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Broadband in School: Impact on Student Performance

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This paper examines the effects of providing broadband to schools on students' performance. We use a rich panel of data on broadband use and students' grades from all middle schools in Portugal. Employing a first-differences specification to control for school-specific unobserved effects and instrumenting the quality of broadband to account for unobserved time-varying effects, we show that high levels of broadband use in schools were detrimental for grades on the ninth-grade national exams in Portugal. For the average broadband use in schools, grades reduced 0.78 of a standard deviation from 2005 to 2009. We also show that broadband has a negative impact on exam scores regardless of gender, subject, or school quality and that the way schools allow students to use the Internet affects their performance. In particular, students in schools that block access to websites such as YouTube perform relatively better.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mnsc.2013.1770.

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1. Introduction

The role of information and communication technologies (ICTs) in our economy can hardly be overemphasized. There is a great amount of literature in both information technology (IT) and economics on how computers and the Internet affect firm productivity (Brynjolfsson and Hitt 1996, Forman et al. 2005). However, the role of technologies in education is also an important policy and managerial issue. It has received much less attention in the information systems (IS) literature though. Predominantly, this has been a domain of research for economists and sociologists. As we will show below, even in this stream of literature, the role of ICTs in education is hardly settled. In this paper, we use an interesting and detailed data set to propose a method to assess the effect of the Internet and broadband on students' grades in schools.

ICTs are perceived by many as potentially powerful tools to improve the quality of education. They facilitate real-time access to information, provide a more hands-on learning experience, and foster new learning methods that promote more interaction and feedback, ultimately increasing students' interest and performance (e.g., Underwood et al. 2005). Governments around the world have been heavily subsidizing computers and broadband access in schools. However, the Internet also offers significant opportunities for students to indulge in leisure and entertainment activities. Without effective monitoring and controls by schools, students may predominantly use broadband to play games, chat, and watch movies. This can distract them from traditional study, which can ultimately hurt the productivity of learning at school. In fact, some studies indicate that children spend considerable amounts of time playing computer games (Malamud and Pop-Eleches 2011). It is also quite likely that teachers may find it hard to effectively use ICTs as part of the curriculum. Despite the large investments in computers and Internet access in schools, there are only a few studies that examine the impact of the Internet in schools on students' performance.[1] Moreover, these studies provide mixed results on whether ICTs indeed help students. Thus,

[1] To the best of our knowledge, Goolsbee and Guryan (2006) is the only study that directly measures the impact of school Internet availability on students' performance. They find no evidence that wiring classrooms with Internet access affects students' grades.

our understanding of how broadband can help learning is still limited.

In this paper, we provide a model for how broadband use in schools contributes to students' performance. We then provide empirical evidence of the impact of *actual usage* of broadband in schools (as opposed to simply availability of a broadband connection) on students' performance by drawing from the case of Portugal. Actual usage is measured by the amount of information exchanged over the Internet using asymmetric digital subscriber line (ADSL) connections. Performance is measured by scores obtained from ninth-grade national exams. We collect a panel of data on broadband use and school performance for all Portuguese middle schools between 2005 and 2009. We use first differences to account for school-specific unobserved effects. Still, the school performance may be endogenous to broadband use. We overcome this by instrumenting the schools' broadband use with the distance between the school and the provider's central offices (COs), which proxies the quality of the ADSL connection. Distance has some unique and desirable properties as an instrument, providing us confidence in the results obtained.

Our estimates indicate that more broadband use is detrimental to students' test scores. We find that, on average, grades declined about 0.78 of a standard deviation between 2005 and 2009 because of broadband use. This finding is robust across gender (although boys seem to be slightly more affected) and subjects (although math grades seem to be slightly more affected). In addition, schools are equally affected by Internet use regardless of their performance prior to the deployment of broadband.

To explore the distraction effect of the Internet in more detail, we conduct a survey to understand how the Internet is used in schools. We focus on the policies that schools enact for Internet use and on whether they block or allow applications and services such as Facebook, YouTube, and file sharing, which are likely to cause distraction. We find evidence that schools that allow these activities perform worse. In particular, the effect of Internet use is significantly more negative when schools allow YouTube use. This result suggests that without proper monitoring and control, broadband access in schools may be more harmful than helpful.

2. Related Work

Economists have been interested in how school resources such as class size, school hours, teacher training, and peer group affect student performance. However, teasing out these effects is quite challenging. Concerns about endogeneity cast doubts on the causality of the relationship between education inputs and students' performance (see Webbink 2005 for a detailed explanation of the endogeneity problem in these studies).

