TECHNOLOGY POLICY INSTITUTE

Do Broadband Subsidies for Schools Improve Students' Performance? Evidence from Florida.

Jakub Tecza, Scott Wallsten, Yoojin Lee

May 2023

2000 L Street NW ● Suite 500 ● Washington, DC 20036
Tel: (202) 828-4405 ● Email: info@techpolicyinstitute.org ● www.techpolicyinstitute.org

Do broadband subsidies for schools improve students' performance? Evidence from Florida.

Jakub Tecza,[*] Scott Wallsten,[†] Yoojin Lee[‡]

May 5, 2023

Abstract

Studies exploring the relationship between technology in the classroom and students' outcomes have yielded mixed results. We contribute to the debate by examining the effects of broadband subsidies to schools on school performance measures in Florida. Specifically, using a nearly universal panel of Florida schools in the period 2016-2019, we assess the effect of federal broadband subsidies to schools via the E-Rate program on school grades. We build on previous studies by separating subsidies into support for internet access and support for internal connections as well as examining performance across subject matter and school levels. Our initial results suggest that the relationship between broadband subsidies and school performance is minuscule at best.

Keywords: E-rate, broadband subsidies, universal service, student outcomes

JEL codes: H52, I21, I28, L86

[*]Postdoctoral Associate, University of Florida - Warrington College of Business
[†]President and Senior Fellow, Technology Policy Institute
[‡]Research Associate, Technology Policy Institute

1 Introduction

Over the past two decades, classrooms have begun using many types of educational technologies, ranging from computers and the Internet to computer-aided instruction, instructional software material, mobile applications, GIS, and other gadgets.[1] Although intuition and conventional wisdom suggest that advanced technologies should help students, existing research results are ambiguous.

This study examines the effectiveness of the E-Rate program, a federal program that provides schools (and libraries) with subsidies for communications and information services, on school performance. Specifically, we assemble a school-level dataset that includes different types of E-Rate subsidies distributed from the Federal Communications Commission's (FCC's) Universal Serivce Fund, and school performance measures for Florida schools compiled by the Florida Department of Education.

While we build our work on existing literature like Goolsbee and Guryan (2006), Hazlett, Schwall, and Wallsten (2018), and others, this paper offers several innovations. First, rather than a single variable measuring subsidies, we split the subsidies into two types: funds used for equipment and funds used for internet services. While equipment and service are complementary, they may have different effects. Second, we attribute E-rate funding to school level, whereas previous studies did not explore below the school district level.[2] Third, Florida's rating system allows us to look at several outcome measures in addition to overall school performance, including math achievement, science achievement, or graduation rate, while also enabling to differentiate based on school level (elementary, middle, high, combination) as well as school type (public, charter).

We find no robust relationship between broadband subsidies and school outcomes: Only a few of our key estimates are statistically significant, many have the "wrong" sign, and the point estimates are tiny in general.

The remainder of the paper is structured as follows: Section 2 provides a broad although not exhaustive literature review. Section 3 describes our data. Section 4 contains our main analysis and interpretation of results. We conclude in Section 5.

2 Background

It is politically popular to advocate for more technology in the classroom, and politicians have been happy to oblige.[3] Unfortunately, the literature does not generally support the idea that technology

[1]See, for example: https://er.educause.edu/articles/2018/7/twenty-years-of-edtech (accessed on: 7/22/2022)

[2]While about 80% of E-rate applications are filed by school districts, the data for 2016 and beyond allows to infer which schools were included on a school district's application. By making assumptions about how funds are distributed within district, this allows to calculate per-school funding. Our default assumption is that funds are disbursed equally.

[3]See, for example, https://www.benzinga.com/tech/22/12/30215816/how-does-technology-improve-student-learning (accessed Jan 3, 2023) and https://www.forbes.com/sites/forbesbusinesscouncil/2022/12/12/the-impact-of-edtech-in-2022-and-beyond/?sh=50dac54f4be2

subsidies, or in many cases even technology itself, helps students succeed.

'Technology' is a broad term, but the literature generally defines three types: 1.) ICT hardware (e.g., computers and tablets), 2.) Internet access, and 3.) Recent technology (e.g., social media and smartphones). Existing research finds ambiguous effects of ICT hardware and broadband access on educational outcomes, while social media and smartphones show negative results. A related literature, which includes this paper, focuses on the effects of educational technology subsidies.

2.1 ICT hardware

Studies show mixed effects of ICT use on educational outcomes. Angrist and Lavy (2002), in one of the seminal studies on the effect of computer-aided instruction (CAI) on student performance, look at an Israeli initiative to sponsor installing computers in elementary and middle schools. Using a two-stage least-squares model to address endogeneity concerns,the authors found that the initiative increased "computer-aided instruction", but that increase did not translate into higher test scores.[4] In another study, Li, Atkins, and Stanton (2006) saw a positive effect of computer use on Head Start childrens' school readiness test skills, but their research was inconclusive on motor skills.[5] Machin, McNally, and Silva (2007) showed mixed effects of public ICT spending on academic performance across different subjects in middle schools in the UK. The study observed a positive effect for English and science, but not mathematics. Leuven, Lindahl, Oosterbeek, and Webbink (2007) used a regression discontinuity design to conclude a negative effect of computer-aided instruction (specifically, a $90 subsidy per student for computers, software, and "language materials" for schools with over 70% disadvantaged students) on primary school educational outcomes in the Netherlands. Barrow, Markman, and Rouse (2009) reported a positive effect of computer-aided instruction on pre-algebra and algebra students in a randomized study in the U.S.

