceeded the responses of other schools; in other cases, traditional public schools had the highest overall measures. States in the Midwest responded more aggressively than those in other regions, especially the South, even after controlling for the full set of additional covariates. Learning management systems were reported by a large majority of schools, followed by video communication tools and tutorial/assessment programs. Several methods are proposed and implemented to address differential website use. We discuss potential implications of these findings for policy and effects on student outcomes.

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I. Introduction

COVID-19 is one of the gravest crises the country has seen in over a century. Few institutions have been affected more than schools. To do their part to control the virus, and protect students, teachers, staff, and their families, essentially all of the nation's schools closed their doors in order to reduce the spread of the virus and protect public health. The vast majority of schools also continued serving their students in some fashion. The purpose of this study is to understand how schools responded and, in the process, to help policymakers understand what schools are likely to do this coming school year and the implications this may have for students.

Prior studies and reports have addressed this general topic of school responses to the COVID-19 crisis, using parent surveys (e.g., AEI/Echelon, 2020; Civis Analytics, 2020; Kamentz, 2020; Henderson et al., 2020) and educator surveys (e.g., Hamilton et al., 2020; Kraft & Simon, 2020; Henderson et al., 2020; Kurtz, 2020). Also, after schools began closing, the American Enterprise Institute (AEI)[1] and Center for Reinventing Public Education (CRPE)[2] both quickly began tracking the websites of a small sample of public school districts, carrying out several waves of data collection.

Our data collection and analysis, focused on school and district website data, extends prior work in at least five ways: (1) we have a large and broad enough sample to present patterns of results by state and for traditional public schools (TPS), charter, and private schools[3]; (2) we combine our large sample of schools with many other forms of data to examine patterns in school responses along a wide variety of dimensions (student demographics, neighborhood internet access, school spending, and more); (3) we analyze not only whether schools are providing online learning, but the specific online tools that schools used and their capabilities, as these tools are especially important under remote learning; (4) we review prior research and combine findings to provide a broader picture of how schools responded; and (5) we propose and implement methods for improving website data validity and reliability for understanding school actions. The overarching contribution is that we can get beyond the average national response to address the question, *how did different schools respond in different ways, and what might be the*

[1] The AEI data collection included a single 250 school districts and were collected in six waves: March 26-27 data (2020a), April 6-7 data (2020b), April 13-14 (2020c), April 23-24 (2020d), May 7-8 (2020e), and May 27-29 (2020f). In the reference list, we refer only to the summaries of these data by the authors. Since there are so many reports from this one organization, we cite "AEI" rather than the individual authors and list them in order they were released (e.g, 2020a is the first report, 2020b is the second, and so on). We refer above to the dates of the data collection as this is most relevant for understanding the trajectory of responses.

[2] The CRPE data collection initially included March 20 publication (2020a; 46 districts), March 28 publication (2020b; 82 districts); April 3 publication (2020c; 82 districts plus 18 CMOs); April 18 publication (2020d; 82 districts plus 18 CMOs); April 27 publication (2020e; 82 districts plus 18 CMOs); May 15 publication (2020f; 82 districts plus 18 CMOs); and June 3 publication (2020g; 82 districts plus 18 CMOs). These initial studies were based on a convenience sample of districts. Later, they created a larger, and nationally representative sample of 447 districts. The word "publication" indicates that this is the date of the public release and that the dates of the data collection were not reported, but likely occurred in the week prior to the report.

[3] The CRPE studies distinguished TPS from charter schools, but only considered charter schools that fell under charter management organizations (CMOs). We use a representative sample of charter schools.

reasons for these differences? In particular, were there inequities in school responses by student demographics? Also, were there differences in school responses that may point toward potential new policies?

We chose to focus on website data for several reasons. First, 93 percent of schools in the country have websites and these percentages are high for all types of schools. Second, as we learned, schools actively use their websites to communicate with students and families, especially at a time when school facilities are closed; 85 percent of the schools with websites also mentioned something about their remote learning under COVID-19. Third, and partly because of the first two reasons, the data could be collected quickly. Fourth, by placing the information on their websites, educators bear some responsibility for carrying out the listed activities. In contrast, educators are not obligated to do what they report in response to anonymous surveys.[4]

School and district websites are particularly useful for learning what specific online tools schools use; 83 percent of websites that had any information about COVID-19 mentioned at least one specific online tool. These include learning management systems (e.g., Google Classroom, Canvas, and Powerschool), video platforms for live and recorded video interaction among students and teachers (e.g., Zoom, Google Hangouts, and Microsoft Teams), and a wide range of tutorial and assessment programs (e.g., Khan Academy). Since these tools are used online, schools seem apt to place them on their websites so that families can link to them. Knowing which specific online tools schools use is informative about the activities that schools are making available to students.

But school/district website data also come with considerable limitations. In particular, they are likely not to report everything that schools are doing, and to report the same piece of information in different parts of their websites. Every site has a different format and varies in organization, function, and complexity. We address the latter problem by training the website coders to look in specific parts of the websites where the probability of observing school responses was highest.

To better understand the problem of under-reporting, we borrow from the analysis of surveys. When analyzing surveys, unit non-response refers to cases where an individual is contacted but provides no response at all. Also, item non-response occurs when an individual responds to some items on the survey, but not others. The general problem is that missingness may not be random, i.e., it may be correlated with latent value of the item and/or what the respondent would have reported if the item were non-missing.

In our website analysis, the equivalent of unit non-response is less frequent than is typical with surveys (as noted above, 77 percent of schools communicated something about their COVID-19 responses). However, item non-response is very high. The reason is the lack of direct interaction between researchers and respondents, i.e., we do not ask respondents to report particular pieces of information on their websites in the way that we ask survey respondents to

[4] For example, surveys are subject to social desirability bias. In this case, educators may have reported more remote activities because their schools and districts had set policies requiring them.

answer particular questions. While item non-response bias is often present in surveys, it is apparently much lower than with websites. In short, we cannot directly separate the absence of an activity (e.g., online learning) from the absence of website reporting about that activity.

Nevertheless, the advantages of websites noted above make their analysis useful in situations such as this. Again, most schools did communicate about their COVID-19 responses via their websites. Also, as we will explain below, the methods we propose and implement for dealing with the above data limitations yield conclusions similar to survey studies.

We designed our data collection to measure school responses within five main constructs: personalization and engagement in instructional activities, personalization and engagement in other teacher-student communications, progress monitoring of student work, equity of educational access schools (e.g., access to computers and internet and special education services), and finally, breadth of services (including free meals and counselors). In addition to reporting results for individual activities that fall within each construct (e.g., providing live instruction), we created an index for each of these constructs based on the website data collected and generated a composite index across all five constructs. These indices are our main variables of interest. We also measured the speed with which schools transitioned to remote instruction, but this is not included in the indices.[5]

To study the patterns of response across schools, we merged the data collected from websites with the National Longitudinal School Database (NLSD), which combines data from the U.S. Census, U.S. Department of Education's Common Core of Data, various education organizations, and other sources. We focus on measures of student and neighborhood demographics, internet access, school/district spending, and school characteristics. We then used regression analysis to examine how school responses varied on these same dimensions. Some prior analysis has suggested, for example, that student experiences under COVID-19 were correlated with student income levels; however, income is correlated with a wide range of other factors, which we try to disentangle.

We find that the strongest predictor of school response is the education level of parents and other adults in the neighborhoods surrounding schools. After we include a full set of controls, income does not predict school responses, nor does the percentage of students who are Black or Hispanic. While this might seem to contradict prior research, we note that the differences by students' family income have centered on student experiences more so than school responses. That is, school responses have been relatively equitable on income/race grounds, but student experiences have been more inequitable, probably because student experiences, especially in the current crisis, have been affected by students' disparate home circumstances.

We also studied two of the key factors that might have driven school responses and could be directly altered through public policy: internet access and school spending. We find that the

[5] Speed of response is different from the other constructs in two ways: first, it already has a natural unit of measure (time, measured in hours) and, second, speed is a different type of construct. The other five constructs about what schools did. Speed is about how fast they did them. This is why we treat speed of response separately.

partial correlation between school responses and internet access is large and significant. Even after controlling for other differences, this relationship persists, especially with regard to personalization and engagement in instruction and equity and access.

School spending, however, is not correlated with school responses once we control for other factors. This does not mean school spending did not causally influence school responses; prior research convincingly demonstrates that school spending does improve schools under normal operating conditions (Jackson, Johnson, and Persico 2017; Hyman, 2017; Lafortune, Rothstien, and Schanzenbach 2018) and there is no reason to expect a different relationship here.[6] School spending (along with broadened internet access) also remains one of the most viable tools in the hands of policymakers for quickly addressing this situation. Many schools are facing a potentially steep drop in state and local funding (McNichol & Leachman, 2020) that would almost certainly hinder schools this coming school year.

We also find that traditional public schools seem to have responded more slowly than charter and especially private schools; however, later in the post-closure period, the overall activities of traditional public schools were not distinguishable from the other sectors. Traditional public schools responded more aggressively with respect to breadth of services and equity of access, but not in personalization and engagement, though charter schools out-performed other schools on other personalization and engagement and progress monitoring. We also see minimal differences by charter management type and by charter authorizer type, though religious private schools appear to have responded less aggressively than other private schools.

The following sections outline prior research on school responses to COVID-19 (Section II), website data collection methods (Section III), data cleaning and statistical methods (Section IV), and results for both the overall responses and patterns of school responses by demographics, internet/computer access, school spending, school sector, other school characteristics, and state (Section V). We discuss caveats and the steps we took to address them, in Section VI, and conclude in Section VII.

II. Prior Research on School Responses to COVID-19

The first statewide order to close schools to in-person instruction occurred on March 16th.[7] Most schools took off at least a few days to plan their transitions, and to allow parents to make their own adjustments, and then shifted to some form of remote learning.

We have identified more than 30 reports, mostly based on survey data, that have examined school actions, educator perspectives, and parent/student experiences. The various studies differ on several dimensions that are likely to influence their results and complicate

[6] It is also possible that school spending genuinely plays a lesser role in this case because the financial cost of the online tools in question are inexpensive. In this respect, school responses might be driven more by the general capacity and leadership of schools (however, we would also expect these to be related to school spending, given what we know about how school spending affects student outcomes).

[7] https://www.edweek.org/ew/section/multimedia/map-coronavirus-and-school-closures.html

comparisons across them: (a) respondent type (students, teachers, parents, educators); (b) timing of data collection (early versus later in the crisis period); (c) data type (mainly surveys or websites); (d) data quality (e.g., response rates and representativeness); and (e) type and specificity of constructs being measured. This last point is important because many studies asked generic questions about activities such as “e-learning” or “teacher-led instruction” that can be defined in different ways. Also, some items pertain to school responses, others to student experiences, and still others mix the two.

We created a spreadsheet to track reports, their characteristics on the above five dimensions, and their findings. In what follows, we focus mainly on the results that are most relevant to our own analysis: those studies using representative samples and rigorous methods; studies focused on the *patterns* of school actions and student experiences across demographic, school type, and other categories;[8] and studies pertaining to the period many weeks after schools closed. We argue that the early-May period is most informative because this gave schools time to adjust and because all the nation’s schools would normally be open during this period (schools in the South normally close mid-May for the summer). This period also roughly aligns with the period of our own data collection, with which we hope to compare results. Below, we summarize the survey results, followed by evidence from school websites.

A. Review of Survey Evidence

Results by Family Income. Hamilton et al. (2020) surveyed educators and compared their results on school activities for target and non-target schools, where a target school is one that has at least 50 percent of students eligible for free or reduced-price lunches and 50 percent racial/ethnic minorities (all others are non-target). They find limited differences in school responses between these target and non-target groups. For example, 37 percent of the target group received letter grades on their remote work versus a slightly higher 40 percent of the non-target group. In addition, target schools reported more fully online or blended learning courses compared with non-target schools (46 versus 40 percent).

A separate pattern emerges when Hamilton et al. (2020) examine communication. While essentially all schools attempted to contact their students, 65 percent of teachers at non-target schools were able to reach all students or families, but only 54 percent of target school teachers were able to do so. Although non-target and target school teachers were just as likely to provide online distance learning, target school teachers were much more likely to also provide hardcopy material (63 percent of target school teachers compared to 47 percent of non-target school teachers). The congruence in the responses suggest communicating with under-privileged students remotely is more difficult and many teachers anticipated this (as evidenced by hard copy materials). In a seperate teacher survey, Kraft and Simon (2020) also report that the level of

[8] With regard to point (a), in some cases, we also focus on the percentages of schools reporting different activities, so that we can establish the validity of the different data sources and methods.

engagement by students diminished as the proportion of low-income students rose.[9] A parent survey by *Education Next* (Henderson et al., 2020) also shows that while students were just as likely to receive grades or feedback from teachers across income levels, the highest-income households were more likely to participate in instruction with a computing device.[10] s Other patterns with regard to instructional content are more ambiguous.[11]

The above surveys suggest that the extent to which *schools* responded to the crisis is largely unrelated to students' family income, but that *student* experiences are worse for students in poverty. This is consistent with a half-century of research that has emphasized that education is subject to "joint production" between schools and families (e.g., Hanushek, 1979). Even in normal times, parent education level is a strong predictor of student achievement (Coleman, 1968; Duncan & Brooks-Gunn, 1997; Magnuson & McGroder, 2001; Davis-Kean, 2005) and college outcomes (Billson & Terry, 1982; Terenzini et al., 1996; Nunez & Cuccaro-Alamin, 1998; Strayhorn, 2007; Cataldi et al., 2018).[12] Given that education unexpectedly shifted from school to home under COVID, it is likely that the role of parent education is even greater than usual. Parents with bachelor's (BA) degrees, for example, are more likely to have white collar jobs that have more flexibility in hours and allow working from home (Dean & Auerbach, 2018).[13] They are also much more likely to have been using the internet before COVID; in 2019, 98 percent of BA-holders used the internet, compared to 71 percent of those with less than a high school diploma.[14] It is likely that schools with high concentrations of parents using the internet were more actively using technological tools prior to COVID-19 and consequently were better prepared to engage in distance learning.

BA-holders were also much less likely to lose their jobs in the current COVID-19 crisis and in the Great Recession (Adams-Prassl et al., 2020; Berube, 2010). Even when they lose their

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[9] Chetty et al. (2020) also find that low-income students using an online tool called Zearn saw much larger drop in their engagement compared with higher-income students.

