The Impact of Internet Subsidies in Public Schools

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Abstract

In an effort to alleviate the perceived growth of a digital divide, the U.S. government enacted a major subsidy for Internet and communications investment in schools starting in 1998. In this paper, we evaluate the effect of the subsidy—known as the E-Rate—on Internet investment in California public schools. The program subsidized spending by 20-90 percent, depending on school characteristics. Using new data on school technology usage in every school in California from 1996 to 2000 as well as application data from the E-Rate program, the results indicate that the subsidy did succeed in significantly increasing Internet investment. The implied first-dollar price elasticity of demand for Internet investment is between –0.4 and –1.1 and the greatest sensitivity is seen among urban schools and schools with large black and Hispanic student populations. Rural and predominantly white and Asian schools show much less sensitivity. Overall, by the final year of the sample, there were about 68 percent more Internet-connected classrooms per teacher than there would have been without the subsidy. Using a variety of test score results, however, we do not find significant effects of the E-Rate program, at least so far, on student performance.

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I. Introduction

As the Internet has grown in recent years, inequality of access and understanding of technology across income and racial lines has led to concern among policymakers about the so-called digital divide. This concern has generated many proposals to help close the divide, by both governments and private entities like the Gates Foundation.

Policymakers and analysts have argued that public schools are the natural place to teach underserved populations about computers. As part of the Telecommunications Act of 1996, the government began actively subsidizing Internet and telecommunications access in U.S. classrooms and libraries through a tax on long-distance services as a new, information-age component of the Universal Service Fund.[1] This new initiative, known as the E-Rate program, began in 1998 and provides up to $2.25 billion per year of subsidies to school and library investment in Internet and communications technology. To understand the magnitude of this subsidy, note that Lake (2000) estimates total public school spending on computers in 1999 (including hardware, software, training, networking, etc.) was only $3.3 billion. The E-Rate subsidy is, by far, the most ambitious federal technology program in schools.[2]

Understanding the extent to which the $2.25 billion subsidy fulfilled its primary goal of increasing Internet usage in schools, particularly disadvantaged ones, versus merely subsidizing spending that was already taking place, is thus of first order importance. There is also considerable interest in—and debate about—whether spending on computers and information technology has any impact on student performance (see Kirkpatrick and Cuban, 1998; Angrist

[1] The tax itself is not without controversy as Hausman (1998) suggests it generates more than a dollar of efficiency cost for every dollar it raises.

[2] It is also large by the standards of other universal service subsidies. Crandall and Waverman (2000), for example, calculate that the annual cost of universal service subsidies for telephone service was less than $2.2 billion (in 1998), for electricity less than $1.2 billion (in 1990), and for natural gas about $1.5 billion (in 1995).

and Lavy, 1999; Cuban, 2001) and the creators of the E-Rate have argued that it can do more than just increase access, that it can improve basic student performance.

In this paper we provide an economic analysis of the impact of the E-Rate program on public schools' technology adoption over the 1996-2000 period. To do so, we use new data on the technology owned in each year by every school in California, covering fully 13 percent of public school enrollment in the U.S[3] We merge these technology data with administrative data on every E-Rate funding application these same schools filed, including the amount of funding, the subsidy rate, and purpose of the funding. We also use demographic data for each school and district from the National Center for Education Statistics Common Core of Data (CCD) and the 1990 U.S. Census.

We seek to determine whether schools with higher subsidy rates made greater investments in technology than they would have without the program and, if so, whether the increase in Internet access had any impact on observed student outcomes in the period. To do so, we must confront three difficulties in analyzing the program.

First, there is a clear upward trend in Internet access among public schools before the E-Rate program began. The data in U.S.D.O.E. (2000) on the share of public school classrooms with access to the Internet, for example, shows the share increasing by a factor of five from 1994 to 1996 (from 3% in 1994 to 15% in 1996) followed by continued growth through 1999 (51% in 1998 and 63% in 1999). While it is true that the time series shows a major increase in access in

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[3] Though it is not clear how they should affect the impact of the E-Rate program, school financing rules in California are particularly stringent relative to the rest of the country in regards to the equality of education spending per pupil across districts. This system essentially leaves every district in the state budget constrained. E-Rate subsidies, however, are considered discounts rather than revenue by the California Board of Education, so the E-Rate subsidies do not lead to offsets in state education funding. We thank Wayne Shimizu, from the California Department of Education, John Gray from School Services of California giving us the details of how the two programs interact.

As California is the only state that collected detailed data on Internet connections before the E-Rate program began, we have no way to compare the results to what would happen under different systems.

the first year of the E-Rate program, it is important to distinguish the program's effect from underlying trends. We do this by exploiting cross-sectional variation in the subsidy rate across schools in the same time periods and by looking at growth rates rather than levels.

The second problem we deal with is the fact that the cross-sectional variation in the subsidy rate (the subsidy rates range from 20 to 90 percent) depends on factors, such as the share of pupils qualifying for subsidized school lunches, which are likely to be correlated with unobserved tastes for technology in the school. To address these issues we explore a regression-discontinuity research design and include in a regression-based design flexible controls for the previous technology histories of these schools as well as the very school demographic characteristics that drive the variation in subsidy rates.

The third problem, which leads to an independently interesting observation, is that districts are allowed to decide which schools to include on their applications. Because the subsidy rate is determined by the distribution of school lunch percentages of participating schools, there are incentives for high-poverty districts to apply and for wealthier schools to convince higher-poverty schools in their district to join their applications. We show evidence that districts and schools did respond on both margins. While this observation is interesting as a window into the workings of public schools, the resulting selection might lead to bias in our estimates and we will need to be rather careful in dealing with this selection when estimating the impact of the subsidy on adoption rates.

The analysis shows several things. First, public schools in California responded to price incentives by increasing their investment in Internet technology. The first-dollar price elasticity of demand is between –0.4 and –1.1 and the greatest sensitivity shows up among urban schools and among schools with large black and Hispanic populations. There were substantially more internet connections in schools in 2000 because of this program. We also present evidence that schools responded to the subsidies and program rules in strategic and optimizing ways. This estimate also raises the interesting and understudied question of how public sector organizations respond to price variation. Finally, we look at how this increase in Internet access impacted test scores and find effects that are not distinguishable from zero.

The paper proceeds in eight parts. In section II, we describe the rules and history of the E-Rate program. In section III, we describe the data and present summary statistics. In section IV we present the identification framework and the basic results. In section V, we address alternative interpretations of these results and present evidence of strategic behavior by public schools. In section VI, we examine which schools were more or less sensitive to the subsidy. And, in section VII we present results on student outcomes. In section VIII we conclude.

II. The E-Rate Program

On May 7, 1997, the Federal Communications Commission (FCC) adopted a Universal Service Order implementing the Telecommunications Act of 1996. The Order was designed to give all eligible schools and libraries affordable access to modern telecommunications and information services. The program began on January 1, 1998 and provided up to $2.25 billion annually (FCC, 1997a). It is known as the E-Rate program.

The E-Rate program was not designed to have the government provide technology to schools but rather to subsidize schools' purchases of such technology and to do so at a progressively sliding rate that depends on poverty rates and urban/rural status. The subsidy rate ranges from 20 to 90 percent depending on the share of students that qualify for the national school lunch program as shown in table 1.[4]

The subsidy can be used for spending on "all commercially available telecommunications services, Internet access, and internal connections." This includes services like basic telephone service, a T-1 line, telecommunications wiring, routers and switches, Local Area Networks, PBX or other services whose primary purpose is delivering services into classrooms or other places of instruction. Support for administrative functions of a library or school is permitted if it is "part of the network of shared services for learning." (Department of Education, 1997a). Schools cannot get subsidies for things like software or computers since they are not directly related to connections. Detailed information on what is eligible can be found in FCC (2001).

