Impact of school district demographics and financial status on E-Rate funding: Analysis of Pennsylvania data for 1999 and 2004

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Abstract

The E-Rate program was mandated by the 1996 Telecommunications Act to bridge the gap in telecommunications and internet access between rich and poor communities in the United States. The funding process has specific formulas to direct support at the most needy schools and school districts. However, observers have also pointed out that the complex, multi-stage application process may prevent some school districts from availing of E-Rate funds due to lack of technical expertise and administrative support. Thus, the intent of the act to provide support to the neediest schools is at least partially neutralized by procedural hurdles and resource constraints. The objective of the paper is to assess the cumulative impact of these two contradictory effects. We also examine learning effects and hypothesize that the funding gap between poor/rural school districts has narrowed over time due to experience and better information. Data on all E-Rate funded projects where the recipient is a school district were collected for two years, 1999 and 2004, for the state of Pennsylvania. Results indicate strong support for the policy intent hypothesis. E-Rate per funding per student for individual projects is significantly positively correlated with percentage of families below the poverty line and percent minority students, and negatively with median family income. However, we also find that rural school districts continue to be disadvantaged compared to their urban peers. Policy implications include further simplifying the E-Rate application process, and using at least part of the E-Rate funding corpus to provide technical information on school networking to poor/rural school districts.

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— Krishna Jayakar and Eun-A Park

The E-Rate program, mandated by the 1996 Telecommunications Act to bridge the gap in telecommunications and internet access between rich and poor communities in the United States, has been instrumental in reducing the digital divide in America's schools, with nearly all schools in the nation now reporting that they are connected to the internet. However, internet access is not fully equalized yet especially in terms of classroom access and the quality of connections: for example, the National Center for Educational Statistics [NCES] (2005) reported that 97 percent of instructional classrooms in town schools have internet access, whereas only 90 percent of classrooms in city schools do; similarly, 98 percent of town schools have broadband connections while only 90 percent of rural schools do. Similar gaps exist in terms of number of computers per student and the variety of instructional software available in rich and poor schools.

It was in order to bridge persistent gaps like these that specific formulas were incorporated into the E-Rate funding mechanisms to direct support at the most needy schools and school districts. Schools receive discounts for telecommunications access ranging from 20 percent to 90 percent of total eligible spending depending on the poverty level prevailing among the school's students—specifically, the percentage of students enrolled in the school lunch program. Data from the Universal Service Administration Company (USAC) shows that poorer schools have indeed benefited significantly from the E-Rate program in every year since the program's inception.

However, observers have also pointed out systemic factors that prevent poorer school districts from fully availing of E-Rate funds: specifically, the complex, multi-stage application process has been criticized as too time-consuming, labor intensive and prone to pitfalls (Dickard, 2003; Bracey, 2004). Poor school districts that want to apply for E-Rate funds may simply lack the technical expertise, administrative support and time to put together effective proposals for funding. Thus, policy aim of supporting the neediest schools is at least partially neutralized by procedural and resource constraints.

How have these contrasting influences affected the ability of school districts of different demographic and financial profiles to apply for and receive E-Rate funding? We examine this question using data on E-Rate funding disbursements and school district characteristics from one state, Pennsylvania. To further limit data needs, we focus only on school districts, though individual schools and libraries are also eligible to receive funding. To identify changes, if any, in these relationships over time, we compare data from two years, 1999 and 2004.

The paper is organized as follows. First, we provide an overview of the E-Rate program, with a special focus on the procedures for the disbursement of funds. Second, we present empirical studies on the patterns of distribution of E-Rate funds, and identify the key variables that have been used in the past as predictors of E-Rate funding. In this section, we also frame a set of hypotheses to be tested in this paper. In the third section, we introduce our data and methodology. We present the results in the next section, and finally discuss the policy implication of our findings.

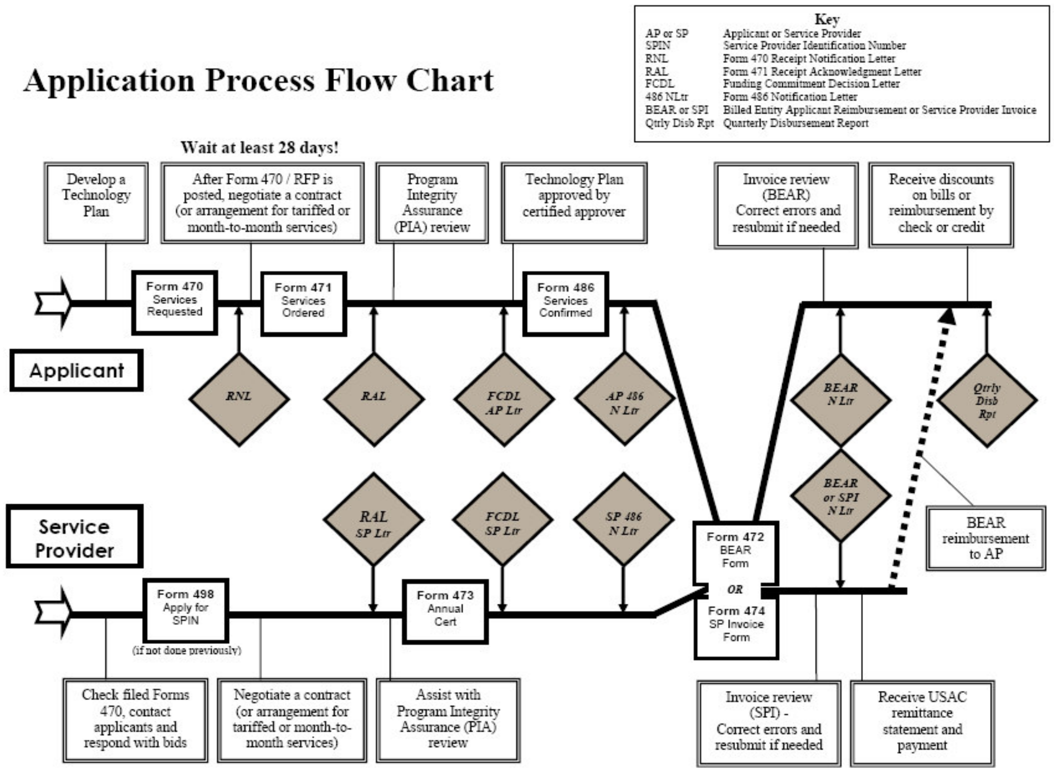
Overview of the E-Rate program

The E-Rate program is one of a set of universal service initiatives mandated by the 1996 Telecommunications Act. Funding from the program is available for libraries, and for all public schools, as well as non-profit private schools and parochial schools with less than $50 million in endowments. These schools will receive discounts for telecommunications access ranging from 20 percent to 90 percent of total eligible spending. The percentage of discounts are be indexed to the poverty level prevailing among the school's students—specifically, the percentage of students enrolled in the school lunch program in the schools that are participating in a E-Rate funded project.