[10] Additional studies yield similar findings. EdWeek reports a similar trend and that 56 percent of teachers in lower poverty districts (<25 percent poverty) were interacting with their students at least once a day, compared with 33 percent in higher poverty districts (Kurtz, 2020). Kurtz & Herold (2010) report that 36 percent of students in the highest poverty districts were truant relative to 20 percent in lowest poverty districts. Similarly, on a parent survey by a non-profit organization, ParentsTogether, highlights that 11 percent of families with the lowest incomes report no remote learning, compared with two percent of the highest-income families; among students in schools that are providing remote learning, 18 percent from the lowest-income families spend more than two hours per day in learning activities, compared with 54 percent of the highest-income students (Kamentz, 2020).

[11] Hamilton et al. (2020) and Education Next (Henderson et al., 2020) show that low-income schools were more likely to be reviewing old topics rather than learning new material. This might seem to contradict the above finding, but this more likely reflects the general tendency of schools, especially after high-stakes testing is over and especially in low-income schools, to stop teaching new material. (We could not find direct evidence, but multiple educators made this point to us.) If this is the case, then the differences by income do not reflect differences in the response to COVID-19 per se.

[12] Parent education also predicts longer-term life outcomes such as earnings and occupation (Whitson and Keller, 2004).

[13] Parents with college degrees also have fewer children in the household, further increasing their flexibility (e.g. room to study and access to available computers). https://www2.census.gov/programs-surveys/demo/tables/families/2016/cps-2016/tabavg3.xls

[14] https://www.pewresearch.org/internet/chart/internet-use-by-education/

jobs, college graduates have higher earnings and savings rates (Dögüs, 2017; Wolla & Sullivan, 2017), allowing them financial security in the midst of a crisis, which may also contribute to student outcomes.

This discussion highlights two general pathways for parent education to affect student outcomes at home. With two families in the same school, the one with higher parent education is better situated to support their children at home. It is also possible that schools with more highly educated parents, recognizing that their parents can do more to support learning, may offer more comprehensive educational services with higher expectations for children. Both factors lead to unequal student experiences, but whether school responses will be unequal by parent education (or other family background measures) is less clear. It could be that schools are responding in a relatively equitable fashion, but that student experiences are diverging because of home conditions. Studying the patterns of school response by parent/adult education is therefore a key contribution of the present study.

Results for Access to Devices. Hamilton et al. (2020) report that 72 percent of students had access to the internet (as reported by school administrators), in the COVID-19 period.[15] Further 88 percent of schools report providing laptops or tablets and 50 percent report providing home internet hotspots.[16] But several surveys have reported gaps in student access to technology (Hamilton et al., 2020; Kraft & Simon, 2020).[17] Access to technology is therefore one likely explanation for the differences in student experiences by income described earlier.

Overall, internet access seems to be a bigger problem than access to devices.[18] The RAND surveys of both teachers and administrators, for example, suggest that a lack of internet as a limitation more often than lack of computers (Hamilton et al., 2020). School leaders also report that the problem of internet and computer access is three times worse in their high-poverty/high-minority target schools. This most likely reflects that many schools have shifted to providing laptops to students and teachers, but almost no schools, prior to the crisis, were providing internet access. Also, schools can give laptops to all students and teachers, while internet access is limited to certain geographic areas.

Results by Student Disability Status. Student experiences under COVID-19 have also varied by special education or disability status. Forty percent of parents of students with

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[15] This is our calculation combining different numbers in their study.

[16] Note that if 50 percent of schools are providing hotspots, more than half of the students in the remaining schools must not have had internet access. This is based on the following assumptions and calculations: If the 50 percent of schools providing internet access are providing it to everyone, then 100 percent of students in those schools should have internet access. The idea that 72 percent of students have internet access means that 28 percent (more than half of the remaining 50 percent do not). One possible explanation is that, in some regions, hotspots might not be functional because of inadequate internet coverage, so schools may be providing internet, but students are not using it.

[17] Similarly, Kamentz (2020) reports that one-quarter of low-income students do not have regular access to a computer, compared with just nine percent of higher-income families. Seventeen percent of teachers in the RAND survey also reported that they themselves needed support for high-speed student internet access in their own homes (Hamilton et al., 2020). Both students and teachers need internet access for this tool to be useful.

[18] This is corroborated by additional survey items in the RAND survey indicating that school leaders report lack of internet as a limitation more often than lack of computers (Hamilton et al., 2020).

disabilities reported that they are not receiving any support at all, while only 20 percent reported that they are receiving all the services to which their children are entitled (Kamenetz, 2020). Thirty-five percent reported that their children are doing little to no remote learning, compared with 17 percent of their general education peers (Kamenetz, 2020). An *Education Week* survey of teachers reported that special education and arts teachers report the lowest level of daily contact with students (Kurtz, 2020).

Results by Sector. Only two studies on our list directly compare schools by sector. EdChoice and Morning Consult (2020) report that, in late March, teachers in traditional public schools (53 percent) were more likely than teachers in either charter (43 percent) or private schools (48 percent) to report that they were providing "e-learning." Education Next (Henderson et al., 2020) surveyed parents and found that children in traditional public schools and charter schools were just as likely to use technological devices (88 percent) while private school students were less likely (70%). On the other hand, they also found that private schools had higher rates of mandatory daily assignments and whole class instructions, followed by charter schools and traditional public schools.

A later EdChoice and Hanover study (2020) focused only on private school employees (primarily administrators) and found that 88 percent reported a shift to online learning with formal curricula (e.g., required assignments, recorded lessons from teachers). In comparison, Hamilton et al. (2020) report that 82 percent of TPS educators reported providing "instructional materials and activities that students are expected to complete." However, the RAND construct requires that students are expected to complete the assignments and the EdChoice survey item did not include that requirement. This, as opposed to actually different activities across sectors, may explain why the EdChoice number is higher.[19]

Some of the research focuses on the academic responses of charter schools. The EdChoice and Morning Consult (2020) and Education Next (Henderson et al., 2020) surveys have mixed reports about sectors that moved to e-learning.. EdChoice reports that traditional schools had moved to e-learning more than charter schools (53 percent versus 43 percent), while Education Next reports charter school students report more daily e-learning than traditional schools (51 percent vs 43 percent).[20] These differences may be due to the timing of the survey or the respondents. EdChoice and Morning Consult conducted their survey with teachers in late March, while Education Next conducted their survey with parents in the middle of May.

We also considered how the various sectors differed in providing access to a breadth of services (especially meals) and equitable access to instruction (especially by providing devices to lower-income students and providing services to students with disabilities). EdChoice and

[19] Note that it is also likely that administrators will report a greater shift to online learning than teachers because they will state an overall response by a school, instead of accounting for individual teacher instances in subjects such as art or physical education, where online learning may be less likely.

[20] Another survey by the advocacy group Educators for Excellence found that roughly 95 percent of all schools reported some online education, and this number was very similar between TPS and charters; however, given the low level of activity implied by "online education," and the very high percentage of schools reporting this, the results are not especially meaningful for understanding cross-sector differences.

Hanover (2020) reports that 62 percent of educators reported that their schools were providing support for special education and 20 percent for ELLs. We could find no direct comparison with traditional public schools, though the above numbers imply that a somewhat higher number of students with disabilities in TPS (65 percent) were receiving some form of remote instruction (Kamenetz, 2020).

Eighty percent of private schools provided devices; and 50 percent were providing internet access (EdChoice & Hanover, 2020). The numbers for devices are very similar in the Hamiliton et al. (2020) study of TPSs (88 percent of schools report providing laptops or tablets, 50 percent report providing home internet hotspots).[21]

However, TPSs have been providing a broader range of services. Many studies have documented that 90 percent or more of traditional public schools were providing access to meals (Hamilton et al., 2020; Malkus et al. 2020, Rogers & Ng, 2020). While EdChoice and Hanover (2020) reports that only 20 percent of private schools were providing meals for students, most likely because they do not serve students from low-incomes who might need school support for food. Also, private schools are much less likely than public schools to participate in the federal free and reduced price lunch program, which funded continued meals in participating schools (USDOE, 2016).

Regarding academically oriented activities, the results are highly mixed with TPS, charter, and private schools each doing more in certain activities, depending on the survey sources. TPSs do seem to have an edge in terms of the use of technology. This is consistent with prior research showing that TPSs were more apt to use educational technology prior to the crisis. However, charter and private schools may have had higher expectations during COVID, which could matter at least as much as the use of technology (Henderson et al., 2020).[22] While these academic responses are less clear, it does seem that TPSs were more likely than private schools to provide meals, likely reflecting the lower-income students that TPSs serve. Overall, from the surveys alone, the results by sector present a mixed and unclear picture.

B. Review of Website Analyses

AEI and CRPE engaged in rapid response and regular website checks in the early weeks of the crisis, with more than a dozen reports in total. For this analysis, the most relevant iterations are a CRPE website analysis in June that used a large and representative sample of 447

[21] Note that if 50 percent of schools are providing hotspots, more than half of the students in the remaining schools must not have had internet access. This is based on the following assumptions and calculations: If the 50 percent of schools providing internet access are providing it to everyone, then 100 percent of students in those schools should have internet access. The idea that 72 percent of students have internet access means that 28 percent (more than half of the remaining 50 percent do not). One possible explanation is that, in some regions, hotspots might not be functional because of inadequate internet coverage, so schools may be providing internet, but students are not using it.

[22] Higher expectations are defined by daily hours of schoolwork and required assignments.

district websites and the later AEI analyses, which used a constant and representative sample of districts.

In the smaller sample used by CRPE over the first six weeks, the authors reported that 33 percent of districts were providing curriculum but no instruction (CRPE, 2020g) and 66 percent of districts providing curriculum and instruction (CRPE, 2020g). But the larger CRPE sample later suggested that these numbers were probably twice as high as the average district. In comparing their two samples, they found that the 66 percent figure for curriculum and instruction had dropped to 33 percent in the nationally representative sample. This provides some evidence that urban schools respond more aggressively than other schools.[23]

These website numbers differ from reports of school principal surveys, however. Forty-four percent of schools reported offering fully online or blended learning (Hamilton, et al., 2020), while 82 percent reported providing instructional materials and activities that students are expected to complete. The CRPE large-sample figure of 33 percent is below the first figure and far below the second. The wording of the survey items is different, but this mainly reinforces our suspicion that website data under-report school activities.

The more important question here, given the purpose of our later analysis, is whether website data bias the *patterns* in results. The large-sample CRPE analysis suggests essentially no difference in school responses in low- versus higher-income schools. This is consistent with the pattern observed above--that school responses were relatively equitable, but student experiences were not. This suggests that the patterns observed in website analyses, despite the under-reporting of school activities, may be a reasonable reflection of the patterns of school response.

The AEI website analyses also make one additional observation that is relevant to what follows. They find that the number of activities schools engaged in began to plateau around May 1. This might be explained by the fact that even the most well-resourced, high-capacity schools needed some time to adjust to this unprecedented situation. Either way, an important implication of this finding is that data, such as ours, collected during the month of May likely represents the peak level of school activity in response to COVID. This is why the timing of data collection is important and why we have emphasized this in our discussion of results.

C. Summary and Discussion of Prior Research

We draw three main conclusions from this review. First, based on survey data alone, student experiences varied by their family incomes (and student disability status), but school responses did not display clear patterns. Second, the patterns of school responses seem similar in the website and survey data (both suggest limited differences in school activities by race and income), which suggests that analysis of patterns in website data have a good chance of yielding valid inferences. Finally, we do not see consistent evidence of differences in school activities by school sector.

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[23] It could also be the later date of data collection with the larger sample, but the AEI analysis discussed later suggests that school responses had plateaued in early May.

While all of these studies make a useful contribution, and they had to do so with very little advanced planning, it is also important to point out some topics excluded from research to date. We found little evidence, for example, about student access to school counselors during the crisis.[24] Also, few of the studies have distinguished between instructionally-oriented communication between students and educators and other kinds of communication, such as office hours. Third, while at least one study has examined each of the factors discussed above, few have examined them simultaneously, or with sufficient data, to facilitate analysis of patterns (e.g., by demographics, internet access, school spending, and school sector) and disentangling the roles of intertwined factors. With further analysis, we can understand the roles of these various factors more deeply.

III. Data Collection

A. Project Timeline

This was an unusual project in that it was designed less for research and more to inform the response to an ongoing crisis. We therefore had to move quickly before the data disappeared. Schools began closing to in-person activities in mid-March. As we detail below, we were able to create our data collection tools and start collection before the official end of the school year. Table 1 summarizes the dates of the main steps in the process. Since some schools, especially in the South, ended in mid-May, we assumed that schools kept their website data posted until June 3. In short, the project moved from the idea stage, to rubric development and personnel recruitment, and to completed data collection, all within 10 weeks.

In the following sections we mostly focus on the collection of the website data, but we start with discussion of the data we merge with the website data for the purposes of examining patterns of school response.

B. NLSD and Demographic Data

A key starting point for this analysis is the National Longitudinal School Database (NLSD), an annual census of all schools in the country from 1991 to 2019 created by many of the co-authors of this report and others with the National Center for Research on Education Access and Choice (REACH). This dataset had already been completed for other research purposes, but proved useful for the present project.

The NLSD starts with data from the federal Common Core of Data (CCD), the federal Private School Survey (PSS-sample), and private school universe list (PSS-universe). Prior to the project, these data had been extensively cleaned, especially with respect to school status (i.e., which schools are closed) and school types (i.e., which schools are charter schools). The NLSD

[24] Seventy-one percent of school superintendents reported providing remote counseling (AASA, 2020).

also includes school neighborhood data from American Community Survey and U.S. Census, including neighborhood household income, adult education, ethnic/racial composition, and internet access.

The NLSD data include two sources of demographic data: the demographics of students in the schools and the demographics of the residents who live in the surrounding community, from the Census. While we are primarily interested in student demographic data, their availability is limited, especially among private schools. This is why we also link each school to its Census block-group level. Census block-groups are the smallest available geographic unit for sampled data. The population threshold for each block-group is between 600 and 3,000 depending on geography.[25] The schools in our sample were linked to their block-group using the geographic coordinates specified in the CCD and PSS.