Some studies focused more narrowly also yield conflicting conclusions of education technologies on educational outcomes. Two papers find positive effects. One, using data from China in 2004 and a difference-in-difference model, found positive effects of computer-assisted learning in long-term student development (Bianchi, Lu, & Song, 2022). Another, using data from Germany and OLS and 2SLS, found that gamification of educational material through mobile application technology improved accounting educational outcomes in Germany (Voshaar, Knipp, Loy, Zimmermann, & Johannsen, 2022).

Other studies find negative effects of technology on outcomes. A study on the effects of laptops on students' use of time at home in Peru found a negative impact (Yamada, Lavado, & Montenegro, 2016). Cristia, Ibarrarán, Cueto, Santiago, and Severín (2017) in a randomized controlled trial in

(accessed Jan 3, 2023)

[4]If anything, they found some negative effects in select categories, concluding that technology could be a source of diversion in the classroom.

[5]They used a randomized experiment with young children between the ages of 3-5, where the treatment group received a 15-20 minutes daily exposure to use of educational software on a computer. After 6 months, there was a significant difference in performance between treatment and control.

the Peruvian context found no effect of the one-laptop-per-child program on students' performance. Spiezia (2010) used PISA test scores to assess whether computer use at home or at school improves performance on the test.[6] He finds that students who report higher computer use also have better test scores, although the effect is primarily driven by at-home, rather than at-school, computer use.[7]

2.2 Internet/broadband access in schools

Although research results on the effects of internet access in schools are similarly inconclusive, most studies hint toward a weak positive link. Badasyan and Silva (2018) found a robust positive effect of home internet access, but only negligible effects of school internet access, on test scores of eighth grade students in Brazil using the propensity score matching methodology. At-home internet access led to a test score increase of up to 2.5%, depending on the subject. Silva, Milkman, and Badasyan (2014) examined the effect of Brazil's 2008 "Broadband at School" program that aimed to bring broadband to all urban public schools and found a slight improvement in ninth grade standardized scores among program participants. Chen, Mittal, and Sridhar (2020) applying a panel-IV approach to Texas data find a positive effect of school internet spending on students' test results in grades 3-11. Grimes (2017) found, using a difference-in-difference approach, that broadband in New Zealand increases primary schools' standardized assessment passing rates by roughly one percentage point. Unlike the aforementioned papers, Belo, Ferreira, and Telang (2014) found a negative effect of broadband in schools on 9th grade students' national exam performance in Portugal using a first-differences specification.

2.3 Social media and smartphones

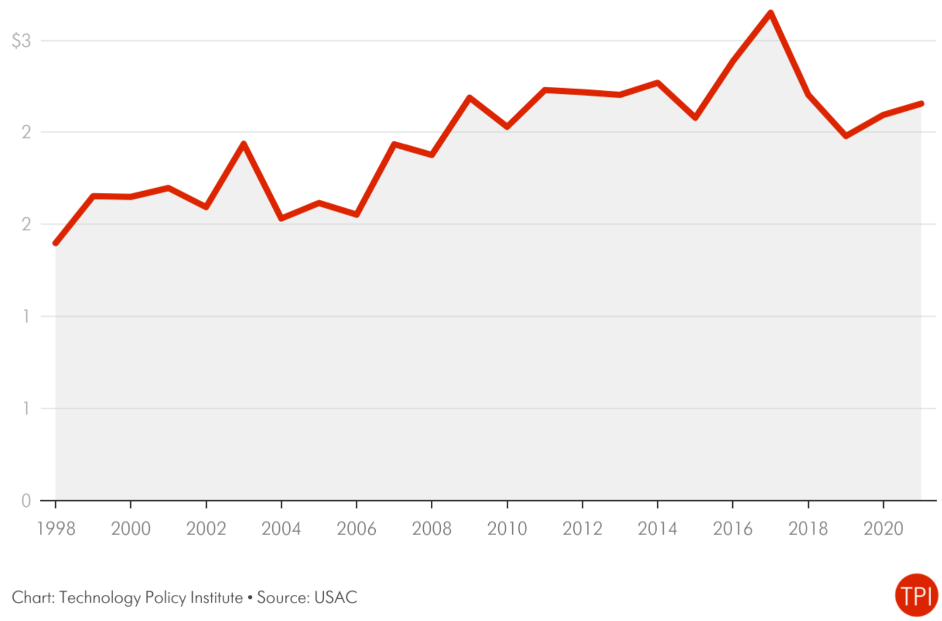
Studies of social media and smartphone use almost unanimously find negative effects on educational outcomes across students in primary, secondary, and higher education. Many cite the addictive and distracting nature of these technologies.

Arefin, Islam, Mustafi, Afrin, and Islam (2017) used structural equation modeling to analyze questionnaires collected from business university students in Bangladesh. They concluded that smartphone addiction resulted in factors such as increased impatience and daily-life disturbance, which were found to be significantly related to the academic performance of the business students of Bangladesh. El Khatib and Khan (2017) concluded in a study in Oman that social media does not support learning. Raganta, Vargas, and Raganta (2021) found, in a study in the Phillipines, a significant negative correlation of social media in most subjects, but a significant positive correlation

[6] The Programme for International Student Assessment (PISA) is a standardized test of reading, mathematics, and science administered to 15-year-olds in OECD countries. For more details see here: `https://www.oecd.org/pisa/test/` (accessed 7/12/2022)

[7] The analysis is performed on a cross-section of students at the age of 15. A challenge in the empirical analysis is that students are likely to self-select into computer use (i.e. the 'treatment') based on certain characteristics. The author addresses the problem by employing a Heckman-type selection model. The model is identified by nonlinearity in the first stage of the model.