Schools may apply for the program individually or as a school district.[5] The subsidy rate for individual schools is determined by the criteria in table 1. The subsidy rate for the district is based on the average share of school-lunch-eligible students across all participating schools (weighted by enrollment) but the rules require that the higher-level entities "must strive to ensure that each school receives full benefit of discount to which entitled" (U.S.D.O.E., 1997b). We, of course, do not observe any type of side payments that might occur.

III. Data

The data are drawn from three sources. First, data from the U.S. and California Departments of Education give information on every public school in California. Well known

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[4] Note that the E-Rate subsidy is large compared to the computer budget of the schools but tiny compared with overall school spending. This makes it extremely unlikely that schools would attempt to modify their school lunch percentages (which are the basis of most other federal programs, as well) to get above the kink points of the E-Rate subsidy schedule. Direct investigation also shows no evidence that schools altered eligibility percentages in response to the E-rate subsidy rules.

[5] Technically, schools may also apply across districts as consortia but this is extremely rare in practice and we exclude the few consortia from our analysis.

data include enrollment counts by race, characteristics of teachers, and the fraction of students eligible for the federal free and reduced price lunch programs. We also use new data that provide detailed school level information on the number of computers used for instructional purposes and of the number of classrooms with Internet access in each school starting with the 1996-1997 school year. Additional demographic characteristics from the school district-level tabulation of the 1990 census, such as the median household income and the median home value are added.

We merge the California data with a second data set comprised of administrative data from the Universal Service Administrative Company (USAC) on every E-Rate subsidy application over the life of the program. Each application lists the total funds requested, the total funds granted, the subsidy rate that applies to the request and a classification of the funds as Internet access, telecommunications services, or internal connections. The breakdown of E-Rate funding by intended use is shown in table 2. Eighty percent of E-Rate funds go to internal connections, 17 percent go to telecommunications services, and the remaining 3 percent are used for Internet access.

For our analysis, we drop E-Rate applications by libraries, private schools and multi-district consortia, which, combined, account for only about 10 percent of E-Rate spending in California. To get a subsidy rate for each school in the sample, we aggregate the application data to the school district level and use the average subsidy faced by applicant schools in the district.[6] The district-level data include funds requested and granted by type of request, and various

[6] The standard errors are corrected to account for within-district correlation resulting from the fact that there is not school level variation in the subsidy rate every year.

measures of the subsidy rate, such as the mean, median, and mode.[7] Since schools within the district can strategically apply in light of the progressive subsidy rate, we compute the subsidy rate that would prevail if all the district's schools applied. As shown in sections IV and V, the results do not substantively change if the predicted discount rate is used in its place.

Table 2 also summarizes the Internet and computer access in California's public schools over time. By the 1997-1998 school year, the year before the first E-Rate funding was awarded, 55 percent of California's public schools had at least one classroom with Internet access, an increase of 9 percentage points from a year earlier. Using the number of teachers as a proxy of the number of classrooms (which we do not observe), we estimate that something like 26 percent of classrooms in California had Internet access.[8] By comparison, 93 percent of California schools used at least one computer for instructional purposes in 1997-1998, while the average school had 2.2 computers per teacher.

As the E-Rate funds grew, Internet access was becoming more widespread. By 2000-2001, 85 percent of California schools had at least one classroom with Internet access, while two-thirds of all classrooms in California had Internet access. The fraction of California schools that used at least one computer for instructional purposes grew to 98 percent by 2000-2001, while the number of computers per teacher grew to 3.1.

Over the same time period, the federal government transferred almost $937 million to the public schools of California as a part of the E-Rate program. The bottom panel of table 2 shows the total E-Rate funding commitment both nationally and in California.[9] As is shown by the

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[7] We have done the analysis using the district level median, mode, maximum and minimum of the subsidy rate. The results are not qualitatively different. We report only results using the mean due to space concerns. This point is only relevant to the estimate shown in column 1 of table 4 that uses the actual subsidy rate.

[8] The number of teachers is almost surely an overestimate of the number of classrooms. Thus, our estimate of the fraction of classrooms with Internet access is a lower bound and probably explains why the national figures cited above are higher.

[9] Evidence describing the funding commitments in more detail can be found in Puma et. al. (2000).

aggregate numbers, national E-Rate funding grew from $1.7 billion in 1998-1999 to $2.1 billion in 2000-2001. About 15 percent of that funding went to applicants in California, where there was a sharp increase in requests in 2000-2001. This increase is entirely explained by the $230 million in E-Rate funding that the Los Angeles Unified School District received that year.[10] The next row of table 2 shows similar estimates of the trend in E-Rate funding using the data in our sample.

The strong time-series correlation between the spread of Internet access and the advent of E-Rate funding does not, of course, establish a causal link. The E-Rate legislation was passed in the midst of a strong upward trend in the fraction of schools with Internet access. Thus, even in the absence of the federal subsidy, many school districts would likely have chosen to make Internet investments. In other words, while the intent of the E-Rate subsidy was to create marginal incentives for school districts to invest in Internet access and to help disadvantaged schools especially, much of the total money spent through the E-Rate program may have gone to inframarginal districts. It is thus instructive to document which districts received E-Rate funding.

Returning to table 1, we can consider who, on average, received the funds from the E-Rate program. On one hand, the E-Rate subsidy is more generous for poor districts, so funding might be greater for the poorer schools. On the other hand, these poor districts tend to have less technology or be less willing to pay for technology. Rich districts may have more investment spending on computers and the Internet and therefore get the lion's share of the subsidy money, despite having a lower subsidy rate. The data suggest that, in fact, the first consideration overwhelmed the second. The table shows that a greater share of the funds went to the poorer schools than would be expected by enrollment alone. Most of the E-Rate funds went to schools

[10] We repeated the analysis in the paper excluding Los Angeles and the results were not affected.

with subsidy rates of 80 and 90 percent—schools with more than 50 percent of their students eligible for free or reduced price lunch from the federal government. The table also shows that the schools that received more generous subsidies had fewer Internet classrooms prior to the E-Rate program. Thus, E-Rate funding went disproportionately to schools with higher poverty rates and fewer Internet classrooms.

Figures 1 and 2 illustrate the data underlying the regressions in the next section. Figure 1 shows the average fraction of classrooms per district with Internet access. The yearly averages are shown separately for each of five groups of districts. Group 1 are the richest districts—those with less than 20 percent of their students eligible for the federal free or reduced lunch programs in 1997-1998. These districts received the least generous E-Rate subsidy. Group 2 are districts with between 20 and 40 percent of their students eligible for the federal free or reduced lunch programs in 1997-1998. Groups 3, 4 and 5 are defined similarly. Group 5 districts have the highest poverty rates and were eligible for the most generous subsidies. Figure 2 presents the ratio of usage for each group relative to group 1.

As shown in figure 1, in 1996-1997 and 1997-1998 there was a strong negative correlation between district poverty rates and Internet access. In the first year of the data, the richest schools had almost 50 percent more Internet classrooms per teacher than the poorest group, for instance. Over the next year (still before the E-Rate program), this discrepancy got even larger. Once the E-Rate program began in 1998, however, and the two lowest groups began receiving a large subsidy relative to the highest group, their relative number of Internet connections accelerated until, by 2000, some actually exceeded the connections in the richest school districts. Figure 2 shows this pattern. For each year, the figure shows the mean number of Internet classrooms per teacher in the wealthiest group of schools relative to each of the other groups. The figure highlights the reversal in Internet access rates of rich and poor schools—a closing of the digital divide—that occurred in the years in which the E-Rate subsidy was offered. It is also clear that most of the catch-up occurred among the poorest sets of schools, those eligible for the largest subsidies.

