Digital Disruption in Schooling and the Pandemic: Documenting the Digital Infrastructure Divide Among School Children

Ananya Sen and Catherine Tucker*

February 8, 2022

Abstract

A global pandemic has led schools across the United States to switch to online instruction. This paper argues that this swift shock has uncovered a persistent and troubling digital infrastructure divide in terms of access to the internet for children. We document a new persistent digital divide for children, whereby children in poor families are far more likely than other households to rely on cellular data for internet access. We present evidence that in the US, limitations on mobile data use mean that mobile data is unlikely to be a useful substitute. We then show that persistently it is poor and black children who lack access to adequate internet in their homes. We also document that though the historic presence of ICT industries in the local area improves the access of disadvantaged children to broadband internet, it only weakly reduces reliance of some poorer households on cellular data. We conclude by showing that this unequal access to internet infrastructure is likely to lead to negative spillovers in the pandemic, as in areas where poor children have relatively lower test scores compared to their peers, there also tends to be the largest digital divide in access to internet infrastructure.

*Ananya Sen is an Assistant Professor at Carnegie Mellon. Catherine Tucker is the Sloan Distinguished Professor at the MIT Sloan School of Management and Research Associate at the NBER, cetucker@mit.edu.
An Earlier Version of this paper was distributed under the title 'Social Distancing and School Closures: Documenting Disparity in Internet Access among School Children'

1 Introduction

The COVID-19 pandemic has led schools to accelerate and embrace digital transformation very swiftly. As a result of the pandemic, school systems in the US have experimented with many digital tools and remote instruction based on evidence from past pandemics (Stebbins et al., 2009; Markel et al., 2007). However, online instruction is only feasible if children have access to the internet in the home. Though there are many studies of the digital divide and the implication that poorer households are less likely to adopt the internet (Keller, 1995; Servon, 2008), there is little work that tries to understand how and why households who have children differ in their access to internet infrastructure. In this age of forced remote instruction, this has become a key policy issue.

In this paper, we document a previously undocumented 'child digital infrastructure divide.' To do this we use data from the American Community Survey, which surveys children and records the level of internet access in their household. In general, households with children are more likely to have access to the internet, across all income levels. However, poorer households with children are far more likely than poor households without children to rely on cellular-based data plans to access the internet. We present evidence that suggests that due to widespread cellular data-usage and data-speed limitations, cellular data access is unlikely to be an adequate substitute for broadband internet access.

We then look to see what factors such as poverty and race lead children to have access to reliable broadband internet or reliance on cellular data. We show that both poverty and race play a key role in driving a child's access to the internet. For example, if a child is in a family which receives SNAP benefits (food stamps), then they are 15 percentage points less likely to have access to high-speed internet, and 9 percentage points more likely to rely on cellular data. Black children are 8 percentage points less likely have access to high-speed internet, and 3 percentage points more likely to rely on access to cellular data. Children who live in temporary living situations are 5% more likely to rely on cellular data, and 30% less likely to have access to high-speed internet.

We then turn to consider how this is affected by local internet infrastructure. We show that where private firms have historically focused on internet, communications and technology, there are positive spillovers to disadvantaged children in terms of increasing their relative likelihood of having access to high-speed internet, though only marginal improvement on lack of reliance of cellular data.

Our results are concerning, as it suggests in general that a shift to online instruction may harm students who are already experiencing disadvantages. To explore this, we use data on reported district math-testing scores, that reveal the extent to which certain disadvantaged groups fall behind their peers. We see that districts where disadvantaged kids are already under-performing are also more likely to have disadvantaged kids in their district who do not have access to the internet.

These results are important due to the rapidly evolving policy debate around remote education via the internet. The CARES Act provided funding of $13.32 billion for emergency education relief - a portion of which is allocated to school districts to allow for 'Purchasing educational technology (including hardware, software, and connectivity) for students who are served by the local educational agency that aids in regular and substantive educational interaction between students and their classroom instructors, including low-income students and students with disabilities, which may include assistive technology or adaptive equipment.'[1] However, it is not clear how schools' reliance on instruction by the internet will affect existing inequalities in the educational system. Our intention is to present some empirical patterns about access to the internet and in particular reliance on limited cellular data among disadvantaged children to help inform policy.

Policy leaders, such as the Education Secretary, are saying that "The transition to dis-

[1] https://www.congress.gov/116/bills/hr748/BILLS-116hr748enr.pdf

tance and online learning needs to happen quickly."[2] While there may be a need to move swiftly, such policies should also take into account unintended consequences which might exacerbate existing inequalities. Keeping this in mind, it could be important to prioritize subsidies for internet use which might encourage take-up in relatively under-privileged communities. In line with this, we provide evidence that states which have encouraged digitization of economic activities in the past saw a spillover effect to a general increase in internet take-up, even among the most disadvantaged sections of society. This mirrors the finding in Belo et al. (2016) which shows how broadband adoption by schools in Portugal spills over to households also adopting high-speed internet. At the moment, policy leaders are debating the extent to which future stimulus packages should subsidize broadband internet.[3] Our results aim to highlight a particular area where subsidies may be particularly useful to avoid reinforcing existing educational disparities.

The paper intends to contribute to the public policy and academic debate regarding the pandemic, the internet and education. In particular, it builds on three strands of the academic literature.

The first is the literature on the the consequences of internet use on educational outcomes. This literature asks whether access to the internet improves educational outcomes. Chen et al. (2018) focus on academic performance and crime while Belo et al. (2013) focus on a distraction effect away from academics which adversely affects test scores. In contrast to the literature, the intention of this paper is to prospectively guide policy around online instruction at a time of widespread school closings.

The second is the literature on the digital divide. Since the early days of the Internet, concerns existed that access to the Internet might echo or even reinforce existing sources

[2]https://www.usnews.com/news/education-news/articles/2020-03-31/many-schools-are-not-providing-any-instruction-amid-coronavirus-pandemic

[3]https://morningconsult.com/2020/04/02/broadband-subsidies-coronavirus-stimulus-package/

of inequality (Keller, 1995; Servon, 2008). Early research documented the digital divide in electronic commerce (Hoffman et al., 2000) and Internet usage (Goldfarb and Prince, 2008). Since then, there have been some efforts to try to quantify the effects of certain digital technologies on the rich relative to the poor (Aker and Mbiti, 2010; Miller and Tucker, 2011; Tucker and Yu, 2019). And work from non-governmental organizations has tended to emphasize the gains made in the adoption of digital technologies despite the persistence of the digital divide (Anderson, 2017). We contribute to this literature by exploring how access to the internet differs for children who may need to rely on it for schooling and whether this has the potential to reinforce inequality.

The last is a very large educational literature that attempts to understand the causes of underperformance by disadvantaged children and why it is widening (Reardon, 2011). Various papers in economics have tried to use shocks such as hurricanes (Imberman et al., 2012) or busing programs (Billings et al., 2014) to disentangle potential mechanisms for this persistent inequality such as peer effects. By contrast our paper tries to evaluate how a large shock is itself prospectively likely to reinforce existing underperformance.

2 Background and Data

2.1 Background to the Policy Challenge

The number of children relying on remote instruction across the US starting in the Fall of 2020 is large. We report the results of a survey of school districts done by 'Education Week' of 907 school districts, which slanted towards the largest school districts in the US.[4] There are 13,588 school districts in the US.[5] Of the 100 largest school districts in the USA, 74% chose remote learning only as their back-to-school instructional model, affecting 9 million children. Almost half of the 49% districts surveyed opened with remote learning. Full

[4] https://www.edweek.org/ew/section/multimedia/school-districts-reopening-plans-a-snapshot.html

[5] https://nces.ed.gov/programs/digest/d12/tables/dt12_098.asp

in-person instruction was available to students in 24% of the surveyed districts.

There has yet to be any form of systematic analysis of the extent of internet support given by school districts which are moving to online instruction as a result of the pandemic. However, some volunteers at the Center for Reinventing Public Education (CRPE) have attempted to collate data from a variety of public sources.[6] By the end of May 2020, they had tracked down policies for 103 school districts (both public and charter). Therefore, this is a small sample. Further, it is likely to be biased in that presumably it is only the more organized and internet-savvy school districts who are posting plans where volunteers can find them. That said, it is still interesting to look at this limited sub-sample. 61% of the school districts were planning to enable some form of wifi access. 54% of school districts were planning to provide some form of computer devices. 49% had a plan for providing resources to special populations.[7]

2.2 Data Used In Analysis

We use three separate sources of data in this paper.

The first source is data on access to the internet from the 2018 1-year American Community Survey (ACS), released in November 2019.[8] The household file provides data on whether the household receives food stamps, and whether they have access to the internet. Several types of internet access are recorded in the household file. These include high-speed internet (which is described as 'cable, fiber optic, or DSL service), dial-up internet access, satellite internet access, and internet access via a smart-phone cellular plan. Another question asked explicitly whether they had any internet access at all. If households responded, for example, that they had both dial-up and high-speed internet access, then we recorded

[6] https://www.crpe.org/content/covid-19-school-closures

[7] These measures mirror some general strategies school districts employed before the pandemic to encourage internet adoption. For example, public schools in Cambridge, MA distributed a Chromebook to every student in high school in the system. See here for more http://www.cambridgeday.com/2018/09/23/crls-community-surprised-by-chromebooks-youre-not-crazy-and-district-is-sorry-for-error/

[8] https://www2.census.gov/programs-surveys/acs/data/pums/2018/?

them as having high-speed internet access. Therefore, our measures of whether a household has dial-up only includes households who only had access to dial-up and not access to broadband internet service. Similarly, our measure of whether a household relies on cellular data excludes households that have access to broadband or satellite internet.

