Social Distancing and School Closures: Documenting Disparity in Internet Access among School Children

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Abstract

Social distancing directives across the United States have led to school closures. Some districts are moving towards online instruction but this requires internet access at home. We examine the factors that determine whether school children have access to the internet at home. We document that poor and non-white children still have lower access to the internet. Moreover, in areas where poor and non-white children have relatively lower test scores, such children are more likely to not have access to the internet. However, there is some evidence of positive spillovers from the historic presence of ICT industries in the local area in improving the access of disadvantaged children to the internet. The empirical insights highlight how the digital divide might exacerbate existing educational inequalities in the face of school closures due to social distancing.

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1 Introduction

Countries across the world are experiencing unparalleled disruption due to the coronavirus (Covid-19) pandemic. In order to avoid overburdening the health system, many countries and regions have decided to announce social distancing directives that have led to school closures, based on evidence from previous pandemics (Stebbins et al., 2009; Markel et al., 2007).[1] Some districts have indicated their intention of switching to online instruction. However, online instruction is only feasible if children have access to the internet in the home. In this paper, we measure how many children have access to the internet in their homes, and what factors drive internet access. We then calibrate how this relates to existing educational disparities for disadvantaged groups of children.

To do this we use data from the American Community Survey, which surveys children and records the level of internet access in their household. We show that both poverty and race play a key role in driving 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 have no access to the internet at all. African-American children are 8 percentage points less likely have access to high-speed internet, and 4 percentage points more likely to have no internet access at all.

This is 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. The only exception that we highlight is that in areas where

[1] https://www.washingtonpost.com/education/2020/03/31/california-inches-closer-joining-list-states-expected-keep-schools-closed-2019-20-school-year/

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.

These results are important due to the rapidly evolving policy debate around remote education via the internet.[2] Though social distancing may be necessary in the wake of a global pandemic, it is not clear how schools relying on instruction by the internet is going to affect existing inequalities in the educational system. Our intention is to present some empirical patterns about access to the internet among disadvantaged children to help inform policy.

Policy leaders such as the Education Secretary are saying that "The transition to distance and online learning needs to happen quickly."[3] 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.[4] Our results aim to highlight a particular area where subsidies may be particularly useful to avoid reinforcing existing educational disparities.

[2] https://www.theguardian.com/world/2020/apr/05/this-is-crisis-teaching-students-with-disabilites-slip-through-cracks-as-coronavirus-shuts-schools

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

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

The paper intends to contribute to the public policy and academic debate regarding appropriate measures to take while implementing social distancing policies. In particular, it builds on two 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 national shutdown.

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 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). 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 quality.

2 Background and Data

2.1 Background to the Policy Challenge

There has yet to be any form of systematic analysis of the number of 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.[5] At the beginning of April they had tracked down policies for

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

100 school districts (both public and charter). There are 13,588 school districts in the US.[6] 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. All but two of the school districts were relying on internet delivery. 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 two 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] 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. The household file provides data on whether the household receives food stamps, and whether they have access to the internet. There are several different types of internet access that 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 them as having access to high-speed internet access. Therefore, our measures of whether a household has dial-up only includes households

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

[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/?

who only had access to dial-up and not access to broadband internet service. In general, we focus primarily on access to high-speed internet as our dependent measure, but our results show a similar patterns looking at other potential measures of internet access.

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 our major 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 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 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

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

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.

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 connection. This is far more common that dialup or satellite alternatives. However, 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.[10] 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.[11]

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.

[10]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/

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

Table 1: Summary Statistics for Internet and IT Access

	Mean	Std Dev	Min	Max
No Internet Access	0.055	0.23	0	1
High Speed Internet	0.77	0.42	0	1
Dialup Only	0.0044	0.066	0	1
Satellite Internet Only	0.030	0.17	0	1
Other Internet Only	0.0048	0.069	0	1
Has Computer	0.83	0.37	0	1
Has Smartphone	0.95	0.21	0	1
Cellular Internet Only	0.15	0.36	0	1
Observations	453107			

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			

3 Empirical Analysis

Our empirical specification is very straightforward: For child i in grade g, their likelihood of having internet action 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 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. They are also 9 percentage points more likely to have access to the internet only through a cellular plan.

The pattern is even more severe for children who are living in housing without kitchen facilities, they 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 have access to the 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 have access to satellite internet rather than mainstream broadband.

In the next section, we discuss how this disparity in access to the internet compares with existing educational disparities.