IV. Estimates of Internet Investment Elasticities

In this section we expand the suggestive analysis presented above to an analysis of school-level microdata. We are interested in estimating the relationship between the fraction of classrooms with Internet access $[I_{st} / C_{st}]$ and the E-Rate subsidy received by district d $[s_{dt}]$. Since we do not have data on the number of classrooms in each school we use the number of classrooms with Internet access and divide by the number of teachers.

Note that s_{dt} is zero in all years prior to 1998, and later is a weighted average of s_{st}, the subsidy for which an individual school applying on its own is eligible. The subsidy for which each individual school is eligible as a lone applier is calculated as

(1) $$s_{st} = f(m_{st})$$

where m_{st} is the fraction of students in school s eligible for the federal school lunch program, and $f(.)$ is the step function shown in table 1. The district's subsidy is then

(2) $$s_{dt} = \frac{\sum_{s \in A_{dt}} e_{st} s_{st}}{\sum_{s \in A_{dt}} e_{st}}$$

where A_{dt} is the set of schools included on district *d*'s E-Rate application in year *t*, and e_{st} is student enrollment in school *s* in year *t*. In other words, the subsidy received by a district is the enrollment-weighted average of the subsidies that individual schools on the application would get if they applied alone.

We observe s_{dt} in the administrative E-Rate data. As shown above, this subsidy rate depends on which schools are included on the E-Rate application. Because the decision of which schools to include on a district's application may be correlated with ε_{st}, we compute an alternative subsidy: the subsidy the district would have received if it had been forced to include every school in the district on the application. This subsidy is simply

$$\tilde{s}_{dt} = \frac{\sum_{s \in D_{dt}} e_{st} s_{st}}{\sum_{s \in D_{dt}} e_{st}} \tag{3}$$

where *D* is the full set of schools in district *d*. Estimates using the actual subsidy received, s_{dt}, can only be computed using schools that received E-Rate funding. Estimates using $\tilde{s}_{dt}$ can be computed for all districts. When we move to the regression estimates, we present estimates using both s_{dt} and $\tilde{s}_{dt}$. We favor the estimates that use $\tilde{s}_{dt}$ and include all schools—both appliers and non-appliers—because they avoid problems stemming from endogenous choice of which schools are included on the application. We discuss this point in more detail in section V.

We next describe two strategies for estimating the relationship between I_{st} / C_{st} and s_{dt}. We begin with, perhaps, the most intuitive approach: a regression-discontinuity (RD) research design in which we compare schools on either side of the cut-offs imbedded in the step-function used to compute the E-Rate subsidy. These estimates definitely suggest a strong investment response, but are too imprecise to draw clear conclusions from just the small number of schools around the cutoff points. This forces us to turn to a regression framework which allows us to draw on the full sample of schools. These estimates are consistent with the RD estimates and are far more precise.

A. Regression-Discontinuity Estimates

Given the stark step function described in table 1, a natural research design would be to focus on schools that are near the cut-offs used to compute the E-Rate subsidy. Because the subsidy awarded to a district (s_{dt}) is a weighted average of the subsidies for which each school is eligible (s_{st}), schools just above and just below these cut-offs may receive quite different price subsidies. For example, an urban school applying alone with a meal percentage of 49 gets a 60 percent subsidy, while a similar urban school applying alone with a meal percentage of 50 gets an 80 percent subsidy. If there is nothing different between these two schools other than the fact that they are eligible for different E-Rate subsidies, then a simple comparison of Internet classrooms per teacher in the two groups would yield the effect of the price subsidy.

We show RD estimates in table 3. Rows 2-6 of the first column reports the difference in $\tilde{s}_{dt}$ for schools just above (i.e. within one percentage point) and just below each of the five cut-offs. The first row shows the pooled difference, controlling for cut-off fixed effects. Around all but one of the cut-offs, the schools with slightly higher meal percentages were eligible for significantly larger $\tilde{s}_{dt}$ than schools with lower meal percentages. The pooled estimate implies that schools just above the cut-offs were eligible for 2.8 percentage point higher subsidies than schools just below. This difference has a standard error of 0.6 percentage points.[11]

[11] Differences are not mechanically the size of the jumps shown in Table 1 because the district's subsidy is a weighted average of each school's s_{st}. Differences in actual subsidies received are even smaller, apparently

Columns 2 and 3 report differences in the level of internet access in schools on either side of the cut-offs. Column 2 shows the differences for a period prior to the introduction of the E-Rate subsidies. Consistent with the RD identifying assumption, there are no significant differences in Internet access between these two groups of schools. Two of the five point estimates are negative, and the pooled estimate is a difference of 0.003 classrooms per teacher. Column 3 reports the differences for the period in which E-Rate subsidies were available. In all but one case the differences are larger, and the pooled difference of 0.055 classrooms is significant at the 10-percent level.

Column 4 reports Wald estimates of the effect of the subsidy on Internet classrooms per teacher. The table shows the difference in Internet access per teacher divided by the difference in the subsidy. This is the two-stage least squares estimate using an indicator for being just above the cut-off as an instrument for the subsidy. The pooled estimate is extremely large but only borderline significant at the 10-percent level. These coefficients are more than ten times larger than the estimates we find below. However, the standard errors are large and the estimates at specific cut-offs are highly variable. All of the RD estimates are quite imprecise, owing to the amount of data we must discard to focus on the schools very close to the cut-offs.

B. Regression Estimates

The RD estimates are too imprecise to draw strong conclusions. We therefore turn to a regression framework and use information from the full sample of schools to estimate the relationship of interest. Motivated by figure 1, we estimate the following investment equation

(4) $$\Delta(I/C)_{st} = \beta\tilde{s}_{dt} + \alpha_s + \delta_t + \gamma_1 m_{st} + \gamma_2 m_{st}^2 + \varepsilon_{st}$$

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because low-subsidy low-poverty schools are more likely to pair with schools that are just above a cutoff and who therefore have a higher s_{st}.

where $\Delta(I/C)_{st} = (I/C)_{st} - (I/C)_{st-1}$ is the change in the number of Internet classrooms per teacher for school s in year t, α_s and δ_t are respectively school and year effects, m_{st} is the fraction of students eligible for the federal school lunch program, and ε_{st} is an error term. The school effects (α_s) identify consistent differences in Internet investment rates over the sample period, or, put differently, school-specific trends in Internet access. The coefficient of interest is β , which measures the effect of the subsidy on Internet investment.

In table 4, we present estimates of equation (1) using the framework developed in the previous section. The suggestive analysis in section III highlights strong secular trends in Internet access but also a significant relative increase in investment by high-poverty schools when the subsidy is offered. Our regression framework includes year effects to control for the secular trends in Internet investment rates, school effects to control for persistent differences in technology investment rates, and poverty measures to control for convergence related to income levels. The analysis asks whether schools with more generous subsidies increased Internet investment rates relative to secular trends in a way unexplained by poverty levels. The dependent variable is the one-year change in the number of Internet-connected classrooms in the school per full-time equivalent teacher.[12] The number of teachers is again used as a proxy for the number of classrooms in a school. Thus, the dependent variable can be thought of as an estimate of the change in the fraction of classrooms in the school with Internet access. Regressions that use the change in the number of Internet classrooms (without dividing by the number of

[12] Because there are some clear measurement errors in the data, we do two things to clean the data. First, in cases where there is a large reported decrease in the number of internet connected classrooms in a school (usually of the form that internet connections are high, drop to zero or 1 for a year and then return to high values) we set the number of connections to be merely unchanged in the year. Second, because the dependent variable is a ratio, in a small number of cases, there are some rather extreme outliers. We exclude the few observations where the reported change in internet connected classrooms per teacher exceeds 1 in a single year. If we do not make either of these adjustments, the baseline results of the impact of the program are even larger.

teachers) yield similar results, and can be found in a previous version of this paper, (Goolsbee and Guryan, 2002).