We also look at data for the children themselves. We use the people-file from the ACS data to identify children in grades 1-12, their age, their race and their disability status. We then match the records of these children to the corresponding household file. We also looked at the type of housing that children lived in. Due to the way that the American Community Survey is conducted, the questions focusing on housing units do not provide an easy proxy for whether the child is homeless. Therefore, we proxied for the state of homelessness by whether or not the child lived somewhere which had kitchen facilities. We focus on whether the family receives SNAP benefits (which used to be referred to as food stamps) as a key measure of child poverty. We do this because not only does this adjust automatically for differences in household size that might affect interpretation of household income, but also because receiving SNAP benefits is one of the qualifying criteria for receiving free school meals. When reporting test scores, schools use students receiving free school meals as a measure of poverty. We also show how our results vary for different quartiles of household income.

We obtained data that measured local school performance. We downloaded data about math test scores in 2018 from the Ed*Facts* website by school district level.[9] This data for 2017-2018 were released in early 2020. The data records the percentage of test-takers who have achieved proficiency in math. It also records the percentage of school children in potentially disadvantaged groups including children who are Black, Native American, Hispanic, Asian, receive free school meals, are disabled or are in foster care. Ed*Facts* is a government initiative to 'govern, acquire, validate and use high-quality elementary and

[9] `https://www2.ed.gov/about/inits/ed/edfacts/data-files/index.html`

secondary performance data in education planning, policymaking and management decision making to improve outcomes for students. It centralizes data provided by state education agencies. One issue is that to protect the privacy of students some data was reported as a range, if there were not many students in that group. When data was reported as a range we took the midpoint of that range. In addition, the initiative did not report data where there were quality concerns over the data being reported by the state. We focused on data where the results were aggregated across grades. We focused on math test scores because unlike English language test scores, they are generally accounted to be a good predictor of future income (Niederle and Vesterlund, 2010).

We then matched the school district data to the data in the American Community survey at the level of the Public Use Microdata Areas (PUMA). This is the most granular geographic level of data that the ACS data is available at. They are designed to have a population of roughly 100,000 or more people.

Last, we use data about earlier investments in broadband from the 2012 'state broadband index'.[10] This study developed an index of broadband investment by states with three inputs: Adoption level in 2012, network speeds, and last, a measure of whether the economic structure of the state is orientated towards ICT industries. The economic orientation measure reflects how many jobs in that state were related to broadband or mobile app development, and we focus on this measure in our empirical specifications. The idea is that the presence of ICT industries in the labor force should have spillovers to general deployment of the internet.

2.3 Summary Statistics

Table 1 shows the variety of different internet measures we use in our specifications. 77% of children have access to high-speed internet. 5.5% of children have no internet access at home. The main alternative form of internet access available is that of a cellular internet

[10] `https://broadband.utah.gov/wp-content/uploads/2014/11/technet-2012-state-broadband-index-report.pdf` Technet has produced two reports on this topic - one in 2003 and one in 2012.

Table 1: Summary Statistics for Internet and IT Access

	Mean	Std Dev	Min	Max
Cellular Internet Only	0.15	0.36	0	1
No Internet Access	0.055	0.23	0	1
High Speed Internet	0.77	0.42	0	1
Satellite Internet Only	0.030	0.17	0	1
Observations	453107			

Data from the American Community Survey evaluating internet access for children in grades 1-12 in the US from 2018

Table 2: Summary Statistics

	Mean	Std Dev	Min	Max
Receives SNAP	0.21	0.41	0	1
English Learner	0.012	0.11	0	1
Learning Disability	0.041	0.20	0	1
Homeless	0.0039	0.062	0	1
Hispanic	0.25	0.43	0	1
African-American	0.14	0.35	0	1
Asian	0.049	0.22	0	1
Native American	0.0021	0.046	0	1
Observations	453107			

Data from the American Community Survey evaluating background of children in grades 1-12 in the US from 2018

connection. This is far more common that dialup or satellite alternatives.

Table 2 shows summary statistics for our demographic variables that describe the children and the households they live in. 21% of children live in a household which receives SNAP benefits.

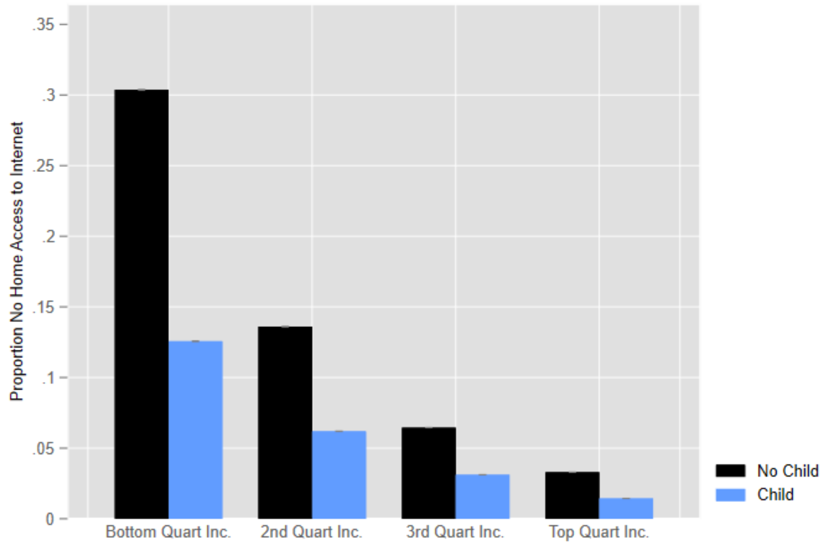


Figure 1: Access to Internet by Income Quartile and Child Presence in Household

3 Empirical Analysis

3.1 The Digital Divide For Households with Children and Households Without Children

We first document how this digital divide varies by households across income by whether they have school-age children. Figure 1 presents the results by quartile of income, and Figure 2 present the results over 20 different household income bands (ventiles). In general, it is clear that there is still a heavy and persistent digital divide in the US as across all households, as richer households are far more likely to have access to the internet. Furthermore, this initial figure suggests a relatively optimistic conclusion, which is that across ever income level, households who have children are more likely to have access to the internet. Given the sudden switch to remote instruction, the generally high level of internet access for households with children seems like good news. However, the next question is what kind of internet these households have access to.

To investigate this we also looked at whether or not the household's access to the in-

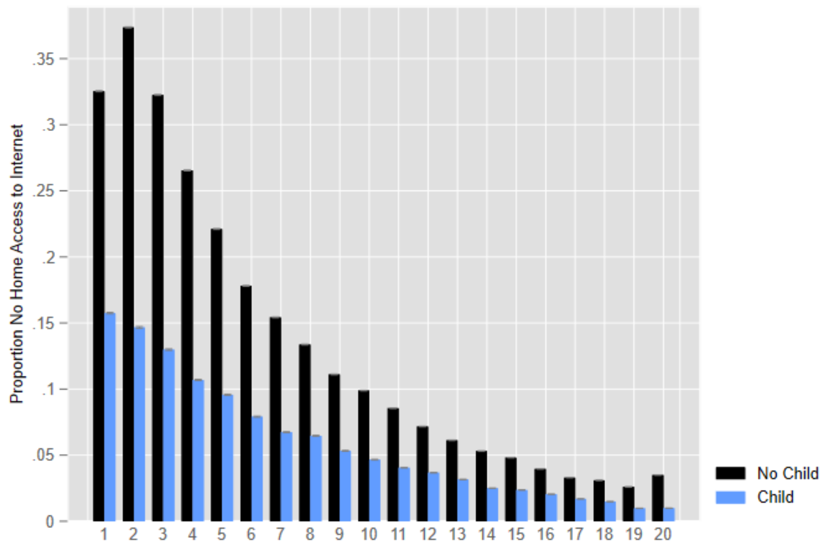


Figure 2: Access to Internet by Income Ventile and Child Presence in Household

ternet was via cellular data only. Figure 3 and Figure 4 present the results over different income quartiles and ventiles. There is a stark and unexpected pattern in this data. Poorer households with children are more likely to rely on cellular data to access the internet. This pattern appear strongest among the very poor, and eventually reverses around the 45th percentile of income. Cellular data plans in the US are ill-equipped to provide enough data bandwidth for class instruction.