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

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

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

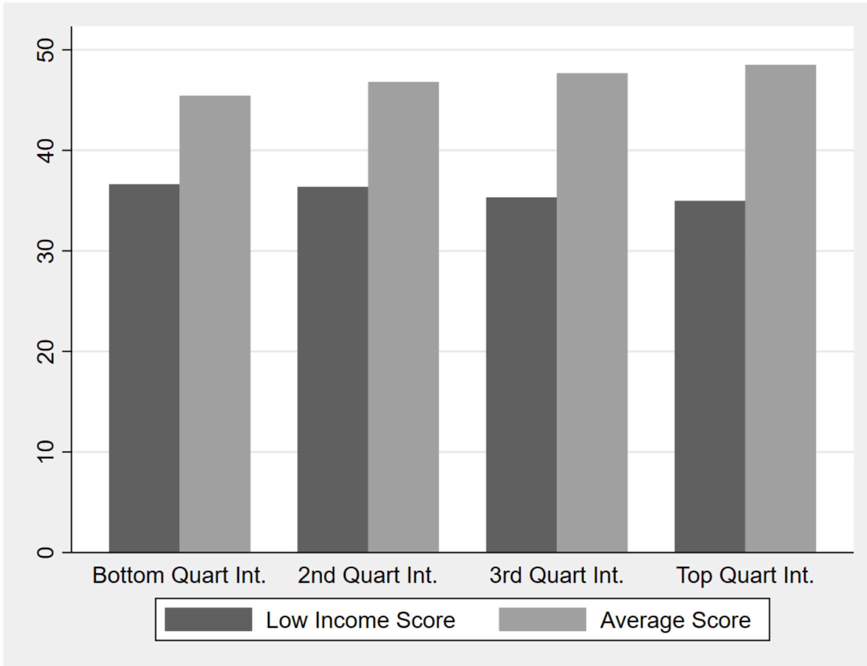

Figure 1: Low-Income Children Are More Likely to Underperform Their Peers in High-Internet Areas

3.1 Relationship with Existing Educational Equality

Figures 1 and 2 present results which reflect our educational testing outcomes. Each graph looks at the different quartiles of high-speed internet diffusion and how they relate to testing inequality in that local area.

They show that both low-income (Figure 1) and African-American children (Figure 2) who live in areas with higher high-speed internet diffusion are more likely to under perform relative to their peers. In general, regions with higher internet diffusion exhibit higher average scores. But the fact that they exhibit higher average scores exacerbates the inequality in testing between the average score and children who receive free school lunches or are African-American. 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

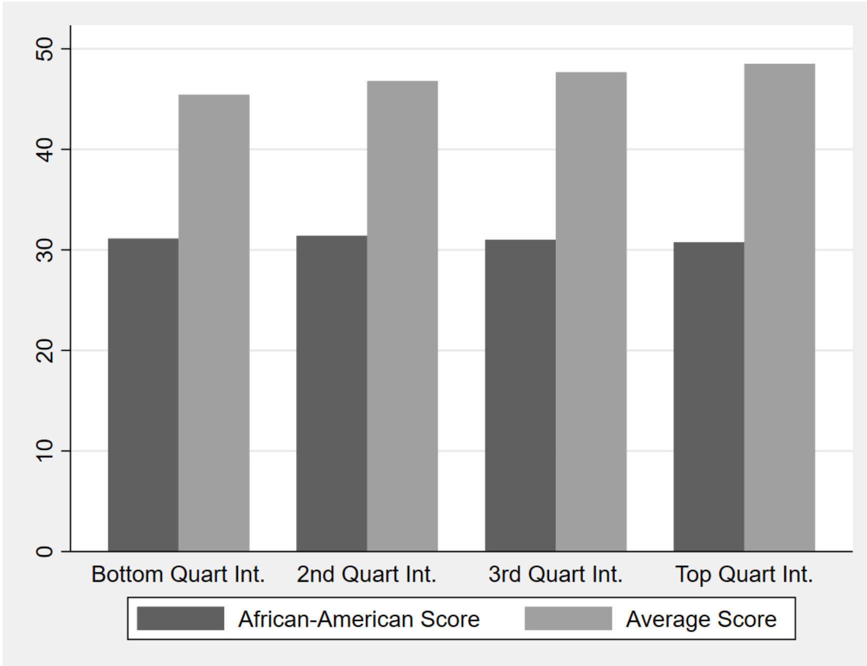

Figure 2: African-American Children Are More Likely to Underperform Their Peers in High-Internet Areas

that these groups also have test scores which are less than average 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 whether African-American or low-income children themselves are also more likely to have access to the internet.

We explore this in Figures 3, 4 and 5. Figure 3 suggests that even in areas where there is more diffusion of the internet in general, there still remains a persistent gap in internet access by kids who are in households who receive SNAP benefits. Figure 4 suggest that even in areas where in general there is greater high-speed internet penetration, African-American children are less likely to have the internet.

Figure 5 looks at the cross-section of these two groups. Worryingly. it suggests that children who are African-American and also receiving SNAP benefits are also the least likely to have access to high-speed internet, even in areas where there is in general a large degree of broadband diffusion.

In the Appendix, we present these results for the different categories of demographics that lead children to have less access to the internet in Table 3 such as being homeless or being Hispanic. The patterns are similar with two exceptions. Figure A5 shows that for homeless children, there is some catchup to non-homeless children if they are living in an area with high internet diffusion. However, we caution that homeless children are already at such a disadvantage in terms of access to the internet that this relative increase,may not be material. There is also a similar pattern for children who are learning English. as shown in Figure A10.