In column 4 of table 4 we present the estimate of the effect of $\tilde{s}_{dt}$ on Internet investment per teacher. This is the preferred base specification because it includes all schools in all districts, and thus is not affected by endogenous application decisions. The estimate of β is positive and significant, implying that schools getting the biggest subsidies starting in 1998 did have larger increases in the growth rate of Internet access.[13] The magnitude indicates that a ten-percentage-point increase in the E-Rate subsidy was associated with an increase in the growth rate of Internet access of 0.0136 classrooms per teacher per year. If we take the number of full-time equivalent teachers in a school as a proxy for the number of classrooms, this estimate implies that a 10 percent increase in the subsidy is associated with a 1.36 percentage point increase in the fraction of classrooms with Internet access per year. This estimate corresponds to an elasticity of Internet investment with respect to the first subsidy dollar of –1.1.[14] Of course, since this is a linear specification, the marginal elasticity declines as the subsidy increases. The marginal elasticity of Internet investment for appliers once they are already at the mean subsidy rate of 63 percent is closer to –0.4.

Using these results, we can estimate the total impact of the E-Rate program on Internet adoptions. For the mean school, if the subsidy rate were zero, the predicted number of Internet connected classrooms per teacher would be 0.396 by the end of the sample period (2000-01). In fact, the true level with the subsidy was some 68 percent higher at 0.664.

[13] The standard errors are corrected to account for within-district correlation resulting from the fact that there is not school level variation in the subsidy rate every year.
[14] Unless otherwise noted, all elasticities are derived from estimates of models that include all schools and the predicted subsidy rate.

Separate from just what they say about the price-sensitivity of Internet investment, these results are interesting in light of the lack of existing evidence on demand elasticities of public sector organizations and the implications for public policy. The debate over school vouchers, for example, centers on the question of how public schools respond to incentives (see the discussion in Greene, 2001; Neal, 2002; Ladd, 2002; and Hoxby, 2003). Our results are consistent with the view that public schools are quite responsive to economic incentives.[15]

V. Alternative Explanations and Strategic Application Behavior

A potential alternative explanation of the results above that schools with high subsidies have faster growth of Internet connection is that as computer prices fall over time, poor schools (i.e., the schools with high subsidy rates) find it worthwhile to get connected where in earlier periods they did not (though this still cannot explain why the gap between rich and poor schools expanded in the year before the E-Rate program started). Similarly, there could be some other unobserved variable, correlated with being poor, that was increasing relative Internet investment in the time period.

To investigate this alternative interpretation of the main result we compare the relationship between the subsidy rate and Internet investment for appliers and non-appliers. In column 1 of table 4, we present estimates for schools listed on E-Rate applications, using the actual subsidy received (s_{st}). The estimated effect for appliers is larger in magnitude (0.173), a fact that has two potential explanations. First, the earlier estimate included many non-applying schools that should not have responded to a subsidy they did not receive. And second, one reason schools apply for the subsidy is that they would have invested in the technology in the

[15] There are a number of studies of the effect of competition on the output of schools (i.e test scores). See e.g. Bettinger (1999), Greene (2001), Hoxby (2000, 2003, 2005), Rothstein (2005).

absence of the subsidy (i.e. appliers have higher ε_{st}'s than non-appliers). The estimate for schools in districts that never applied for the E-Rate subsidy is reported in column 2 of table 4. In contrast with the estimate for the appliers, the estimate for non-appliers is not significantly different from zero and the point estimate is much smaller. This contrast suggests that the base result is not driven by unobserved factors that happen to be correlated with the subsidy.

We do not take the appliers' estimate that uses the actual subsidy as our base specification because we believe it to be biased by endogenous application choices. Because subsidy rates do not reach 100 percent, districts with greater demand for Internet investment should be more likely to apply for E-Rate funds. Further, because subsidy rates are determined by the poverty rates of applicant schools, applying districts have an incentive to include high-poverty (and exclude low-poverty) schools on their applications. This incentive is offset by efforts to ensure that E-Rate funds only go towards work done at applicant schools. However, the effects of these incentives are apparent in the data. Table 5 compares three groups of schools in 1998-99 and 1999-2000[16]: schools that applied for E-Rate funds (column 1), schools that did not apply but were in districts where other schools applied (column 2), and schools that did not apply in districts where no one applied (column 3).

Districts that applied had higher meal percentages (i.e., higher subsidy rates) than districts that did not. And within districts that applied, the schools that took part in the E-Rate subsidy program had higher meal percentages than those that did not take part. Note that schools appear to have reacted fairly strongly to the economic incentives created by the program rules. This piece of evidence is a window into the management of public schools and may suggest how they respond to outside economic forces. It also highlights a selection problem that

[16] We do not have school-level data on application status for the 2000-01 school year.

almost certainly biases the estimates using a sample of only appliers. Note, however, that in our regression results, we control for the school's poverty rate in a flexible way so bias can only result if selection is based on something other than just the school lunch percentage.

The apparently strategic application behavior documented in table 5 raises another interesting question. Is there any evidence of spillovers from appliers to non-appliers within districts? In a Coasian sense, one might expect that spillovers would be largest in districts with large within-district differences in poverty rates across schools, because the gains to the high-poverty schools from excluding the low-poverty schools would be the greatest. We investigate this hypothesis by adding to the base specification for all non-applying schools an interaction of the subsidy rate, $\tilde{s}_{dt}$, with the difference between the maximum and minimum of s_{st} within the district. This estimate is shown in column 3 of table 4. The estimated interaction is significant and positive, showing that districts with greater disparity across schools in eligible subsidy rates exhibit larger spillovers. Non-appliers in districts with no differences in subsidy rates across schools have an insignificant, negative correlation between the district subsidy rate and Internet growth rate per teacher. Non-appliers in districts with large differences in subsidy rates across schools look like they respond to the program. The largest possible difference across schools is 0.7 (90 percent rate– 20 percent rate). A school in such a district that did not apply for the E-rate responds to the subsidy rate with a coefficient of 0.060 (-0.060 + 0.172*0.7).

A third alternative explanation is that there are diminishing returns to expanding Internet connections so schools that already have a lot of Internet connections will eventually slow down their growth relative to schools that do not. To some extent, this must be true since the fraction of classrooms with Internet access cannot exceed one so the constant growth rate assumption embodied in the fixed effects cannot literally be true. To the extent the late-adopters are high-poverty schools, the diminishing returns story could generate a spurious correlation with the subsidy rate. In our specification, which assumes each school has a permanent trend in Internet investment, we have ruled out diminishing returns. We examine this possibility in column 5 of table 4 by interacting the subsidy rate with the number of Internet connections per teacher the school had at the start of the sample. If the diminishing returns argument is relevant in our time period, this interaction should come in with a negative sign (greater initial connections leads to less price sensitivity). Note that we do not include the initial number of connections at the school on its own because this is absorbed in the school fixed effect.

The results, shown in column 5 of table 4, are consistent with the convergence story. The interaction estimate is significantly negative. The magnitude, however, of the effect is much too small to explain our results. To see this, compare how much the responsiveness differs for schools at the 10^{th} and 90^{th} percentile of the initial Internet per teacher distribution. These schools have, respectively, zero and 0.75 Internet classrooms per teacher in the 1996-97 school year. The estimated coefficients are very close at 0.138 and 0.104. The corresponding first-dollar price elasticities are –1.1 and –0.8.

We also estimate the regression interacting the effect of the subsidy with the initial number of computers per teacher. This estimate, presented in column 6 of table 4, is also consistent with a small convergence effect. Schools with more computers per teacher in the 1996-97 school year are slightly less price sensitive. However, the estimate of the interaction is not significant.

VI. Who is Most Price Sensitive?

The previous results, then, point to a significant impact of the E-Rate subsidy on public schools' Internet investment decisions. In this section we explore what types of schools are most sensitive to the subsidy.