Figure 2.1: E-rate Distributions from the Universal Service Fund in $ Billions



in Technology and Livelihood Education in the Philippines. Deng, Cheng, Ferreira, and Pavlou (2022) conducted a field study on a vocational school in China and found a significant decrease in student performance associated with free smartphone use and a significant increase in student performance associated with smartphone use for instructional assistance.

2.4 E-Rate

The federal Universal Service Fund subsidizes connectivity in schools (and libraries) by making the relevant equipment and services more affordable through the Schools and Libraries Program, generally called "E-Rate".[8] As Figure 2.1 shows, the US spends about $2-3 billion per year on E-Rate.

The financial support provided depends on the level of poverty in the area and whether the school is located in an urban or rural area. The support ranges from 20% to 90% of the costs of eligible services. Eligible services include Internet access and internal networking.

Empirical research results about the effects of E-Rate are ambiguous and do not support the argument that the subsidies improve student performance.

Studies on E-Rate subsidies for Internet access specifically have shown an increase in classroom connectivity, but not that this increase necessarily translates into improved academic performance or outcomes. Goolsbee and Guryan (2006) found that E-Rate subsidies increased the number of connected classrooms, but did not lead to higher test scores in California primary and secondary

[8] For a full program description, see https://www.usac.org/wp-content/uploads/e-rate/documents/Handouts/E-rate-Overview.pdf (accessed Jan 23, 2023)

public schools. Furthermore, in Hazlett et al. (2018), no gain in student test results associated with Internet subsidy levels was found in North Carolina public high schools between 2000-2013. Violette (2017) in a correlational study finds no association between E-Rate subsidies and graduation rates in Florida. One paper has shown more positive effects of broadband and Internet on student performance.

One explanation for the apparent ineffectiveness of E-Rate on outcomes may stem from the lack of program analysis, which prevents it from learning from any failures or successes. USAC, the administrator of the funds, does not support any evaluations, despite having more than $200 million for administrative expenses. In fact, the Government Accountability Office has called on the FCC to better define goals and find ways to determine whether the subsidies help meet those goals.[9]

3 Data and descriptive statistics

Our data come from two sources: E-Rate spending by school from the FCC and school performance ratings from the Florida Department of Education (FDOE). This section describes the data in more detail, including descriptive statistics.

3.1 E-Rate

Data on E-Rate subsidies to Florida schools come from the Universal Service Administrative Company (USAC), which administers E-Rate along with several other connectivity programs under the direction of the FCC.

E-Rate funds fall into two broad categories: (1) Voice and data transmission/internet access services and (2) internal connections, managed internal broadband services, and basic maintenance of internal connections. Generally speaking, the first category covers Internet service and the second covers networking equipment. The first category is typically disbursed in monthly recurring payments, while the second category is associated with one-time payments, although we do observe exceptions to this dichotomy in the data.[10]

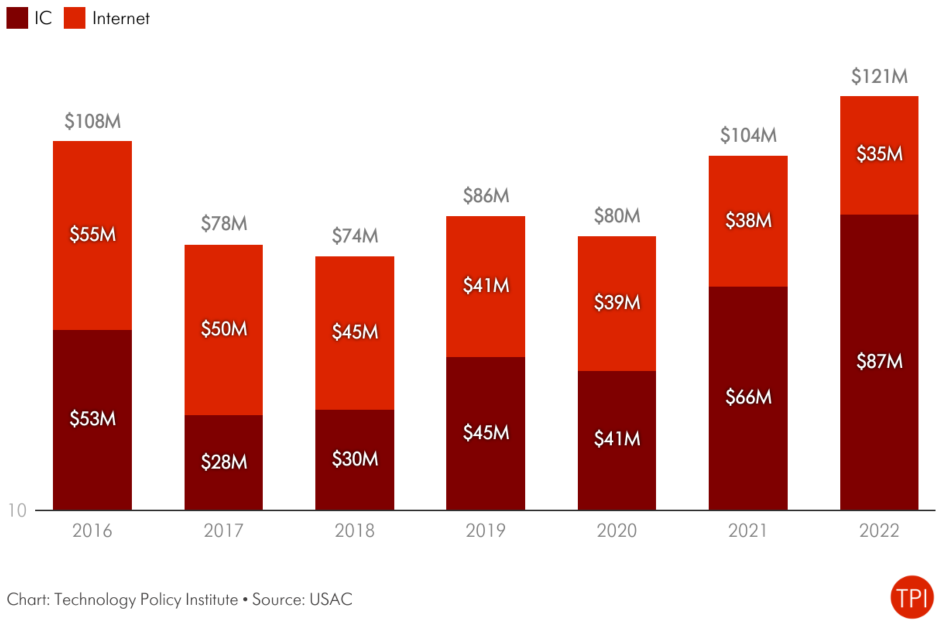
3.2 Florida school grades

We observe school characteristics, such as location, school type (public/charter), school level (elementary/middle/high/combination school), percentage of students eligible for free lunch, percentage of minority students, percentage of disadvantaged students, total number of students - and most importantly - the school grade and its components.

[9] See, for example, https://www.gao.gov/products/gao-05-151

[10] The correlation between category-1 E-rate amounts and E-rate paid monthly is 0.97, while the corelation between category-2 E-rate amounts and one-off E-rate payments is 0.8.