While the NLSD is longitudinal data and covers several decades, we limit our analysis in this study to the most recently available data: the 2017-18 and 2018-19 academic years (for private schools and TPS/charter schools, respectively).[26] See Harris & Martinez-Pabon (2020) for additional details with regard to the construction of the NLSD.

C. Collection of School Names and Web Addresses

We identified 98,068 regular, in-person schools that primarily serve primary and secondary grades (K-12). Our focus on regular schools excludes "alternative schools" and "special schools." The focus on in-person schools means that we excluded a very small number of fully online schools. Primary and secondary schools exclude those that did not serve any grade above grade 2.

We started identifying the websites of these schools by taking the school names and addresses from the NLSD and submitting this information to Bing's Application Programming Interface (API). We then manually checked accuracy on a sample of more than 200 schools; 73 percent of the urls were correct and pertained to a specific school's web domain, while an additional 8.5 percent returned the website of the school's corresponding school district. After this initial API search, we replaced missing websites from records contained in the NLSD. In total, we linked over 93 percent of schools to a web address.

These addresses were the starting point for the manual website coding. However, when coders visited the websites, they checked website address accuracy again. Schools were included in the sample regardless of whether we had found a website in the above process (again, seven percent did not have addresses at this stage). For the schools without initial web address, the coders searched themselves. If they still did not find one, then they marked it as missing. They also checked the non-missing addresses for accuracy. If the website was inaccurate, they searched again to find one.

[25] There are 217,740 block-groups in the United States, roughly twice as many as the number of schools.

[26] The private school data are only available every other year; this is the most recently available Census data.

D. Sampling Design

We created a sample that is representative at the state-by-sector level. Another distinguishing feature of our project is that we created data from both schools and districts, rather than the CRPE and AEI approach of using only school districts. We took this different approach in part because we are interested in schools across all sectors, and charter and private schools are not generally governed by school districts. Also, what schools report might be more accurate and detailed than school districts because the schools are the ones ultimately responsible for their activities.

The sample was stratified by state, sector, urbanicity, and grade level. Within each state, we randomly selected 40 TPS, 20 charter, and 20 private schools (80 total). Within each state-sector cell, we selected 50 percent urban and 50 percent non-urban schools. Finally, within each urbanicity category, we also selected a fixed number of schools in various grade levels.[27] Therefore, we sampled charter and private schools using different grade spans. Table 2 below summarizes the sampling design.

This yielded a (potential) total of 40 x 50 = 2,000 TPS schools (two websites each) and 20 x 50 = 1,000 schools per charter/private sector. In total, this means 4,000 schools and 6,000 potential websites. Some states did not have enough schools in each cell, in which case we took all the schools in the cell. The total actual sample included 3,511 schools and 1,931 districts. (Later, we discuss missing school website data and how we combine school and district website data.)

In all the analyses, we used sampling weights to account for the sampling design (using the NLSD as the population figures). Since we are sampling schools, the resulting statistics might not be representative based on student enrollments. However, as we are primarily interested in how schools are responding, we leave the adjustments for student enrollment to future analysis.

E. Constructs

We identified a list of constructs to help guide the identification of rubric items and to guide the analysis. There are five main constructs of interest, which we describe below. Table 3A provides descriptive statistics of the items we code in each construct:

- *Personalization and engagement - instructional activities.* This is reflected in the use of live instruction and various types of online tools. We operationalized personalization engagement based on, for example, whether instruction was synchronous and gave students feedback on their work. We focused on this in part because of evidence that personalization is an important element of instruction (e.g., Walkington, 2013). Also,

[27] TPS schools almost always fit cleanly into the elementary, middle, and high school categories, while charter and private schools have more alternative grading schemes, such as K-12.

student engagement is a strong predictor of student learning gains (Bodovski & Farkas, 2007).[28]

- *Personalization and engagement - other student/teacher communication.* We measure this by how students and teachers are expected to interact, availability of teachers for office hours, and whether teachers held "morning meetings" or "advisories." As with personalization of instructional activities, we counted synchronous and video-based communication more positively than asynchronous and other forms. While there is little evidence about this type of personalization, we use the same logic here as with instruction.

- *Progress monitoring*. We measured this by whether schools were still attempting to track attendance, continuing to grade work, and counting remote work toward final grades. Schools that are making work optional and/or not tracking participation are considered to have lower expectations.

- *Equity of access*. We measured this with website references to special education and ELL students; and by school offers to provide computers and internet access to students who do not have them.

- *Breadth of services*. We measure this through references to school meals and counseling services.

In addition to using these constructs to identify rubric items, we also used those items to create indices, one for each of the above constructs using theory and evidence (see later). We also collected data regarding the speed of response to remote learning (from the point of closure) and information about which schools expected students to use one or more of 105 common online tools. These are analyzed separately from the above constructs.

F. Website Coding Rubric

We used an iterative process to create the final data collection rubric. After identifying our rubrics, we viewed several dozen websites to determine what kind of information might be available. We also examined the other efforts to code school/district websites for responses to COVID-19 by AEI and CRPE.

In the second stage, several of the co-authors carried out the following steps: (a) developed preliminary rubric items and general guidance; (b) coded a small number of pilot websites (including all three sector); (c) checked reliability on the pilot sites; (d) identified

[28] A much more extensive literature on student engagement exists at the higher education level and comes to similar conclusions (Pascarella & Terenzini, 1991; Renninger & Shumar, 2002; Tinto, 1993).

reliability problems with specific items and general guidance; and (e) edited the rubric and guidance. Simultaneously, we calculated the number of coders we would need to complete the process within a few weeks. In the end, we used 24 coders, most of whom were undergraduate students from Tulane University with limited experience in education (beyond their personal experience).

Once the above first-stage process converged sufficient agreement 0.7 among the research team members, we moved to a second stage with our entire set 24 coders in which we went through four more iterations of the above process, until we again reached average reliability above 0.7. All of the work described above (including the training) was carried out remotely because, like the schools we were studying, the research team, too, had shifted to remote work.

The rubric was accompanied by five pages of general guidance, designed primarily to explain to coders what portions of the websites they should code. For example, coders were directed not to leave the web domain of the school/district (e.g., to go to the Facebook page) and not to watch posted videos.[29] We also provided guidance on roughly how much time they spend on each site and how they should take breaks to prevent miscoding.

The guidance document also provided nine pages of guidance with additional details about how to code specific items. When coders ran into difficulties during the coding process, they consulted the guidance document. If necessary, they sent questions to one of the co-authors who responded to the coding question and, in some cases, updated the guidance document for that item.

Once we launched the actual coding process, we continued to check reliability, with a final Cohen's κ was 0.61 (82 percent agreement).[30] Each coder received a file with 60 schools (and somewhat more websites because some schools were associated with school districts). The full coding scheme, with 43-50 items per website (school and districts, respectively), and general guidance are shown in an appendix. On average, school websites took eight minutes to code and districts took 16 minutes.

IV. Data Cleaning and Methods

We transformed the raw website data into a set of indicator variables for specific school activities, as well as a few continuous variables (e.g., days from closure to remote learning and hours of instruction). Each response item was generally treated as a separate variable.

[29] Many schools posted either very general videos about the COVID-19 response, which, based on our initial piloting process, rarely provided relevant information that was not available in the website text. Other schools posted videos from individual teachers, directed to their students, but these, too, were rarely information. Eliminating these videos was meant to speed the data collection process.

[30] Six sites in each file were identical with one file, and this provided the basis for reliability checks. Over five percent of the entire sample was double-coded and these are the schools used in the final reliability calculations. The coders used a version of this embedded within a Google form that fed the results into a spreadsheet in real-time, allowing us to check reliability as the process unfolded.

For TPSs, we started with the data available for each school, then replaced only missing values with school district data. Specifically, school district websites often describe school responses by grade level (elementary, middle, and high) and we coded the data separately for these grades where possible. We also applied blanket policies (i.e., those not distinguishing grade levels) to all grade levels when necessary. When a TPS elementary school had missing data on the school website for a given item in the rubric, and the district had (non-missing) data on the same item, we replaced the missing school data with the district data; otherwise, we left the school website data untouched. In some cases, discussed later, we also ignored the district data to facilitate comparability across sectors.

A. Missing Data

We define unit non-response as schools having no website information about their COVID-19 response. This can occur either because we could not find a correct website or because we found the correct site and found no information about COVID-19 response.[31] All items in the non-responding units (no website and/or no COVID-19 information) are left as missing.

To understand the frequency of non-response, it is important to consider how we identified websites. We did not distinguish between schools with and without websites when identifying the sample. Rather, when no website was available from the API search, or from the NLSD, we directed coders to manually search for the website using the school name and location information we provided to them for all schools. Therefore, we are confident that, if no web site was found, then either no website exists or it is rarely used and contains very little information. (Websites show up more prominently in API and manual search engines when they are used more often.)

For websites that have some information about COVID-19 response, coders were forced to answer each item in the rubric prior to submitting the data. When no information was found, they were directed to code “no mention.” Among the responding units, we initially recoded missing items to zero. We therefore view the estimates from these data as being a conservative lower-bound on school responses as it assumes that if the site did not mention an activity then the activity was not occurring at the school. (Among the non-responding units, we handle this

[31] To be more specific, in the first step, we identified schools with websites, then we looked at two rubric questions: “Q06. If a website WAS NOT provided in the spreadsheet, did you find a website?” and “Q07. If a website WAS provided in the spreadsheet, was the original website provided to you correct?” If the answers to both were no, then the site is coded as having no website and as being a non-responding school. In the second step, we considered schools with websites and identified whether schools have responses to COVID-19 on their websites. A school is considered responding if and only if the answer is yes to one of the following questions: “Q09. Does the website's homepage include any content related to COVID-19?” and “Q13. Is the school closed due to COVID-19?” Note that schools could close due to COVID-19 without any COVID-19 specific information on their websites. See the full rubric in the appendix.

differently; missing data in these cases are left as missing and handled with non-response weights.)

The initial overall missing rates of school website addresses, prior to coders manually searching for missing websites, were: TPS (3%), charter (2%), and private (10%); however, only 0.89 percent of traditional public schools are missing both school and district websites. These numbers dropped somewhat after the coders manually searched websites.

In addition to having a website, our definition of unit response requires that websites provide information about schools' COVID-19 responses. The greatest gap in these rates arise when we use the data where missing school data have been replaced by district data. In that case, unit non-response is: 6.9 percent for public schools, 19.8 percent for charter schools, and 57.3 percent for private schools. In the analyses without non-response weights, these missing observations are omitted from the analysis. In the analyses with non-response weights, we assume that the response is random and implicitly assign the response values of the non-missing observations to the missing observations within the same sampling cell. Despite large, differential non-response rates, the non-response weights have essentially no impact on the results, however, as we show later.

Among schools with some type of COVID-19 response on their website, the rates of item non-response are: 31.2 percent (TPS), 39.3 percent (charter), and 47.3 percent (private). Note that, in some cases, these numbers may simply reflect that schools are not carrying out certain activities. They are likely to report what they are doing rather than what they are not doing. So, these numbers could reflect that private schools responded less aggressively or that they did not use their websites for communication. Left unaddressed, these differentials would upwardly bias the TPS school responses measures relative to charter and especially private schools. The later discussion of our statistical methods discusses multiple ways in which we address these sector differentials.

We analyzed patterns in missingness in two ways. First, we regressed an indicator of unit response on a vector of student demographic variables, school characteristics, and state fixed effects. Second, among the non-missing schools, we calculated the percentage of items that were missing (ignoring those that were not applicable). In both cases, for ease of interpretation, we predict non-response using Ordinary Least Squares (OLS).

Two factors stand out as being strongly predictive of school missingness. First, information was much less likely to be missing for schools located in neighborhoods with high adult education levels. A one percentage point increase in the share of neighborhood families with a BA or higher increased the probability of response by 0.51 percentage points. The other key predictor was school sector. Consistent with the above missing data rates above, being a private school reduced the probability of response by 46 percentage points. Importantly, these results hold even after controlling for income and other factors that are correlated with parent education and private school attendance.

This has potentially important implications for the subsequent analysis. The types of schools that are less likely to have any relevant website data may also be less likely to report their activities. This could give the false appearance that schools were not engaging in activities when, in fact, they just did not mention it on the websites. (They may, for example, have communicated with families more by email.)

Later, we discuss various tests for whether these patterns in non-response lead to bias in the estimated patterns of school responses to COVID-19.

B. Weights

In the analysis of the data, we weight schools by the inverse probability of sample selection (and, sometimes, response). The weights therefore sum, within sectors, to equal the total number of schools in that sector. Further when adding the weights across sectors, they sum to the total population of regular, brick-and-mortar K-12 schools in the country. The sampling weights are applied in all the analyses that follow.

The non-response weights are created similarly. Nonmissing observations/units were weighted based on the inverse probability of response, within each state-sector-urbanicity-grade level cell. Roughly 10 percent of the cells have no nonmissing observations, so that this portion of the population is not represented. The non-response weights are only applied in some cases, though this has a very limited influence on the results.

In the cases where we apply both sampling and non-response weights, the overall weight is the product of the two separate weights. Given the use of survey weights, the analysis of these data will be carried out using the svy commands within Stata.

C. School Response Indices

With so many different rubric items, and with the intent of summarizing school responses, we also combined school activities into indices. This index is based in part on the five constructs that guided instrument development (see above). Also, there is clear theory and evidence to guide the weighting of different items based on their educational importance, as opposed to common statistical methods.[32] For these reasons, we use a professional judgment/evidence-based approach to constructing the indices. In particular, research suggests that online learning works best when combining live video-based classes with asynchronous classes where students think deeply and engage with the subject matter and other students independently are preferable to fully online courses (Bernard, et al., 2009; Means et al., 2009; Tallent-Runnels et al., 2006). Therefore, we give greater weight to live instruction and/or count live instruction more when combined with other methods.

[32] One reviewer suggested principal components analysis (PCA), an atheoretical method for reducing data that combines the relatively large number of items into a smaller set of statistically independent component variables. While we could implement this method separately for each of our constructs (e.g. carry out one PCA for progress monitoring separately), this would still neglect theory and research about the importance of these items for student learning.