Our first results, presented in table 6, examine differences in price-sensitivity between primary and secondary schools.[17] These are shown in columns 1 and 2. We observe significant investment responses only by primary schools. High school point estimates are quite close to zero, but are imprecise. These regressions include all schools (appliers and non-appliers) to fully account for the selection biases**.**

Next, in columns 3 and 4 of table 6, we present estimates for urban and rural schools. The results indicate that the rural schools are rather substantially less responsive to the subsidy program than are urban schools. One possible explanation is that rural schools may face higher prices for Internet services than urban schools do or are, perhaps, unable to get broadband at all, so that their net price of investment is greater despite having higher subsidy rates. In column 5 we interact the subsidy rate with the share of students in the school that are black, Hispanic, white and Asian. Interestingly, the sensitivity is significantly higher among schools that are heavily black and Hispanic. The sensitivity of schools with high white and Asian student populations is significantly smaller than for those with high black and Hispanic enrollments. Again note that these regressions do control for the school lunch percentage so race is not just a simple proxy for poverty level. It is possible, however, that conditional on poverty status, higher minority population schools are more budget constrained and therefore more sensitive to the subsidy rate.

[17] Secondary schools, or high schools, are those that house at least one grade above 9th. Primary schools are those whose highest grade served is 9th or less. These definitions are chosen to be mutually exclusive.

VII. Outcomes

The analysis above presents evidence that the E-Rate program succeeded in regards to its primary goal of getting classrooms connected to the Internet, particularly at disadvantaged schools (see the original statements of the program's proponents such as Riley, Glickman and Kantor, 1996; Gore, 1997). In this section, however, we extend the evaluation to the next logical level, which is to look at the impact of such investment on student performance. Many of the most prominent supporters of the E-rate program, such as Clinton's Secretary of Education Richard Riley, argued that the program should aspire to more than just wiring schools, that it "must show that it really makes a difference in the classroom, and that means helping students to learn the basics and other core subjects to high standards." (Riley, 1997).

If the subsidy induced Internet investment, it is natural to ask whether this increase in Internet access led to changes in student achievement. To this end, we estimate the following test score equation

$$(5) \qquad \Delta T_{st+1} = \beta' \tilde{s}_{dt} + \alpha'_s + \delta'_t + \gamma'_1 m_{st} + \gamma'_2 m^2_{st} + \varepsilon'_{st}$$

where $\Delta T_{st+1} = T_{st+1} - T_{st}$ is the one-year change in the test score. All test-score regressions are estimated on the full sample of schools. The specification shown in (5) allows a year for Internet access to affect student achievement. We also allow for the possibility that achievement effects appeared with longer lags. Note that if $\tilde{s}_{dt}$ is a valid instrument for $\Delta(I/C)_{st}$ then β'/β is the Instrumental Variables (IV) estimate the effect of the change in Internet access per teacher on the change in test scores.

We measure student achievement with the Stanford Achievement Test, which has been given every year to each public school student in California beginning with the 1997-98 school year. We use three measures of school-level achievement: the normalized mean test score in the school, the fraction of students scoring above the 75th percentile score for the nation, and the fraction of students scoring above the 25th percentile score for the nation. The mean is normalized so that the sample mean is zero and the standard deviation across schools is one. Thus the estimates are reported in units of school-level standard deviations. We allow Internet access to affect student achievement with a one-year lag, and estimate specifications analogous to those reported in table 4.

The results are presented in table 7. The dependent variable is the increase in the school's test score and the regressor of interest is the subsidy rate. In the reported specifications, we use the subsidy rate that the district would face if each school were included on the application. We include all California schools, both those who applied for the subsidy and those who did not. We report estimates for math, reading and science test scores.[18]

The results do not show evidence that Internet investment had a significant effect on student test scores. None of the estimates reported in the table are statistically different from zero, and all are quite small in magnitude. To see this, notice that the coefficient estimate of 0.023 on the mean math score for primary schools implies a 90 percent subsidy rate would increase math test scores by about two percent of a cross-school standard deviation.

While the standard errors are large, they are tight enough to rule out a substantial effect. A relevant comparison might be to ask whether, even at the most extreme end of the confidence interval on the subsidy coefficient, the E-Rate program increased test scores as much as did, say, other successful interventions in public schools such as the 0.22 student-level standard deviation

[18] Results for language, spelling and social studies tests are substantively the same.

increase observed in Krueger's (1999) study of the Tennessee STAR class-size reduction experiments.[19] In our sample, the typical district was eligible for a 63 percent subsidy. Using the upper end of the 95-percent confidence interval of the primary school math estimate, a 63 percent subsidy would lead to an increase of about .099 school-level standard deviations.[20] The 95-percent confidence interval for a 63-percent price subsidy is listed in brackets for all estimates in the table.

Point estimates are larger for the fraction of students scoring above the national 75th percentile, though none is statistically significant. It is also notable that point estimates are larger for primary than for secondary schools, in light of primary schools' larger investment response. However, neither is statistically different from zero, and the difference between the primary and secondary test score results is not significant.

Of course test scores are not the only measure of student performance and the Internet might enhance students' learning in ways that do not show up on standardized tests. For the few non-test outcomes we have, though, such as the probability of taking advanced classes, the share of graduates going into the UC system (i.e., the system with higher standards), and the overall dropout rate, we found no significant impact of Internet connections on performance. It is probably a stretch to expect to find the impact of technology subsidies on most of these variables, especially given the fact that we find no significant effect on Internet subsidies for high schools.

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[19] Krueger (1999) reports effects in standard deviation units across students rather than across schools. We have only school and district level data. The micro level standard deviation across students is likely to be significantly greater than across schools (the standard deviation across schools is about 15-20% greater than across districts) so a comparable comparison in our data would find effects smaller than what we report.

[20] It is worth noting, though, that the comparable cost of the STAR experiment was much greater than the cost of the E-Rate.

The E-Rate subsidy had two stated goals: to increase Internet access in schools and to improve student achievement. The evidence suggests rather strongly that it did the first. Regarding performance, there is no significant evidence of an impact, though the estimates are fairly imprecise. An absence of large student achievement gains might arise for any number of reasons. For one, this technology may not help measurable student achievement, though it may build skills that are unmeasured by standard tests. An equally plausible explanation is that people simply did not use the technology once they got it. This would certainly be consistent with the evidence discussed in U.S. Department of Education (2000b) that only one third of teachers reported that they were well prepared or very well prepared to use computers and the Internet, or in Clarkson (2000) that most teachers surveyed are "novice or completely inexperienced" with computers. Without direct evidence on teacher time-use in the classroom we can only estimate the effect of Internet *access* and not of Internet *usage*.

It is also possible that technology improves education but only with a lag so that it is too early to detect the impact on performance. Perhaps it takes time for the teachers to learn how to use the Internet in their classes. A lagged effect is unlikely to result from the cumulative nature of education, however, since the elementary school test results (where cumulative effects are not relevant) do not show any increase in performance. We address the possibility of a longer lagged effect on test scores directly in table 8. The table shows test score estimates that correspond to those in table 7, except that they measure test score effects two years after observed Internet investment, rather than one year later. It does not appear that effects two years after the investment are larger in magnitude. Many of the point estimates go down over time, not up. One exception is the results for science mean test scores. These estimates, however, have exceptionally large standard errors. At least in the short-run, there is no evidence supporting the view that schools are learning how to use Internet technology in a way that affects test scores with a lag.

Even if there were a large benefit to Internet investment that we cannot yet measure, we should not view such a lagged effect as having no cost. The subsidy costs more than two billion dollars per year and the subsidies may lead schools to get locked in to inferior technologies or, at the least, lead them to buy at higher cost (given the extremely rapid declines in the price of computer related goods). As an example, note that in table 2, almost 80 percent of total E-Rate funds were allocated to "Internal Connections," which includes the cost of wiring schools. Had the subsidy not accelerated investments, many schools could have avoided the costs of physical infrastructure by using the now common (and inexpensive) wireless networks.