Schools entitled to receive support from the E-Rate program can use the funds for a variety of purposes related to telecommunications and internet access. But in order to prevent abuse or diversion of funds to non-eligible uses, an elaborate list of covered and non-covered expenditure categories have been evolved over time. In general, telecommunications services and internet access services are eligible for support from the E-Rate fund. In addition, internal wiring such as cabling and file servers for serving multiple users is also eligible (USAC, 2003). End user equipment, software (unless it is file server or e-mail software) and content are not eligible for support. Further, the E-Rate program also requires that schools have to obtain telecommunications and internet access services from an 'eligible' telecommunications provider, namely one that has been approved by state and federal regulators to offer telecommunications services in that area. Any commercial vendor can install internal wiring and connections.

Currently, a non-profit organization called the Universal Service Administration Company [USAC] implements that E-rate program. Incorporated in 1997, the USAC has four divisions – High Cost, Low Income, Rural Health Care and Schools and Libraries – active in each of the areas in which Congress had mandated universal service support (USAC, 2005). The Schools and Libraries Division (SLD) is responsible for the E-Rate program. The SLD is responsible, in addition to other duties, for generating projections of funding demand for the E-Rate program; determining discount levels; administering the review process and disbursing funds.

The source of funding for the E-Rate program, as well as for all other universal service initiatives administered by the USAC, is the federal Universal Service Fund (USF). The 1996 Telecommunications Act mandated that all telecommunications service providers must contribute in an equitable and non-discriminatory manner to a fund that will support universal service programs for low-income customers, high cost areas, schools and libraries, and rural health-care providers. The FCC determines contributions from each telecommunications provider based upon a calculation involving the total expected quarterly funding demand for the various USAC universal service programs, and the projected quarterly interstate and international end-user telecommunications revenues for all telecommunications providers (FCC, 2003). In 2002, the USAC received $7.06 billion dollars from contributors and distributed over $6.52 billion through its various universal service programs (USAC, 2005). The E-Rate program alone is authorized to distribute a maximum of $2.25 billion per year to schools and libraries—actual disbursements in the last five years have varied between $1.41 billion to $1.68 billion annually.



Source: Schools and Libraries Division [SLD] (2005)

Funding under the E-Rate program is provided on an annual funding cycle that runs from July 1 through the following June 30. In order to claim E-Rate discounts, schools and libraries have to follow a multi-step process, beginning with the preparation of a technology plan. In it, the applicant identifies goals for the use of ICTs in the school or library, the staff training strategies, hardware and software requirements, overall budget (including expenditures not covered in the E-Rate program) and post-installation evaluation procedures (USAC, 2002c). The applicant then prepares a formal request for service to the Schools and Libraries Division, which will be posted at the division's web site for service providers to view and respond. Applicants are expected to wait at least 28 days for potential service providers to respond, and to give all bids fair and equal consideration. At the end of this bid review process, the applicant chooses a provider and files a second form with the SLD during a specially designated time period (a 'filing window') for each annual funding cycle. If the funding request is approved, the SLD sends out letters to both the applicant and the chosen service provider. This stage is also used to determine the discount percentage that the applicant is entitled to receive, which could range from 20% to 90% of total program costs. On receipt of the letter, the applicant and the service provider may begin work on the program. Payments are then made as and when the approved products and services are delivered. Applicants can either make payment in full for all services received and receive reimbursement from the SLD up to the approved funding level, or receive discounts on their bills from service providers in which case the SLD will make payments directly to the service provider. A flowchart for the entire process is provided above, courtesy of the USAC (2005).

Analyses of E-Rate Funding Patterns

As discussed in the preceding section, the E-Rate program has put in place a complicated, multi-stage process for reviewing applications. Given the many allegations of fraud and misuse of funds that have periodically surfaced, it is perhaps necessary to thoroughly review each application. However, complicated and resource-intensive nature of the application process also implies that at least some school districts may not have the expertise or personnel required to put together quality proposals. As one survey revealed, excessive paperwork and lack of proper training were the principal reasons that school districts mentioned for their failure to get E-Rate funding (Harris, 2001). It therefore becomes necessary to examine the patterns of funding disbursements taking into account school district demographics and financial profiles. We begin by reviewing the data on school internet access, and analyses available in the literature.

Data on internet and telecommunications access seem to indicate that the gaps in telecommunications and internet access have significantly narrowed in the years since the inception of the E-Rate program.[1] In 1997, when the E-Rate program was initiated, 78 percent of all American public schools were connected to the internet (NCES, 2005). By 2004, the last year for which data is currently available, internet access had increased to 100 percent of schools. In 1997, there were significant gaps in access between inner city schools (74 %), rural schools (79%) and “town” schools (84%). By 2004, this gap had vanished with all schools reporting that they have internet access. In 1997, a large gap existed across poverty levels: 86 percent of schools with affluent students (with less than 35% of students eligible for the free or reduced-price lunch program) had internet access, whereas only 62 percent of schools with poor students (with more than 75% of students eligible for the free or reduce-price lunch program) did. By 2004, this gap had become negligible (100% and 99%).

This is not to say that the objectives of the E-Rate program have been fully achieved. While almost all schools now have internet access, there are still gaps in the

[1] Needless to say, correlation is not causation, and we do not argue that the E-Rate was the only, or even the principal, factor that narrowed the access gap. Other government programs such as the Technology Innovation Challenge Grants and the Technology Literacy Challenge Funds have supported school technology as well (Office of Educational Technology, 2000). However, the E-Rate program is by far the best funded of government programs supporting school technology: in the first three years of the E-Rate program, the E-Rate program accounted for 74.5% of all federal spending on school technology. Still, as others too have pointed out (Goolsbee & Guryan, 2006), the E-Rate legislation was passed amidst a broad-based Internet boom; schools might have adopted telecommunications and Internet access even in the absence of E-Rate subsidies, but the program may certainly have influences school districts at the margin to adopt the technology.

percentage of instructional classrooms with internet access between rich and poor schools and in urban and rural areas. In 2003, only 90 percent of classrooms in schools with the highest concentration of poor students had access to computers with internet access, compared to 95 percent in schools with the lowest concentration of poor students (NCES, 2005). There are also differences in the number of students per internet-accessible computer: inner city schools have 5 students on average for each computer, while "town" schools have 4.1 students per computer and rural schools only 3.8 students per computer. All gaps have narrowed across the board between 1997 and 2003, but the digital divide still exists in American schools.