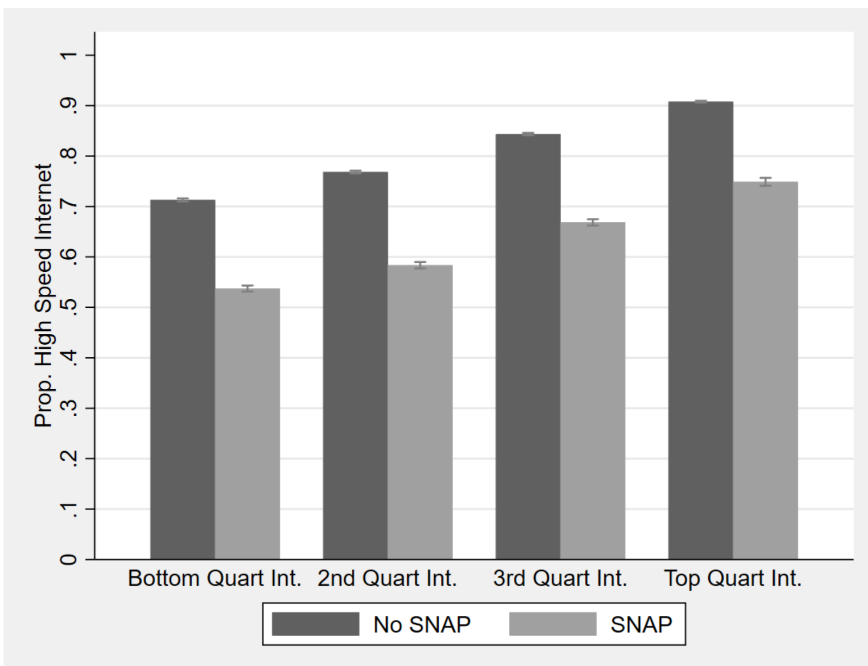

Figure 3: There is Still Disparity in Access to High-Speed Internet for Children Receiving SNAP Benefits In Areas with High Broadband Diffusion

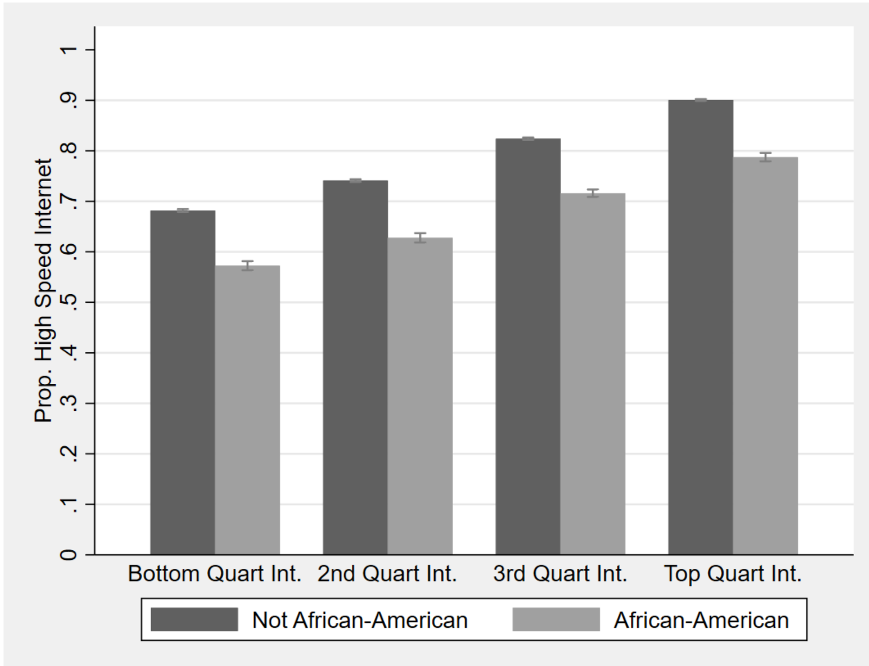

Figure 4: There is Still Disparity in Access to High-Speed Internet for African-American Children In Areas with High Broadband Diffusion