In general, cellular internet connections may be less than satisfactory as conduits for internet for school work. Typically, cellular data plans are either metered, making them expensive for high-intensity internet usage such as video-conferencing, or they have limits in terms of how much the user can use them to tether devices.[11] Even despite phone companies saying they would add extra data to cell phone plans during the pandemic, it is not clear that this extra data would be provided at sufficiently high speed.[12] Furthermore, there is evidence

[11]For example many unlimited mobile plans limit tethering of devices to 10 gigabytes of usage https://www.usatoday.com/story/tech/columnist/2017/06/14/nervous-about-using-all-your-data-on-a-hotspot/102689496/

[12]https://www.theverge.com/2020/3/23/21191573/verizon-coronavirus-covid-19-unlimited-data-giveaway-overage-fees-waived

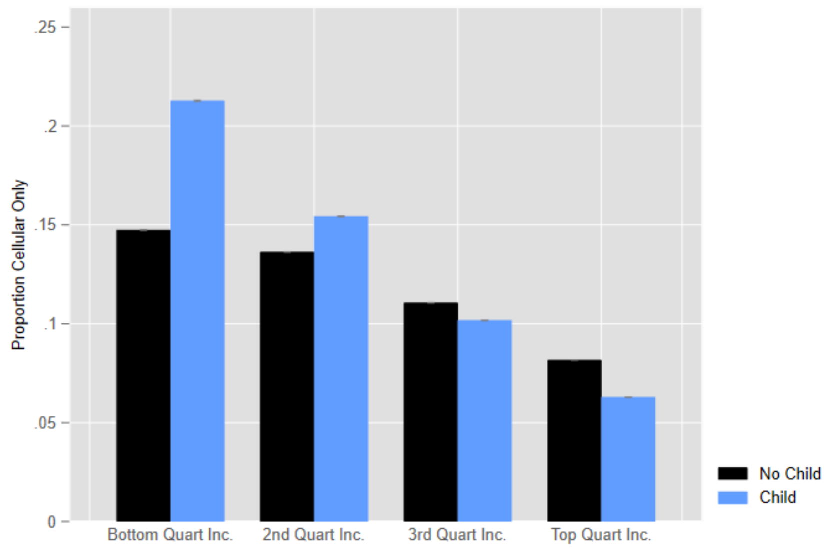


Figure 3: Reliance on Cellular Data for Internet by Income Quartile and Child Presence in Household

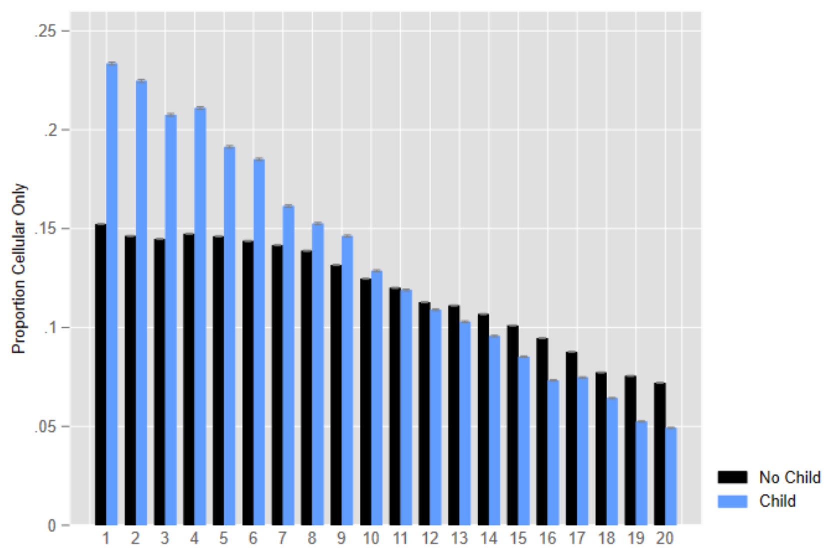


Figure 4: Reliance on Cellular Data for Internet by Income Ventile and Child Presence in Household

that most major cell phone data providers stopped offering incremental data allowances due to the pandemic in June.[13] For example, AT&T waived overage feeds for data users until June of 2020, but after that there were no such waivers. Similarly, US Cellular started charging for data overages again after July 2020.

[13] https://www.ctia.org/covid-19.

3.2 Which Children Do Not Have Access to the Internet?

We then look at empirical variation within the households that have children to understand what factors mean that children are more likely to rely on cellular data to access the internet. Our empirical specification is very straightforward: For child i in grade g, their likelihood of having a certain type of internet access is a function of:

$$InternetAccess_i = \beta Demographics_i + \alpha_g + \epsilon$$

We estimate this specification using ordinary least squares for simplicity of interpreting the coefficients in a linear probability model. Since the dependent variable is binary, we also report results for a logit specification in the Appendix as Table A1. This shows similar results and suggests that our choice of functional form is not driving our results.

Table 3 presents our initial results which show the correlations between different child demographics and their access to the internet. The results show reasonably consistent patterns. Children who live in a household that receives SNAP benefits are 9 percentage points more likely to have access to the internet only through a cellular plan. They are 16 percentage points less likely to have access to high-speed internet. They are 10 percentage points more likely to have no access to the internet.

The pattern is even more severe for children who are living in housing without kitchen facilities. These households are 30 percentage points less likely to have access to high-speed internet. In general, all races with the exception of Asian children are less likely relative to the baseline to rely on cellular data for their internet. The baseline group is people who were white or of mixed-race descent. There are smaller negative effects of the child having a learning disability on their access to the internet - it appears that children who have learning disabilities are more likely to rely on cellular access to the internet or satellite internet rather than mainstream broadband.

Table 3: There is Systematic Inequality in Access to the Internet for Children

	(1) Cellular Internet Only	(2) No Internet Access	(3) High Speed Internet	(4) Satellite Internet Only
Receives SNAP	0.0898***	0.0644***	-0.167***	-0.000803
	(0.00205)	(0.00157)	(0.00240)	(0.000792)
English Learner	0.0383***	0.104***	-0.157***	-0.00470
	(0.00710)	(0.00688)	(0.00868)	(0.00255)
Learning Disability	0.0141***	-0.00179	-0.0321***	0.00486**
	(0.00372)	(0.00253)	(0.00437)	(0.00178)
Homeless	0.0533***	0.243***	-0.303***	0.00000410
	(0.0130)	(0.0140)	(0.0154)	(0.00465)
Hispanic	0.0386***	0.0351***	-0.0817***	-0.00452***
	(0.00179)	(0.00127)	(0.00212)	(0.000772)
African-American	0.0296***	0.0352***	-0.0817***	-0.00575***
	(0.00242)	(0.00180)	(0.00290)	(0.00102)
Asian	-0.0381***	-0.0200***	0.0680***	-0.0150***
	(0.00248)	(0.00136)	(0.00288)	(0.00114)
Native American	0.0948***	0.0480***	-0.149***	0.0161
	(0.0183)	(0.0140)	(0.0201)	(0.00957)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	453107	453107	453107	453107
R-Squared	0.0177	0.0336	0.0522	0.000744

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Person-weights used from American Community Survey. Robust standard errors reported in parenthesis below. Ordinary Least Squares (linear probability model). Dependent variable is type of internet access in the household.

In general, the results of Table 3 suggest that the demographic variables which have historically led children to not have access to the internet, are now making it more likely that they are living in a household which relies on cellular data for the internet.

In the next section, we discuss how this disparity in access to the internet is related to historical broadband investments.

3.3 Relationship of Inequality to Broadband Investment by States

In general, there has been less attention on broadband investments in policy circles in the past decade (Greenstein, 2020). However, there are still lingering questions of whether broadband investment can help address this disparity that we observe in our data.

To investigate this we use the data on historic broadband investment at the state level. Though, of course data at the state level is more coarse than our educational performance and internet adoption data, it does reflect historic reality that broadband investment was influenced by state-level policies.

This study developed an index of broadband investment by states which have three inputs: Adoption level in 2012, network speeds, and last, a measure of whether the economic structure of the state is orientated towards ICT industries. We focus on the third of these three components, the economic structure of the state in 2012, as our focal measure but show robustness to using the entire index in the Appendix in Tables A2 and A3. The economic orientation measure reflects how many jobs in that state were related to broadband or mobile app development. The idea is that the presence of ICT industries in the labor force should have spillovers to general deployment of the internet.

Tables 4 and 5 show the results of these specifications. They show that there are spillovers to children who live in households that receive SNAP benefits and Black children in states which historically have had a large presence of ICT jobs that use broadband. This suggests that the presence of private firms, and the spillovers they generate for broadband deployment, help reduce inequality. However, the data also suggest that these spillovers have been small when it comes to reducing children living in households that have a reliance on cellular data, and insignificant when it comes to poor children living in households that rely on cellular data.