Data on E-Rate fund disbursements show interesting variations when taking into account school district demographics and financial status. For 2005, the USAC (2005) reported that fully 49% of funding went to applicants in the highest discount bands (with more than 50% of students eligible for the free or reduced rate lunch program) (see Table 1 below). A comparison of data from prior years (1998-2000) revealed a similar pattern. (GAO, 2001). Thus the data indicate that E-Rate program followed the legislative intent of supporting the neediest schools in its disbursements.

Table 1: E-Rate Funding by Discount Bands ($ millions), 2005

Discount Band	Telecom Services	Internet Access	Internal Connections	Total	% of Total
20-29%	1.6	0.4	0.0	2.0	0.17%
30-39%	5.0	1.0	0.0	6.0	0.52%
40-49%	76.9	20.8	0.0	97.6	8.51%
50-59%	76.0	21.5	0.0	97.5	8.50%
60-69%	118.7	30.3	0.0	149.0	12.99%
70-79%	183.1	50.1	0.0	233.2	20.33%
80-89%	205.9	47.5	0.0	253.4	22.10%
90%	46.1	16.6	245.4	308.2	26.87%
Total	713.2	188.1	245.4	1146.8	100.00%

Source: USAC (2005); Notes: Discount bands are determined based upon the percentage of students eligible for the free or reduced rate lunch program; In 2005, only applicants in the 90% discount band were eligible to receive funding support for internal connections.

Several studies have analyzed E-Rate funding data using the state as the unit of analysis, using comparison of means (Hudson, 2002; Staihr & Sheaff, 2001) and multivariate regression techniques (Panagopoulos, 2005). Hudson (2002) analyzed patterns of E-Rate disbursements across states for the period 1998-2001, correlating income and rurality with E-Rate funding support per capita of population. She found a wide range of outcomes, from Alaska that received more than 278 percent of its population-based share, to New Hampshire that received only 14 percent. Though several of the states that received more than their share in population-based terms were very rural (Alaska, New Mexico), other rural states received less than their population-based share (Utah, South Dakota, Maine, Iowa). Surprisingly, Hudson found that New York and Illinois, "prosperous states with a mix of rural and urban areas" (pp. 313-314) were among the outperformers. She speculates that better local-level organization or professional assistance might have helped these states claim more than their share of E-Rate funding support.

Staihr and Sheaff (2001) also looked at state-by-state variations in E-Rate support, focusing on rural counties. Analyzing data from a subset of 15 states, they found that practically all rural counties received some E-Rate funding, though the per capita funding varied from as little as $0.02 for one rural county in Arkansas, to a high of $285.60 for a New Mexico rural county. But on average, there was less variation across states, than there was within the same state. Also, contrary to the intent of the 1996 Telecommunications Act that E-Rate funding should serve to equalize internet access between rural and urban areas, average per capita funding for rural counties in 6 of the 15 states analyzed was lower than the statewide average. Staihr and Sheaff speculate that three factors might account for these observed variations in E-Rate funding patterns: the age of the existing infrastructure, with states having older internal wiring and equipment having a greater incentive to apply for E-Rate funds; the local geography, that can affect the cost of providing service; and how aggressive school districts are in pursuing funding.

Panagopoulos (2005) conducted a multivariate regression analysis of E-Rate funding data by state, using population, percentage of population in the rural areas, the state's education level (using the proportion of the state's population with at least a bachelor's degree), computer penetration, and median income as the predictors. Using data for 2002, Ordinary Lease Squares (OLS) estimation showed that only population was a significant predictor of E-Rate funding support, with more populous states receiving more funding. None of the other variables were significant.

In contrast to the above studies that have utilized statewide data, several others have used school districts or individual schools as the unit of analysis (Goolsbee & Guryan, 2006; Harris, 2001; Puma, Chaplin & Pape, 2000). Puma, Chaplin and Pape (2000) conducted a massive study of all E-Rate funding applications nationally, covering the first two years of the program. They found that poor and rural school districts increased their application rate, and their average funding per application between the two years. However, the found that the most impoverished school districts had lower participation rates, perhaps due to "limited knowledge of the E-Rate program, limited capacity to apply for E-Rate funds, limited funds for the co-payments, and/or limited technical expertise to use the purchased services" (p. 99).

Other studies have narrowed their focus to a single state, due to the sheer number of funded applications each year. For example, Goolsbee and Guryan (2006) analyzed panel data on school internet access in California for the period 1996-2000, using the school district subsidy rate as a predictor variable. The school district subsidy rate is calculated as the average E-Rate subsidy rate faced by applicant schools in the school district, which in turn is correlated with the poverty rate in the school district. They found that the annual change in the number of internet-accessible classrooms per teacher in each school was positively affected by the district subsidy rate: this effect was more pronounced in schools that applied for E-Rate funds, than in those that did not. The authors interpreted these results to say that the growth rate of internet access was higher in poorer schools during the 1996-2000 period (i.e. those most eligible to receive E-Rate support), with the highest growth rates recorded in schools that actually received E-Rate support. They estimate that the E-Rate program speeded the rate of internet adoption by 3.8 years—it would have taken that many years of additional growth at the prevailing trend to match the Internet access levels recorded in the last year. Disaggregating the data by the type of school, the authors found that internet growth rates in elementary schools was most responsive to the subsidy rate, and less responsive in middle schools, with growth rates in high schools practically unaffected. Growth rates in urban schools were more strongly correlated with district subsidy rates than in rural schools. Internet access grew more in schools with a higher percentage of minority students.

Harris (2001) conducted an analysis of E-Rate funding patterns using the school district as the unit of analysis, with data from Arkansas. Using a combination of survey data, U.S. Census Bureau poverty statistics, and E-Rate funding data from the USAC's Schools and Libraries Division, Harris investigated the relationship of E-Rate funding per pupil to the school district poverty level; percent students enrolled in the free and reduced lunch program; and school district size. Most interestingly, Harris specifically examined whether the ability of school districts to prepare high quality proposals influenced the amount of funding received. He argued that affluent school districts would be able to spend more on educational technology and employ better qualified technology personnel, with the result that their capacity to obtain and utilize E-Rate funds would be greater. "(S)chools that can afford to spend more money on telecommunications and on approved technology areas will receive more E-Rate money regardless of the poverty level corrections" (p. 8). Thus, data on the availability of at least one full-time technology person at the school district (coded as a dummy variable) and the technology person's level of education and knowledge of E-Rate funding processes were collected through the mailed survey and used as independent variables. Data were analyzed using two-way ANOVA and regression methods. Harris's results showed that E-Rate funding per pupil was negatively correlated with school district size, and positively with poverty level and the percentage of students eligible for the free or reduced rate lunch program. Mixed results were obtained when district size and status of technology person were considered. Medium and large school districts with at least one full-time technology person got more money than school districts with only part-time technology persons. However, small school districts with part-time technology persons got more funding than small school districts with full-time technology persons—perhaps because of an interaction with poverty levels, because poorer school districts (i.e., those with higher E-Rate discount rates) are also more likely to have only part-time technology persons.