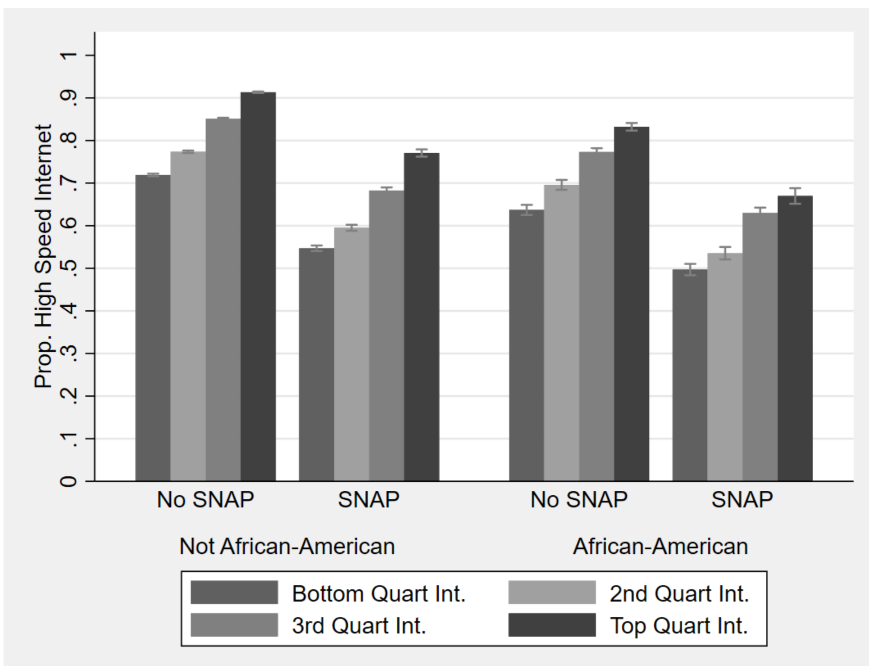

Figure 5: There is Disparity in Access to High-Speed Internet for African-American Children Receiving SNAP benefits In Areas with High Broadband Diffusion

3.2 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.

We use data about earlier investments in broadband from the 2012 'state broadband index'.[12] 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 these results of these specifications. They show that there are spillovers to children who live in households that receive SNAP benefits and African-American 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.

[12] `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 4: Access to the Internet: Relationship to Poverty and Broadband Economic Orientation

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

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 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) High Speed Internet	(2) No Internet Access	(3) Satellite Internet Only	(4) Cellular Internet Only
African-American=1	-0.135***	0.0732***	0.000966	0.0448***
	(0.00904)	(0.00579)	(0.00323)	(0.00752)
Economic Orientation Internet (2012)	0.000646***	-0.000196***	-0.0000997***	-0.000395***
	(0.0000189)	(0.0000104)	(0.00000766)	(0.0000161)
African-American=1 × Economic Orientation Internet (2012)	0.000509***	-0.000354***	-0.0000674**	-0.000152*
	(0.0000750)	(0.0000460)	(0.0000257)	(0.0000619)
Receives SNAP	-0.163***	0.0627***	-0.00135	0.0874***
	(0.00241)	(0.00156)	(0.000788)	(0.00205)
English Learner	-0.158***	0.105***	-0.00459	0.0384***
	(0.00865)	(0.00688)	(0.00255)	(0.00710)
Learning Disability	-0.0302***	-0.00217	0.00466**	0.0130***
	(0.00436)	(0.00253)	(0.00178)	(0.00372)
Homeless	-0.300***	0.242***	-0.000511	0.0513***
	(0.0154)	(0.0139)	(0.00466)	(0.0131)
Hispanic	-0.0939***	0.0389***	-0.00264***	0.0460***
	(0.00214)	(0.00130)	(0.000778)	(0.00181)
Asian	0.0506***	-0.0148***	-0.0123***	-0.0274***
	(0.00292)	(0.00138)	(0.00115)	(0.00252)
Native American	-0.141***	0.0454**	0.0148	0.0894***
	(0.0201)	(0.0139)	(0.00959)	(0.0184)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	452456	452456	452456	452456
R-Squared	0.0572	0.0358	0.00148	0.0201

* 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).

4 Conclusions

This paper is intentionally a descriptive paper that aims to provide some facts about children's likely access to the internet. This has become a pressing policy issue because of the decision of many school districts to start instruction via the internet, due to the 2020 global pandemic.

In this paper, we present evidence that such a switch threatens to exacerbate existing inequality without policy intervention. In general, children in demographic groups who are already lagging behind in testing scores, are also the groups who are less likely to have internet access. We show that even in areas where there is a high level of broadband penetration, children who are low-income, lacking proper housing, African-American, English learners, or of Hispanic ethnicity still lag behind their peers in terms of internet access. 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 particularly behind in test scoring.

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.

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Table A1: Access to the Internet (Logit Specification)

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

* 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.