Table 4: Access to the Internet: Relationship to Poverty and Broadband Economic Orientation

	(1) Cellular Internet Only	(2) No Internet Access	(3) High Speed Internet	(4) Satellite Internet Only
SNAP	0.0888***	0.0888***	-0.186***	0.00295
	(0.00590)	(0.00444)	(0.00683)	(0.00233)
Economic Orientation Internet (2012)	-0.000409***	-0.000188***	0.000660***	-0.0000994***
	(0.0000161)	(0.00000992)	(0.0000192)	(0.00000827)
SNAP × Economic Orientation Internet (2012)	-0.0000109	-0.000222***	0.000194***	-0.0000365*
	(0.0000469)	(0.0000340)	(0.0000542)	(0.0000174)
English Learner	0.0383***	0.105***	-0.158***	-0.00459
	(0.00710)	(0.00688)	(0.00865)	(0.00255)
Learning Disability	0.0130***	-0.00243	-0.0299***	0.00462**
	(0.00372)	(0.00253)	(0.00436)	(0.00178)
Homeless	0.0513***	0.242***	-0.300***	-0.000487
	(0.0131)	(0.0139)	(0.0153)	(0.00466)
Hispanic	0.0462***	0.0397***	-0.0948***	-0.00251**
	(0.00181)	(0.00130)	(0.00214)	(0.000779)
African-American	0.0280***	0.0337***	-0.0783***	-0.00655***
	(0.00243)	(0.00180)	(0.00290)	(0.00100)
Asian	-0.0270***	-0.0144***	0.0496***	-0.0122***
	(0.00252)	(0.00138)	(0.00292)	(0.00115)
Native American	0.0891***	0.0439**	-0.139***	0.0145
	(0.0184)	(0.0139)	(0.0201)	(0.00958)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	452456	452456	452456	452456
R-Squared	0.0201	0.0356	0.0570	0.00147

* p <0.10, ** p <0.05, *** p <0.01. Person-weights used from American Community Survey. Robust standard errors reported in parenthesis below. Ordinary Least Squares (linear probability model).

Table 5: Access to the Internet: Relationship to Race and Broadband Economic Orientation

	(1) Cellular Internet Only	(2) No Internet Access	(3) High Speed Internet	(4) Satellite Internet Only
African-American	0.0448***	0.0732***	-0.135***	0.000966
	(0.00752)	(0.00579)	(0.00904)	(0.00323)
Economic Orientation Internet (2012)	-0.000395***	-0.000196***	0.000646***	-0.0000997***
	(0.0000161)	(0.0000104)	(0.0000189)	(0.00000766)
African-American × Economic Orientation Internet (2012)	-0.000152*	-0.000354***	0.000509***	-0.0000674**
	(0.0000619)	(0.0000460)	(0.0000750)	(0.0000257)
Receives SNAP	0.0874***	0.0627***	-0.163***	-0.00135
	(0.00205)	(0.00156)	(0.00241)	(0.000788)
English Learner	0.0384***	0.105***	-0.158***	-0.00459
	(0.00710)	(0.00688)	(0.00865)	(0.00255)
Learning Disability	0.0130***	-0.00217	-0.0302***	0.00466**
	(0.00372)	(0.00253)	(0.00436)	(0.00178)
Homeless	0.0513***	0.242***	-0.300***	-0.000511
	(0.0131)	(0.0139)	(0.0154)	(0.00466)
Hispanic	0.0460***	0.0389***	-0.0939***	-0.00264***
	(0.00181)	(0.00130)	(0.00214)	(0.000778)
Asian	-0.0274***	-0.0148***	0.0506***	-0.0123***
	(0.00252)	(0.00138)	(0.00292)	(0.00115)
Native American	0.0894***	0.0454**	-0.141***	0.0148
	(0.0184)	(0.0139)	(0.0201)	(0.00959)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	452456	452456	452456	452456
R-Squared	0.0201	0.0358	0.0572	0.00148

* p <0.10, ** p <0.05, *** p <0.01. Person-weights used from American Community Survey. Robust standard errors reported in parenthesis below. Ordinary Least Squares (linear probability model).

3.4 Relationship with Existing Educational Equality

We next turn to consider how existing disparity in access to internet infrastructure, is correlated with existing educational outcomes. We focus on relative differences in math-testing scores within school districts.

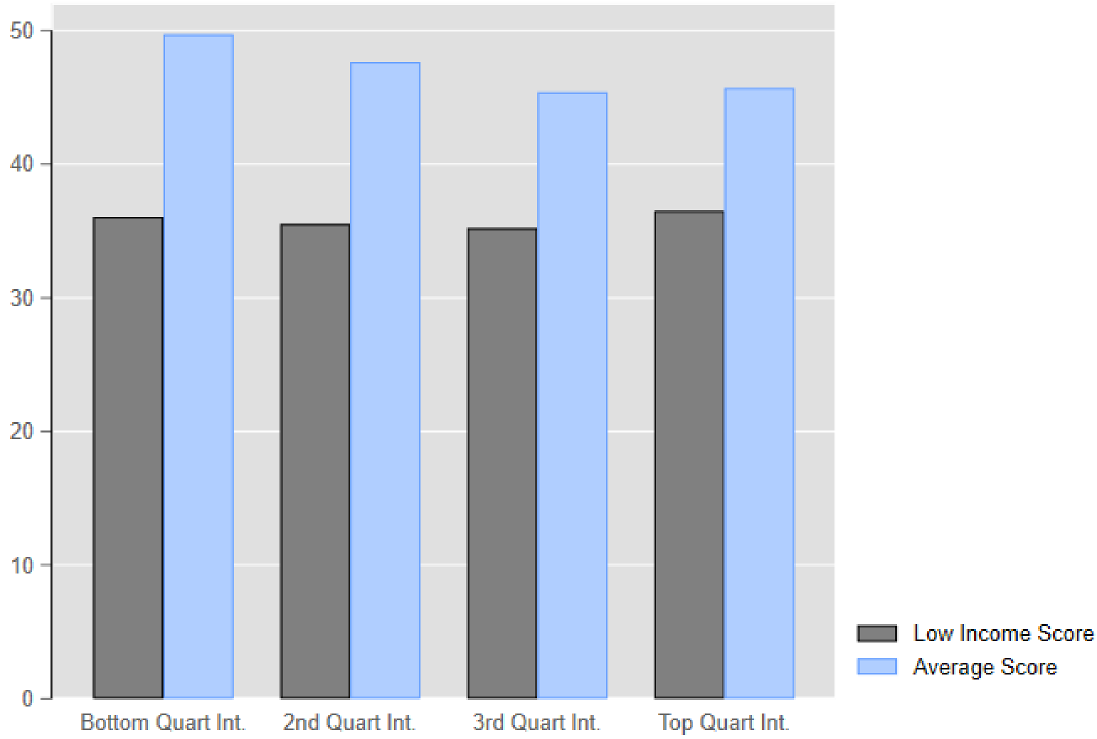
Figures 5 and 6 present results which reflect educational testing outcomes. Each graph looks at the different quartiles of high-speed internet adoption and how they relate to math score inequality in that local area.

They show that both low-income (Figure 5) and black children (Figure 6) who live in areas with higher high-speed internet diffusion are more likely to underperform in math tests relative to their peers. In general, regions with higher internet diffusion exhibit higher average math scores. But the fact that they exhibit higher average math scores exacerbates the inequality in testing between the average math score and children who receive free school lunches or are black. We extend this analysis in the Appendix, where we compare relative scores for children who are in the demographic groups that tend to predict they are less likely to have access to high-speed internet, such as being Hispanic or being homeless. In all cases, we see that these groups also have lower than average math test scores.

This is concerning because it is precisely in those areas where the internet has diffused more broadly, where there may be more of an assumption that children are able to connect easily to online instruction via the internet. However, this graph also suggests that such regions are already experiencing the greatest educational disparities. It leaves open the question whether in areas where there is above-median high-speed internet diffusion, black or low-income children themselves are also more likely to have access to high speed internet, or instead are more likely to be reliant on other less adequate forms of internet access such as cellular data.

We explore this in Figures 7, 8 and 9. Figure 7 suggests that even in areas where there

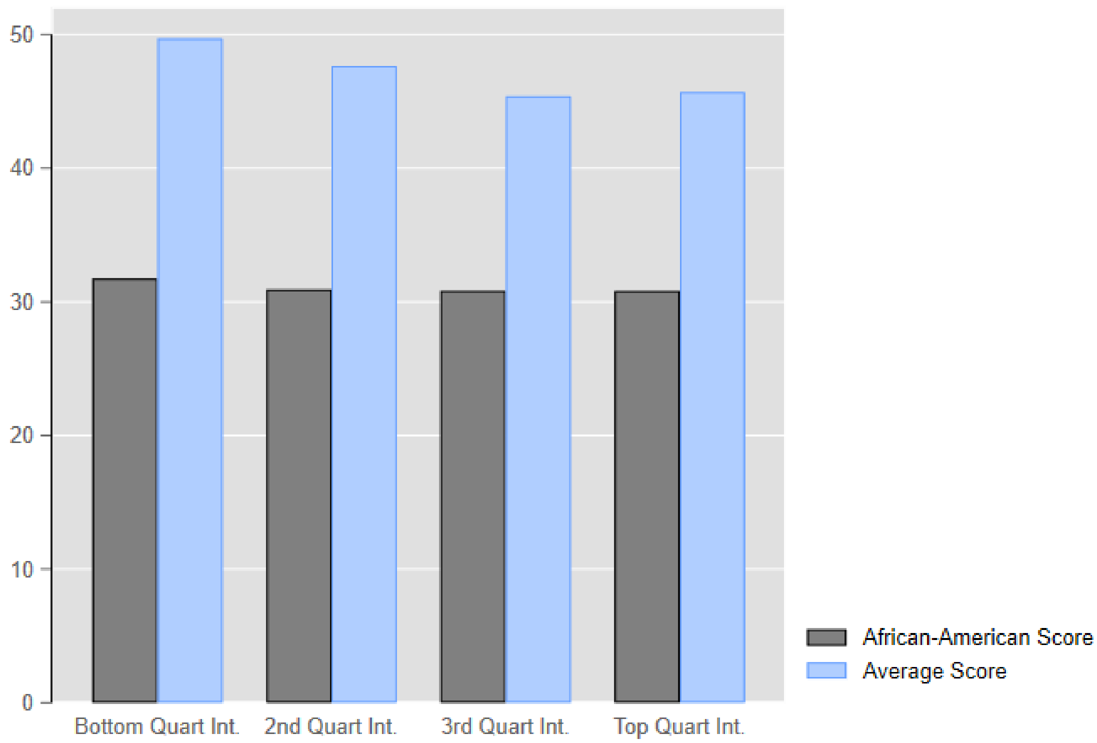
Figure 5: Low-Income Children Are More Likely to Underperform Their Peers in High-Internet Areas



Data on internet quartile of local area from American Community Survey. Data on educational performance from the Ed*Facts* database.