The above review of the literature reveals a number of variables that are likely to influence the disbursement of E-Rate funds across states, school districts and individual schools. In this paper, we follow the example of Goolsbee and Guryan (2006) and Harris (2001) in focusing on funding support for school districts. We extend prior work by hypothesizing two contrasting influences at work in determining the amount of E-Rate funds that school districts receive. First, from the E-rate policy guidelines, we may expect that the higher the proportion of traditionally disadvantaged groups a school district has, the greater will be the E-Rate program support: specifically, a higher proportion of students eligible for the free/reduced lunch program the school districts has; the more rural the school district; the higher the poverty level as measured by the per capita income; and the higher the proportion of minority students in the school district, the higher will be the E-Rate program support.

Second, we may also hypothesize that the ability of a school district to apply for and receive E-Rate funding is related to the availability of financial, managerial and technical resources. Poorer and/or rural school districts would generate fewer proposals for E-Rate funding than rich and/or urban school districts, other factors remaining the same. This may be because they do not have the technical and/or managerial expertise to put negotiate the application process, or because they do not have the educational infrastructure and training necessary to absorb educational technology. Therefore, the higher the total revenue per student of the school district, the more staff school districts has; the higher the number of schools in the school district; the higher the total number of total students in the school district, the higher will be the E-rate funding.

In addition to the two contrasting influences discussed above, we are also interested in learning effects. It is likely that the resource gap confronting poor/rural school districts has narrowed over time due to experience, as well as the numerous online resources and best practice guides that have come up over time to help school districts claim E-Rate funds. Previous studies have documented that school districts have become better at negotiating the E-Rate filing process over time, with a greater percentage of school districts applying in each funding cycle: for example, Chaplin (2001) reported that schools run by the Bureau of Indian Affairs (BIA) increased their application rate from 35 percent in 1999 to over 95 percent in 2000, and received more than three times the national average E-Rate funding per student. It is therefore appropriate to compare the impact of school district demographics and resource availability on E-Rate funding over two funding cycles. The following hypotheses are therefore tested.

Table 2. Hypotheses and corresponding statistics

Hypotheses	**Unit of Observation**	**DV**
H1: Poor and/or rural school districts produce fewer applications than rich and/or urban districts	School District	The number of applications in a district
H2: Applications generated by poor and/or rural school districts would be better funded than those by rich and/or urban districts	Application	The natural log of committed amount for each application
H3: Poor and/or rural school districts receive less total E-Rate funding than rich and/or urban school districts	School District	The natural log of aggregated committed amount in a school district
H4: Over time, differences in E-Rate funding for rich and/or urban and poor and/or rural school districts will narrow, other factors being the same	School District	The natural log of aggregated committed amount in a school district

Data

Two years of data, for 1999 and 2004, on E-Rate funding amounts, school district demographics etc was collected for all school districts in Pennsylvania from several databases: the USAC Schools and Libraries database[2], the National Center for Education Statistics (NCES) database[3], and the US Census 2000[4]. The USAC Schools and Libraries allows searches for various information regarding applications, funding commitments and disbursements online. The NCES provides a program called the Common Core of Data (CCD), which annually collects fiscal and non-fiscal data about all public schools and districts in the U.S. The information about school districts such as the number of students eligible for free and reduced lunch, a district's total revenue, and a district's residential status were obtained through the CCD *Build a Table* tool. This application enables users to create customized tables of CCD public school data from five CCD surveys and a Census Special Tabulation. Some socio-demographic information on each district was also collected from the U.S. Census 2000.

An initial query to the USAC database yielded a total of 2523 applications in 1999 and 3160 applications in 2004 for the state of Pennsylvania. After deletions for missing data, our database included 2170 funded applications for 1999 (86.0% of all applications) and 2728 (86.3%) for 2004. Since the unit of analysis is a district, we aggregated the applications data for each district and obtained a total of 423 districts in 1999 and 514 districts in 2004. The USAC data was paired with school district demographic and fiscal data from the NCES Common Core of Data (CCD) database. Table 3 provides summary data on E-Rate funded applications, and their allocation to internet access, telecommunications and internal connections.

Table 3. E-rate funds committed ($ millions) (1999 and 2004)

	Funds committed (U.S. $ mill)	Funds committed (PA, total)	Funds committed (PA, analyzed data)	Internet access	Telecomm unications	Internal connections
1999	$2,154.01	$81.56	$71.75	$2.43	$16.64	$52.67
		(4% of U.S.)	(88% of PA, total)	(3% of PA, analyzed data)	(23% of PA, analyzed data)	(73% of PA, analyzed data)
2004	$2,301.69	$77.84	$65.49	$68.47	$27.82	$65.24
		(3% of U.S.)	(84% of PA, total)	(10% of PA, analyzed data)	(42% of PA, analyzed data)	(47% of PA, analyzed data)

[2] http://www.sl.universalservice.org/funding/opendatasearch/Search1.asp
[3] http://nces.ed.gov/ccd/bat/
[4] http://nces.ed.gov/surveys/sdds/about.asp

For each application, the USAC database provided the *committed amount* defined as "total amount committed by USAC," indicating the funding authorized by the USAC for that application for that year, that can be disbursed to a service provider as the sanctioned project is implemented. Since our unit of observation is the school district and each district has multiple applications, we aggregated the committed amounts into total committed amount per district. To transform the data into a form appropriate for linear regression analysis, the dependent variable was transformed into the natural log form.[5] Table 4 presents the definitions of the dependent variables and independent variables used in the analysis.

Table 4: Dependent and Independent Variables

Variable Name	Definition
Dependent Variables	
LNAPPLICATIONS	Natural logarithm of number of applications for each school district
LNCOMAMT	Natural log of the total committed amount for school district
Independent Variables	
FREELUNCH	Percent of students who are eligible for free and reduced lunch in a district
MINORITY	Percent of minority students in a district
REVSTU	District total revenue per student (district total revenue divided by the number of students in the district)
SUBURBAN	A dummy variable for the residential status of a district (If a district is located in the suburban area, then 1, otherwise 0)
RURAL	A dummy variable for the residential status of a district (If a district is located in the rural area, then 1, otherwise 0)
POVERTY	District percent of total population at/below poverty level
SCHOOLS	Total number of schools in a district
TOTSTUDENTS	Total number of students in districts (UG, PK12)
PCINCOME	District per capita income
TOTSTAFF	Total number of staff in a district
MEDFAMINC	Median Family Income for the school district

Summary statistics on these variables are provided overleaf in Table 5, for both years 1999 and 2004.