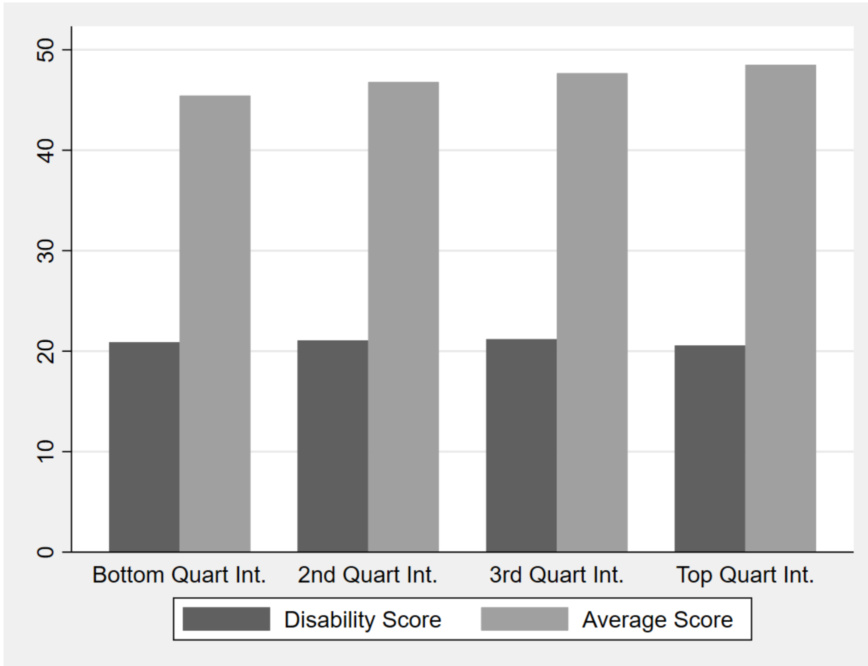

Figure A1: Educational Disparity for Disabled Children

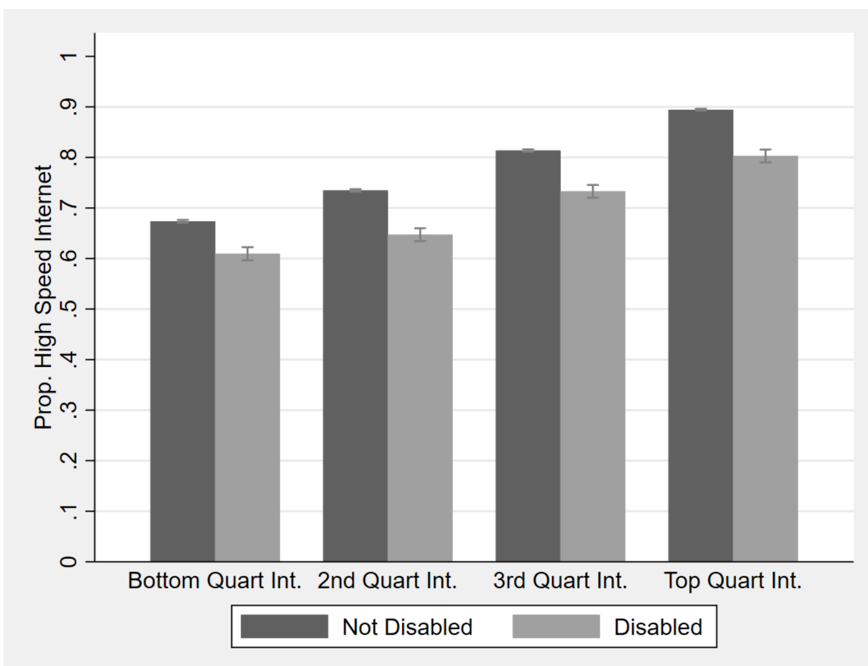

Figure A2: Disparity in Access to the Internet for Disabled Children

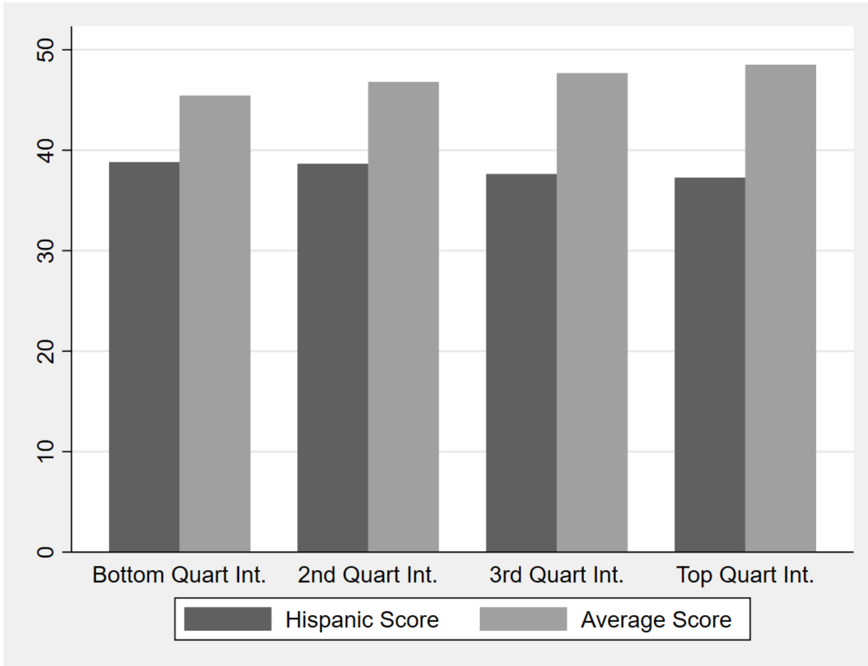

Figure A3: Educational Disparity for Hispanic Children

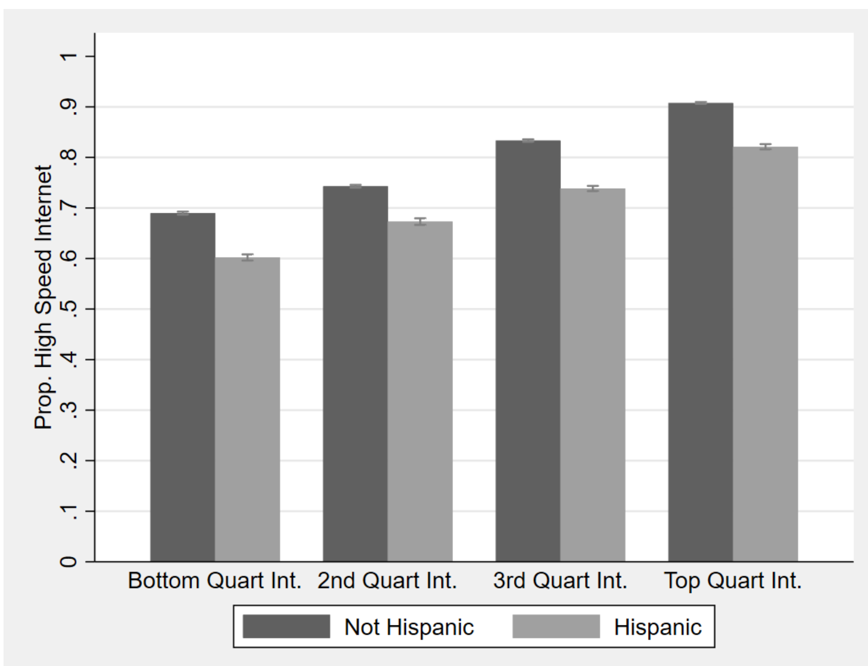

Figure A4: Disparity in Access to the Internet for Hispanic children

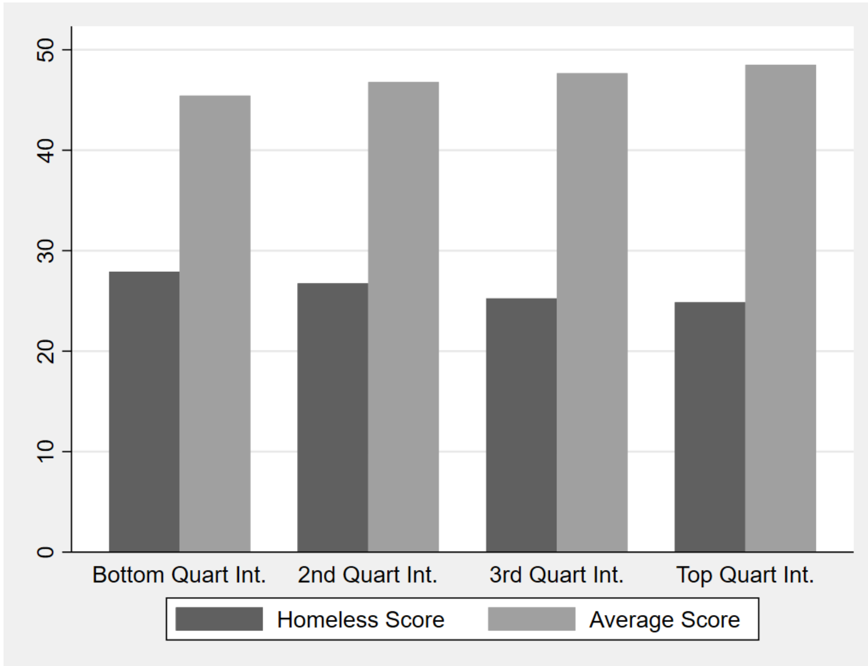

Figure A5: Educational Disparity for Homeless Children

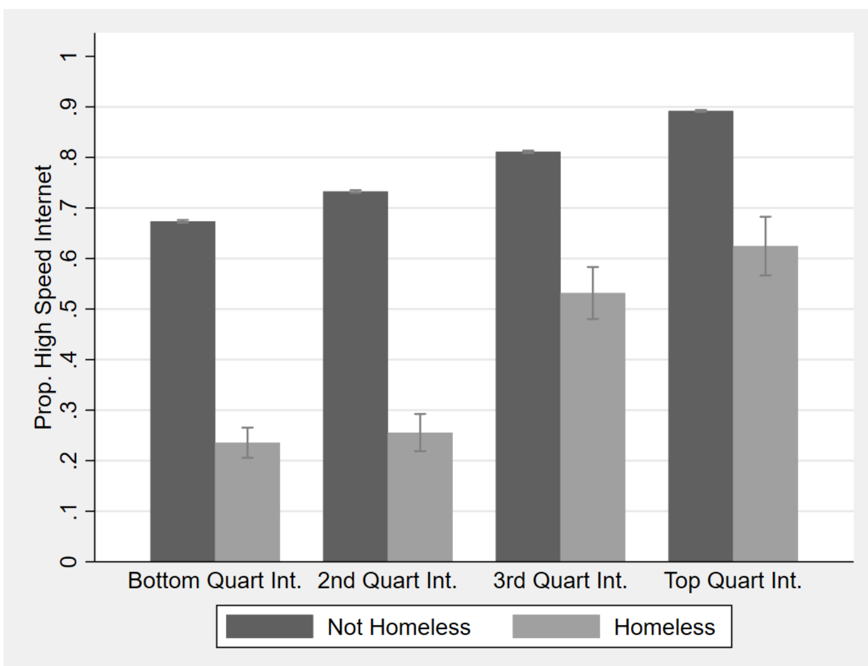

Figure A6: Disparity in Access to the Internet for Homeless Children