Figure 3.1: E-Rate Disbursements in Florida in $ Millions



The state of Florida assigns letter grades to schools in the state in order to provide comparable information about school quality to interested parents and the general public. The grades follow a school letter grade scale, and thus can take on 5 discrete values: $\{A, B, C, D, F\}$ (there is no E). As described in Florida Department of Education (2019), the final school grade is a composite of up to eleven different scores in five general areas. Figure 3.2 demonstrates the components that go into the final school grade calculation (each cell represents one of the 11 components).

Each of the 11 grade components is measured on a percentage scale (0% to 100%). Not every school can be scored on all 11 of these measures. For example, the graduation rate is only collected at the high school and combined school level. In other words, elementary and middle schools do not have a score on the graduation rate metric. Moreover, schools may have missing scores on different metrics for other reasons. The FDOE's rule is that a school has to have a score on at least 6 of the 11 components in order to receive an overall grade. If a school is measured on fewer than 6 components, no overall grade is reported for that school.

Each of these grade components has an equal weight in the overall grade calculation. To determine a school's letter grade, first an arithmetic mean is taken over the non-missing components, and then the mean is translated into a letter according to the discretization given in Table 3.1.

Figure 3.2: Grade components going into the overall school grade calculation

English Language Arts (FSA, FSAA)	Mathematics (FSA, FSAA, EOCs)	Science (NGSSS, FSAA, EOCs)	Social Studies (EOCs)	Graduation Rate	Acceleration Success
Achievement (0% to 100%)	Achievement (0% to 100%)	Achievement (0% to 100%)	Achievement (0% to 100%)	4-year Graduation Rate (0% to 100%)	High School (AP, IB, AICE, Dual Enrollment or Industry Certification) (0% to 100%)
Learning Gains (0% to 100%)	Learning Gains (0% to 100%)				
Learning Gains of the Lowest 25% (0% to 100%)	Learning Gains of the Lowest 25% (0% to 100%)				Middle School (EOCs or Industry Certifications) (0% to 100%)

Source: Florida Department of Education (2019)

Table 3.1: Conversion chart between school percentage score and letter grade

Letter Grade	Percentage Score
A	$\geq 62\%$
B	54% - 61%
C	41% - 53%
D	32% - 40%
F	$\leq 31\%$

Source: Adapted from Florida Department of Education (2019)

Over the time period in our sample there has been a visible upward trend in terms of school grades, as seen in Figure 3.3: The distribution of grades has clearly moved up year over year. This suggests that school and student performance in Florida has generally improved over the recent years, although it is also possible that schools have learned how to game the system, much like the USNews College Rankings.[11] Another possible reason for grade improvement in our data is the trend of grade inflation (Denning, Eide, Mumford, Patterson, & Warnick, 2022). In our empirical analysis we will include year fixed-effects to account for such time-specific idiosyncracies.

[11] See for example: https://www.theguardian.com/us-news/2022/sep/13/us-news-college-ranking-controversy-columbia-university

Figure 3.3: Distribution of school grades over time

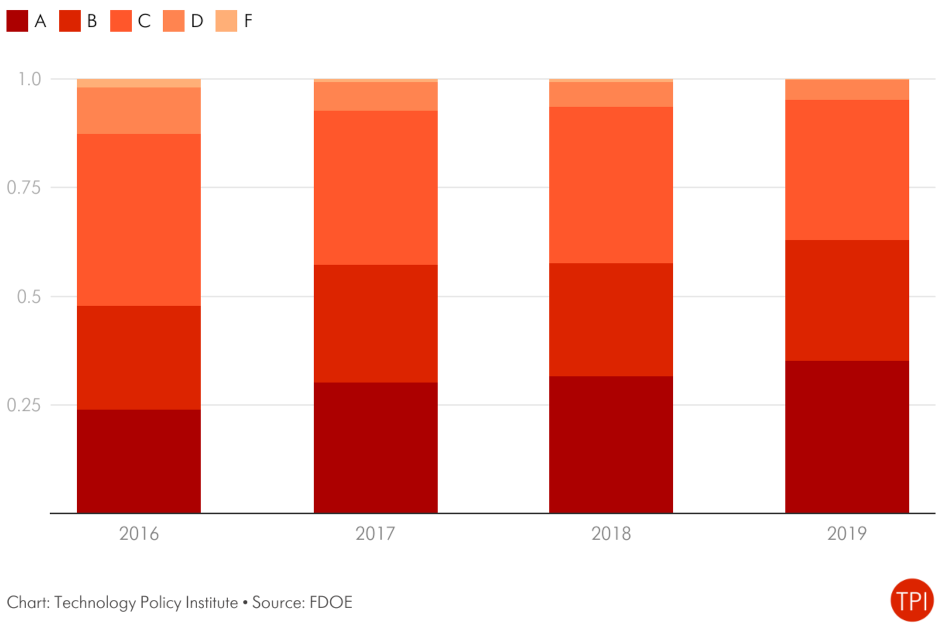


Table 3.2 shows summary statistics for the variables in our full sample. Tables .1 - .4 display the same summary statistics grouped by school level (elementary, middle, high, and combination schools)

Table 3.2: Summary statistics: Full sample

Statistic	Mean	Median	St. Dev.	Min	Max	N
% grade	56.96	56	11.36	22	100	9,145
Internet E-rate	33.16	17.64	117.93	0.00	4,451.02	9,147
IC E-rate	14.75	0.00	38.53	0.00	1,508.91	9,147
total E-rate	47.92	24.05	133.15	0.00	5,959.92	9,147
% free lunch students	69.96	74.96	26.30	0.00	100.00	9,150
total # of students	860.60	718.00	559.15	7.00	4,715.00	9,150
% minority students	63.42	64.80	26.58	1.30	100.00	9,147
% disadvantaged students	71.27	76.90	25.95	0.00	100.00	9,150

3.3 Merging Datasets

Since the two databases we use (USAC and FDOE - see above) identify schools in different ways, we match the schools based on geographical coordinates, name, and time period. An additional complication is that While the E-rate data is reported by calendar year, the school grades data is reported by school year. To match the two, we match E-rate funding in year t to school grades in year $t : (t+1)$.[12] Matching time periods this way makes most sense, because, according to the USAC Glossary of Terms, "The funding year is a time during which program support is being provided. The FY begins July 1 and ends June 30 of the following calendar year".[13] Therefore, our matching method guarantees an almost perfect overlap between the funding period and the school year.