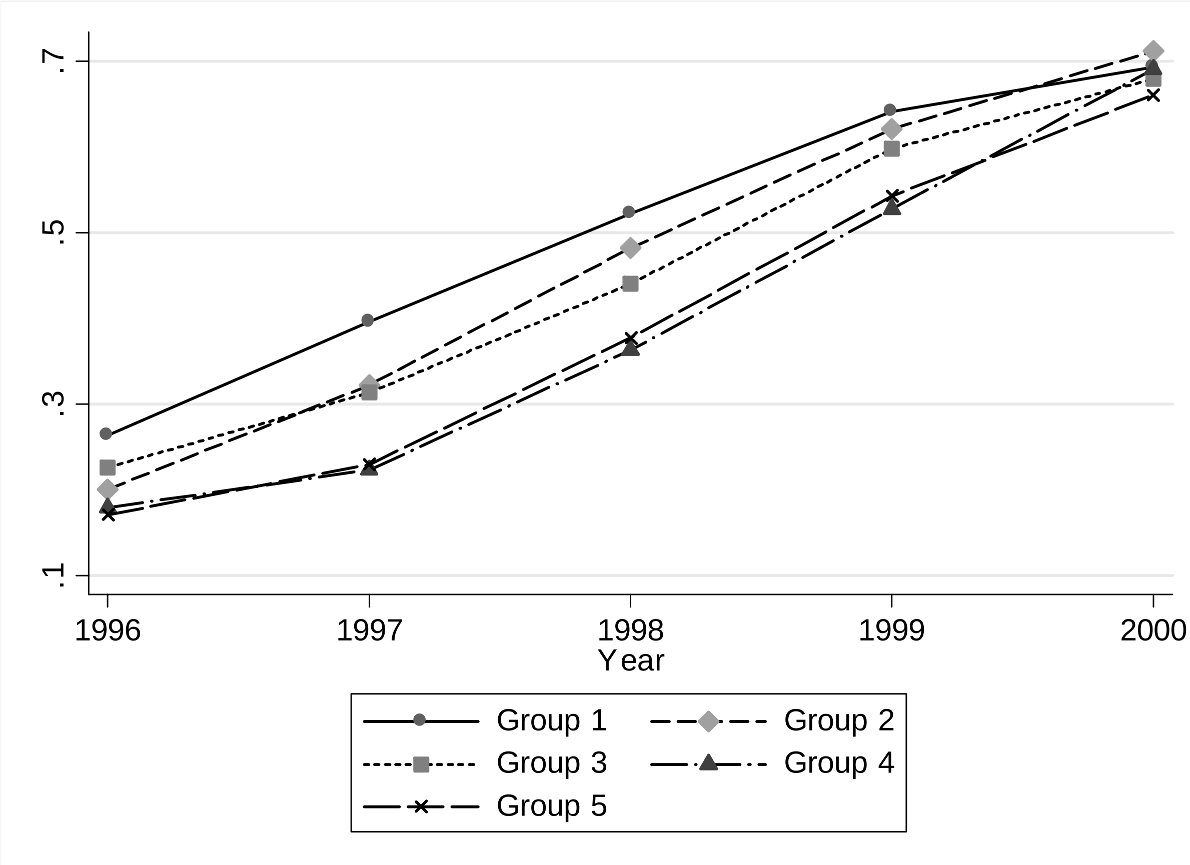
VIII. Conclusion

The rise of the Internet and the spread of a digital divide led to concern among policy-makers about the implication for long-term economic inequality. This concern inspired the expansion of the Universal Service Fund to subsidize Internet and communication technology investment by more than $2 billion per year (itself more than half of all public school computer spending in the year). The expansion was implemented in 1998 and provided a sliding scale subsidy, called the E-Rate, between 20 and 90 percent.

In this paper, we have taken a first step towards evaluating the effect the E-Rate subsidy had on Internet investment in California's public schools. We find that despite the strong pre-1998 income gradient of Internet access, E-Rate funding went disproportionately to low-Internet schools. We also show evidence that the E-Rate subsidy led to significant increases in Internet investment. By 2000, there were some 68 percent more classrooms with Internet connections than there would have been without the subsidy. Urban schools, predominantly black and Hispanic schools and primary schools are disproportionately responsive to the subsidy. Predominantly white and Asian schools, rural schools and high schools show less sensitivity to the subsidy rates. Judged as a policy to close the digital divide among schools, the program clearly succeeded.

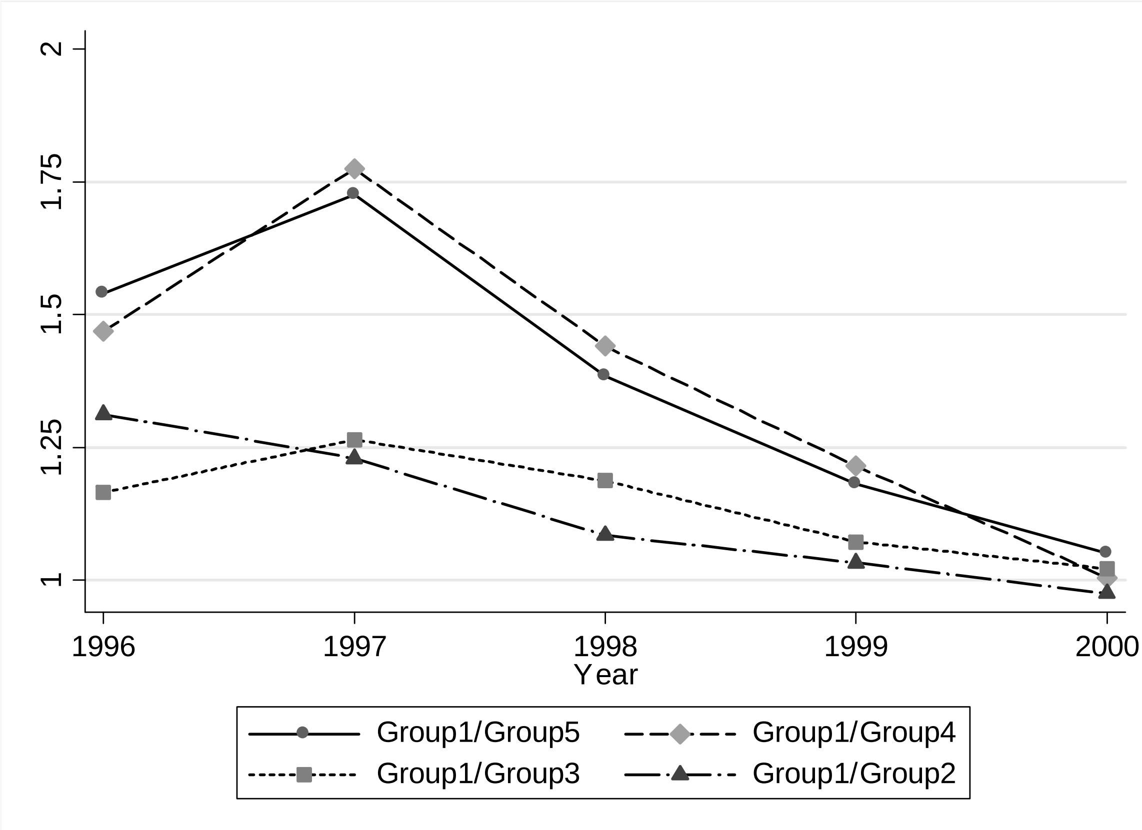
Judged as a means of improving student performance, however, we fail to find strong evidence of success. Despite the noticeable impact on the expansion of the Internet, estimated effects on test scores in a variety of subjects are indistinguishable from zero.