The effect of the modes of instruction are also interconnected with the incentives students have to study and complete assignments. The near universality of course letter-grading reflects a widespread belief that these provide (extrinsic) incentives that motivate students to put forth effort. Even switching from letter grades to pass/fail, which still provides some effort incentive, leads to substantially reduced performance (e.g., Gold et al., 1971, Roberts & Dorstyn, 2017). For this reason, we not only include progress monitoring as a separate construct, but in some cases, inflate the two personalization/engagement constructs when student participation was clearly expected.

A limitation of this approach is that it necessarily relies more on judgment than evidence, which means some decisions are somewhat arbitrary. Research is rarely sufficient to establish the contribution of each rubric item to student outcomes, or even a correlation. Instead, we use multiple sets of decision rules to check the robustness of our results. Below, we discuss each construct, how we created the base index, then how we created two alternative indices.

The indices discussed below, without further adjustment, yield varying ranges. We next placed each of them all on the same 0-10 scale. For example if the points above added to 16 for a given index, this was rescaled proportionally so that the maximum was 10. For each index, 10 means that the school did everything we tried to measure and 0 means they did none of the things we tried to measure.

Personalization and Engagement - Instructional Activities. We started by summing up the following indicators: live instruction, recorded videos, online instructional platform, instructional packets, and assignments are given and submitted (the coders could check all that applied, so they are not mutually exclusive). In the base index, we gave an extra point (double weight) for live instruction and for the use of an instructional platform. In the first alternative index, we instead only gave extra points if live instruction was combined with one of the other instructional activities mentioned above; and dropped the multiplier when activities were expected (versus optional). The second alternative counts each item equally (i.e., unweighted).

As shown in Table 3A, some instructional activities were reported in more than 40 percent of school websites. Almost two-thirds of schools reported using online platforms. (For this reason, we provide an entire section on the types of online platforms used, later in the report.) Forty percent of websites mentioned using learning packets and that assignments were being given and submitted. Also, nearly half of schools reported that activities were "required" for students. Combining results across these and other items using the above weights, as shown in Table 3B, the average base index value for this construct is 3.3 out of 10.

Personalization and Engagement - Other Communication. For this construct, we started by summing the following indicators: teachers are expected to reach out to students by video, teachers are expected to reach out to students by email, students are expected to reach out to teachers by video, students can reach out to teachers by email, other communication, and group communication (e.g., morning meetings and advisories). In the base index, we gave an extra point if there was other communication or other group meetings or if video/phone were available.

As with the personalization and engagement in instruction, the first alternative index drops the multiplier for expected activities; and does not distinguish communication based on who is expected to initiate it (students versus teachers). The other alternative gives equal weight to each factor mentioned above.

We see that schools generally placed the onus on students to reach out to teachers. More than 75 percent of schools reported an option for students to reach out to teachers, while only 43 percent mentioned teachers reaching out to students. Of those, the websites were about twice as likely to mention email communication (which we view as less engaging) as compared with phone or video. Combining results across these and other items, the average base index value for this construct is 1.8 out of 10. In the second alternative index, we weight all items equally.

Progress monitoring. The items for this construct focused on grading and feedback that schools provided, including both final semester grades and the grading of remote work and their contribution to the final grades.[33] A value of zero was assigned for schools where final grades were based entirely on pre-remote assignments and the final grades were pass/fail. At the other extreme, schools that kept using letter grades, and based them on both pre- and post-closure assignments, were given a value of nine. There were various combinations in between that received between one and eight points, e.g., some schools allowed students to choose between pass/fail and letter grades, and other schools said that post-remote assignments could only increase final grades, not reduce them from the pre-remote level. Schools that based assignment only on pre-closure work and switched to pass/fail were given the lowest score of zero.

Many schools also communicated expectations by giving specific learning schedules and/or communicating expected learning hours. One point was given if schools mentioned specific subjects (e.g., math) or a specific amount of time (e.g., 90 minutes per day); two additional points were added if schools mentioned they were tracking attendance. Also, 2-3 points were added if there was a schedule listing specific times of day for specific subjects (e.g., "9-10 am, math"); if this was done for 2 or fewer subjects, two points were added and, for 3+ subjects, three points were added. The grading and schedule portions are given equal weight in the base index.

In the first alternative index, we gave fewer points for having a specific schedule, and weighted grading guidance as ⅔ of the construct index and mentioning a schedule as ⅓ weight (this is the reverse of the base index). In the second alternative, we weigh all items equally.

Only 40 percent of schools made any reference to end-of-course grades. Among this group, roughly one-quarter mentioned continuing with A-F letter grades and another one-quarter mentioned switching to pass/fail. Of the schools giving course grades, 37.7 percent mentioned including both pre- and post-closure assignments and 12.6 percent mentioned including only pre-closure work.

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[33] The weighting of progress monitoring in the prior constructs utilize do not utilize grades or schedules, but instead focus on a measure of the general language used on the website and whether it conveyed an expectation of completion.

Among the schools that mentioned specific learning hours, the average was 2.8 hours per day.[34] While this might seem much lower than in-person instruction, only 50-60 percent of the typical in-person school day is typically devoted to instruction, or 3.25-3.90 hours per day (Hollowood et al., 1995). While teachers were likely not as directly involved in the Therefore, the total This is only slightly less the learning hours we documented, although it is likely that students were not being instructed 2.8 hours per day, int he way they would have been in-person. Also, since the 2.8-hour calculation is conditioned on reporting any hours, we suspect that the average across *all schools* is less than this. Combining results across these and other items, the average index value for this construct is 1.4 out of 10.

Breadth of Services. This construct consists of school efforts to provide meals and make counseling services available (each component was counted equally toward the overall breadth index). For counselors, one point was given if any access to counselors was mentioned with an added point for a specific mention of counselors focused on mental health (e.g., psychologists) and/or those focused on academics (e.g, guidance counselors). Finally, we accounted for the mode of communication, giving one extra point for office hours and two added points if counselors were available by phone, video, or in-person. In the first alternative index, we did not distinguish between types of counselors or mode of communication and simply gave full points for any mention of this topic. In the second alternative, we weigh all items equally.

For school meals, we gave one point for any mention of meals, an extra point if it mentioned a specific organization providing them, two extra points if the meals were being provided in partnership with the school district, CMO, or church organization (in the case of religious private schools), and three extra points if the school itself was providing meals.

As with progress monitoring, only 40 percent of schools mentioned counselors; 22.7 percent of all schools reported access to counselors focused on mental health, while just under 10 percent reported academic (guidance) counseling. Among those mentioning counselors, 58 percent mentioned that the communication would be by email; 27.8 percent mentioned communication by phone or video.

More than half of schools mentioned providing free meals. Overwhelmingly, the meals were being provided by the school, school district or other schooling organization, such as a CMO. Combining results across counseling and meals, and across the items within them, the average index value for this construct is 2.9 out of 10.

Equity of Access. This consists of three parts: efforts to make computers and the internet accessible to all students and efforts regarding students with disabilities and English language learners, respectively. For the technology component, schools received one point for referring to either community hotspots, home hotspots, and/or allowing school laptops to go home. Schools then received two additional points for a home hotspot but no laptops, three additional points for

[34] This is consistent with some surveys of parents. One suggests that students spent 1.92 hours of online learning with teachers. Another suggests (3-4 hours of online learning per day). However, the validity of these surveys is difficult to establish. Also, this likely over-states the true average as it likely reflects parents whose students are engaged in online learning and roughly 20 percent were not engaged at all (Kurtz, 2020).

providing a laptop but no home hotspot, and seven additional points for providing both a laptop and a home hotspot.[35]

For special education, schools received one point each for mentioning: continuation of Individual Education Plans (IEPs), that special education teachers would be in touch with families by phone, that special education teachers would meet with families in person (presumably with social distancing), or that special education teachers would coordinate with general education teachers. One extra point was given if the communication between special education teachers and families was by phone/video and three extra points were given if the communication was in person.

In the first alternative index, we dropped the added points for providing both a laptop and hotspot. Also, as with counselors, the alternative index gives the maximum points if special education is mentioned or ELL is mentioned. In the second alternative, we weight all items equally.

Overall Activity Index. The overall index of school response, which summarizes each school's activities in a single number, is the sum of the five indices detailed above. (We also measured speed of response to remote learning, but since this is only a single number, measured in days, so we do not convert this to an index.) This summation approach is the same for the base and alternative indices.

Again, this professional judgment/evidence approach cannot be completely objective and scientific. Instead, we took several steps to reinforce validity to the extent possible: (a) following prior research to the extent possible; (b) creating both base and alternative indices to check the sensitivity of our findings to these decisions; (c) reporting results for both the overall index and the construct-specific indices, to avoid concern about how each construct contributed to the overall index.

The indices range from roughly 1-3 on the 10-point scales, across the five constructs, with an average of 9.0 (out of 50) in the base case. This means that the average school was far from carrying out all of the activities. Put differently, since the normal operating procedures of schools involve all of these activities, this implies that schools were functioning at a level well below the norm. Some of this is due to the under-reporting problem, but this is not the only cause.

The appendix provides data regarding the distribution of the overall school response index and the specific construct indices. School responses vary considerably, consistent with prior research. The distributions are also heavily right-skewed, reflecting that most of the schools had very low responses.

It is difficult to compare across constructs/indices to one another, but these results do provide a sense (reinforced by the appendix data for individual rubric items) that schools responded most aggressively with respect to providing meals and instruction. Other forms of communication and progress monitoring were more limited.

[35] Community hotspots generally required students to leave their homes and travel to a location such as a library.

We place little emphasis on the absolute value of the indices because of the under-reporting problem. In what follows, we instead focus on the patterns in these data across demographic groups, school types, and states.

D. Empirical Framework

This study relies on simple descriptive statistics and regression analysis. Our dependent variables are the overall school response indices and the construct-specific indices that comprise it. Schools with no COVID-19 response data are treated as missing and dropped from the analysis (the results are robust to application of non-response weights). Given this, when we report the shares or percentages of schools reporting a specific activity, the denominator is always the number of schools that have any COVID-19 response information. (In some cases, where the response to one question is conditional on the response to a prior question, we note any change in the denominator.)

The school responses measured by Y_s are a function of student demographics D_s, neighborhood characteristics N_s, and school characteristics C_s.

$$Y_s = \beta_1 D_s + \beta_2 N_s + \beta_3 C_s + \theta W_s + \gamma + e_s$$

In some models, we also include a measure of the extent of website use (natural log) W_s (see explanation below). In most models we also include a vector of state fixed effects γ so that the other parameters are identified from within-state variation.[36] This accounts for any time-invariant differences across states that might also contribute to school responses, such as state education policies. Only the results without state fixed effects are directly comparable to other studies looking at national descriptive patterns in results.

In most tables, we report results from five different versions of the above model: (1) include D_s, N_s, and C_s, but exclude W_s and γ; (2) include D_s, N_s, C_s and γ, but exclude W_s; (3) include all variables (D_s, N_s, C_s, W_s and γ); (4) same as model (2) except limit the TPS sample to those where the district websites contributed little data; and (5) same as model (2) except exclude the 25 percent of schools with the highest item non-response.

The last three models address the non-response bias problem in different ways. With regard to model (3), we have scraped the data from all the sampled websites and counted the number of files and links, of all types (not just COVID-related), to obtain a measure of W_s.[37] Loosely speaking, by controlling for W_s, we absorb that portion of the relationship between Y_s and the other covariates that is due to the correlation with the use of websites for communication

[36] We omit the subscript on the state fixed effects to avoid confusion with “s” for school in the other variables.
[37] These include a simple count of the number of .doc, .pdf, and .gdoc files, as well as links to internal and external web pages.

purposes with the intent of isolating the relationship between the predictors and schools' actual COVID-19 responses.[38]

Column (4) addresses the non-response bias that might particularly influence the cross-sector comparisons. We re-estimated the above models using only those traditional public schools, which we had partially replaced with district data (see above). If using school and district websites gave TPS an advantage, then the differences between TPS and private schools should become smaller (less likely to favor TPS).

Finally, with column (5), if we assume that when schools have more non-missing data, the data that are reported are likely more accurate.[39] Within each item in our rubric, there is variation in the intensity of school activities (e.g., in the questions about non-live learning activities, some reported teacher videos and some only reported using packets). Therefore, if we see the same pattern of coefficients when restricting to this sample, it would reinforce that reporting bias is not the main explanation for the results.

We estimate all of the models with Ordinary Least Squares (OLS) using the svy package in Stata, which clusters standard errors at the sample cell level. Sampling weights are always applied, meaning that these are population estimates. Given the likely underreporting of activities generally, these regressions results are the core of the study. That is, we are primarily interested in the patterns of response reflected in the regression coefficients rather than the overall averages, which under-count school activities.

V. Results

Similar to the cross-tabulations in prior work on school COVID-19 responses, we start by reporting the relationship between each key covariate separately in univariate regressions (Table 4). A key contribution of the present study, however, is understanding the pattern of results in greater depth, given that all of the various covariates are correlated with one another. Any correlation between student demographics and school responses, for example, could reflect lower spending, internet access, or other factors influencing school responses. For this reason, most of the remaining tables are from multivariate regressions.

Given the data issues involved, we only conclude that a factor predicts school activities in response to COVID-19 if the signs are consistent across specifications shown in Table 5, and at least one of the coefficients is statistically significant. Note that the precision of the estimates in the last three columns is lower because of the addition of the website use variable (column (3))

[38] We also used a variation on this approach where we regressed the index on only W, took the residual from this first-stage model and used it as the residual in a second stage. This makes somewhat different assumptions about the relationships among the variables, but the results are similar.

[39] We also considered adding the proxy as a covariate, so that the coefficients reflect their influence on school activities, having controlled for the extent of reporting. This would "over-control," however, to the extent that the probability of having school activities and the probability of reporting them are correlated. We are also considering using survey techniques where the probability of reporting is correlated with the dependent variable of interest; however, these would only apply to those schools with no missing data at all (the missing units).

and the reduction in the sample size (columns (4) and (5)). In each of the sections below, we discuss univariate regressions (Table 4) first, then the multivariate regressions for the overall school response index (Table 5), and, finally, multivariate regressions for individual construct indices (Tables 6A-6E).

A. Results by Demographics

Table 4 shows no clear relationship between school responses and student race (this is also true of the specific construct indices; see the appendix). The univariate coefficient on poverty is also insignificant for the overall index, but negative and significant for several construct indices (see the appendix). (An exception is that we find a consistently positive and sometimes significant relationship between percent other race (mostly Asian) and school responses.