The time period of our data is constrained by the availability of granular USAC E-rate data. Prior to 2016, only the total E-rate amounts per applicant (typically a school district) were reported. Since 2016, the USAC data have included information on which schools a given E-Rate application included and a breakdown of E-rate funding into Category 1 (mostly Internet) and Category 2 (mostly internal connections). At the other end, the time period of our data is constrained by the COVID pandemic. Because of it, FDOE did not report school grades for the school year 2019-2020, while grade reporting for the school year 2020-2021 was voluntary (on an opt-in basis). The usual grading procedure returned in 2021-2022. As a result, our final dataset includes 3112 schools in 3 funding years 2016-2018 (corresponding to school years 2016-17 - 2018-19).

4 Empirical analysis

4.1 Estimation

We explore the relationship between E-Rate subsidies and school performance by estimating a linear model whose general form is given by Equation 4.1:

$$performance_{it} = \mathbf{x_{it}}\boldsymbol{\beta} + \mathbf{w_{it}}\boldsymbol{\delta} + f_i + f_t + \varepsilon_{it} \tag{4.1}$$

Our dependent variable is a performance measure for school i in funding year t. In our default specification, this will be the school's overall %-score. Our other overall performance measure is the letter grade the school received. We believe the %-score is superior to the letter grade in our regression, not just because letter grades are ordinal while %-scores are continuous, but because mapping from percentages to letters as shown in Table 3.1, transforms a 'nice' distribution into a skewed one (many A's, B's and C's, few D's and F's). Additionally, the percentage score is the original (raw) measure.

The vector $\mathbf{x_{it}}$ in Equation 4.1 contains measures of E-Rate subsidies, that is, our main explanatory variables of interest. In our preferred specifications we use the following: Category 1 E-Rate ($ per student) and Category 2 E-Rate ($ per student). As a reminder, the Category 1 subsidy is principally being spent on broadband and voice subscriptions, while the Category 2 subscription is primarily used for Internal Connections (IC) and maintenance thereof. The vector $\mathbf{w_{it}}$ contains

[12] For example, in our assembled dataset E-rate funding in 2016 is matched to school grades in 2016-2017.
[13] https://www.usac.org/e-rate/resources/glossary-of-terms/

control variables that vary both across schools and over time. We have four control variables: % of students eligible for free lunch, total # of students, % of minority students and % of disadvantaged students.[14]

In addition to the variables already mentioned, we include year fixed-effects (f_t) in order to account for the time trend apparent in Figure 3.3, and school fixed-effects (f_i) to control for any school characteristics which remain invariant over time that we cannot observe.

4.2 Results

Table 4.1 shows the results of estimating our preferred specification. The first column contains full-sample results, while columns (2)-(5) display results by school level (elementary, middle, high, and combination schools). Given that we include time and school fixed effects, our analysis addresses the following question: Comparing two schools in the same funding year, that are identical except for the level of E-rate funding, what is the difference in their performance? Full sample results show that E-rate subsidies have no statistically significant effect on school performance. Moreover, IC subsidies show no association with school grades in any of the sub-samples. However, we find significant negative estimates for Internet subsidies in two of the sub-samples: middle schools and combination schools. Even though these effects are different from zero statistically speaking, their magnitude is small: An increase in subsidies of $1 per student roughly translates into a -0.015 and -0.005 percentage point (!) change in school score respectively. An alternative interpretation is that a one-standard-deviation increase in Internet E-rate decreases school's score by 0.06 and 0.16 standard deviations respectively.

There are at least two plausible explanations for why Internet spending might affect student outcomes negatively. First, any educational benefits from using technology in the classroom might be outweighed by students' distraction in the spirit of literature referenced in Section 2.3. Second, it could be that spending on technology (including Internet) or the E-rate application process might not constitute the most productive use of a school's finite resources.

The results in Table 4.1 account for heterogeneity across the school level and the category of the E-rate subsidy. An additional issue is that not all schools were graded separately on all 11 measures, as discussed in Section 3.2. Most schools, however, have scores for the first six components. Therefore, we create a new variable, *overall adjusted score*, which is the average of those six scores. This variable reflects a more consistent comparison across schools.

In short, we have 4 school types and the combined sample, 11 score components, and 2 overall scores, generating a possible (4 + 1) x (11 + 2) = 65 results for each of the two E-rate subsidy categories. Since not all school types are scored on all of the grade components (e.g. graduation rates are not available for elementary or middle schools), our data yield 58 results for each of the E-Rate categories. The Appendix includes this extended set of results. For ease of interpretation

[14]For some of the observations in our sample, the percentage of lunch students exceeds 100%. In those instances, we force the fraction of lunch students to unity.