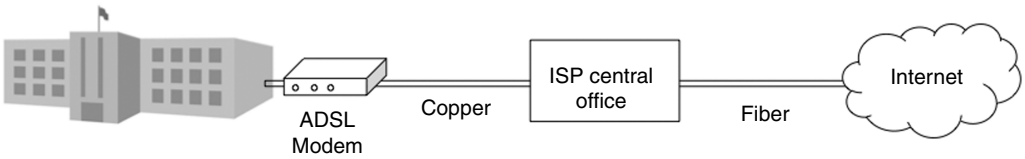
Some of the more recent studies overcome the endogeneity problem in different ways and find a positive impact of class size (e.g., Krueger 1999, Angrist and Lavy 1999), school hours (e.g., Lavy 1999), and peer-group effects (e.g., Sacerdote 2001).[2] The impact of other characteristics, such as teacher training and computer use, either remains nonsignificant or exhibits mixed results (e.g., Angrist and Lavy 2002, Webbink 2005, Barrera-Osorio and Linden 2009).

Most studies look at students' test scores on a standardized test as an outcome measure (e.g., Angrist and Lavy 2002, Goolsbee and Guryan 2006, Leuven et al. 2007, Machin et al. 2007). Even though test scores have some obvious limitations, they are used mainly because they are reliably measured and provide a tangible and standard way to measure student performance. Test scores are also a barometer used by policy makers and administrators to assess a school's performance, which affects teacher benefits, school subsidies and parents' demands. As a consequence, schools, teachers, and students all have incentives to improve test scores.

Research on the contribution of ICTs to students' performance has produced mixed results. Angrist and Lavy (2002) exploit a randomization (determined by a lottery) in the timing of school computerization in Israel. They find no effect on students performance, except for a negative effect in math exam scores for fourth graders. Goolsbee and Guryan (2006) study the impact of subsidizing schools' Internet access in the United States and find no evidence that having the Internet in classrooms has an effect on students' performance, as measured by the Stanford Assessment Test (SAT). Leuven et al. (2007) exploit a discontinuity in a subsidy given to schools in the Netherlands. Using a differences-in-differences framework, they find that this subsidy had a negative impact on students' performance, especially on girls. Malamud and Pop-Eleches (2011) exploit a discontinuity in a subsidy provided to acquire a computer for low-income families in Romania in 2008. They find that the students of families that used this subsidy to buy a home computer obtained significant lower school grades in math, English, and Romanian. They also find that these students obtained higher scores in tests of computer skills and in self-assessment tests of computer fluency. Vigdor and Ladd (2010) use fixed

[2] All these studies take advantage of an exogenous source of variation to overcome the endogeneity problem. For example, Krueger (1999) use an experimental setting, Angrist and Lavy (1999) take advantage of a maximum class size, Lavy (1999) taps on variations on the allocation of school hours, and Sacerdote (2001) uses random dorm assignments.

Figure 1 Broadband Schools' Connection to the Internet



Notes. Schools connect through a copper line to the ISP's central office. From there, the ISP ensures connectivity to the Internet backbone through fiber.

effects to estimate the impact of home computer and Internet access on students' performance in North Carolina. They use a panel on the state's public school students between 2000 and 2005 and find a small, but statistically significant, negative effect of home computer access on students' math and reading test scores. They also report a decrease of 3% of a standard deviation in male reading test scores.

An exception to this recent trend of nonsignificant or negative results is provided by Machin et al. (2007), who use changes in investment rules in the United Kingdom to find evidence of a positive effect of ICT investment on educational outcomes in elementary schools.

Similarly, the effects of computer-aided learning software on students' performance is also ambiguous (see Rouse and Krueger 2004, Banerjee et al. 2007, Barrow et al. 2009). In some cases, the effects are positive, but in other cases, computer-aided learning makes no difference. Their effectiveness also varies between math and reading and between boys and girls.

In summary, the impact of ICTs on students' performance is an empirically challenging question. Many studies published so far look at the impact of investments in ICTs (e.g., the availability of computers or the Internet) on student's performance and not at the impact of actual usage. Mere availability does not translate into usage nor does it explain heterogeneity in usage. Thus, availability data alone are too crude a measure to provide an explanation for the mechanisms that drive outcomes. Furthermore, the lack of granularity is more likely to produce a nonresult. Also, when ICTs are already available to almost all subjects in the sample (which is increasingly true where most schools have the Internet and computers), one cannot even perform any useful empirical exercise without the usage data. Our paper differs from prior work in that we examine the impact of *actual broadband* use on student performance. We examine the impact of specific applications and services, which allows us to provide additional insights for the reasons that drive outcomes. We also provide a credible instrument to alleviate the endogeneity concerns. Overall, we find that broadband usage between 2005 and 2009 had an adverse effect on the performance of ninth-grade students in Portuguese schools.