We actually find a positive and sometimes significant coefficient on percent poverty, suggesting that schools actually responded more comprehensively in high-poverty schools. Upon closer examination of the construct indices, however, we see that that is driven by school responses in providing a breadth of services and equitable access. This is expected given the greater needs of students in poverty. On academic measures we see no relationship between poverty and school responses, consistent with prior studies.

Adult education level, however, is a strong correlate of school responses. Increasing the percent of families where parents have a BA or above from 0 to 100 percent is associated with a 4-8 point increase in the overall index (roughly one school-level standard deviation). In the regressions with specific constructs, parent education is most predictive of personalization and engagement in other forms of communication, progress monitoring, breadth of services, and equitable access.

The strong connection with parent/adult education is not especially surprising. Parent education is generally the strongest predictor of the educational outcomes of their children, more so than income or race (e.g., Duncan & Brooks-Gunn; Davis-Kean, 2005; Cataltdi et al., 2018). In the present crisis, this may be compounded because more educated parents have white collar jobs that allow them to work at home, maintaining their economic security, and with the flexibility to take breaks to work with their children.

B. Results by Internet Access

The COVID-19 crisis has raised attention to the Digital Divide, i.e., the lack of access to the internet and computers among low-income families and rural areas. The Digital Divide is especially likely to matter here because of the increased dependence of schools on these forms of technology under remote learning.

We measured internet access by the percentage of households in the school's block-group that had Broadband access, as reported in the Census/ACS. We used this metric, as opposed to a broader measure that includes all forms of internet, because other forms of internet are generally too slow to support video-based instruction.[40] While this measure is not significantly related to school overall COVID-19 responses, it is positively related to the constructs: personalization and engagement in instruction and equity of access. Recall that the former construct index is based heavily on the availability of video-based instruction, which depends on internet access. Also, with equity of access, schools may have been more likely to provide laptops if a larger share of the community had internet access.

Like parent education, the role of internet access is likely two-fold. First, as we show, it influences what services schools provide to students. Second, conditional on what schools provide, it also likely influences how well students can access those services. Therefore, when surveys indicate that some students are not experiencing engaging learning activities, it reflects some combination of both of these factors.

C. Results by Sector

Research described earlier suggests that school responses did not follow a clear pattern by sector, except perhaps that charter and private schools had more aggressive progress monitoring and were less likely than TPS to provide meals (e.g., Henderson, et al., 2020). If true, then government regulation is one possible cause. Traditional public schools are subject to a wide range of local, state, and federal laws, while charter and private schools are subject to less regulation and have more autonomy to make educational decisions on their own. In a crisis, this might mean that they could respond more quickly and flexibly. Special education is a particular area of regulation that has received attention, as schools worried that they might not be able to provide remote instruction that was consistent with federal law (Hess, 2020).

On the other hand, switching to remote learning, especially live instruction through video conferencing, is also aided by having capacity and expertise in information technology and teacher professional development. In this respect, even if they have more rules and regulations, school districts can take advantage of economies of scale (Harris, forthcoming). Some charter and private schools, which are usually managed by smaller organizations, may have had greater difficulty. Traditional public schools have also, historically, been more apt than private schools to use technology, so may have been ahead of the curve. In any event, this is also speculation and we are interested in what the data show.

In Table 4, private schools appear to have responded less aggressively. These differences get larger when we start controlling for differences in student demographics and other factors (presumably because they have more advantaged students), but the differences also get smaller again, and become null, in specifications (3)-(5), which are meant to test for differential non-response bias. When using the sample that drops most district data from TPSs, private schools

[40] The ACS measure of internet access is combined with computer access, in the sense that Broadband access is only counted if there is also a computer in the home.

and TPSs show no difference and charter schools appear to have responded more aggressively than TPS.

The sector results also vary by construct in Tables 6A-6F. When we focus just on equity of access and breadth of services, traditional public schools out-perform charter and private schools. Compared with private schools, traditional public schools serve more students who need these services, as well as students with disabilities and English language learners. In contrast, students who attend private schools come from families with higher incomes who already have internet (and computer) access and have little need for school meals and who more rarely have disabilities. Even if they did serve the same students, private schools might be less inclined to put their COVID-19 responses for these students on their websites because they would be less concerned about legal compliance.

However, charter schools exceed traditional public schools on other personalization/engagement and progress monitoring. This, too, seems consistent with the reputation of charter schools, especially those with a No Excuses approach, as being focused on academic achievement and providing fewer services that are not directly tied to academics (even if they might be indirectly important).

Table 7 provides an even more detailed picture, breaking down charter and private schools into different subtypes. (Only the coefficients of interest are reported in Table 7 even though the regressions include the same covariates Table 5 and 6A-6E.) Charter schools authorized by non-profit (NFP) organizations responded more effectively than others in the overall response (those authorized by municipal governments (MUN) may also have been more effective). We find that the type of charter authorizer (e.g., school district (LEA), state education agency (SEA), university (HEI) did not predict the overall index, but this evidence is less consistent across specifications). Also, we see no evidence that the type of management structure (CMO/EMO or standalone) yielded consistent differences with traditional public schools.

The above findings conflict with prior research by the Center for Reinventing Public Education (CRPE, 2020d), which found that charter schools, especially those managed by CMOs, responded more aggressively than traditional public schools. One explanation is that CRPE selected a non-random sample districts and CMOs that differ from the national average. Also, CMOs might have been more aggressive on certain activities, especially personalization and engagement. However, in contrast to private schools, the low scores under breadth of service and equity of access seem more problematic, given the disadvantaged populations that charter schools serve. Prior research suggests that charter schools are less likely to label students as disabled and more likely to serve special education students in ways similar to regular education students.

With private schools, we break down the results into three groups: Catholic, other religious, and secular. Most of the results suggest that Catholic and secular schools responded less aggressively than TPS (the omitted category), but this seems to be driven partly, again, by the additional information that district websites provide for TPS. In column (4), where this issue is addressed, the private school differences are small and insignificant (though still negative).

Overall, the results are consistent with both prior research and with our predictions. Charter and private schools responded relatively effectively in the areas where they typically focus their attention. Private schools, in particular, seem to have responded in ways that align with the needs of the specific types of students they serve.

D. Results by School Spending (Public Schools Only)

School spending is not included in the prior tables because it is only available for traditional public schools. In Table 8, we restrict the sample to TPS and use instructional spending per student. Since these data are not available at the school level, we apply the district-level spending to each school within the district. This might seem problematic, given that spending often varies across schools within districts; however, in this case, it seems that the district response was a key part of school responses, in which case district spending is perhaps the more relevant metric.

In the univariate regression (not shown), we find a positive and statistically relationship between school responses and the overall index. (Each one percent increase in school spending is associated with 0.0247 increase in the overall index.) However, this becomes insignificant and the sign sometimes changes when we add additional covariates. This is not surprising given that both parent education and school spending are correlated with school quality, and the inclusion of parent education might absorb some of the role of school quality, and therefore of school spending.

This should not be interpreted to mean that money does not matter for school effectiveness. The most rigorous research consistently shows that increased school spending leads to improved student outcomes (Jackson, Johnson, and Persico 2017; Hyman, 2017; Lafortune, Rothstien, and Schanzenbach 2018). Indeed, part of the misunderstanding about this point in prior decades came from the studies, like this one, that used more correlational regression methods to study the effects of school spending.

We also included district size in this TPS-only model. (This measure is not especially relevant to charter and private schools, which are not generally governed by districts.) We see no relationship between school responses and district size per se, but Table 5 does show a consistent and positive relationship between urbanity and school responses; and urbanicity is closely related to district size.

The patterns across the other coefficients are quite similar in Table 8 for TPS alone relative to Table 5 for all types of schools. This is not surprising, given that, once the sampling weights are applied, TPS comprise the vast majority of schools in the country. For example, as before, parent education seems to be the dominant predictor of school responses to COVID.

E. Results by State

We used the same regression specifications as in Table 5 to obtain the results by state. To avoid ranking schools based on their demographics, we use the four specifications with state fixed effects and report the fixed effects themselves, which were not shown earlier. (Alaska is the omitted state in each case).

Table 9 reports the results by state (including Washington, DC), sorted by the average fixed effects. Two clear patterns emerge from this. First, states in the Midwest responded more aggressively than the states in the South. Some states display results that are inconsistent across specifications. Michigan and Rhode Island appear high on average and in three of the four specifications (exempting the third specification). The results for California are generally erratic across specifications. The Southern states, however, are consistently at the bottom.

Interestingly, even though the state fixed effects are adjusted for state income, there is still a visual correlation with state income. Southern states have lower income levels on average, but, even within the South, these results largely track income. The three highest ranked Southern states (Virginia, Tennessee and Georgia) also have the highest income per capita in the South. Northeastern and Western states are more evenly spread throughout the list.

One possible explanation for the less aggressive response among Southern states is that their schools open earlier in the fall and close earlier in the spring (usually by mid-May). Our data collection was not completed until June 3, roughly two weeks after the school year would have normally ended. Schools may have removed data from their websites once the school year ended. We do not believe, however, that this explains the pattern, for two reasons. First, the results focus on those schools which did provide information on their websites. The only way the removal of data could explain our findings is if schools only removed some remote learning data, but not all of it. Second, our coders did not see any evidence that data were removed from any of the websites, likely because schools did not see this as a priority after such a difficult transition.

It is possible that Southern schools responded less aggressively because they knew students would have less time to benefit from their transition to remote learning. We have no data to examine this possibility and; therefore, leave this question for future research.[41]

F. Results for Use of Online Tools

Only one study has also examined the specific online tools that schools are using, though that study pertains only to private schools; according to the Hanover/EdChoice study, many schools reported using online tools: Zoom (83 percent), Google Classroom (73 percent), and

[41] We also calculated state fixed effects from regression models reported later. These can be interpreted as the difference between the state and national average, after controlling for demographics, school spending, and the full list of controls listed later. The ranking of the state fixed effects is very similar to the unadjusted state means, meaning, for example, that the lower standing of Southern schools is not explained by the lower adult education and incomes in these states.

Khan Academy (66 percent). (See also the study of the Chetty et al. analysis of the online tool Zearn.)

While not part of the above analysis, we also collected data on the use of 105 specific online tools and report here some additional descriptive statistics. As mentioned above, the most common school activity was the use of online tools, with 59 percent reporting use. Most schools were probably already using these tools to some degree prior to the crisis, and made greater (relative) use of them afterwards.

Table 10 lists the specific online tools and the percentages of school websites mentioning them. We place them into three main categories: learning management systems (LMSs), video communication tools, and tutoring/assessment.[42] Again, we did not count references to these tools if they were only mentioned as "resources" on school websites. This is consistent with the earlier principle of giving more weight or attention to those things that students are expected to do.

LMSs were most commonly mentioned. These allow educators and students to share files electronically (e.g., assignments and deadlines), email (especially in groups), and keep track of grades, among other functions. Over 50 percent of all schools listed Google Classroom. Seesaw was a distant second at 13 percent, followed by Canvas (12 percent), Schoology (10 percent), and Clever (9 percent).

Video-based tools were mentioned next most often. Zoom was the most widely used (28 percent of schools). However, Google Hangouts/Meets was a close second (23% of schools). Many schools likely adopted Google as the overall platform, using both Google Classroom and Google Hangout/Meets. As with LMSs, the functionality of these tools varies. Zoom and Google Hangouts/Meet are meant more for live interaction and interaction between students, teachers, and counselors. (Note that one-quarter of schools reported providing live video instruction.) In contrast, Youtube (2.5 percent of schools), for example, is used almost strictly for recorded videos. These recordings can include both the teachers themselves and other videos that teachers might direct students to watch.

Compared with LMSs and video tools, there are much larger numbers of tools that provide tutorials and assessments, but each is reported by a much smaller number of schools. Khan Academy had the highest number of mentions at 5 percent. More so than LMS and video tools, the use of specific tutorial/assessments tools is probably significantly under-counted because these vary by grade, subject, and teacher. Teachers might, for example, have provided guidance to students about which of these tools to access by communicating through Google Classroom or another learning management system, which apply to all students. But the

[42] We visited the websites of each of the 105 tools to collect information about their functionality. We also placed these tools into more detailed categories: file sharing capability, data collection/grade management, video interaction, recorded lessons (with real people versus animation), practice opportunities, feedback from practice, and discussion boards. Also, we collected information on: whether a fee is generally required, whether that fee was waived during the crisis, whether the tool is customizable, and whether the instruction was aligned to Common Core Standards.

tutorial/assessment tools often do not apply to all students. But, again, the relative number of mentions provides a reasonable picture of which tools were used most often.

We leave for further research questions about the patterns of usage of these different platforms. However, it is noteworthy that this analysis reinforces the earlier finding that schools actively used a wide variety of online tools in their COVID-19 responses, as reflected in the construct index for personalization and engagement in instruction.

VI. Discussion

This study has two main limitations: non-response bias and the professional judgment/evidence approach to creating the indices. The non-response bias is likely worse with website data because of the unstructured nature of the data. While we used a common rubric for coding the websites, those rubrics were not used to create the websites, so "response" is necessarily more erratic compared with surveys. This is reflected in the high overall rate of missing data and the distribution of the indices, which skews heavily to the left. Rather than the usual, approximately normal, distribution, the overall index gradually tapers off. This is the pattern we expect to see if some schools under-report on their websites.

For this reason, we conclude that evidence about the frequency of various activities likely undercounts them--a problem that applies to all of the website-based studies. This is why we have largely ignored the percentages of schools reporting various kinds of activities. But we are able to answer a wide variety of other questions that other studies have not.Because it is so easy to collect website data, it is possible to obtain a large enough sample to study many different and important patterns.

We address the limitations in website data in seven different ways. The first is the focus on patterns. To the extent that the COVID-19 responses of both groups are under-counted, this partially "cancels out" when we look at the differences between the groups.

Second, we applied non-response weights, distinguishing schools that showed some type of response on their website from those that showed no response. If non-response bias were present, we might expect the results to change when applying these weights. This was not the case. The results were very similar with and without weights.