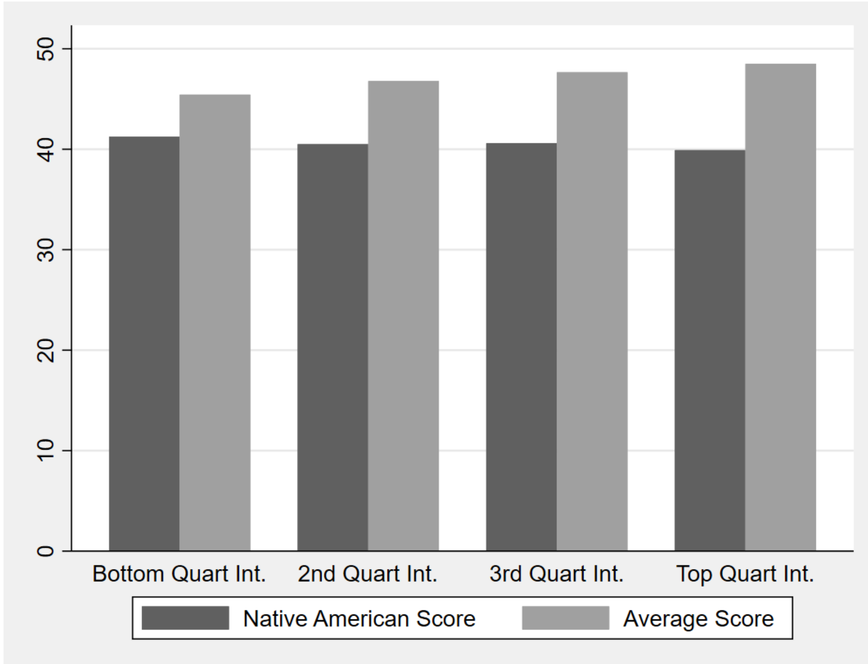

Figure A7: Educational Disparity for Native American Children

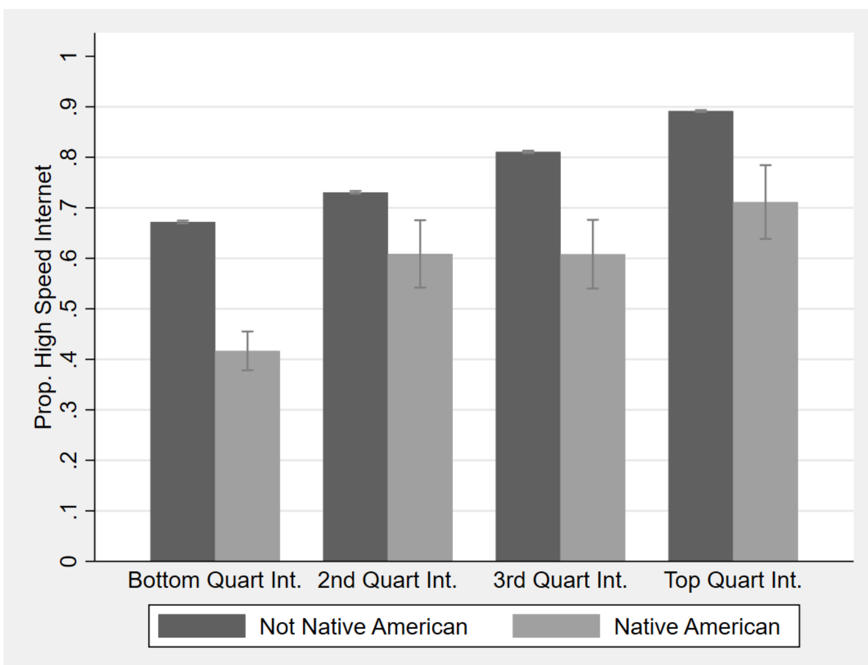

Figure A8: Disparity in Access to the Internet for Native American children

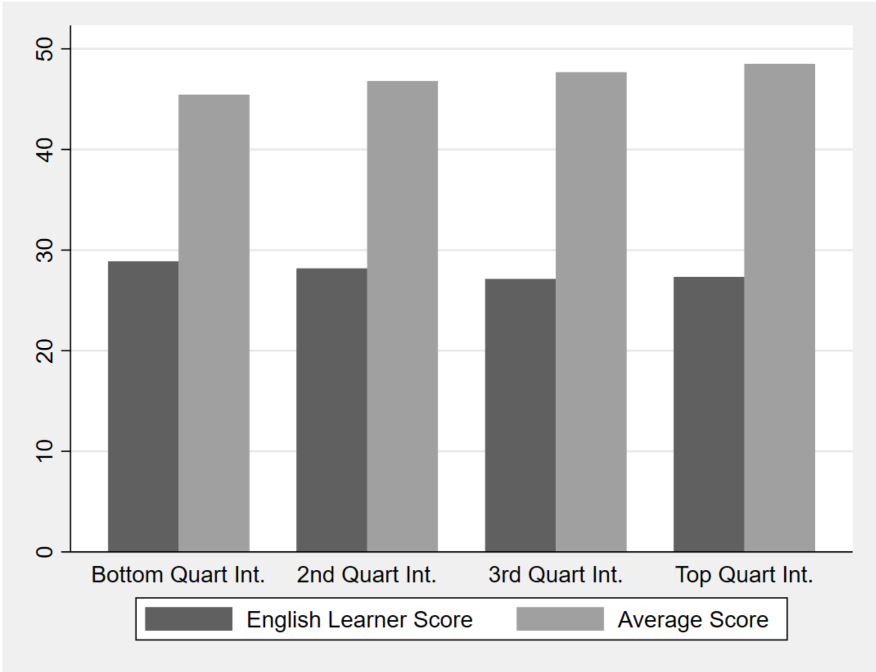

Figure A9: Educational Disparity for English Learners

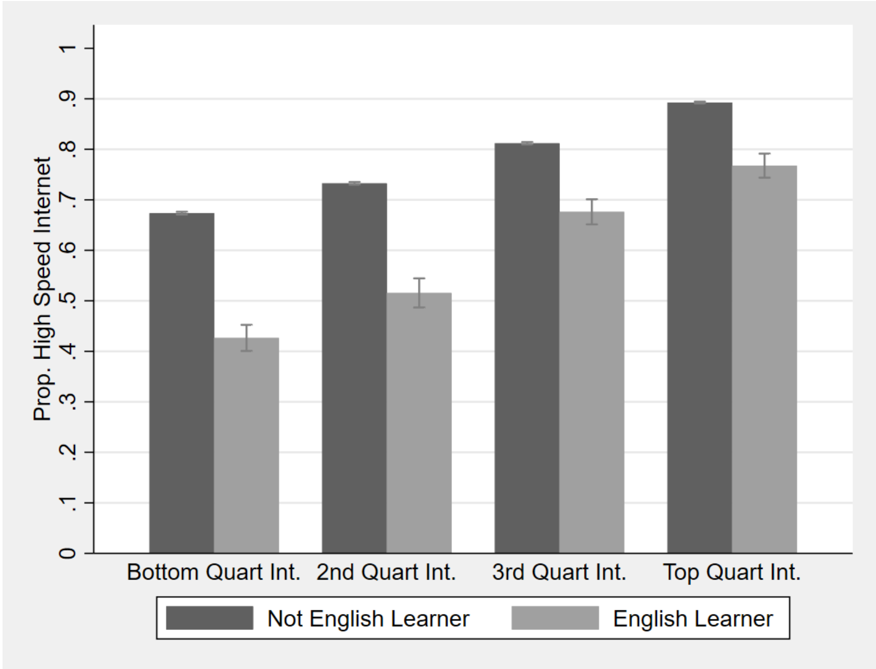

Figure A10: Disparity in Access to the Internet for English Learners

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

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

* $p<0.10$, ** $p<0.05$, *** $p<0.01$. 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) High Speed Internet	(2) No Internet Access	(3) Satellite Internet Only	(4) Cellular Internet Only