FIGURE 1: TREND IN CLASSROOMS WITH INTERNET ACCESS PER TEACHER BY 1997-1998 POVERTY STATUS



Note: The figure shows yearly averages of the number of classrooms with Internet access per teacher for five groups of districts. The 1996-1997 school year is labeled 1996, etc. Group 1 is districts with 0 to 20 percent of their students eligible for the federal free or reduced lunch programs in 1997-1998, the year before the availability of the E-Rate subsidy. Similarly, Group 2: 20 to 40 percent eligible; Group 3: 40 to 60 percent eligible; Group 4: 60 to 80 percent eligible; Group 5: 80 to 100 percent eligible.

FIGURE 2: RELATIVE TREND IN CLASSROOMS WITH INTERNET ACCESS PER TEACHER



Note: The figure shows yearly ratios of the number of classrooms with Internet access per teacher for four groups of districts, relative to a fifth group. The 1996-1997 school year is labeled 1996, etc. Group 1 (the reference group) is districts with 0 to 20 percent of their students eligible for the federal free or reduced lunch programs in 1997-1998, the year before the availability of the E-Rate subsidy. Similarly, Group 2: 20 to 40 percent eligible; Group 3: 40 to 60 percent eligible; Group 4: 60 to 80 percent eligible; Group 3: 80 to 100 percent eligible.

TABLE 1: SCHOOL SUBSIDY RATES AND FUNDING TOTALS FOR THE E-RATE PROGRAM

% of Students Eligible for National School Lunch Program	Urban Discount Percentage	Rural Discount Percentage	% of California Districts in Category	Total E-Rate Funds (in $ millions)	Total E-Rate Funds per Pupil (in $)	Internet Classrooms per Teacher in 1996-97
(1)	(2)	(3)	(4)	(5)	(6)	(7)
< 1	20	25	10.1	16	127	.45
1-19	40	50	16.1	14	17	.21
20-34	50	60	19.7	38	35	.14
35-49	60	70	15.5	36	40	.15
50-74	80	80	24.8	597	248	.12
75-100	90	90	13.8	178	341	.08

Note: The table lists the subsidy rate awarded to schools in each of six categories based on the fraction of students eligible for the federal free and reduced price school lunch programs. Columns 5 and 6 of the table also lists the totals of E-Rate funds awarded to California public schools in each category in the first three years of the program. Column 7 of the table lists the ratio of Internet classrooms in 1996-97 to full-time equivalent teachers in California public schools in each category.

TABLE 2: MEANS OF TECHNOLOGY AND E-RATE VARIABLES

	1996-1997	1997-1998	1998-1999	1999-2000	2000-2001
Technology					
Fraction of Schools with Any Internet Connections in Classrooms	.46 (.50)	.55 (.50)	.70 (.46)	.77 (.42)	.84 (.36)
Classrooms with Internet Connections	4.5 (12.4)	7.7 (16.8)	11.8 (12.9)	17.7 (33.4)	21.7 (29.3)
Classrooms with Internet Connections per Teacher	.17 (.42)	.26 (.90)	.38 (.54)	.54 (.74)	.66 (.81)
Fraction of Schools with Any Computers for Instructional Purposes	.94 (.23)	.93 (.26)	.96 (.18)	.97 (.17)	.98 (.14)
Computers for Instructional Purposes	62.2 (63.4)	70.1 (73.0)	80.6 (83.7)	92.0 (97.0)	102.6 (107.7)
Computers for Instructional Purposes per Teacher	2.1 (1.8)	2.2 (2.4)	2.5 (3.4)	2.8 (2.2)	3.1 (2.2)
Number of Districts	1,056	1,053	1,057	1,055	1,055
Number of Schools	7,991	8,186	8,340	8,641	8,812
E-Rate Funds: (in $000)					
Total Funds Committed: U.S.			1,712,000	2,127,000	2,123,000
Total Funds Committed: CA			208,000	254,000	475,000
Total Funds Committed: CA in Data Used in the Analysis			181,000	222,000	446,000
Internet Access			3,723	7,370	5,119
Telecommunications			46,300	47,300	54,700
Internal Connections			126,000	166,000	386,000

Note: The top panel of the table reports school-level means of technology measures. The data come from the California Department of Education. Unless otherwise noted, values report counts of Internet classrooms or counts of computers. Standard deviations are reported in parentheses. The bottom panel of the table reports aggregate annual E-Rate dollar commitments. Values are reported in thousands of dollars.

TABLE 3: REGRESSION-DISCONTINUITY ESTIMATES

	First Stage	Reduced Form		Wald Estimate
Cutoff	$\Delta\tilde{s}_{dt}$	Pre E-Rate: $\Delta(I_{st}/C_{st})$	E-Rate: $\Delta(I_{st}/C_{st})$	$\frac{\Delta(I_{st}/C_{st})}{\Delta\tilde{s}_{dt}}$
Pooled	.028 (.006)	.003 (.038)	.055 (.030)	1.933 (1.149)
1%	.089 (.019)	-.134 (.211)	.152 (.157)	1.709 (1.830)
20%	.024 (.012)	.085 (.091)	-.013 (.045)	-.536 (1.845)
35%	-.014 (.014)	.038 (.059)	.070 (.052)	-5.166 (6.029)
50%	.031 (.015)	.007 (.054)	.109 (.057)	3.609 (2.744)
75%	.038 (.012)	-.071 (.066)	.007 (.062)	.183 (1.638)

Note: The table shows the difference in the subsidy and Internet classrooms per teacher between schools just above and just below each of the five cut-offs in the E-Rate subsidy formula. "Just above" and "just below" is defined as having a meal percentage within one percentage point of the respective cutoffs. The pooled row reports regression estimates of the pooled difference across all cut-offs controlling cut-off fixed effects. The Pre-E-Rate column refers to data from 1996 to 1997. The E-Rate column refers to data from 1998 to 2000. The Wald estimate column reports the ratio of the difference in Internet classrooms per teacher and the difference in subsidy rates.

TABLE 4: FIXED-EFFECT ESTIMATES OF THE EFFECT OF THE E-RATE SUBSIDY ON THE GROWTH RATE OF INTERNET ACCESS

	Actual Subsidy	*Subsidy Faced if All Schools had Applied*				
	Appliers	District Non-appliers	School Non-appliers	All Schools		
	(1)	(2)	(3)	(4)	(5)	(6)
District Subsidy Rate	.173 (.068)	.076 (.086)	-.060 (.083)	.136 (.042)	.138 (.042)	.146 (.044)
* Max – Min School Subsidy in district			.172 (.082)			
* Internet per teacher ’96-‘97					-.046 (.017)	
* Computers per teacher ’96-‘97						-.007 (.005)
School Lunch Percentage	-.068 (.152)	-.083 (.248)	-.080 (.296)	-.033 (.119)	-.092 (.119)	-.091 (.119)
School Lunch Percentage^2	.146 (.148)	-.146 (.235)	.161 (.272)	.064 (.119)	.129 (.119)	.129 (.119)
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	.24	.24	.35	.20	.18	.18
Observations	24,061	3,684	4,340	31,243	29,667	29,667

Note: The dependent variable is the increase in the number of classrooms with Internet access per teacher since last year. All standard errors account for district-level correlation in the error term. Observations are at the school-level. There is a separate observation for each year of the sample, from 1997-1998 to 2000-2001. District non-appliers are schools in districts in which no school ever applied during the sample period. School non-appliers are schools that did not apply in the current year. Appliers are schools that applied in the current year. The Max – Min of School Subsidy in the district is equal to the difference between the maximum and the minimum subsidy for which individual schools within the district are eligible as lone appliers.