3. Broadband in Portuguese Schools

3.1. Broadband Provision to Schools

Most elementary and secondary schools in Portugal are public schools, funded either by the central government or the local government, with limited autonomy to manage their resources. The provisioning of the Internet to schools has been managed by FCCN (the Portuguese National Foundation for Scientific Computation).

The Portuguese government undertook many initiatives to connect schools with computers and the Internet. For example, by mid-2001, all elementary and middle schools in the country had been equipped with at least one computer connected to the Internet through an integrated services digital network (ISDN) (FCT 2001). In 2004, the same ministry launched another major initiative, this time aimed at replacing all the existing ISDN connections with broadband ADSL.

By 2006, most schools (>95%) received a DSL modem from FCCN and an ADSL connection of at least 1 Mbps over a copper line that connects them to the CO of Portugal Telecom (PT), the Internet service provider (ISP) from which FCCN buys connectivity to the Internet (Figure 1). Connecting schools with broadband was a decision of the central government. Schools did not have a say in whether they wanted a broadband. In other words, some schools might not have been prepared to receive broadband at the time. The ministry covered all up-front capital costs to deploy broadband to schools. City halls footed the broadband monthly bill for elementary schools, and the ministry covered these costs for the remainder of the schools.

There is no information about whether some schools had already purchased broadband from the market by the time this intervention took place, but the schools' tight budgetary constraints must have allowed only a small fraction of them to do so, if at all. More importantly, FCCN strongly encouraged schools to use the broadband connection provided by the government. After all, traffic over this broadband connection is free of charge to schools, so even if some schools had bought a DSL connection before, they had a strong incentive to shut it down and use only the FCCN's connection. Therefore, the broadband use over the Internet connection provided by

FCCN seems to be a good measure for the school's overall broadband use.

3.2. Internet Use at School

We conducted preliminary informal interviews with teachers in eight different schools to learn more about how the Internet is used in schools. Some teachers are comfortable with using ICTs in the classroom and consider the Internet a good tool to capture the students' interest and to improve the learning process.[3] Other teachers look at the Internet as just another resource that students can possibly use for learning. However, not all teachers felt that the Internet always provides an easy way to obtain and use information.[4] Differences in skills and in the attitude of teachers toward the Internet translate into significant differences in how much students use the Internet in the classroom.

School-specific Internet access policies may also explain part of the differences in the patterns of Internet use across schools. Although some schools provide an open wireless network that any computer can tap into (such as the students' laptops), other schools disallow access to their wireless network to all but school computers. Some schools block access only to a restricted set of websites (mainly adult content sites), but other schools block access to a whole range of sites considered inappropriate in the school context.[5] All these factors influence how students use the Internet at school and, consequently, their incentive to bring their laptop to school if they happen to have one. Students in some schools bring their laptops several days a week to school and use them pervasively, while in other schools, students seldom make use of their own laptops.

The time that students spend at school is also heterogeneous. In some schools, students usually stay at school after class, but in other schools, most students leave school right after classes. Most students that stay at school after hours often do so to use the school's computers and the Internet, most likely, in some unsupervised way.

Finally, students that do not have the Internet at home may exhibit different usage patterns than those who do. All in all, there is a wide variation across schools in terms of how students use the Internet. Teacher knowledge and attitude toward the use of ICTs in the classroom, the school's Internet access policies, and the time spent at school after classes are some of the factors that contribute to such a variation.

4. Data

School traffic data were obtained from the monitoring tools set up by FCCN. From the ISDN project, we obtained data for all ISDN sessions between November 2002 and January 2005 for all schools in the country. From the ADSL project, we obtained monthly reports that include download and upload traffic per school between November 2005 and June 2009. School traffic is measured at the school's edge router and consists of all traffic exchanged between the school and the Internet. For our measure of school broadband use, we average the total monthly traffic (upload plus download) over the entire academic period.[6]

Internet use in schools grew significantly since the introduction of ADSL in late 2005. Before 2006, Internet use was virtually zero, compared to usage levels in 2008 and 2009 (see Figure 2(a)), probably because the ISDN connections could not carry more traffic. Inbound traffic is the major contributor for this increase; outbound traffic remains relatively modest across most schools. Broadband use per student exhibits high variability across schools (see Figure 2(b)). In 2009, students used 111 MB at school per month on average, which corresponds to watching almost one hour of YouTube video (at 260 Kbps), browsing 350 webpages (at 320 KB per page), or exchanging 850 emails (at 130 KB per email).[7] There is significant heterogeneity in usage (a large standard deviation (95 MB)).