Third, we collected additional data, through web scraping, allowing us to measure how much schools used their websites generally. Schools that used their websites to communicate about school schedules, school activities, and other matters before COVID-19 are also probably more likely to use their websites to communicate about COVID-19. Controlling forW_s in the equation in some of the analyses allows us to test for this.

Fourth, we focused just on schools that had low rates of missing data. Specifically, we dropped the 25 percent of schools that had the least amount of information about their COVID-19 responses on their websites. (Note that we had already dropped schools with no information available, so this step uses the same logic but takes it a step further.)

A related problem is that traditional public schools naturally had more data because they have both school and district websites. The fact that we used both websites for these schools, but did not do so with charter and private schools, means that we could be giving an unfair advantage to traditional public schools when we compare results across sectors. To address this issue, our fifth method involves carrying out analyses that restrict traditional public schools just to the data from *school* websites, largely ignoring the district data.

Sixth, we only draw conclusions that relationships exist between school responses and the various factors like demographics and internet access if the results are consistent (and at least sometimes statistically significant) across all the various versions of the analysis discussed above. It is likely that if we find a consistent pattern of results across all of these methods, then it is likely that it reflects real differences in school responses.

Seventh, we compare some of our patterns to those from other studies that have studied similar questions using different data (especially parent and educator surveys). Where we can make direct comparisons, our results reinforce prior studies, or they differ in predictable ways, giving us confidence that the patterns we observe reflect real differences in school responses.

It is also important to recognize that the probability with which schools placed information on their websites also likely tells us something about how clearly expectations were communicated to families, which may have influenced how students and parents responded. In this respect, concern that we cannot directly distinguish actual school activities from reporting about those activities on websites is lessened.

For all of these reasons, we believe these findings are informative about how schools responded. They also provide guidance for the analysis of website data generally, for analyses of COVID-19 but also for the wide range of other activities about which schools might wish to communicate.

VII. Conclusions

We find that the demographics of students' families—especially adult and parent education—were the strongest predictors of school responses. Prior studies of school responses found no or weak response patterns by family income. This is partly because they were not studying the demographic characteristic that matters most: parent education. This is consistent with past research that finds parent education as the strongest predictor of student educational outcomes, a relationship that is likely reinforced in a crisis where learning activities are guided much more by parents in their home environments.

Traditional public schools were slower to shift to remote learning, but they eventually caught up overall, and even surpassed other schools on breadth of services and equity of access. Charter schools out-performed TPS on other personalization/engagement and progress monitoring. Private schools did not out-perform either sector on any dimension. Prior, survey-based research on this point has been inconsistent regarding the results by sector and this study adds to that empirical base.

The differences in results by sector are partly explained by the populations served and missions of the different sectors. Private schools' less aggressive response on breadth of service and equity of access is likely because private schools serve advantaged populations that are less likely to have disabilities or be English language learners, or need computers and internet access (reflected in our equity of access measure). For the same reason, private schools did not need to provide meals to their students (as reflected in our breadth of services measure).

Midwestern states responded most aggressively on average, while Southern states responded least aggressively. This holds even after controlling for income levels and other demographic measures. We leave for future research questions about why schools responded differently across states. Pre-existing policies and union contracts might have had some influence, along with new policies regarding closure and remote learning put in place by state governments.

Our analysis also provides evidence related to current policy discussions regarding internet access. Schools in neighborhoods with more widespread internet access responded more aggressively in providing personalized and engaging instruction. This is likely because students cannot take advantage of online tools without internet (and computer) access, and school leaders took this into account when deciding how to respond to the crisis.

School spending levels did not predict school responses. Based on what we know from prior research, however, this should not be interpreted to mean that "money doesn't matter." That issue has been settled by prior research showing clearly that, under regular operating conditions, school spending makes schools more effective. For this reason, if we were able to conduct analyses of the causal effect of school spending under COVID-19, then we would very likely find that schools with greater resources responded more effectively to the COVID-19 crisis.

The above conclusions reinforce that we should not interpret the above school responses as evaluations of schools themselves. We are aware of cases where schools responded impressively; in other cases, they may have fallen short. But the more limited responses by some schools and districts were clearly constrained by external forces (e.g., limited internet access, factors related to parent education levels), which are outside the control of schools.

Ultimately, we are interested in school responses to COVID-19 because schools play an important role in the development of children and communities. Prior research suggests that students who attended schools that more effectively carried out the above educational activities also fare better—academically, socially, economically, and otherwise—as a result.

These findings have important potential policy implications: We find little evidence that any inadequacy in response by the nation's schools is due to traditional public schools having fallen behind the times or been hampered by heavier regulations, as some analysts have suggested. While regulation may have slowed the responses of some schools—the worst cases made national headlines—the average difference was just a few days. By May, traditional public schools were on par with charter and private schools. The centralization of school districts may have actually increased the capacity of traditional public schools to respond, by facilitating the development of administrative expertise in areas like information technology and teacher professional development. Also, consistent with prior evidence, traditional public schools reported greater use of the online tools that are so important under remote learning.

Also, gaps in educational opportunity—by race, income, and class—are likely widening as a result of school closures and addressing them will require considerable effort. Inequality in educational opportunity by family demographics is a longstanding and widespread problem. It was therefore not a surprise when early studies suggested that student experiences under COVID-19 were related to students' family income. But that could have just reflected internet access or school spending that are correlated with poverty and which could be rectified through schools and changed policies. The strong role for parent education may be because such parents are better situated to facilitate learning at home, e.g., because they have white collar jobs that can be done from home and with enough flexibility that parents can also help their children learn at the same time. If so, then this may make it more difficult to address rising opportunity gaps.

Federal, state, and local policymakers have options that could improve educational outcomes. Schools could direct resources, and perhaps open their doors, to those specific students who have fallen behind. Governments could expand internet access. Also, though school spending did not predict school responses, the large cuts that seem to be looming will unquestionably lead to less aggressive responses by schools this fall—less engaging and personalized instruction and smaller values on our overall index of school response, unless federal policymakers step in. Finally, state and federal governments could ease the economic security that falls hardest on parents who have lower incomes and less education.

These are only ideas, meant to show the connection between our findings and options that lay before policymakers. While we make no specific recommendations, we believe this evidence, combined with other research described in the accompanying technical report, can help improve decision-making over the coming year, during a crisis that is still unfolding. Whether to continue remote learning is fundamentally a decision about public health, but the educational responses to those public health decisions can take many forms.

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Table 1: Project Timeline

March 26	Began outlining the project
April 10	Requested funds from USDOE-IES
April 15	USDOE-IES approved funding
April 18	Collected websites of all schools through API
April 20	Began first pilot of data collection rubric with all coders
May 5	After completing fourth pilot, and achieving sufficient inter-rater reliability, launched manual coding for entire sample
June 3	Completed manual coding of websites for 3,519 schools

Table 2: Sampling Design
(for each state)

	TPS		Charter		Private	
	Urban	Non-Urb	Urban	Non-Urb	Urban	Non-Urb
Elem	8	8	4	4	4	4
Middle	4	4	NA	NA	NA	NA
High	8	8	4	4	4	4
Other/Middle	0	0	2	2	2	2
Totals	20	20	10	10	10	10

Notes: There are extremely few charter and private schools that focus on middle school only and these are excluded from the population and therefore the sample.

Table 3A: Descriptive Statistics for Website Rubric Items

Category / Variable	**N**	**Mean**	**Min**	**Max**
Personalization / Engagement (Instructional)				
Recorded videos by teachers	2689	0.11	0	1
Online classroom platform	2689	0.66	0	1
Learning packets	2689	0.40	0	1
Assignments given and submitted	2689	0.40	0	1
Other online resources students are EXPECTED to use (Khan Academy,	2689	0.15	0	1
Teachers are required to provide most of the above activities	2689	0.48	0	1
In general, the school requires instructional actions	2689	0.48	0	1
School's Response Varies by Grade	2689	0.43	0	1
Personalization / Engagement (Other)				
Teachers reach out to students individually - by email or online platform	2689	0.31	0	1
Teachers reach out to students individually - by phone/video	2689	0.11	0	1
Students can contact teachers - by email or online platform (e.g., email office	2689	0.57	0	1
Students can contact teachers - by phone/video (e.g., phone/video office hours)	2689	0.24	0	1
Whole-school or whole-grade meetings (e.g., morning meetings)	2689	0.01	0	1
Academic Expectations				
School is tracking attendance during closure	2686	0.23	0	1
Student Participation in remote learning is mandatory	2682	0.33	0	1
Recommended hours of work	780	2.85	0.5	5
Grade transcript records				
A-F	2689	0.08	0	1
P/F	2689	0.09	0	1
Students choose A-F or P/F	2689	0.02	0	1
Grades are provided, but type not specified	2689	0.10	0	1
Grade Basis				
Based on students' work before the closure	930	0.11	0	1
Based on students' work before and during the closure	930	0.39	0	1
Students have choice to include post-closure assignments	930	0.11	0	1
Equity of Access				
School website provides information about COVID-19 in another language	2702	0.34	0	1
Technology				
Community hotspot	2689	0.13	0	1
Home hotspot	2689	0.07	0	1
Referral to free wifi from an internet provide	2689	0.31	0	1
PC and tablets	2684	0.50	0	1
Disability				
Reference to a plan	2685	0.37	0	1
Will continue IEPs	885	0.57	0	1
Teachers will have regular contact by phone/video	885	0.28	0	1
In person instruction offered (with social distancing)	885	0.00	0	1

Special education teachers will work with regular education teachers	885	0.13	0	1
English Language Learners				
References to a plan	2682	0.17	0	1
Will continue ELL instruction	420	0.52	0	1
Teachers will have regular contact by phone/video	420	0.18	0	1
In person instruction offered (with social distancing)	420	0.02	0	1
ELL teachers will work with regular education teachers	420	0.14	0	1
Breadth of Service				
Counselor Availability				
For mental health	2689	0.23	0	1
For academics	2689	0.10	0	1
Available but unspecified	2689	0.17	0	1
Counselor Communication				
Email	1130	0.58	0	1
Phone/video	1130	0.27	0	1
Reached out individually	1130	0.10	0	1
Hold office hours	1130	0.07	0	1
Meals provided by				
School	2702	0.53	0	1
District or charter management organization	2702	0.62	0	1
Other organization (e.g., other government entity, nonprofit)	2702	0.07	0	1

Table 3B: Descriptive Statistics for Indices

Index	Count	Mean	S.D.	Min	Max	Index Max
Overall Response	2251	9.0	6.9	0	35.1	50
Speed	1257	8.3	7.0	0	49	N/A
Personalization/engagement (Class)	2772	3.3	2.3	0	10	10
Personalization/engagement (Non-Class)	2772	1.8	2.0	0	10	10
Academic Expectations	2255	1.4	1.9	0	10	10
Overall Equity	2762	1.8	1.8	0	10	10
Technology Equity	2767	2.5	2.6	0	10	10
Special Education Equity	2768	1.1	1.7	0	10	10
English Language Learner Equity	2764	0.5	1.2	0	10	10
Overall Breadth of Service	2772	2.9	2.1	0	9.4	10
Counselor Service	2772	1.4	2.1	0	10	10
Meal Service	2787	4.5	3.4	0	10	10

Note: This table reports descriptive statistics for the six indices we created using schools' website information. Sampling weights are applied.

Table 4: Univariate Regressions with Overall School Response Index

Variable	1	2	3	4	5
Neighborhood race, % of White	0.27	-0.50	-1.16	-2.30	-0.56
	(0.95)	(1.25)	(1.57)	(1.61)	(1.46)
Neighborhood race, % of Black	-0.16	1.64	1.92	2.44	0.93
	(1.35)	(1.43)	(1.73)	(1.76)	(1.48)
Neighborhood race, % of Hisp.	-0.90	-1.52	0.17	1.63	-1.98
	(1.30)	(1.87)	(2.70)	(2.25)	(2.18)
Student race, % of White	-1.01	-2.18**	-2.37**	-1.94	-1.96*
	(0.79)	(1.00)	(1.15)	(1.28)	(1.19)
Student race, % of Black	0.07	1.60	1.92	0.49	1.06
	(1.02)	(1.12)	(1.30)	(1.30)	(1.17)
Student race, % of Hispanic	0.84	1.27	1.95	2.65	0.32
	(1.03)	(1.58)	(1.93)	(1.77)	(1.86)
% of Bachelor's Degree +	6.75***	6.15***	4.40**	3.70*	7.07***
	(1.53)	(1.57)	(1.89)	(1.93)	(1.83)
% of Families below Poverty	-3.45	-1.23	0.91	4.46	-1.06
	(2.62)	(2.64)	(3.16)	(3.53)	(2.86)
% with Broadband	5.23**	3.69*	3.06	-0.64	3.72
	(2.07)	(2.13)	(2.64)	(2.61)	(2.40)
School size (unit: 1000 students)	1.47**	1.80***	2.36***	1.44*	1.31
	(0.65)	(0.69)	(0.78)	(0.83)	(0.80)
Charter	-0.60	-0.81	-0.07	2.91***	-0.31
	(0.81)	(0.85)	(1.08)	(0.99)	(1.05)
Private	-3.60***	-3.90***	-3.82***	-0.14	-2.24***
	(0.68)	(0.71)	(0.90)	(0.85)	(0.78)
Urban	2.01***	1.90***	1.48***	2.21***	1.59***
	(0.47)	(0.44)	(0.54)	(0.51)	(0.53)
Grade Level	Y	Y	Y	Y	Y
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole.	Whole.	Whole.	Repl. <= 5	Low % Missing

Notes: Each coefficient (cell) is from a separate OLS regression that includes only the variable in question and grade-level fixed effects, but not other variables. While not shown, we also re-estimated the public school model (see Table 8) with only school spending (in natural logs) and obtain a coefficient of +2.47** without state fixed effects and -0.67 with state fixed-effects. Asterisks indicate significance levels: * $p<.10$, ** $p<.05$, *** $p<.01$