Table 4.1: OLS regressions of school percentage scores on E-rate subsidies, by school type

Dependent Variable:			% grade		
	All	Elem.	Middle	High	Combination
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Internet E-rate	-0.0007	0.0019	-0.0153***	-0.0021	-0.0054**
	(0.0016)	(0.0015)	(0.0052)	(0.0056)	(0.0028)
IC E-rate	0.0003	-0.0020	0.0047	-0.0051	-0.0021
	(0.0027)	(0.0032)	(0.0034)	(0.0050)	(0.0053)
% free lunch students	0.0064	-0.0104	0.0184	-0.0163	0.0452*
	(0.0124)	(0.0160)	(0.0205)	(0.0203)	(0.0246)
total # of students	0.0018	0.0031	-0.0028	0.0000	0.0017
	(0.0012)	(0.0027)	(0.0017)	(0.0013)	(0.0022)
% minority students	-0.2336***	-0.2583***	-0.2918***	-0.3132**	-0.0167
	(0.0428)	(0.0562)	(0.0909)	(0.1436)	(0.1111)
% disadvantaged students	0.0072	-0.0164	-0.0008	0.0206	0.0048
	(0.0107)	(0.0194)	(0.0206)	(0.0217)	(0.0190)
Fixed-effects					
school	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	9,139	5,152	1,604	1,353	1,030
R^2	0.89533	0.86263	0.94813	0.95311	0.92777

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

and better comparability, all results therein are displayed in standardized terms.

Tables 4.2 and 4.3 summarize these results. We find that in 42 out of 58 cases, Internet subsidies have no statistically significant effect on school performance. In 12 cases, the effect is negative and statistically significant at at least 10% level (8 at 1% level, 2 at 5% level, 2 at 10% level). In only 4 cases is the effect positive and statistically significant (1 at 1% level, 2 at 5% level, and 1 at 10 % level). In terms of magnitude, the strongest effect is observed for graduation rates in combination schools: One standard deviation in broadband subsidies increases the graduation rates by 0.47 standard deviations. It is somewhat puzzling that this result does not carry over to high schools. The other two results that stand out in terms of magnitude, are the negative effects of Internet E-Rate on math progress of the bottom quartile of middle school students and of all middle school students. An increase of one standard deviation in Internet E-rate is correlated with a decrease of 0.36 and 0.27 standard deviations, respectively. Again, it is somewhat surprising that this pronounced negative effect holds only for middle school students, but not others.

Table 4.2: Internet E-rate: Summary of regression results

$(-)^{***}$	$(-)^{**}$	$(-)^{*}$	insig.	$(+)^{*}$	$(+)^{**}$	$(+)^{***}$
8	2	2	42	1	2	1

Table 4.3: Internal connections: Summary of regression results

$(-)^{***}$	$(-)^{**}$	$(-)^{*}$	insig.	$(+)^{*}$	$(+)^{**}$	$(+)^{***}$
0	0	1	52	5	0	0

Internal Connections subsidies do not appear to be at all associated with school performance. Out of 58 results, 52 are not statistically significant. Only six out of 58 results are significant, and only at the 10% level, which is consistent with observing statistical significance due to pure chance.

5 Summary

In this paper, we study the possible effects of E-rate subsidies for broadband and internal connections in Florida schools, on the performance of those schools. In our full sample, we find no statistically significant links between subsidies and school performance.

The nature of the data allowed us to explore heterogeneity across school level, subsidy category, and performance metric. We looked at all possible combinations of the 3 dimensions, and found no statistically significant association in most cases. Only three combinations exhibited a statistically and economically significant effect, two of them negative, and one of them positive.

Our investigation suggests that broadband subsidies do not improve student achievement, further corroborating the results of previous studies on E-rate effectiveness. Whether these results reflect an ineffective program or ineffective use of technology in schools is a question for another day.

References

Angrist, J., & Lavy, V. (2002, oct). New evidence on classroom computers and pupil learning. *The Economic Journal*, *112*(482), 735–765. doi: 10.1111/1468-0297.00068

Arefin, M. S., Islam, M., Mustafi, M., Afrin, S., & Islam, N. (2017). Impact of smartphone addiction on academic performance of business students: A case study. *Independent Journal of Management & Production*, *8*(3). Retrieved from https://ssrn.com/abstract=3035776

Badasyan, N., & Silva, S. (2018). The impact of internet access at home and/or school on students' academic performance in urban areas in brazil. *International Journal of Education Economics and Development*, *9*(2), 149. doi: 10.1504/ijeed.2018.092198

Barrow, L., Markman, L., & Rouse, C. E. (2009, jan). Technology's edge: The educational benefits of computer-aided instruction. *American Economic Journal: Economic Policy*, *1*(1), 52–74. doi: 10.1257/pol.1.1.52

Belo, R., Ferreira, P., & Telang, R. (2014, feb). Broadband in school: Impact on student performance. *Management Science*, *60*(2), 265–282. doi: 10.1287/mnsc.2013.1770

Bianchi, N., Lu, Y., & Song, H. (2022, sep). The effect of computer-assisted learning on students' long-term development. *Journal of Development Economics*, *158*, 102919. doi: 10.1016/j.jdeveco.2022.102919

Chen, Y., Mittal, V., & Sridhar, S. H. (2020, nov). Investigating the academic performance and disciplinary consequences of school district internet access spending. *Journal of Marketing Research*, *58*(1), 141–162. doi: 10.1177/0022243720964130

Cristia, J., Ibarrarán, P., Cueto, S., Santiago, A., & Severín, E. (2017, jul). Technology and child development: Evidence from the one laptop per child program. *American Economic Journal: Applied Economics*, *9*(3), 295–320. doi: 10.1257/app.20150385

Deng, Z., Cheng, Z., Ferreira, P., & Pavlou, P. A. (2022). From smart phones to smart students: Distraction versus learning with mobile devices in the classroom. *SSRN Electronic Journal*. doi: 10.2139/ssrn.4028845

Denning, J. T., Eide, E. R., Mumford, K. J., Patterson, R. W., & Warnick, M. (2022, jul). Why have college completion rates increased? *American Economic Journal: Applied Economics*, *14*(3), 1–29. doi: 10.1257/app.20200525

El Khatib, D. M., & Khan, F. R. (2017). Implications of social media networks technology in interpersonal skills and academic performances. *International Journal of Management, Innovation & Entrepreneurial Research EISSN*, *3*(2), 99-110.