[5] Linear regression assumes that scatter of points around the best-fit line has the same standard deviation all along the curve. The assumption is violated if the points with high or low X values tend to be further from the best-fit line (Weisberg, 2005). The exploratory statistics for the data showed that the response variable does not have normality and homoskedasticity which are critical assumptions required for the OLS linear regression analysis. Non-normality and non-equal variance seem to be caused by several outliers such as Philadelphia and Pittsburgh districts. Thus, it was decided to transform the dependent variable to the natural log form which makes the outliers less influential and brings the data into both normality and non-equal variance.

Table 5: Summary Statistics by School Districts

Variables	Year	N	Minimum	Maximum	Mean	Std. Deviation
No. of Applications from each school district (*APPLICATIONS*)	**1999**	423	1	134	5.96	9.77
	2004	514	1	56	6.15	5.20
Committed Amount ($)	**1999**	404	661	42469293	177587	2116818
	2004	514	0	30875386	127409	1376400
Percent Free/Reduced Lunch Eligible Students (%) (*FREELUNCH*)	**1999**	392	1	81	25.95	15.89
	2004	466	0	99.05	25.08	16.8
Percent Minority Students (%) (*MINORITY*)	**1999**	236	0.64	92.49	9.93	15.19
	2004	466	0.11	100	10.8	17.92
District Total Revenue per Student ($) (*REVSTU*)	**1999**	397	6406	29477	8677	1626
	2004	465	7323	19251	9939	2200
Percent Population at/below Poverty Level (%) (*POVERTY*)	**1999**	393	1.74	26.43	9.57	4.99
	2004	455	1.74	34.71	9.41	5.15
Total Number of Schools (No.) (*SCHOOLS*)	**1999**	399	1	259	6.41	13.95
	2004	477	1	263	6.01	12.97
Total Students (UG, PK-12) (No.) (*TOTSTUDENTS*)	**1999**	397	44	205199	3758.3	10603.4
	2004	474	218	189779	3465.37	9074.53
Per Capita Income (Census 2000) ($) (*PCINCOME*)	**1999**	393	12174	54181	19762.62	5854.81
	2004	473	12067	54181	19280.35	6985.9
Total Staff (No.) (*TOTSTAFF)*	**1999**	405	13	24360	423.34	1250.648
	2004	476	35.5	22553.6	425.04	1084.61
Median Family Income (Census 2000) ($) (*MEDFAMINC)*	**1999**	393	29556	112644	48508	13753
	2004	473	25898	112644	47257	16669
Log(ComAmount) (n. log) (*LNCOMAMT*)	**1999**	404	6.49	17.56	10.32	1.28
	2004	509	4.56	17.25	10.42	1.11
Average Committed Amount per Application	**1999**	404	83	987658	15718	54703
	2004	514	0	571766	11427	29815

Note: Fractional values for Total Staff is because part-time employees are counted as fractions of FTE.

Table 5 clearly shows that the number of applicants has increased since 1999. Nevertheless, school districts received less total funding in 2004 than in 1999. A greater standard deviation in 1999 compared to that of 2004 indicates that the E-rate funding distribution was more variable in 1999 than that in 2004. The percent free/reduced lunch eligible students, percent of total population at/below poverty level, total number of schools and total students seem to have decreased in 2004, whereas the percent of minority student, total revenue per student, and total staff appear to have increased.

Simple bivariate correlations (Tables 6 A and B) among the predictor variables and response variable indicates that some variables are highly correlated. This indicates that multicollinearity may be a potential problem in the regression analyses.

Tables 6 A and B: Correlation tables in 1999 and 2004

1999	LnComAmt	Free Lunch	Minority	Suburban	Rural	Revstu	Poverty	Schools	Total Student	Total Staff	PC Income
LnComAmt	1										
FreeLunch	**.347	1									
Minority	**.501	**.494	1								
Suburban	.042	.084	*-.150	1							
Rural	**-.233	-.001	**-.255	**-.307	1						
Revstu	**.163	-.075	**.386	**-.147	*-.123	1					
Poverty	**.311	**.829	**.337	*.108	.003	*-.119	1				
Schools	**.439	**.152	**.432	-.023	*-.123	.001	**.163	1			
TotalStudent	**.419	*.120	**.411	-.040	*-.112	-.004	**.130	**.981	1		
TotalStaff	**.412	*.124	**.413	-.038	*-.114	.014	**.136	**.985	**.999	1	
PCIncome	.016	**-.661	-.029	**-.176	**-.193	**.538	**-.643	.019	.042	.046	1

** Significant at the 0.01 level (2-tailed).
* Significant at the 0.05 level (2-tailed).

2004	LnComAmt	Free Lunch	Minority	Suburban	Rural	Revstu	Poverty	Schools	Total Student	Total Staff	PC Income
LnComAmt	1										
FreeLunch	**.167	1									
Minority	**.422	**.330	1								
Suburban	.015	*.100	*-.109	1							
Rural	**-.228	*.108	**-.309	**-.260	1						
Revstu	**.200	-.009	.020	**-.126	-.042	1					
Poverty	**.194	**.807	**.395	**.137	.078	-.001	1				
Schools	**.486	**.125	**.279	-.013	**-.118	*.095	**.128	1			
TotalStudent	**.464	.089	**.278	-.034	**-.122	.077	.092	**.982	1		
TotalStaff	**.479	.089	**.287	-.038	**-.128	*.100	*.096	**.984	**.995	1	
PCIncome	.085	**-.559	**-.136	**-.124	**-.176	**.610	**-.653	.076	*.098	.088	1

** Significant at the 0.01 level (2-tailed).
* Significant at the 0.05 level (2-tailed).

The *SUBURBAN* and *RURAL* dummies show negative and significant relationships with *REVSTU*, *SCHOOLS*, *TOTSTUDENT*, *TOTSTAFF* and *PCINOME* while they seem to have positive relationships with percent of population below poverty level (although *RURAL* was not significant in both years). This indicates that school districts located in either suburban or rural areas might have less financial resources (total revenue per student), smaller size of school districts (less number of schools and total students and total staff) and be poorer (lower per capita income and greater percent of population below poverty level). This might point out that rural schools have less financial resources to use on behalf of their students compared to urban schools ($r=-.123$, $p< .05$).

Statistical Analysis

Hypothesis 1: Poor and/or rural school districts produce fewer applications than rich and/or urban districts

Due to the problem of non-normality and heteroskedasticity in the data discussed earlier, the dependent variable for testing this hypothesis was the natural logarithm of the number of applications submitted by each school district. Beginning with a larger number of explanatory variables, we identified a model that best fit the data through step-wise backward elimination. The final model included total revenue per student (*REVSTU*), per capita income (*PCINCOME*), a rural dummy (*RURAL*) and total number of schools in the school district (*SCHOOLS*). Separate OLS estimations were run for 1999 and 2004. The results are reported in Table 7 below.