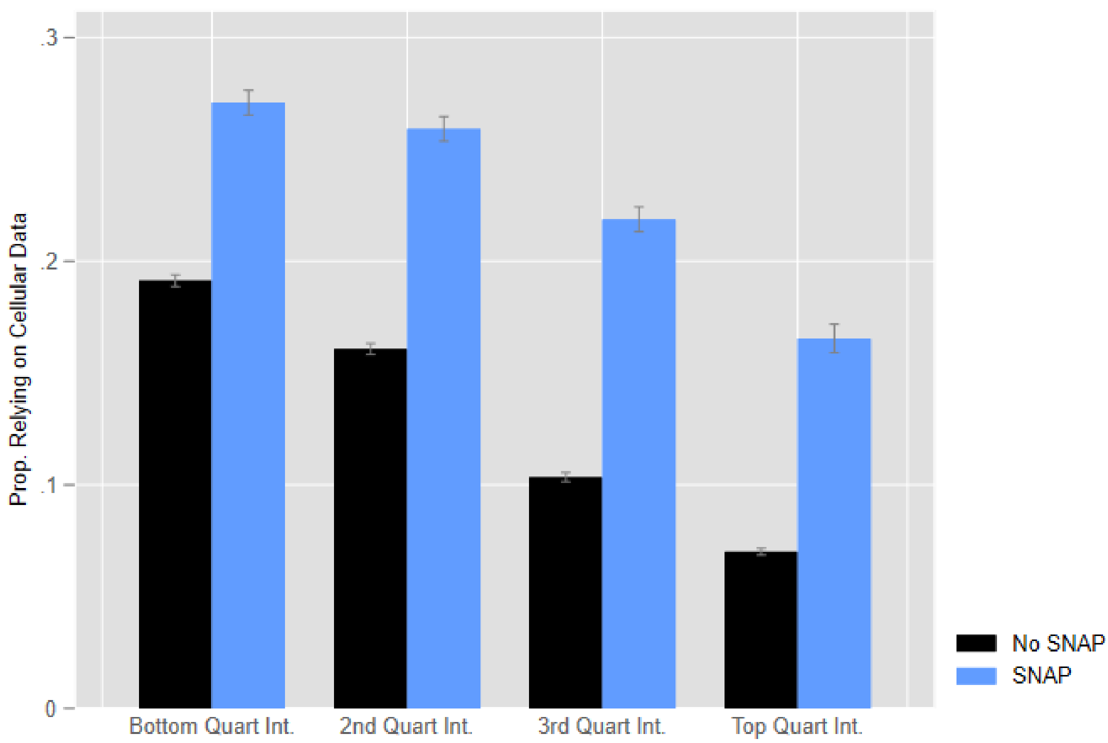
is more adoption of broadband internet in general, there still remains a persistent gap in reliance on cellular data by kids who are in households who receive SNAP benefits. Figure 8 suggests that even in areas where in general there is greater high-speed internet penetration, black children are relatively more likely to rely on cellular data. For children who are living in living situations which means they don't have access to regular kitchen facilities the pattern is even starker, as shown in Figure 9. In general, this analysis suggests that in areas of high broadband internet diffusion there is still a large digital divide which manifests itself in disadvantaged children being more likely to rely on cellular data access to the internet.

Figure 6: Black Children Are More Likely to Underperform Their Peers in High-Internet Areas



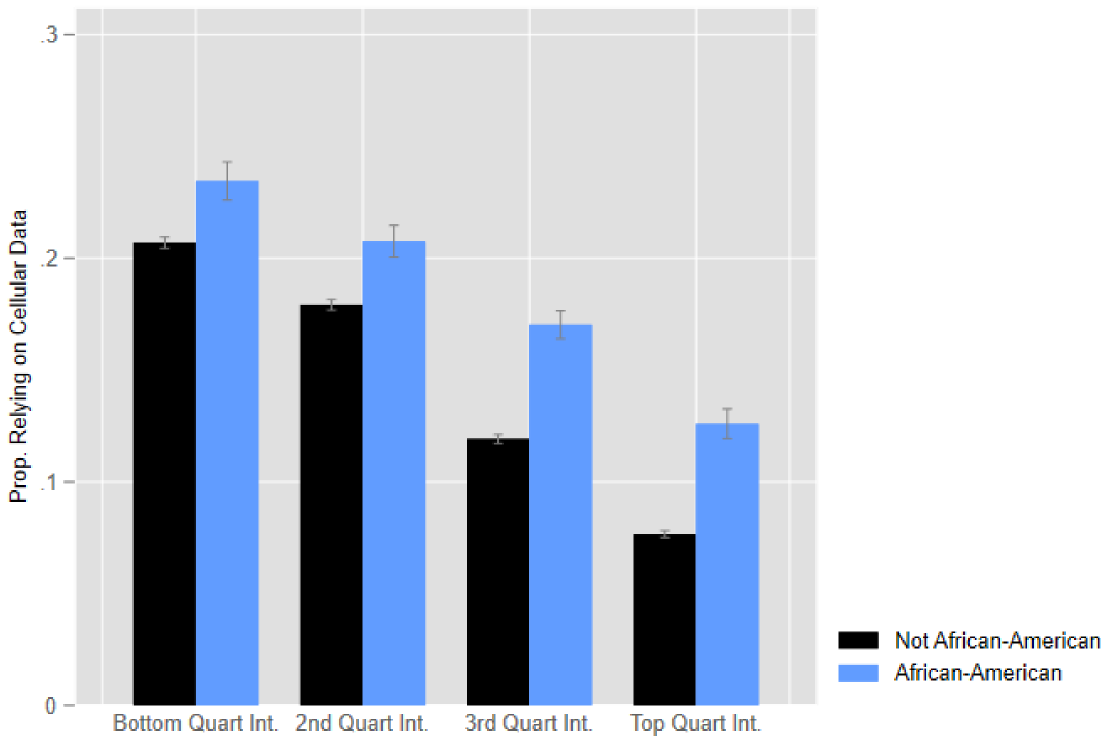
Data on internet quartile of local area from American Community Survey. Data on educational performance from the Ed*Facts* database.

Figure 7: Larger Relative Divide in Children Relying on Cellular Data for Children Receiving SNAP Benefits In Areas with High Broadband Diffusion



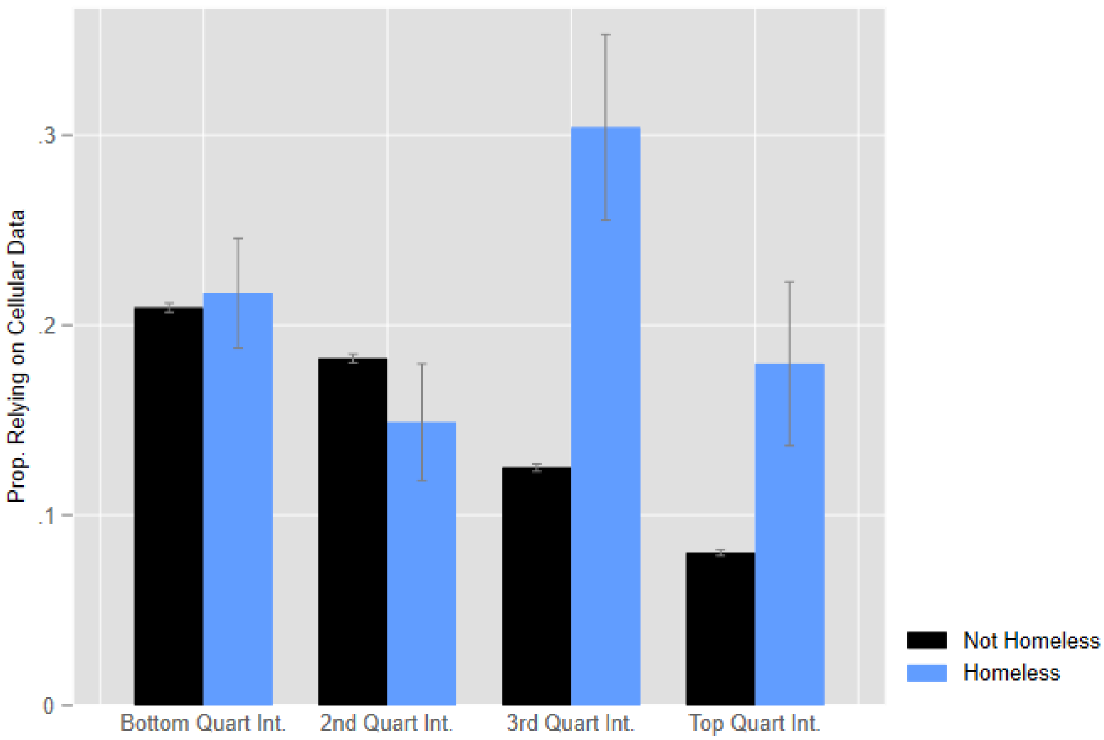
Data is presented by whether that region exhibits high to low broadband internet adoption by quartile. Data on internet in child's household from 2018 American Community Survey.