Table 5: Predictors of Overall School Response Index (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			0.21		
			(0.21)		
% of Black	-0.08	1.24	1.73	-0.96	0.88
	(1.16)	(1.26)	(1.44)	(1.44)	(1.36)
% of Hispanic	-0.25	0.71	0.75	1.64	1.09
	(1.12)	(1.72)	(2.04)	(1.81)	(1.89)
% of Other	0.00	1.28	1.81	0.94	4.55**
	(1.70)	(1.88)	(2.12)	(2.79)	(2.09)
% of Bachelor's Degree +	6.53***	6.65***	4.00*	5.04**	7.82***
	(2.14)	(2.13)	(2.39)	(2.43)	(2.38)
% of Families below Poverty	2.66	3.86	5.42	5.95	5.15*
	(3.09)	(2.85)	(3.34)	(3.76)	(2.99)
% with Broadband	2.17	1.79	4.61	-0.41	0.78
	(2.62)	(2.56)	(3.16)	(2.60)	(2.88)
School size (unit: 1000 students)	-0.50	-0.14	0.61	0.72	-0.07
	(0.70)	(0.74)	(0.88)	(0.98)	(0.82)
Elementary	-0.15	-0.73	-1.41	0.11	-1.06
	(0.77)	(0.79)	(0.96)	(0.92)	(1.14)
Middle	1.24	0.75	-0.47	2.84**	0.19
	(1.00)	(1.04)	(1.29)	(1.27)	(1.32)
High	1.22	0.48	-0.51	1.65	0.28
	(0.81)	(0.86)	(1.07)	(1.09)	(1.12)
Urban	1.67***	1.27**	0.85	1.33*	0.66
	(0.55)	(0.55)	(0.61)	(0.68)	(0.64)
Charter	-1.21	-1.57*	-1.06	2.35**	-0.79
	(0.87)	(0.93)	(1.21)	(1.17)	(1.15)
Private	-4.87***	-4.84***	-4.46***	-0.41	-3.54***
	(0.83)	(0.87)	(1.11)	(1.22)	(0.99)
Constant	4.30**	2.98	-0.72	2.83	4.76
	(2.14)	(2.58)	(3.00)	(2.94)	(3.06)
R-sq	0.10	0.18	0.18	0.17	0.20
N	2224	2224	1721	1407	1572
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Each column is a separate OLS regression. The "website use" variable is the total number of files and links on the website. The fourth column limits the TPS portion of the sample to schools where fewer than six missing rubric items at the school level were replaced by district data. The fifth column is limited to 75 percent of the total sample that has the most limited missing data. Grade-level fixed effects are also included but not shown. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 6A: Predictors of Construct Indices: Speed of Response (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			0.15		
			(0.21)		
% of Black	1.65	3.99**	4.82**	7.77***	3.84*
	(1.93)	(1.90)	(2.21)	(2.67)	(2.09)
% of Hispanic	4.48	2.60	3.48	0.66	2.13
	(3.01)	(2.50)	(2.75)	(3.24)	(2.77)
% of Other	4.57	0.36	4.76	-5.98	-1.00
	(4.09)	(4.07)	(3.32)	(8.01)	(6.00)
% of Bachelor's Degree +	-3.32	-3.88	-1.22	-0.61	-4.60
	(3.45)	(3.12)	(2.52)	(3.04)	(3.42)
% of Families below Poverty	-3.46	-4.05	-1.19	-4.28	-3.67
	(4.15)	(3.34)	(3.54)	(4.57)	(3.30)
% with Broadband	2.51	-0.08	-1.23	4.39	2.55
	(4.53)	(3.12)	(3.48)	(4.98)	(3.49)
School size (unit: 1000 students)	-0.47	1.27*	1.05	1.21	1.34
	(0.88)	(0.76)	(0.85)	(1.31)	(0.84)
Elementary	0.08	1.97*	0.60	1.51	2.20**
	(1.03)	(1.03)	(0.85)	(1.19)	(1.01)
Middle	1.46	3.51**	2.09*	5.13***	3.65**
	(1.47)	(1.47)	(1.23)	(1.48)	(1.55)
High	1.55*	2.29**	0.77	2.36**	2.55***
	(0.93)	(0.98)	(0.87)	(1.07)	(0.93)
Urban	0.61	0.03	-0.79	0.04	-0.01
	(0.78)	(0.79)	(0.75)	(0.92)	(0.83)
Charter	-0.86	-0.02	-0.64	0.89	0.20
	(1.06)	(0.83)	(0.80)	(1.13)	(0.87)
Private	-3.61***	-1.14	-1.94**	-0.98	-1.01
	(0.92)	(0.95)	(0.88)	(1.53)	(1.19)
Constant	5.24	7.55**	4.90	3.72	5.72*
	(3.39)	(2.94)	(3.53)	(3.98)	(2.99)
R-sq	0.06	0.36	0.39	0.36	0.37
N	1246	1246	948	715	1085
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5 except that the dependent variable is speed of responses (in days). Each column is a separate OLS regression. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 6B: Predictors of Construct Indices: Personalization/Engagement on Instruction (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			0.11		
			(0.07)		
% of Black	0.19	0.34	-0.01	-0.03	0.21
	(0.41)	(0.40)	(0.46)	(0.46)	(0.45)
% of Hispanic	0.68	0.28	-0.61	0.62	0.22
	(0.48)	(0.55)	(0.61)	(0.78)	(0.63)
% of Other	-0.40	-0.52	-0.05	-0.71	-0.74
	(0.47)	(0.52)	(0.61)	(0.70)	(0.70)
% of Bachelor's Degree +	0.59	0.56	0.56	0.47	0.54
	(0.71)	(0.76)	(0.73)	(0.99)	(0.83)
% of Families below Poverty	0.22	0.55	0.37	0.07	0.46
	(0.87)	(0.82)	(0.92)	(1.17)	(0.86)
% with Broadband	1.93**	1.89**	1.51*	0.83	1.65**
	(0.77)	(0.76)	(0.92)	(1.06)	(0.76)
School size (unit: 1000 students)	-0.12	-0.10	-0.17	-0.15	-0.11
	(0.19)	(0.20)	(0.25)	(0.23)	(0.19)
Elementary	-0.06	-0.15	-0.34	-0.06	-0.79**
	(0.26)	(0.26)	(0.31)	(0.28)	(0.34)
Middle	-0.01	-0.11	-0.18	-0.24	-0.85**
	(0.35)	(0.35)	(0.41)	(0.41)	(0.42)
High	-0.17	-0.30	-0.43	-0.26	-0.99***
	(0.27)	(0.27)	(0.32)	(0.32)	(0.33)
Urban	0.38**	0.34*	0.44**	0.60**	0.14
	(0.18)	(0.19)	(0.19)	(0.26)	(0.21)
Charter	-0.16	-0.20	0.25	0.59*	0.01
	(0.27)	(0.28)	(0.33)	(0.32)	(0.30)
Private	-0.65***	-0.71***	-0.66**	0.07	-0.09
	(0.24)	(0.25)	(0.32)	(0.30)	(0.29)
Constant	1.41**	1.11	-0.82	1.47	2.74***
	(0.59)	(0.70)	(0.83)	(0.97)	(0.72)
R-sq	0.05	0.13	0.14	0.13	0.13
N	2742	2742	2121	1658	2067
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5 except that the dependent variable is the construct index for personalization and engagement in instruction. Each column is a separate OLS regression. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 6C: Predictors of Construct Indices: Personalization/engagement – Other (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			-0.01		
			(0.06)		
% of Black	-0.29	-0.05	0.10	-0.55	-0.20
	(0.33)	(0.34)	(0.39)	(0.46)	(0.40)
% of Hispanic	0.09	0.10	0.16	0.64	0.08
	(0.41)	(0.44)	(0.49)	(0.60)	(0.53)
% of Other	-0.49	-0.73	-0.48	0.29	-0.81
	(0.68)	(0.70)	(0.60)	(1.06)	(1.08)
% of Bachelor's Degree +	1.05*	1.10*	0.98	1.09	1.24*
	(0.60)	(0.61)	(0.65)	(0.80)	(0.71)
% of Families below Poverty	-0.01	0.15	0.88	0.18	0.01
	(0.86)	(0.79)	(0.90)	(0.97)	(0.94)
% with Broadband	0.19	0.16	0.82	-0.29	-0.05
	(0.71)	(0.72)	(0.82)	(0.92)	(0.90)
School size (unit: 1000 students)	-0.17	-0.07	0.06	-0.15	-0.07
	(0.18)	(0.19)	(0.21)	(0.27)	(0.23)
Elementary	0.19	0.05	-0.09	0.13	0.00
	(0.21)	(0.22)	(0.23)	(0.25)	(0.27)
Middle	0.45	0.30	0.02	0.51	0.18
	(0.30)	(0.30)	(0.34)	(0.44)	(0.36)
High	0.35	0.15	-0.03	0.32	0.10
	(0.22)	(0.23)	(0.26)	(0.30)	(0.27)
Urban	0.28*	0.24	0.11	0.41*	0.12
	(0.15)	(0.16)	(0.17)	(0.23)	(0.18)
Charter	0.25	0.19	0.16	0.63**	0.38
	(0.22)	(0.22)	(0.27)	(0.27)	(0.26)
Private	-0.34	-0.33	-0.37	0.07	0.12
	(0.26)	(0.27)	(0.31)	(0.39)	(0.35)
Constant	1.02*	1.13	0.06	0.92	1.86*
	(0.58)	(0.80)	(0.79)	(0.91)	(1.01)
R-sq	0.02	0.08	0.08	0.08	0.08
N	2742	2742	2121	1658	2067
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5 except that the dependent variable is the construct index for personalization in other communication. Each column is a separate OLS regression. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 6D: Predictors of Construct Indices: Progress Monitoring (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			0.08		
			(0.05)		
% of Black	0.61	0.85**	1.15**	-0.04	0.96**
	(0.41)	(0.41)	(0.45)	(0.46)	(0.47)
% of Hispanic	0.46	0.03	0.05	0.15	0.09
	(0.52)	(0.51)	(0.55)	(0.58)	(0.62)
% of Other	0.81	1.13	0.59	-0.26	2.10
	(0.89)	(0.97)	(0.60)	(0.63)	(1.59)
% of Bachelor's Degree +	1.46*	1.39*	0.95	1.81**	1.44
	(0.77)	(0.76)	(0.66)	(0.78)	(0.88)
% of Families below Poverty	-0.16	0.23	0.67	1.30	0.22
	(0.85)	(0.85)	(1.00)	(1.07)	(1.05)
% with Broadband	0.34	0.20	1.16	-0.02	-0.08
	(0.66)	(0.66)	(0.73)	(0.69)	(0.85)
School size (unit: 1000 students)	0.32	0.32	0.32	0.35	0.36
	(0.27)	(0.30)	(0.26)	(0.35)	(0.37)
Elementary	-0.09	-0.20	-0.75***	-0.10	-0.41
	(0.22)	(0.23)	(0.28)	(0.26)	(0.41)
Middle	0.57*	0.48	-0.04	1.09***	0.31
	(0.30)	(0.32)	(0.37)	(0.38)	(0.49)
High	0.38	0.30	-0.23	0.46	0.15
	(0.24)	(0.27)	(0.33)	(0.32)	(0.40)
Urban	0.19	0.10	0.02	0.27*	-0.02
	(0.13)	(0.13)	(0.15)	(0.16)	(0.17)
Charter	0.23	0.18	0.15	0.70*	0.36
	(0.29)	(0.30)	(0.36)	(0.36)	(0.39)
Private	0.04	-0.05	-0.37	0.50*	0.50
	(0.22)	(0.25)	(0.24)	(0.28)	(0.36)
Constant	-0.06	0.15	-0.45	-0.26	0.70
	(0.51)	(0.61)	(0.66)	(0.71)	(0.81)
R-sq	0.08	0.14	0.21	0.18	0.15
N	2228	2228	1725	1407	1575
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5 except that the dependent variable is the construct index for progress monitoring. Each column is a separate OLS regression. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 6E: Predictors of Construct Indices: Equity of Access (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			-0.01		
			(0.06)		
% of Black	0.28	0.75**	0.62	0.58	0.84**
	(0.31)	(0.36)	(0.41)	(0.41)	(0.41)
% of Hispanic	0.08	0.62	0.55	0.19	0.70
	(0.39)	(0.46)	(0.56)	(0.55)	(0.54)
% of Other	-0.17	0.41	1.00**	0.28	0.88
	(0.45)	(0.44)	(0.47)	(0.58)	(0.58)
% of Bachelor's Degree +	1.18**	1.29***	0.84	0.95	1.36***
	(0.48)	(0.45)	(0.57)	(0.70)	(0.52)
% of Families below Poverty	0.04	0.44	0.53	1.92**	0.45
	(0.74)	(0.70)	(0.84)	(0.88)	(0.85)
% with Broadband	1.21*	1.34**	1.49*	1.44**	1.29
	(0.69)	(0.66)	(0.79)	(0.62)	(0.81)
School size (unit: 1000 students)	-0.06	0.03	0.08	0.12	0.03
	(0.16)	(0.17)	(0.22)	(0.25)	(0.18)
Elementary	-0.23	-0.36*	-0.42**	-0.26	-0.54*
	(0.18)	(0.19)	(0.21)	(0.22)	(0.29)
Middle	-0.32	-0.42	-0.61**	-0.14	-0.70*
	(0.26)	(0.27)	(0.31)	(0.33)	(0.37)
High	-0.24	-0.41**	-0.59***	-0.23	-0.55*
	(0.19)	(0.19)	(0.22)	(0.23)	(0.29)
Urban	0.45***	0.29**	0.29*	0.19	0.24
	(0.14)	(0.13)	(0.15)	(0.15)	(0.16)
Charter	-0.36*	-0.53**	-0.49*	0.33	-0.55**
	(0.20)	(0.21)	(0.27)	(0.27)	(0.24)
Private	-1.58***	-1.58***	-1.58***	-0.68**	-1.57***
	(0.20)	(0.21)	(0.27)	(0.29)	(0.27)
Constant	0.56	-0.15	-0.47	-0.53	0.12
	(0.57)	(0.62)	(0.76)	(0.65)	(0.76)
R-sq	0.10	0.19	0.18	0.15	0.20
N	2733	2733	2114	1658	2060
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5 except that the dependent variable is the construct index for equity of access. Each column is a separate OLS regression. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 6F: Predictors of Construct Indices: Breadth of Services (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			0.06		
			(0.06)		
% of Black	-0.30	-0.02	-0.23	-0.23	-0.10
	(0.33)	(0.36)	(0.41)	(0.33)	(0.41)
% of Hispanic	-0.53	0.06	-0.07	0.09	0.19
	(0.40)	(0.49)	(0.56)	(0.43)	(0.51)
% of Other	-0.20	0.01	-0.14	0.21	0.47
	(0.57)	(0.67)	(0.67)	(0.57)	(0.73)
% Bachelor's Degree +	0.85	1.01*	0.17	0.27	1.49**
	(0.59)	(0.59)	(0.63)	(0.48)	(0.66)
% of Families below Poverty	1.55**	1.67**	1.64**	1.23	1.96**
	(0.71)	(0.70)	(0.78)	(0.78)	(0.77)
% with Broadband	0.39	0.33	0.66	-0.22	-0.18
	(0.72)	(0.72)	(0.88)	(0.61)	(0.83)
School size (unit: 1000 students)	-0.14	-0.03	0.12	0.25	-0.03
	(0.18)	(0.19)	(0.22)	(0.19)	(0.20)
Elementary	0.05	-0.05	-0.02	0.16	-0.15
	(0.17)	(0.17)	(0.19)	(0.18)	(0.26)
Middle	0.08	0.01	-0.03	0.36	-0.14
	(0.23)	(0.24)	(0.27)	(0.26)	(0.31)
High	0.18	0.02	-0.01	0.29	0.01
	(0.19)	(0.19)	(0.21)	(0.20)	(0.26)
Urban	0.42***	0.33**	0.39**	0.31*	0.10
	(0.16)	(0.16)	(0.17)	(0.17)	(0.18)
Charter	-1.56***	-1.68***	-1.40***	0.05	-1.71***
	(0.19)	(0.20)	(0.24)	(0.23)	(0.24)
Private	-2.85***	-2.77***	-2.63***	-1.00***	-2.87***
	(0.19)	(0.20)	(0.24)	(0.22)	(0.23)
Constant	2.39***	2.41***	1.51*	1.74**	3.25***
	(0.55)	(0.69)	(0.81)	(0.79)	(0.81)
R-sq	0.15	0.21	0.23	0.17	0.21
N	2742	2742	2121	1658	2067
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5 except that the dependent variable is the construct index for breadth of services. Each column is a separate OLS regression. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 7: Detailed School Types as Predictors of Overall Response