Florida Department of Education. (2019). *2018-19 guide to calculating school grades, district grades, and the Federal Percent of Points Index* (Tech. Rep.). Bureau of Accountability Reporting; Division of Accountability, Research and Measurement. Retrieved from https://www.fldoe.org/core/fileparse.php/18534/urlt/SchoolGradesCalcGuide19.pdf

Goolsbee, A., & Guryan, J. (2006, may). The impact of internet subsidies in public schools. *Review of Economics and Statistics*, *88*(2), 336–347. doi: 10.1162/rest.88.2.336

Grimes, A. (2017). The effect of fibre broadband on student learning. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2946583

Hazlett, T. W., Schwall, B., & Wallsten, S. (2018, oct). The educational impact of broadband subsidies for schools under e-rate. *Economics of Innovation and New Technology*, *28*(5), 483–497. doi: 10.1080/10438599.2018.1527554

Leuven, E., Lindahl, M., Oosterbeek, H., & Webbink, D. (2007, nov). The effect of extra funding for disadvantaged pupils on achievement. *Review of Economics and Statistics*, *89*(4), 721–736. doi: 10.1162/rest.89.4.721

Li, X., Atkins, M. S., & Stanton, B. (2006). Effects of home and school computer use on school readiness and cognitive development among head start children: A randomized controlled pilot trial. *Merrill-Palmer Quarterly*, *52*(2), 239–263. doi: 10.1353/mpq.2006.0010

Machin, S., McNally, S., & Silva, O. (2007, jul). New technology in schools: Is there a payoff? *The Economic Journal*, *117*(522), 1145–1167. doi: 10.1111/j.1468-0297.2007.02070.x

Raganta, I., Vargas, D., & Raganta, J. (2021). Gender social media exposure and academic performance of high school students. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3838172

Silva, S., Milkman, M. I., & Badasyan, N. (2014). The impact of the 'broadband at school' federal program on students' academic performance in brazil. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2413976

Spiezia, V. (2010, dec). Does computer use increase educational achievements? student-level evidence from PISA. *OECD Journal: Economic Studies*, *2010*(1), 1–22. doi: 10.1787/eco_studies-2010-5km33scwlvkf

Violette, D. (2017). *A study of internet spending and graduation rates: A correlational study* (Unpublished doctoral dissertation). University of Central Florida.

Voshaar, J., Knipp, M., Loy, T., Zimmermann, J., & Johannsen, F. (2022, feb). The impact of using a mobile app on learning success in accounting education. *Accounting Education*, 1–26. doi: 10.1080/09639284.2022.2041057

Yamada, G., Lavado, P., & Montenegro, G. (2016). The effect of one laptop per child on teachers' pedagogical practices and students' use of time at home. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2889678

Appendix

Table .1: Summary statistics: Elementary schools

Statistic	Mean	Median	St. Dev.	Min	Max	N
% grade	55.89	55	11.21	22	100	5,154
Internet E-rate	35.73	19.91	133.44	0.00	4,451.02	5,155
IC E-rate	17.23	0.00	45.67	0.00	1,508.91	5,155
total E-rate	52.96	25.80	154.36	0.02	5,959.92	5,155
% free lunch students	74.08	81.75	25.98	0.00	100.00	5,156
total # of students	647.70	638.00	233.01	13.00	2,104.00	5,156
% minority students	64.07	65.80	26.58	1.30	100.00	5,155
% disadvantaged students	75.64	84.00	25.53	0.00	100.00	5,156

Table .2: Summary statistics: Middle schools

Statistic	Mean	Median	St. Dev.	Min	Max	N
% grade	57.22	56	11.27	31	93	1,606
Internet E-rate	22.30	15.00	34.55	0.00	592.52	1,605
IC E-rate	12.90	0.00	27.64	0.00	181.08	1,605
total E-rate	35.20	21.27	43.34	0.02	592.52	1,605
% free lunch students	67.97	70.70	24.90	0.00	100.00	1,606
total # of students	902.81	895.00	374.27	44.00	3,442.00	1,606
% minority students	63.09	62.90	25.22	9.60	100.00	1,605
% disadvantaged students	69.45	73.20	24.57	0.60	100.00	1,606

Table .3: Summary statistics: High schools

Statistic	Mean	Median	St. Dev.	Min	Max	N
% grade	57.98	56	11.43	32	100	1,355
Internet E-rate	26.54	8.57	130.60	0.00	2,967.12	1,355
IC E-rate	10.52	0.00	23.05	0.00	154.95	1,355
total E-rate	37.06	15.13	133.41	0.75	2,967.12	1,355
% free lunch students	60.65	60.42	23.90	0.00	100.00	1,356
total # of students	1,682.00	1,723.00	855.53	40.00	4,715.00	1,356
% minority students	61.47	59.50	25.61	9.70	100.00	1,355
% disadvantaged students	61.94	62.45	22.89	0.00	100.00	1,356