TABLE 5: CHARACTERISTICS OF SCHOOLS BY APPLICATION STATUS, 1998-99 AND 1999-2000

	Applied:		
	School: Yes District: Yes	School: No District: Yes	School: No District: No
School Lunch Percentage	.51 (.30)	.40 (.34)	.33 (.30)
Enrollment	773 (599)	502 (599)	574 (544)
Pupil-Teacher Ratio	20.7 (4.0)	21.2 (25.1)	19.6 (9.7)
Fraction White	.38 (.29)	.43 (.30)	.56 (.27)
Fraction Black	.09 (.13)	.11 (.15)	.04 (.07)
Fraction Hispanic	.41 (.29)	.35 (.27)	.30 (.26)
Fraction Asian	.11 (.14)	.08 (.10)	.07 (.10)
Elementary School	.70 (.46)	.55 (.50)	.63 (.48)
Middle School	.57 (.49)	.55 (.50)	.53 (.50)
High School	.17 (.38)	.39 (.49)	.26 (.44)
Computers per Student	.14 (.12)	.21 (.48)	.19 (.34)
Internet Classrooms per Student	.02 (.03)	.04 (.12)	.04 (.09)

Note: The table reports means of selected characteristics for three groups of California schools in 1998-99 and 1999-2000. The year 2000-2001 is dropped because we do not have the necessary data. The first column includes schools that received E-Rate funds. The second column includes schools that did not receive E-Rate funds, but that are in districts in which other member schools received E-Rate funds. The third column includes schools in districts in which no schools received E-Rate funds. All category definitions are year-specific.

TABLE 6: WHO IS MOST PRICE SENSITIVE?

	Primary Schools (1)	Secondary Schools (2)	Urban (3)	Rural (4)		All (5)
District Subsidy Rate	.158 (.049)	.062 (.058)	.173 (.050)	-.013 (.067)	Subsidy Rate * % White	.029 (.052)
					* % Hispanic	.122 (.044)
					* % Black	.226 (.093)
					* % Asian	.005 (.107)
					* % Other	-.028 (.097)
School Lunch Percentage	.109 (.167)	-.068 (.148)	.045 (.132)	-.252 (.209)		-.024 (.118)
School Lunch Percentage ^{2}	-.014 (.160)	.036 (.145)	.023 (.133)	.170 (.182)		.061 (.116)
Year Effects	Yes	Yes	Yes	Yes		Yes
School Effects	Yes	Yes	Yes	Yes		Yes
R^2	.20	.22	.20	.20		.20
No. Obs.	24,837	6,322	27,305	3,934		31,240

Note: The dependent variable is the increase in the number of classrooms with Internet access per teacher since last year. All standard errors account for district-level correlation in the error term. Observations are at the school-level. There is a separate observation for each year of the sample, from 1997-1998 to 2000-2001. Primary Schools are defined as schools that house no grades above 9^{th} grade. Secondary Schools, or High Schools are defined as schools that house at least one grade above 9^{th}. The first four columns report estimates from separate regressions run on samples indicated by the column headings. Column 5 reports results from a single regression in which the subsidy rate is interacted with the percent in each racial/ethnic category.

TABLE 7: THE E-RATE SUBSIDY AND THE INCREASE IN STUDENT TEST SCORES:
(Standard errors in parentheses, 95-percent confidence interval at the mean subsidy in brackets.)

	Test Score Mean (Std. Dev.)	All Schools	Primary Schools	Secondary Schools
	(1)	(2)	(3)	(4)
Mean:				
Math	638.2 (39.6)	.001 (.064) [-.080, .082]	.023 (.067) [-.069, .099]	-.197 (.178) [-.348, .100]
Reading	640.7 (38.4)	-.025 (.083) [-.121, .089]	.019 (.087) [-.098, .122]	-.298 (.199) [-.438, .062]
Science	662.7 (40.4)	-.003 (.224) [-.284, .280]		-.051 (.222) [-.312, .248]
75th Percentile:				
Math	25.2 (18.3)	.95 (.83) [-.44, 1.64]	1.17 (1.00) [-.53, 2.00]	-.32 (1.06) [-1.54, 1.13]
Reading	20.4 (16.3)	.11 (.84) [-.99, 1.13]	.52 (.98) [-.91, 1.57]	-1.12 (.89) [-1.82, .41]
Science	14.0 (12.3)	.29 (1.21) [-1.35, 1.71]		.10 (1.22 [-1.48, 1.60]
25th Percentile:				
Math	69.7 (18.8)	-1.84 (.94) [-2.34, 0.03]	-1.71 (.98) [-2.32, .16]	-3.38 (3.14) [-6.09, 1.83]
Reading	65.7 (21.1)	-1.40 (1.62) [-2.93, 1.17]	-.34 (2.09) [-2.85, 2.42]	-5.31 (2.35) [-6.30, -.39]
Science	63.7 (18.8)	-1.82 (2.64) [-4.47, 2.18]		-1.79 (2.67) [-4.49, 2.25]

Note: Column 1 reports state-wide means (and school-level standard deviation) of test scores. Percentile test scores are the percent of students in each school-year that scores above the 75th or 25th percentile as calculated for the nation. Each entry in columns 2–4 of the table is the coefficient estimate on the subsidy variable ($\tilde{S}_{dt}$) from a separate regression. The dependent variable in these regressions is year *t* to year *t+1* change in the relevant test score. Standard errors that account for district-level correlation in the error term are listed in parentheses. In brackets is the 95-percent confidence interval of the estimate for a district with a 63 percent subsidy, the sample average.

TABLE 8: THE E-RATE SUBSIDY AND THE INCREASE IN STUDENT TEST SCORES TWO YEARS AFTER
(Standard errors in parentheses, 95-percent confidence interval at the mean subsidy in brackets.)

	Test Score Mean (Std. Dev.)	All Schools	Primary Schools	Secondary Schools
	(1)	(2)	(3)	(4)
Mean:				
Math	638.2 (39.6)	-.178 (.096) [-.234, .009]	-.058 (.073) [-.128, .055]	-.042 (.393) [-.522, .469]
Reading	640.7 (38.4)	-.187 (.110) [-.257, .021]	-.045 (.076) [-.124, .067]	-.094 (.373) [-.529, .411]
Science	662.7 (40.4)	.573 (.476) [-.239, .961]		.629 (.471) [-.198, .990]
75th Percentile:				
Math	25.2 (18.3)	1.86 (1.45) [-.65, 3.00]	2.51 (1.67) [-.53, 3.69]	.30 (1.75) [-2.02, 2.40]
Reading	20.4 (16.3)	.50 (1.30) [-1.33, 1.95]	.99 (1.50) [-1.27, 2.52]	-.66 (1.00) [-1.67, .85]
Science	14.0 (12.3)	1.00 (1.41) [-1.14, 2.40]		.83 (1.42) [-1.26, 2.30]
25th Percentile:				
Math	69.7 (18.8)	-3.94 (1.44) [-4.29, -.67]	-2.98 (1.76) [-4.10, .34]	-8.55 (3.32) [-9.57, -1.21]
Reading	65.7 (21.1)	-1.89 (2.49) [-4.33, 1.95]	-.414 (2.99) [-4.03, 3.50]	-7.01 (2.82) [-7.97, -.87]
Science	63.7 (18.8)	-4.47 (3.54) [-7.27, 1.64]		-4.35 (3.57) [-6.93, 2.31]

Note: Column 1 reports state-wide means (and school-level standard deviation) of test scores. Percentile test scores are the percent of students in each school-year that scores above the 75^{th} or 25^{th} percentile as calculated for the nation. Each entry in columns 2–4 of the table is the coefficient estimate on the subsidy variable ($\tilde{S}_{dt}$) from a separate regression. The dependent variable in these regressions is year *t* to year *t+2* change in the relevant test score. Standard errors that account for district-level correlation in the error term are listed in parentheses. In brackets is the 95-percent confidence interval of the estimate for a district with a 63 percent subsidy, the sample average.

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