African-American=1	-0.169***	0.112***	0.00188	0.0349*
	(0.0163)	(0.0101)	(0.00552)	(0.0138)
Broadband Investment Index	0.00165***	-0.000439***	-0.000322***	-0.00108***
	(0.0000430)	(0.0000241)	(0.0000173)	(0.0000366)
African-American=1 × Broadband Investment Index	0.000843***	-0.000738***	-0.0000772	-0.0000542
	(0.000150)	(0.0000905)	(0.0000491)	(0.000127)
Receives SNAP	-0.162***	0.0627***	-0.00153	0.0872***
	(0.00240)	(0.00156)	(0.000791)	(0.00205)
English Learner	-0.161***	0.106***	-0.00415	0.0398***
	(0.00865)	(0.00689)	(0.00255)	(0.00709)
Learning Disability	-0.0305***	-0.00203	0.00465**	0.0132***
	(0.00436)	(0.00253)	(0.00178)	(0.00372)
Homeless	-0.299***	0.242***	-0.000845	0.0505***
	(0.0153)	(0.0140)	(0.00467)	(0.0130)
Hispanic	-0.0949***	0.0388***	-0.00199*	0.0470***
	(0.00214)	(0.00130)	(0.000777)	(0.00180)
Asian	0.0493***	-0.0151***	-0.0113***	-0.0258***
	(0.00291)	(0.00138)	(0.00115)	(0.00251)
Native American	-0.132***	0.0435**	0.0128	0.0836***
	(0.0202)	(0.0139)	(0.00963)	(0.0185)
Grade Fixed Effects	Yes	Yes	Yes	Yes
Observations	452456	452456	452456	452456
R-Squared	0.0583	0.0358	0.00209	0.0209

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