Figure 8: Larger Relative Divide in Children Relying on Cellular Data for Black Children In Areas with High Broadband Diffusion



Data is presented by whether that region exhibits high to low broadband internet adoption by quartile. Data on internet in child's household from 2018 American Community Survey.

Figure 9: Larger Relative Divide in Children Relying on Cellular Data for Black Children In Areas with High Broadband Diffusion



Data is presented by whether that region exhibits high to low broadband internet adoption by quartile. Data on internet in child's household from 2018 American Community Survey.

4 Conclusions

This paper is a descriptive paper, aiming to provide facts about children's access to the internet in the event of digital disruption. This is a pressing policy issue because of the decision of many school districts to switch instruction to the internet during the pandemic.

In this paper, we present evidence that such a switch threatens without policy intervention to exacerbate existing inequality. First, we show a persistent pattern that though households with children are more likely to have some access to the internet across income levels, that households with children are more likely to rely on cellular data for that internet. In general, children in demographic groups who are already lagging behind in testing scores, are also the groups who are less likely to have high speed dedicated internet access and instead erly on cellular data. We show that even in areas where there is a high level of broadband penetration, children who are low-income, lacking proper housing, Black, English learners, or of Hispanic ethnicity still lag behind their peers in terms of internet access and also are more likely to rely on cellular data. This is concerning because it is precisely the school districts where there is already a high general degree of internet access, where such children are falling farthest behind in test scores.

There are of course limitations to this paper. First, it is intentionally correlational in nature. We do not try to tease apart the underlying causal relationships between internet access, demographics and test scores. Second, our analysis of existing educational inequality and how it relates to inequality is not at the school level, but at a less granular geographical area, due to the need to protect the privacy of its survey-takers. Third, as of yet we do not have comprehensive data on how many school districts are resorting to internet-based instruction. Notwithstanding these limitations, we believe this paper is a useful first step in establishing what the consequences may be for disadvantaged children of instruction moving online.

References

Aker, J. C. and I. M. Mbiti (2010). Mobile phones and economic development in africa. *Journal of economic Perspectives 24*(3), 207–32.

Anderson, M. (2017). Digital divide persists even as lower-income americans make gains in tech adoption. *Pew research center 22*.

Belo, R., P. Ferreira, and R. Telang (2013). Broadband in school: Impact on student performance. *Management Science 60*(2), 265–282.

Belo, R., P. Ferreira, and R. Telang (2016). Spillovers from wiring schools with broadband: The critical role of children. *Management Science 62*(12), 3450–3471.

Billings, S. B., D. J. Deming, and J. Rockoff (2014). School segregation, educational attainment, and crime: Evidence from the end of busing in charlotte-mecklenburg. *The Quarterly Journal of Economics 129*(1), 435–476.

Chen, Y., V. Mittal, and S. Sridhar (2018). Broadband Internet Access: A Double-Edged Sword for K-12 Education? *Mays Business School Research Paper* (3162837).

Goldfarb, A. and J. Prince (2008). Internet adoption and usage patterns are different: Implications for the digital divide. *Information Economics and Policy 20*(1), 2–15.

Greenstein, S. (2020, March). *Digital Infrastructure*. University of Chicago Press.

Hoffman, D. L., T. P. Novak, and A. Schlosser (2000). The evolution of the digital divide: How gaps in internet access may impact electronic commerce. *Journal of computer-mediated communication 5*(3), JCMC534.

Imberman, S. A., A. D. Kugler, and B. I. Sacerdote (2012). Katrina's children: Evidence on the structure of peer effects from hurricane evacuees. *American Economic Review 102*(5), 2048–82.

Keller, J. (1995). Public access issues: An introduction. In *Public access to the Internet*, pp. 34–45. MIT Press.

Markel, H., H. B. Lipman, J. A. Navarro, A. Sloan, J. R. Michalsen, A. M. Stern, and M. S. Cetron (2007). Nonpharmaceutical interventions implemented by US cities during the 1918-1919 influenza pandemic. *Jama 298*(6), 644–654.

Miller, A. R. and C. E. Tucker (2011). Can health care information technology save babies? *Journal of Political Economy 119*(2), 289–324.

Niederle, M. and L. Vesterlund (2010). Explaining the gender gap in math test scores: The role of competition. *Journal of Economic Perspectives 24*(2), 129–44.

Reardon, S. F. (2011). The widening academic achievement gap between the rich and the poor: New evidence and possible explanations. *Whither opportunity 1*(1), 91–116.

Servon, L. J. (2008). *Bridging the digital divide: Technology, community and public policy.* John Wiley & Sons.

Stebbins, S., J. S. Downs, and C. J. Vukotich Jr (2009). Using nonpharmaceutical interventions to prevent influenza transmission in elementary school children: parent and teacher perspectives. *Journal of Public Health Management and Practice 15*(2), 112–117.

Tucker, C. E. and S. Yu (2019). Does it lead to more equal treatment? an empirical study of the effect of smartphone use on customer complaint resolution. *An Empirical Study of the Effect of Smartphone Use on Customer Complaint Resolution (June 12, 2019).*

Table A1: Access to the Internet (Logit Specification)

	(1) Cellular Internet Only	(2) No Internet Access	(3) High Speed Internet	(4) Satellite Internet Only
Receives SNAP	0.621***	0.968***	-0.837***	-0.0283
	(0.0130)	(0.0206)	(0.0113)	(0.0281)
English Learner	0.260***	1.090***	-0.754***	-0.193
	(0.0449)	(0.0531)	(0.0386)	(0.114)
Learning Disability	0.106***	-0.0192	-0.176***	0.153**
	(0.0264)	(0.0446)	(0.0227)	(0.0524)
Homeless	0.361***	1.996***	-1.406***	-0.0000468
	(0.0792)	(0.0798)	(0.0676)	(0.163)
Hispanic	0.296***	0.661***	-0.459***	-0.154***
	(0.0130)	(0.0209)	(0.0112)	(0.0274)
African-American	0.229***	0.637***	-0.449***	-0.201***
	(0.0171)	(0.0259)	(0.0146)	(0.0381)
Asian	-0.399***	-0.759***	0.536***	-0.637***
	(0.0297)	(0.0715)	(0.0266)	(0.0633)
Native American	0.591***	0.642***	-0.724***	0.441*
	(0.0975)	(0.145)	(0.0882)	(0.215)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	453107	453107	453107	453107
Log-Likelihood	-20680791.1	-9983843.4	-25970840.6	-6752719.4

* p <0.10, ** p <0.05, *** p <0.01. Person-weights used from American Community Survey. Robust standard errors reported in parenthesis below. Logit specification utilized for estimation.