	1	2	3	4	5
Charter Management					
Mgmt. Type: CMO/EMO	-2.07	-2.43	-1.63	1.58	-0.67
	(1.43)	(1.59)	(1.91)	(1.70)	(1.79)
Mgmt. Type: Freestanding	-0.62	-1.02	-0.54	2.83**	-0.77
	(0.86)	(0.90)	(1.19)	(1.16)	(1.07)
Mgmt. Type: Missing	-3.27*	-3.65**	-3.95*	-0.39	-3.93**
	(1.77)	(1.46)	(2.18)	(1.66)	(1.57)
Charter Authorizers					
Authorizer Type: HEI	-1.41	-4.02	-3.43	1.63	-2.27
	(2.56)	(3.17)	(3.35)	(3.29)	(3.31)
Authorizer Type: ICB	-3.22**	-1.26	0.81	3.08*	-0.53
	(1.31)	(1.50)	(1.82)	(1.69)	(1.47)
Authorizer Type: LEA	-2.00*	-2.65**	-2.24	1.04	-2.05
	(1.03)	(1.20)	(1.51)	(1.36)	(1.41)
Authorizer Type: MUN	4.49***	0.09	0.60	3.93**	-1.56
	(0.89)	(1.67)	(1.89)	(1.83)	(1.76)
Authorizer Type: NFP	4.53*	2.30	1.64	8.35***	0.01
	(2.45)	(2.35)	(2.32)	(2.78)	(2.43)
Authorizer Type: OTHER	-2.36*	-3.45**	-3.21	-0.83	-4.86***
	(1.40)	(1.40)	(2.70)	(1.87)	(1.75)
Authorizer Type: SEA	-0.15	0.11	0.69	3.22*	1.79
	(1.49)	(1.53)	(1.77)	(1.67)	(1.84)
Private					
Catholic	-5.66***	-5.80***	-5.09***	-1.46	-5.09***
	(0.90)	(1.01)	(1.19)	(1.36)	(0.94)
Other Religious	-5.04***	-5.12***	-4.33***	-0.45	-3.72**
	(1.18)	(1.13)	(1.41)	(1.35)	(1.44)
Nonsectarian	-2.65*	-1.87	-2.01	2.50	0.19
	(1.46)	(1.39)	(1.80)	(1.82)	(1.27)
R-sq	0.10	0.18	0.18	0.19	0.20
N	2224	2224	1721	1407	1572
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are similar to Table 5 except that the charter and private school variables are broken down into the sub-groups of schools listed in the left-hand column. The covariates from Table 5 are also included but not shown. Each set of schools (charter management, charter authorizers, and private schools) are from separate regressions, to avoid placing charter schools in overly small categories. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 8: Predictors of Overall School Response: Traditional Public Schools Only (Multivariate)

	1	2	3	4	5
Log Num. of Website Files			0.28		
			(0.20)		
% of Black	0.40	2.24*	3.48**	-1.26	1.21
	(1.16)	(1.27)	(1.46)	(1.66)	(1.31)
% of Hispanic	0.49	2.02	2.32	2.86	1.88
	(1.13)	(1.75)	(1.94)	(2.18)	(1.96)
% of Other	1.33	3.82*	5.76*	5.88	6.72***
	(1.65)	(1.95)	(3.49)	(5.21)	(2.58)
% of Bachelor's Degree +	7.13***	7.42***	5.66**	5.96**	7.95***
	(2.21)	(2.15)	(2.43)	(2.81)	(2.34)
% of Families below Poverty	2.39	3.58	4.75	7.69*	4.78
	(3.15)	(2.84)	(3.24)	(4.13)	(2.99)
% with Broadband	2.21	1.35	3.99	-1.55	1.18
	(2.66)	(2.63)	(3.14)	(3.07)	(2.83)
Log Per Pupil School Spending	1.28	-1.45	-0.67	0.41	-2.29
	(1.04)	(1.51)	(1.83)	(2.42)	(1.87)
District size (unit: 1,000,000 students)	-4.30*	-3.52	-12.31*	-2.27	0.02
	(2.60)	(3.10)	(6.55)	(3.02)	(2.74)
School size (unit: 1000 students)	-0.59	-0.35	0.43	0.65	-0.49
	(0.68)	(0.72)	(0.88)	(1.06)	(0.77)
Middle	1.26**	1.40**	0.87	2.50***	1.46**
	(0.63)	(0.63)	(0.74)	(0.68)	(0.72)
High	1.52***	1.44**	1.16	1.60*	1.91***
	(0.57)	(0.59)	(0.72)	(0.85)	(0.68)
Urban	1.59***	1.10**	0.55	1.27	0.59
	(0.55)	(0.55)	(0.61)	(0.84)	(0.60)
Constant	-7.30	14.92	5.25	-0.05	23.24
	(9.33)	(13.99)	(17.07)	(21.94)	(17.19)
R-sq	0.09	0.19	0.18	0.23	0.22
N	1445	1445	1066	635	1109
State fixed effects	N	Y	Y	Y	Y
Website Use	N	N	Y	N	N
Sample	Whole	Whole	Whole	Repl. <= 5	Low % Missing

Notes: Results are the same as Table 5, except with the sample limited to public schools only. This allows us to add two predictors: school spending and district size. Because school spending is not available at the school level, we attributed districts spending to the respective school. Each column is a separate OLS regression. Grade-level fixed effects are also included but not shown. Asterisks indicate significance levels: * p<.10, ** p<.05, *** p<.01

Table 9: Results by State

State	Overall Average	Spe. 1	Spe. 2	Spe. 3	Spe.4
ND	8.15	8.05	10.71	4.41	9.44
MN	6.10	7.11	7.51	1.05	8.72
MI	5.10	6.69	8.46	-1.39	6.62
WY	4.62	4.91	6.32	0.17	7.08
IN	4.53	5.14	5.45	1.59	5.95
RI	4.32	5.24	6.30	-3.03	8.76
PA	4.06	4.47	5.90	1.05	4.82
CO	3.74	3.33	6.83	1.23	3.55
WI	3.28	3.48	5.25	0.68	3.70
CA	2.45	1.02	9.02	-0.09	-0.17
CT	2.40	2.32	4.82	-1.95	4.41
NM	2.35	2.75	3.78	-0.73	3.60
NH	2.27	1.71	3.60	0.83	2.92
ME	2.12	1.64	3.73	1.59	1.51
VA	2.11	2.24	3.58	-0.01	2.61
MA	2.10	2.16	3.70	1.06	1.47
OR	2.03	2.21	3.36	-0.18	2.72
KS	1.96	2.29	4.09	-1.77	3.21
NE	1.75	1.85	3.89	-0.71	1.98
IL	1.60	2.60	3.23	-3.13	3.71
NY	1.45	0.59	3.03	-0.63	2.81
MO	1.43	2.10	3.24	-2.20	2.56
WA	1.24	1.74	2.88	-2.29	2.63
NV	1.23	1.35	2.86	-0.68	1.38
OK	1.22	1.53	1.94	-1.49	2.90
DC	1.22	1.67	2.52	-0.89	1.57
DE	1.21	0.12	0.98	-0.97	4.72
MT	1.10	2.07	0.93	-3.43	4.81
TX	1.02	1.37	2.42	-0.78	1.05
TN	0.91	0.79	2.80	-1.46	1.52
MD	0.84	1.33	2.33	-2.27	1.97
UT	0.78	1.13	2.76	-3.31	2.52
OH	0.66	0.39	1.85	-0.89	1.28
GA	0.64	0.24	1.53	-0.08	0.86
VT	0.64	0.15	1.19	-0.07	1.27
FL	0.50	0.79	1.75	-2.95	2.42
AL	0.46	-0.38	1.58	-0.35	0.97
NJ	0.34	1.02	2.66	-3.91	1.59
NC	0.14	0.29	1.27	-1.14	0.12
AK	0.00	0.00	0.00	0.00	0.00
IA	-0.33	-0.08	1.76	-3.00	0.00
ID	-0.51	-0.97	-0.20	-2.22	1.34
AR	-0.64	-0.14	-1.11	-1.67	0.37
WV	-0.71	-0.15	-0.19	-2.30	-0.19
SD	-0.73	-0.92	1.58	-3.11	-0.48
KY	-1.32	-1.79	-0.34	-2.70	-0.44
AZ	-1.36	-1.33	1.23	-5.54	0.22
LA	-1.48	-1.07	-0.11	-3.46	-1.28
MS	-1.79	-1.72	-0.64	-3.69	-1.12
SC	-2.06	-1.83	-1.60	-3.35	-1.46
HI	-2.59	-2.92	-1.27	-2.69	-3.46
ate fixed effects		Y	Y	Y	Y
Website Use		N	Y	N	N
Sample		Whole.	Whole.	Repl. <= 5	Low %

Notes: The last four columns of Table 9 report the state fixed effects from columns (2)-(5) in Table 5. The first column reports the average of these state fixed effects, on which states are sorted from high to low.

Table 10: Use of Online Tools By Type (% of Schools)

Instructional Practice(IP)		**IP (Continued.)**		**Learning Management Systems(LMS)**	
Khan Academy	4.28%	Coolmath4Kids	0.00%	Google Classroom	53.92%
Ck-12	0.71%	Emathinstruction	0.00%	Seesaw	11.35%
Brainpop Jr.	0.68%	Everfi	0.00%	Canvas	10.11%
Game Classroom	0.33%	Explain Everything	0.00%	Schoology	8.02%
Abcya	0.32%	Fact Monster	0.00%	Clever	7.40%
Newsela	0.28%	Labxchange	0.00%	Powerschool	3.26%
Teach Tci	0.25%	Learning.Com	0.00%	Class Link	2.12%
Kahoot	0.24%	Math Fact Café	0.00%	Skyward	0.96%
Mystery Science	0.24%	Math Playground	0.00%	Edmodo	0.56%
Prodigy	0.23%	Mathnook	0.00%	Castle Learning	0.03%
Abcmouse.Com	0.19%	Mathrightnow.Com	0.00%	Eboard	0.01%
Xtramath	0.18%	Pebblego	0.00%	Buncee	0.00%
Raz Kids	0.15%	Phet Interactive Simulations	0.00%	Century	0.00%
Edpuzzle	0.15%	Rozzy Career Adventures	0.00%	Class Kick	0.00%
Quizlet	0.15%	Science Buddies	0.00%	Eduplanet	0.00%
Gizmos	0.13%	Sheppard Software	0.00%	Habyts	0.00%
Icivics	0.12%	Smartlab	0.00%	Ims Global	0.00%
Go Math	0.10%	Studycat	0.00%		
Duolingo	0.10%	Thatquiz	0.00%	**IP & LMS**	
Storyline Online	0.10%	Topmarks	0.00%	Iready	3.97%
Delta Math	0.09%	Unite For Literacy	0.00%	Ixl	3.67%
Pbs Kids	0.09%	Usa Learns	0.00%	Pearson	1.44%
Akeba	0.09%	Zinc Learning Labs	0.00%	Study Island	1.39%
Epic	0.08%			Discovery Education	0.63%
Common Lit	0.06%	**Video Tool**		Nearpod	0.24%
Time For Kids	0.06%	Zoom	23.67%	Kami	0.15%
Think Central	0.04%	Google Hangouts/Meet	18.75%	Carnegie Learning	0.00%
Classcraft	0.04%	Microsoft Teams	5.89%	Education Perfect	0.00%
Quia	0.04%	Flipgrid	2.31%		
Edulastic	0.04%	Youtube	1.93%	**Other**	
Quizziz	0.03%	Screencastify	0.92%	Class Dojo	9.43%
Albert	0.02%	Webex	0.71%	Remind	4.28%
Bookflix	0.02%	Loom	0.39%	Bloomz	0.35%
Gale	0.01%	Owl Labs	0.00%	Talking Points	0.11%
Age Of Learning	0.00%			Padlet	0.04%
Bamboo Learning	0.00%			Team Biz	0.01%
Beast Academy	0.00%			Biz Kids	0.00%
Boclips	0.00%			Varsity Tutors	0.00%
Ccc! Streaming Media	0.00%				

Notes: Table 10 reports the percent of responding schools that mentioned the above tools.