Table 7: OLS Estimation for Natural Logarithm of Number of Applications submitted by School Districts, 1999, 2004

	1999	2004
CONSTANT	1.414 [5.179]***	1.468 [11.627]***
REVSTU	3.96E-5 [1.100]	3.71E-5 [2.400]**
PCINCOME	- 2.1E-5 [-2.705]***	- 1.2E-5 [-2.336]**
RURAL	- 0.045 [-0.559]	- 0.140 [-2.363]**
SCHOOLS	0.012 [4.488]***	0.012 [5.854]***
R^2	0.068	0.099
N	392	464

[T-statistics within square brackets; *** = p<0.01; ** = p<0.05; * = p<0.10]

The results indicate only weak support for the hypothesis. Higher revenues per student are associated with an increase in the number of applications: in 2004, for example, every $100 increase in revenue per student will lead to an increase of about 0.4% in the number of applications. This implies that school districts with more financial resources at their command generate a higher number of applications. However, the per capita revenue in the school district, other factors remaining the same, is associated with a lower number of applications. This is contrary to our expectation that richer school districts will generate a larger number of applications. Rural schools, in both years, generate fewer applications, but the effect is significant only in 2004. As can be expected, school districts with a larger number of schools apply more frequently to the E-Rate program. It may be also noted that the models do not have a lot of explanatory power, as indicated by the low R-squared values.

Hypothesis 2: Applications generated by poor and/or rural school districts would be better funded than those by rich and or/urban districts.

This hypothesis tests whether the policy intent built into the E-Rate discount formulas, namely that applications submitted by poor and/or rural school districts would be better funded than those by rich and/or urban school districts, other factors remaining the same. The dependent variable for this regression is the natural logarithm of the E-Rate committed amount for each application, for reasons discussed earlier. Again, the best fit models for both years were estimated by starting with the full set of explanatory variables and then deleting by stepwise backward elimination. The results are provided in Table 8 below.

Table 8: OLS Estimation for Natural Logarithm of E-Rate Committed Funding for each application, 1999, 2004.

	1999	2004
CONSTANT	5.481 [14.330]***	7.781 [52.730]***
REVSTU	0.000 [2.496]**	9.50E-5 [5.498]***
PCINCOME	4.80E-5 [3.314]***	- 3.49E-5 [-5.804]***
POVERTY	0.063 [4.407]***	0.000 [6.140]***
RURAL	- 0.031 [-0.295]	- 0.195 [-2.795]***
SCHOOLS	0.014 [10.322]***	0.057 [9.300]***
R^2	0.120	0.161
N	2012	2399

[T-statistics within square brackets; *** = p<0.01; ** = p<0.05; * = p<0.10]

Again, the results were mixed on this hypothesis as well. Schools with access to higher revenues per student in federal, state and local dollars had higher committed amounts on their E-Rate applications as well, though the coefficient for 1999 was negligibly close to zero. Richer school districts, as measured by local per capita incomes, did better in 1999 and worse in 2004 when other factors were kept constant. This may indicate a learning effect by poorer school districts, as they gained the knowledge to put together better E-Rate proposals. Higher district poverty rates were associated with more generous E-Rate funding in both years, whereas rural schools did worse in both time periods, though the 1999 coefficient was not significant. In spite of the specific discount formulas mandated by the E-Rate program to favor poor and/or rural schools, the data reveal a more complex picture in implementation.

Hypotheses 3: Poor and/or rural school districts receive less total E-Rate funding than rich and/or urban school districts

The main objective of this paper is to examine the impact of two contrasting influences on E-Rate funding, namely the policy intent built into the program to favor disadvantaged school districts, and the inability of some poor and/or rural schools to avail of E-Rate funds due to the lack of managerial or technical expertise. Hypothesis 3 aims to test for the cumulative impact of these two factors, by using the total E-Rate funding for all applications submitted by school districts as the dependent variable. The independent variables were the percentage of students eligible for the free/reduced rate lunch program in the school district (*FREELUNCH*), the percentage of minority students (*MINORITY*), dummy variables for suburban and rural location (*SUBURBAN* and *RURAL*), total school district revenues per student (*REVSTU*), the percentage of the population at or below the poverty level (*POVERTY*), the number of schools in the school district (SCHOOLS), total number of students (*TOTSTUDENTS*), district per capita income (*PCINCOME*) and the total number of staff in the school district (*TOTSTAFF*). Since this hypothesis is concerned with the overall impact of different variables on E-Rate funding, we present five alternative specifications of the model in Table 9 (for 1999) and Table 10 (for 2004). As before, the full model includes as the independent variables, while the others are developed by deleting variables through stepwise backward elimination.

Interestingly, a comparison of Tables 9 and 10 shows that the fully specified models in each year have yielded different significant parameter estimates: in 1999, the percent of free/reduced lunch eligible students, rural location, number of schools, total students, total staff and per capita income produced rather robust significant parameter estimates. Although the number of schools and total staff were significant in both the full model and reduced models, the results are questionable because of high correlations between variables. The correlations in Tables 6A and 6B, and a multicollinearity test[6] signified that some variables would need to be deleted from the final reduced model to prevent multicollinearity. Thus, the final reduced model was specified with total number of students (*TOTSTUDENTS*) standing in for all the variables measuring the size of a district (see Model 5).

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[6] Mulitcollinearity was inferred from the collinearity diagnostics table in SPSS. A condition index greater than 15 indicates a possible problem, while an index greater than 30 suggests a serious problem with collinearity. Alternative collinearity statistics such as tolerance and VIF (Variance Inflation Factor) indices are also available—a low tolerance value of a variable indicates that it is contributing little useful information for the model, whereas large VIF values are indicators of multicollinearity (see Neter, et al., 1996 for a fuller discussion of collinearity diagnostics).

Table 9: OLS Estimation of Natural Logarithm of Total Committed Amounts for School Districts, 1999

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	6.962 ****9.858*	6.872 ****13.580*	7.146 ****17.486*	7.503 ****19.861*	7.844 ****21.512*
FREELUNCH	.289 ***2.500*	.394 ****4.925*	.411 ****5.345*	.524 ****9.024*	.519 ****8.960*
MINORITY	.061 *.783*				
SUBURBAN	-.050 *-.831*	.016 *.352*			
RURAL	-.092 *-1.541*	-.118 ***-2.515*	-.123 ****-2.849*	-.130 ****-2.994*	-.144 ****-3.310*
REVSTU	.183 ***2.091*	.055 *.891*			
POVERTY	.146 *1.470*	.161 ***2.075*	.170 ***2.226*		
SCHOOLS	.851 ***2.368*	.849 ****3.288*	.810 ****3.192*	.804 ****3.151*	
TOTSTUDENT	3.075 ***2.371*	2.563 ****2.797*	2.201 ****2.666*	1.926 ***2.346*	.324 ****7.570*
PCINCOME	.177 *1.615*	.355 ****4.385*	.395 ****6.415*	.357 ****6.000*	.322 ****5.479*
TOTSTAFF	-3.584 ***-2.440*	-3.080 ****-3.006*	-2.685 ****-2.896*	-2.394 ****-2.594*	
Prob >F	***.000	***.000	***.000	***.000	***.000
R^2	.429	.388	.386	.378	.359
Adj. R^2	.402	.373	.375	.368	.352