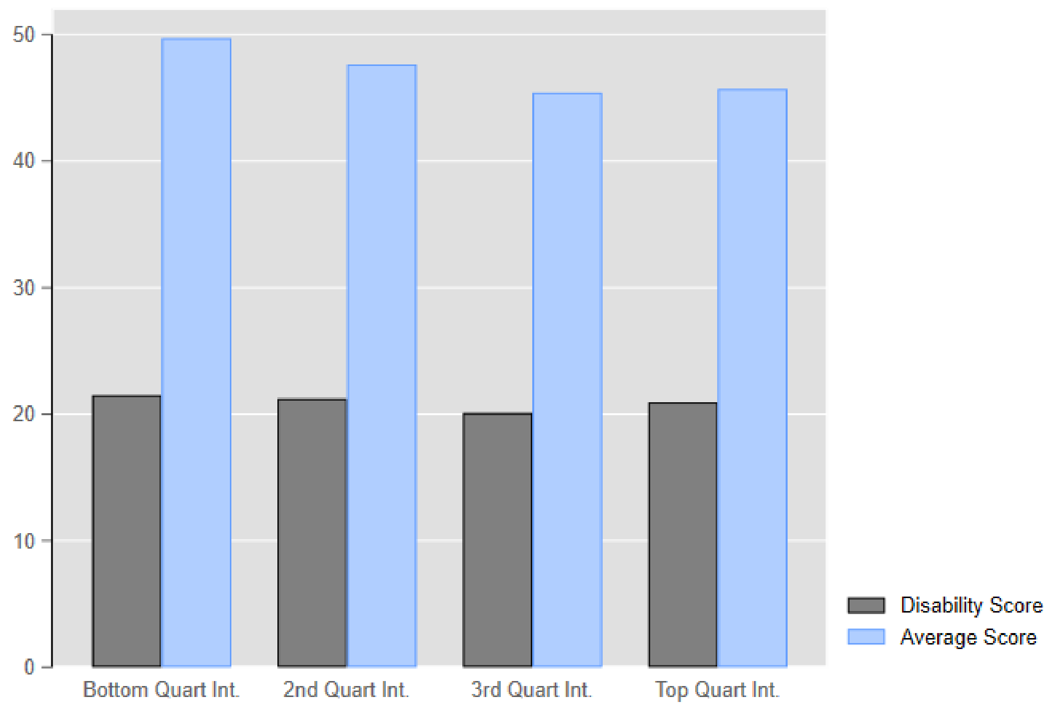


Figure A1: Educational Disparity for Disabled Children

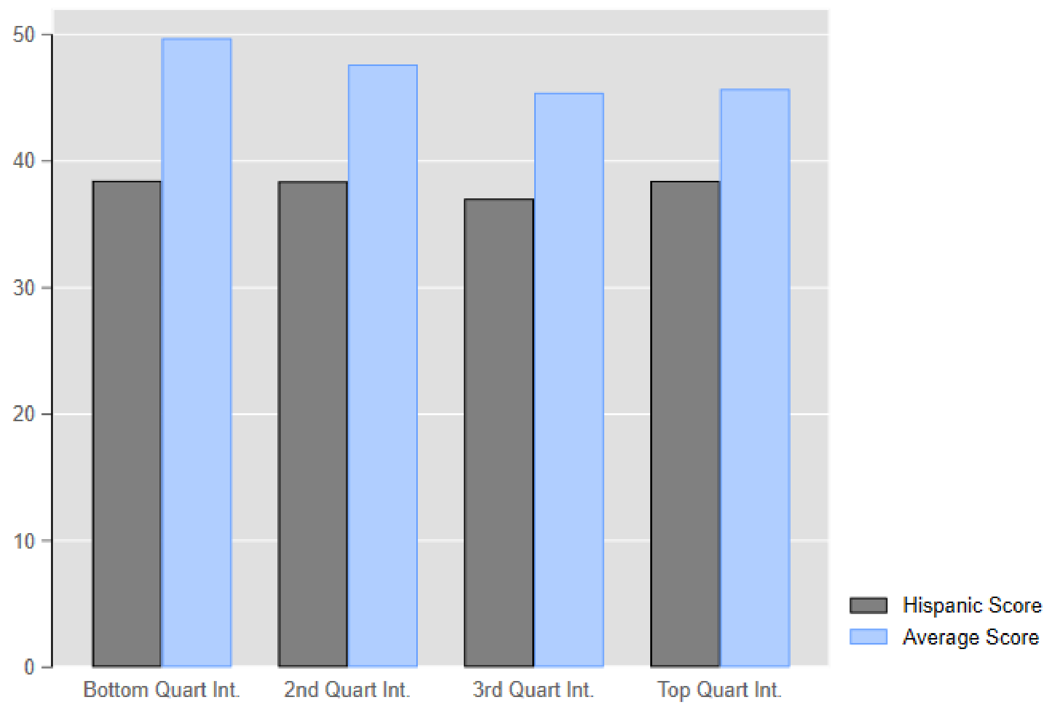


Figure A2: Educational Disparity for Hispanic Children

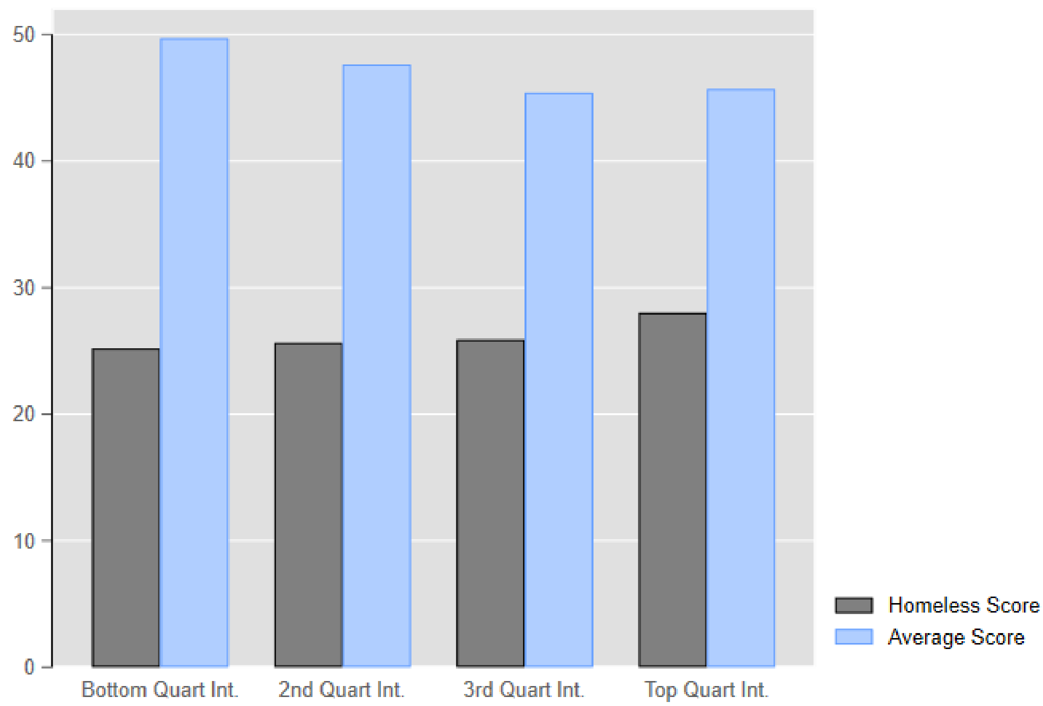


Figure A3: Educational Disparity for Homeless Children

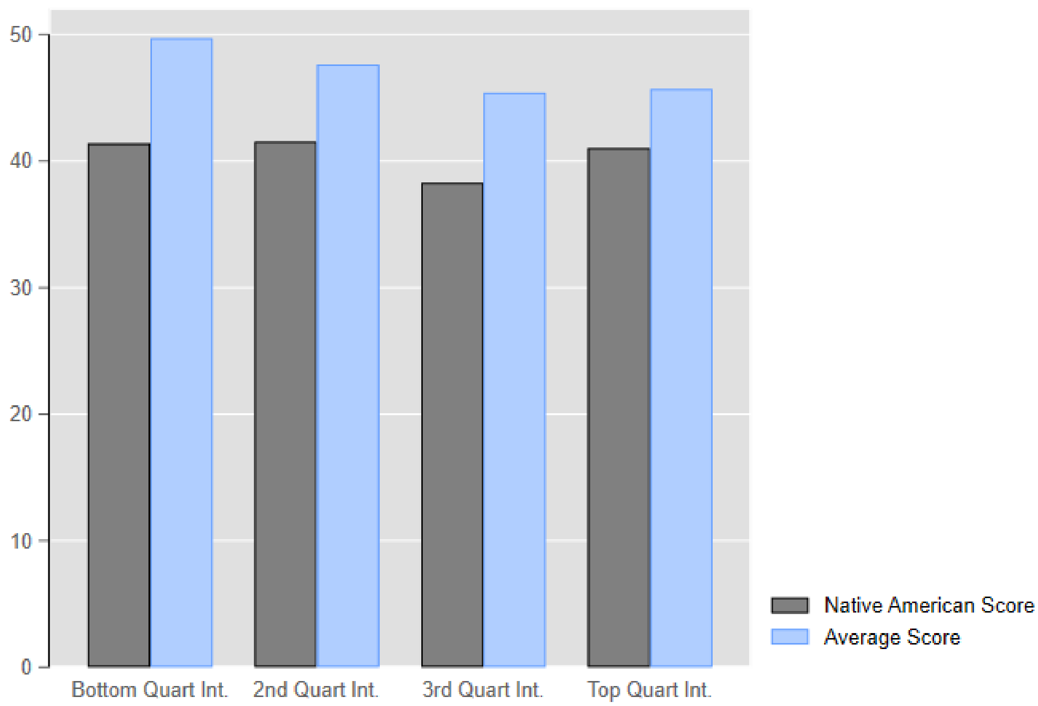


Figure A4: Educational Disparity for Native American Children

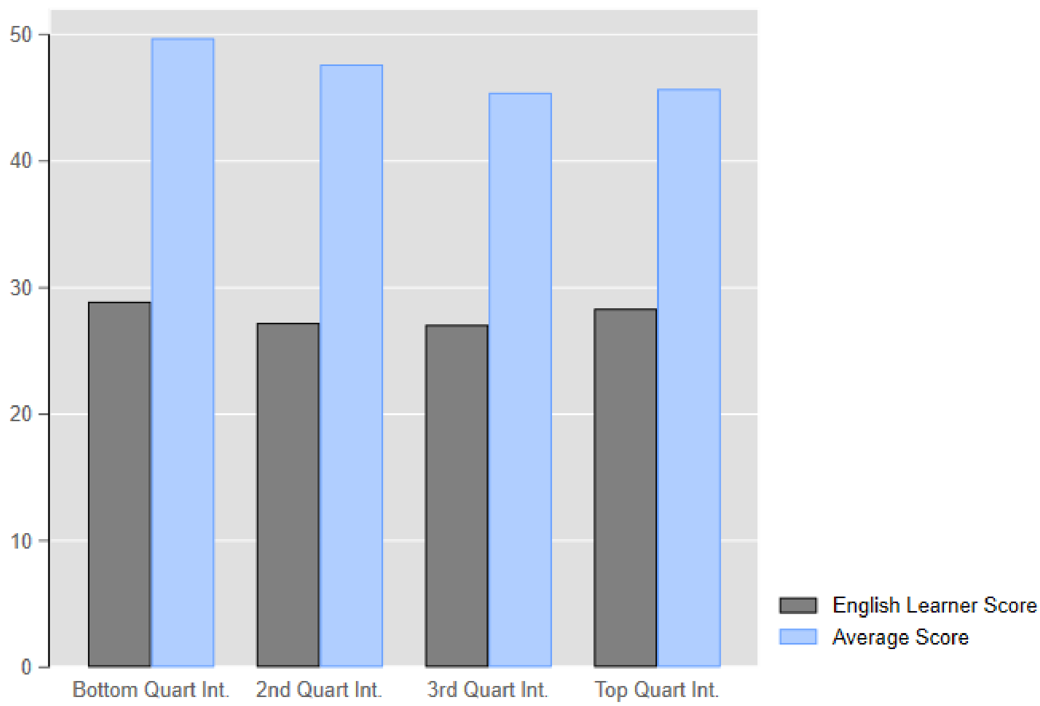


Figure A5: Educational Disparity for English Learners

Table A2: Access to the Internet: Relationship to Poverty and Broadband Index

	(1) Cellular Internet Only	(2) No Internet Access	(3) High Speed Internet	(4) Satellite Internet Only
SNAP	0.103***	0.125***	-0.230***	-0.00305
	(0.0115)	(0.00871)	(0.0133)	(0.00437)
Broadband Investment Index	-0.00106***	-0.000418***	0.00163***	-0.000335***
	(0.0000366)	(0.0000227)	(0.0000434)	(0.0000183)
SNAP × Broadband Investment Index	-0.000147	-0.000588***	0.000639***	0.0000147
	(0.000105)	(0.0000788)	(0.000122)	(0.0000387)
English Learner	0.0399***	0.106***	-0.161***	-0.00417
	(0.00709)	(0.00689)	(0.00865)	(0.00255)
Learning Disability	0.0131***	-0.00219	-0.0304***	0.00464**
	(0.00372)	(0.00253)	(0.00436)	(0.00178)
Homeless	0.0505***	0.242***	-0.299***	-0.000814
	(0.0130)	(0.0140)	(0.0153)	(0.00467)
Hispanic	0.0472***	0.0397***	-0.0959***	-0.00195*
	(0.00181)	(0.00130)	(0.00214)	(0.000779)
African-American	0.0291***	0.0344***	-0.0803***	-0.00616***
	(0.00243)	(0.00180)	(0.00290)	(0.00100)
Asian	-0.0258***	-0.0146***	0.0486***	-0.0112***
	(0.00251)	(0.00138)	(0.00291)	(0.00115)
Native American	0.0831***	0.0410**	-0.129***	0.0127
	(0.0185)	(0.0139)	(0.0201)	(0.00962)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	452456	452456	452456	452456
R-Squared	0.0209	0.0358	0.0583	0.00208

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Person-weights used from American Community Survey. Robust standard errors reported in parenthesis below. Ordinary Least Squares (linear probability model).

Table A3: Access to the Internet: Relationship tp Race and Broadband Index

	(1) Cellular Internet Only	(2) No Internet Access	(3) High Speed Internet	(4) Satellite Internet Only
African-American	0.0349*	0.112***	-0.169***	0.00188
	(0.0138)	(0.0101)	(0.0163)	(0.00552)
Broadband Investment Index	-0.00108***	-0.000439***	0.00165***	-0.000322***
	(0.0000366)	(0.0000241)	(0.0000430)	(0.0000173)
African-American × Broadband Investment Index	-0.0000542	-0.000738***	0.000843***	-0.0000772
	(0.000127)	(0.0000905)	(0.000150)	(0.0000491)
Receives SNAP	0.0872***	0.0627***	-0.162***	-0.00153
	(0.00205)	(0.00156)	(0.00240)	(0.000791)
English Learner	0.0398***	0.106***	-0.161***	-0.00415
	(0.00709)	(0.00689)	(0.00865)	(0.00255)
Learning Disability	0.0132***	-0.00203	-0.0305***	0.00465**
	(0.00372)	(0.00253)	(0.00436)	(0.00178)
Homeless	0.0505***	0.242***	-0.299***	-0.000845
	(0.0130)	(0.0140)	(0.0153)	(0.00467)
Hispanic	0.0470***	0.0388***	-0.0949***	-0.00199*
	(0.00180)	(0.00130)	(0.00214)	(0.000777)
Asian	-0.0258***	-0.0151***	0.0493***	-0.0113***
	(0.00251)	(0.00138)	(0.00291)	(0.00115)
Native American	0.0836***	0.0435**	-0.132***	0.0128
	(0.0185)	(0.0139)	(0.0202)	(0.00963)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	452456	452456	452456	452456
R-Squared	0.0209	0.0358	0.0583	0.00209

* p <0.10, ** p <0.05, *** p <0.01. Person-weights used from American Community Survey. Robust standard errors reported in parenthesis below. Ordinary Least Squares (linear probability model).

5 Text of America Cares Act Section 18003

ELEMENTARY AND SECONDARY SCHOOL EMERGENCY RELIEF FUND SEC. 18003. (a) GRANTS.—From funds reserved under section 18001(b)(2) of this title, the Secretary shall make elementary and secondary school emergency relief grants to each State educational agency with an approved application. The Secretary shall issue a notice inviting applications not later than 30 days of enactment of this Act and approve or deny applications not later than 30 days after receipt.

(b) ALLOCATIONS TO STATES.—The amount of each grant under subsection (a) shall be allocated by the Secretary to each State in the same proportion as each State received under part A of title I of the ESEA of 1965 in the most recent fiscal year.