Table .4: Summary statistics: Combined schools

Statistic	Mean	Median	St. Dev.	Min	Max	N
% grade	60.61	60	11.27	30	94	1,030
Internet E-rate	45.97	22.94	98.29	0.00	1,283.41	1,032
IC E-rate	10.79	0.00	27.92	0.00	400.47	1,032
total E-rate	56.76	30.11	106.03	0.00	1,331.46	1,032
% free lunch students	64.68	67.07	28.53	0.00	100.00	1,032
total # of students	779.33	730.40	446.64	7.00	2,325.00	1,032
% minority students	63.28	67.45	29.64	2.10	100.00	1,032
% disadvantaged students	64.54	68.60	28.75	0.00	100.00	1,032

Dependent Variable:	scale(overall_score)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0075	0.0196	-0.1590***	-0.0215	-0.0565**
	(0.0169)	(0.0159)	(0.0536)	(0.0585)	(0.0287)
scale(cat2)	0.0009	-0.0069	0.0160	-0.0173	-0.0071
	(0.0091)	(0.0109)	(0.0116)	(0.0168)	(0.0181)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(overall_adjusted)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0047	0.0198	-0.1076***	-0.0592	-0.0471
	(0.0170)	(0.0135)	(0.0349)	(0.0814)	(0.0354)
scale(cat2)	0.0079	0.0032	0.0013	-0.0031	0.0046
	(0.0053)	(0.0058)	(0.0112)	(0.0187)	(0.0235)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(eng_achievement)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0266***	-0.0115**	-0.0793***	-0.0482*	-0.0848***
	(0.0086)	(0.0053)	(0.0288)	(0.0287)	(0.0287)
scale(cat2)	0.0039	0.0033	0.0010	0.0045	-0.0217
	(0.0055)	(0.0067)	(0.0062)	(0.0103)	(0.0148)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(eng_gains)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0286	-0.0007	-0.1137	-0.0742	-0.1099***
	(0.0181)	(0.0177)	(0.0999)	(0.0590)	(0.0414)
scale(cat2)	0.0119	0.0089	-0.0138	0.0046	0.0065
	(0.0118)	(0.0142)	(0.0153)	(0.0238)	(0.0283)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(eng_gains25)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0080	0.0196	-0.0495	-0.0665	-0.0745
	(0.0222)	(0.0250)	(0.1322)	(0.0608)	(0.0492)
scale(cat2)	0.0032	-0.0005	-0.0312*	-0.0141	-0.0232
	(0.0098)	(0.0116)	(0.0185)	(0.0307)	(0.0433)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(mat_achievement)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0119	-0.0007	-0.0588	-0.0514	-0.0178
	(0.0130)	(0.0102)	(0.0373)	(0.0819)	(0.0306)
scale(cat2)	-0.0016	-0.0039	0.0109	-0.0272	-0.0052
	(0.0060)	(0.0072)	(0.0096)	(0.0220)	(0.0170)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(mat_gains)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	0.0177	0.0547**	-0.2685***	-0.0438	-0.0090
	(0.0249)	(0.0234)	(0.0616)	(0.0953)	(0.0435)
scale(cat2)	-0.0084	-0.0211	0.0199	-0.0404	0.0160
	(0.0119)	(0.0148)	(0.0189)	(0.0339)	(0.0306)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(mat_gains25)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	0.0231	0.0668**	-0.3597***	-0.0117	0.0116
	(0.0306)	(0.0301)	(0.0750)	(0.1376)	(0.0531)
scale(cat2)	0.0068	-0.0097	0.0196	-0.0187	0.0488
	(0.0101)	(0.0119)	(0.0214)	(0.0321)	(0.0447)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(sci_achievement)				
school_lvl	Full sample	Elem.	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
scale(cat1)	-0.0099	-0.0022	0.0052	-0.0498	-0.0439
	(0.0142)	(0.0154)	(0.0408)	(0.0323)	(0.0420)
scale(cat2)	0.0096**	0.0097*	0.0118	0.0215	-0.0043
	(0.0048)	(0.0056)	(0.0110)	(0.0256)	(0.0245)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(social_achievement)			
school_lvl	Full sample	Middle	High	Comb.
Model:	(1)	(2)	(3)	(4)
Variables				
scale(cat1)	-0.0243*	-0.0802	0.0155	-0.0434
	(0.0147)	(0.0545)	(0.0151)	(0.0272)
scale(cat2)	0.0095	0.0250*	0.0039	-0.0378
	(0.0124)	(0.0145)	(0.0175)	(0.0405)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(middle_acc)		
school_lvl	Full sample	Middle	Comb.
Model:	(1)	(2)	(3)
Variables			
scale(cat1)	-0.0347	-0.0539	-0.0047
	(0.0539)	(0.0863)	(0.0656)
scale(cat2)	0.0400*	0.0346*	0.0303
	(0.0208)	(0.0206)	(0.0547)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(graduation_rate)		
school_lvl	Full sample	High	Comb.
Model:	(1)	(2)	(3)
Variables			
scale(cat1)	0.0459	-0.0497	0.4662***
	(0.0481)	(0.0499)	(0.1225)
scale(cat2)	-0.0286	-0.0266	0.0464
	(0.0240)	(0.0287)	(0.0533)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dependent Variable:	scale(career_acc)		
school_lvl	Full sample	High	Comb.
Model:	(1)	(2)	(3)
Variables			
scale(cat1)	0.0473	0.0755*	-0.1119
	(0.0417)	(0.0450)	(0.0889)
scale(cat2)	0.0219	0.0206	-0.0051
	(0.0178)	(0.0215)	(0.0408)

Clustered (school) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*