[T-statistics in italics; *** = p<0.01; ** = p<0.05; * = p<0.10]

The linear combination of the four predictor variables (*FREELUNCH*, *RURAL*, *TOTSTUDENT* and *PCINCOME*) was significantly related to the E-rate funding committed by the USAC [F(4, 368) = 51.535, p <.000)]. The *FREELUNCH* variable has a positive coefficient, showing support for the policy intent. However, *TOTSTUDENT* and *PCINCOME* variables too have positive relationships with the E-rate funding indicating that larger and richer schools draw more E-Rate funding as well. Meanwhile, only rural location shows a negative coefficient, indicating that if a school district is located in the rural area, it is less likely to have the E-rate funding compared to districts located in the suburban and urban areas. In other words, for the districts that have similar free/reduced lunch rate, number of students and per capita income, rural districts are likely to see a reduction in E-Rate funding.

Table 10: OLS Estimation of Natural Logarithm of Total Committed Amounts for School Districts, 2004

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	9.343 ***25.587	9.495 ****31.266*	9.585 ****35.214*	9.615 ****35.952*	9.419 ****51.367*
FREELUNCH	-.006 *-.086*				
MINORITY	.272 ****5.089*	.273 ****5.396*	.274 ****5.430*	.267 ****5.438*	.289 ****7.039*
SUBURBAN	.030 *.721*	.028 *.673*	.026 *.623*		
RURAL	-.086 **-1.863*	-.090 ***-1.977*	-.099 ***-2.249*	-.109 ****-2.700*	-.094 ***-2.372*
REVSTU	.077 *1.400*	.058 *1.152*	.078 **1.899*	.074 **1.831*	.170 ****4.485*
POVERTY	.067 *.970*	.062 *1.010*	.034 *.757*	.041 *.944*	
SCHOOLS	.973 ****3.657*	.824 ****3.991*	.803 ****3.938*	.815 ****4.014*	
TOTSTUDENT	.092 *.145*	-.444 ***-2.144*	-.421 ***-2.062*	-.432 ***-2.130*	.368 ***9.328
PCINCOME	.051 *.681*	.046 ***.670*			
TOTSTAFF	-.685 *-.888*				
Prob >F	***.000	***.000	***.000	***.000	***.000
R^2	.385	.384	.384	.383	.353
Adj. R^2	.371	.373	.374	.375	.347

[T-statistics in italics; *** = p<0.01; ** = p<0.05; * = p<0.10]

In contrast, the final regression model for the year 2004 show significant parameters for the percentage of minority students, rural location, total revenue per student, and total students in a district (see Model 5 in Table 10 above). The linear combination of the four predictor variables (*MINORITY*, *RURAL*, *REVSTU* and *TOTSTUDENTS*) was significantly related to E-ate funding committed by the USAC [F(4, 456) = 62.221, p <.000]. Interestingly, the variables indicating the size of a district such as total students and the number of schools predict the funding amount more strongly than other predictors. Along similar lines, rural location shows a negative coefficient indicating that if a school district is located in a rural area, it is likely to have less E-rate funding compared to districts located in the suburban and urban areas.

The comparison of results in the two years reveals several interesting findings in terms of the funding distribution. First, the coefficient estimates in both years generally show the expected signs except for rural location, per capita income and total staff. In

1999, free lunch, population percentage below poverty, number of schools, and total number of students were clearly positive and significant while total staff, per capita income and rural were negative and significant. The percentage of minority students was positive but not significant. In 2004, percentage of minority students, revenue per student, number of schools and total number of students were positive and significant while total staff, per capita income and rural consistently showed negative relationship with the funding amount. Unexpectedly, the free/reduced lunch rate was not positive but it was not significant as well.

Second, the rural residence of a district deserves more attention by being negative and very robustly significant in both years, indicating that the location of districts has a negative effect on the funding amount, controlling for other variables such as financial status (total revenue per student) and the size (total number of students) of a district. Rural districts are likely to have less E-rate funding compared to urban and suburban districts consistently in both years. In other words, the multiple regression results suggest that school districts that have similar revenues and size, i.e. the number of total students, are likely to have less E-rate funding if they are located in a rural area.

Third, between 1999 and 2004, the factors that influence the funding level seem to have changed from the fundamental thresholds such as the percentage of free/reduced lunch eligible students to the districts' financial status and size variables. For example, in 1999, the free/reduced lunch rate was a significant determinant of E-rate funding per district. After five years, the percent of free/reduced lunch student was not significant any more. Thus, the proposition that the more students eligible for free/reduced lunch program a school district has, the greater the E-rate funding support it received was not valid anymore in 2004. Instead, the percentage of minority students and total revenue per student in a district replaced the free/reduced lunch rate.

Hypothesis 4: Over time, differences in E-Rate funding for rich and/or urban and poor and/or rural school districts will narrow, other factors being the same

The final objective of this paper is to examine the changes over time, if any, in the influence of the independent variables on E-Rate funding. To study this, we constructed a combined database of 1999 and 2004 observations and estimated models with interaction terms between all the independent variables and a year dummy (1999=0; 2004=1). The expectation was that, if indeed there were no significant differences in the influence of the independent variables between the two years, the coefficients on the interaction terms would be insignificant. The results are reported on Table 11 overleaf. Model 1 is the full specification including all the independent variables and their interactions with the year dummy. Models 2 and 3 were obtained by deleting variables through stepwise elimination, using t-statistics as the criterion. Interaction terms were preferentially deleted in Model 2, since we were interested in retaining the main effects in the model. Finally, in Model 3, we also deleted the main independent variables that were not robustly significant.