(c) SUBGRANTS TO LOCAL EDUCATIONAL AGENCIES.—Each State shall allocate not less than 90 percent of the grant funds awarded to the State under this section as subgrants to local educational agencies (including charter schools that are local educational agencies) in the State in proportion to the amount of funds such local educational agencies and charter schools that are local educational agencies received under part A of title I of the ESEA of 1965 in the most recent fiscal year.

(d) USES OF FUNDS.—A local educational agency that receives funds under this title may use the funds for any of the following: H. R. 748—286

(1) Any activity authorized by the ESEA of 1965, including the Native Hawaiian Education Act and the Alaska Native Educational Equity, Support, and Assistance Act (20 U.S.C. 6301 et seq.), the Individuals with Disabilities Education Act (20 U.S.C. 1400 et seq.) ("IDEA"), the Adult Education and Family Literacy Act (20 U.S.C. 1400 et seq.), the Carl D. Perkins Career and Technical Education Act of 2006 (20 U.S.C. 2301 et seq.) ("the Perkins Act"), or subtitle B of title VII of the McKinney-Vento Homeless Assistance Act (42 U.S.C. 11431 et seq.).

(2) Coordination of preparedness and response efforts of local educational agencies with State, local, Tribal, and territorial public health departments, and other relevant agencies, to improve coordinated responses among such entities to prevent, prepare for, and respond to coronavirus.

(3) Providing principals and others school leaders with the resources necessary to address the needs of their individual schools.

(4) Activities to address the unique needs of low-income children or students, children with disabilities, English learners, racial and ethnic minorities, students experiencing homelessness, and foster care youth, including how outreach and service delivery will meet the needs of each population.

(5) Developing and implementing procedures and systems to improve the preparedness and response efforts of local educational agencies.

(6) Training and professional development for staff of the local educational agency on sanitation and minimizing the spread of infectious diseases.

(7) Purchasing supplies to sanitize and clean the facilities of a local educational agency, including buildings operated by such agency.

(8) Planning for and coordinating during long-term closures, including for how to provide meals to eligible students, how to provide technology for online learning to all students, how to provide guidance for carrying out requirements under the Individuals with Disabilities Education Act (20 U.S.C. 1401 et seq.) and how to ensure other educational services can continue to be provided consistent with all Federal, State, and local requirements.

(9) Purchasing educational technology (including hardware, software, and connectivity) for students who are served by the local educational agency that aids in regular and substantive educational interaction between students and their classroom instructors, including low-income students and students with disabilities, which may include assistive technology or adaptive equipment.

(10) Providing mental health services and supports.

(11) Planning and implementing activities related to summer learning and supplemental afterschool programs, including providing classroom instruction or online learning during the summer months and addressing the needs of lowincome students, students with disabilities, English learners, migrant students, students experiencing homelessness, and children in foster care.

(12) Other activities that are necessary to maintain the operation of and continuity of services in local educational H. R. 748—287 agencies and continuing to employ existing staff of the local educational agency.

(e) STATE FUNDING.—With funds not otherwise allocated under subsection (c), a State may reserve not more than 1/2 of 1 percent for administrative costs and the remainder for emergency needs as determined by the state educational agency to address issues responding to coronavirus, which may be addressed through the use of grants or contracts.

(f) REALLOCATION.—A State shall return to the Secretary any funds received under this section that the State does not award within 1 year of receiving such funds and the Secretary shall reallocate such funds to the remaining States in accordance with subsection (b).