Table 11: OLS estimates for natural logarithm of total committed amount for each school district with interaction terms, combined 1999/2004 database

	Model 1	Model 2	Model 3
CONSTANT	7.727	8.051	8.102
	***[14.830]	***[19.656]	***[20.341]
FREELUNCH	0.026	0.027	0.031
	***[3.078]	***[4.153]	***[5.207]
MINORITY	0.011	0.015	0.015
	*[1.862]	***[4.979]	***[5.023]
RURAL	-0.236	-0.229	-0.243
	*[-1.728]	***[-2.880]	***[-3.079]
REVSTU	8.96E-05	5.55E-05	7.51E-05
	[1.294]	*[1.802]	***[2.780]
POVERTY	0.030	0.019	
	[1.350]	[1.571]	
SCHOOLS	0.024	0.026	0.023
	[1.308]	[1.567]	***[6.565]
TOTSTUDENTS	-6.54E-07	-4.61E-06	
	[-0.028]	[-0.212]	
PCINCOME	4.57E-05	4.62E-05	3.98E-05
	**[2.264]	***[3.090]	***[2.744]
TOTSTAFF	0.000	0.000	
	[-0.370]	[-1.449]	
YEAR	1.758	1.257	1.343
	***[2.694	***[2.748]	***[2.997]
*YEAR*FREELUNCH*	-0.027	-0.028	-0.030
	***[-2.746]	***[-4.220]	***[-4.642]
*YEAR*MINORITY*	0.007		
	[0.987]		
*YEAR*RURAL*	0.021		
	[0.126]		
*YEAR*REVSTU*	-4.65E-05		
	[-0.590]		
*YEAR*POVERTY*	-0.016		
	[-0.603]		
*YEAR*SCHOOLS*	0.046	0.045	0.049
	*[1.667]	*[1.659]	**[2.370]
*YEAR*TOTSTUDENTS*	-2.40E-05		
	[-0.301]		
*YEAR*PCINCOME*	-4.00E-05	-3.91E-05	-4.62E-05
	[-1.626]	**[-2.396]	***[-2.649]
R^2	0.401	0.399	0.395
Adjusted R^2	0.384	0.387	0.385
N	667	667	671

[T-statistics in square brackets; *** = p<0.01; ** = p<0.05; * = p<0.10]

As can be seen from Model 3 in Table 11, there were significant differences in the effects of three independent variables between 1999 and 2004. In 1999, the percentage of students eligible for the free/reduced rate lunch program was a significant and positive predictor of E-Rate disbursements; in 2004, there was practically no impact of this variable once the interaction term was also taken into account. In 1999, there was a weak but significant positive effect of district per capita income on E-Rate distributions, i.e., richer school districts were obtaining more E-Rate funds; by 2004, this trend had reversed. In both 1999 and 2004, larger school districts as measured by the number of schools were obtaining more E-Rate funds; however this relationship had been considerably strengthened in 2004. [It may be noted that other measures of school district size, such as total staff and total number of students, were included in the first full model. They were eliminated in later rounds because of low t-scores, possibly since number of schools was providing a better measure of size effects.] These results are discussed in greater detail in the next section.

Discussion and conclusions

This article was motivated by the concern that, despite the policy preferences for poor/rural school districts built into the E-Rate program, there were certain procedural impediments that may prevent some school districts from making full use of the program. These include the complicated, time-consuming and technically challenging E-Rate application process, and the lack of managerial and technological resources for some school districts. We hypothesized that there were two contradictory effects in the E-Rate funding process: poor and/or rural school districts may be applying less frequently for E-Rate funds; however, due to the inbuilt policy preferences, proposals generated by poor and/or rural school districts may be obtaining higher E-Rate funding support. The objective of the paper was to assess the cumulative impact of these contradictory forces on the total quantum of E-Rate funding awarded to school districts. Since we were also interested in changes in the effects of predictive variables over time, we compiled two years of data, for 1999 and 2004, for the state of Pennsylvania.

Regression results for the number of applications generated by school districts generated a mixed bag of results. As expected, bigger school districts (as measured by the number of schools) and those with more financial resources (with higher total revenue per student, from federal, state and local sources) generated a higher number of applications. Rural school districts too generated fewer applications than their urban or suburban counterparts when other factors were held constant, but this effect was significant only in 2004. However, contrary to expectation, richer school districts, i.e., those in which the population has higher per capita revenue, generated a lower number of applications.

The second effect we investigated was that, the applications generated by poor and/or rural school districts would be better funded than those by rich and/or urban school districts, other factors being the same. Schools with higher revenues had higher committed amounts on their E-Rate applications as well, though the coefficient for 1999 was negligibly close to zero. Richer school districts, as measured by local per capita incomes, did better in 1999, but this had reversed by 2004. This may indicate a learning effect by poorer school districts, as they gained the knowledge to put together better E-Rate proposals. Higher district poverty rates were associated with more generous E-Rate funding in both years, as per the policy intent.

However, a common theme that emerged in the regressions for both number of applications and the E-Rate funding support for each application was the situation of rural school districts. Rural school districts generated fewer applications than their urban counterparts, and also received less funding on the applications that they did generate. While this was not a significant effect in 1999, there was a significantly negative impact on both counts—number of applications, and funding per application—in 2004. These effects persist even when other factors, such as size of the school district, revenue per student, and poverty levels, are controlled. This is indeed a worrisome trend. Not surprisingly, the rural disadvantage is a noticeable finding in the third set of results, in which we assessed the combined impact of the two effects discussed above. The predicament of rural school districts may require some form of policy intervention, not limited to the preferential rates that they now receive. This may include further simplifying the E-Rate application process while preserving its integrity, and using at least part of the E-Rate funding corpus to provide technical information on school networking to poor/rural school districts. Legislative authorization, for example, as part of the current rewrite of the 1996 Telecommunications Act, to permit least part of the E-Rate funding corpus to provide technical information on school networking to poor/rural school districts may also be advisable.

Finally, in tracking changes over time, there were significant differences in the effects of three independent variables between 1999 and 2004: percentage eligible for the free/reduced rate lunch program, district per capita income, and size of school district. Two of these effects are worthy of further discussion: first, the effect of the free/reduced rate lunch program percentage. As discussed earlier in the paper, E-Rate discount percentages are specifically indexed to the percentage of students in the participating schools eligible for the free/reduced rate lunch program. It is therefore surprising that in 2004, there was practically no impact of this variable once the interaction term was also taken into account. This may be partially explained by an apparently widespread practice when schools put together E-Rate applications—as Goolsbee & Guryan (2006) point out, schools have become adept at convincing high-poverty schools in their districts to collaborate on E-Rate proposals. Since the discounts are calculated based on the data for all participating schools, higher subsidies are made available when high-poverty schools are included on proposals. Evidently, schools have become better over time at this form of 'proposal sharing' which explains why eligibility for the free/reduced lunch program, that significantly predicted E-Rate funding in 1999, no longer does so in 2004. Since this study used the district-wide measure of eligibility for the free/reduced lunch program (and not for the specific schools participating in an E-Rate application), it may not have fully captured this sort of selection behavior. Nevertheless, this finding highlights the fact that at least part of the E-Rate funding intended for high-poverty schools is actually flowing to richer schools with the technical and administrative skills to put together competitive proposals—in some ways, a win-win situation, but in other ways a diversion of much needed-resources away from the poorest schools. The USAC may need to specify clearer allocation formulas in multi-school projects, to ensure that all participating schools receive their fair share of E-Rate funding.

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