Performance is measured by the school's average score on the ninth-grade national exams. Ninth grade is the last year of middle school and was the mandatory education level in Portugal until 2009. The Ministry of Education has published anonymous disaggregated data at the exam level since 2005, including information on exam score, course, gender, age, and school of the examinee. Ninth graders are examined in two subjects, Portuguese and math, and their exam scores constitute part of their final score on these subjects. These scores determine whether the student graduates from the ninth grade. Therefore, students have clear incentives to perform well in these exams.[8]

[3] Some of the teachers interviewed explained that students engage more in discussions and are more motivated when the Internet is used in class.

[4] One of the teachers interviewed pointed out that he had a hard time explaining to students that Wikipedia is not a reliable source of information and that they should always check their sources.

[5] Video, chat, social network, and adult content sites are among the categories most often blocked. In §8 of this paper, we provide more details on these policies.

[6] We use the period between September and June as the academic year in accordance to the academic calendar published by the Ministry of Education of Portugal.

[7] Average webpage size was obtained from http://code.google.com/speed/articles/web-metrics.html, accessed March 22, 2011. We use the average email size of one of the authors as a reference because we found no reliable information on this statistic.

[8] Even though this is a standardized exam, it is not a multiple-choice response only exam. The students have to write detailed answers.

Figure 2 **Middle School Internet Traffic and Monthly Average Internet Use per Student in 2009**

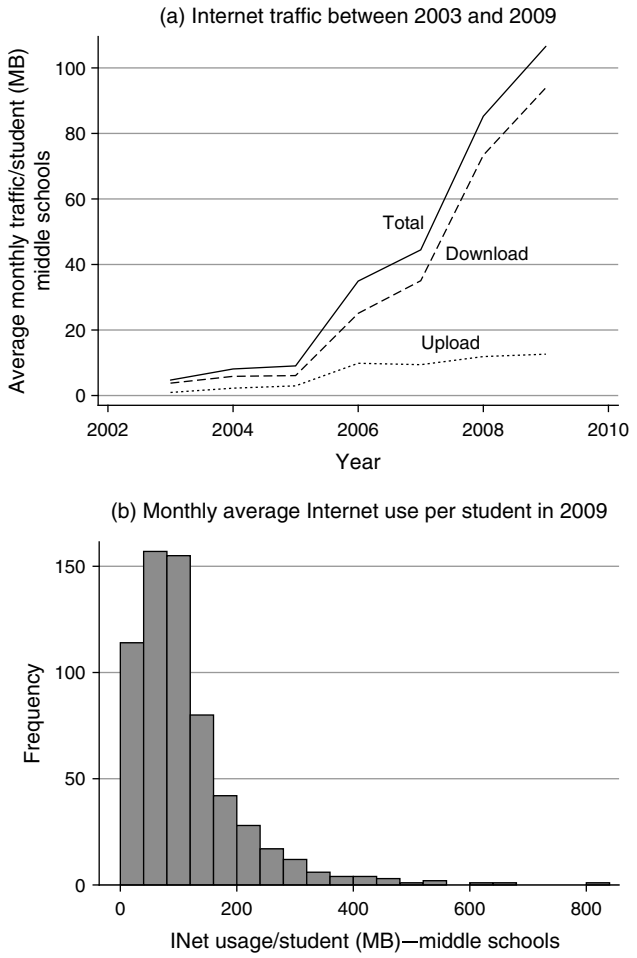


Figure 3 **Ninth-Grade Average Exam Scores Between 2005 and 2009**

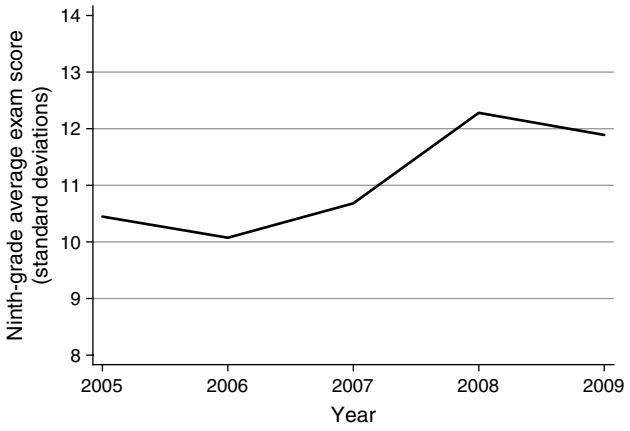


Table 1 **Summary Statistics**

Variables	(1) *N*	(2) Mean	(3) s.d.	(4) Min	(5) Max
Avg. Grade 2009 (s.d.)	628	11.59	1.135	7.888	15.21
Avg. Grade 2008 (s.d.)	628	11.97	1.117	7.898	15.88
Avg. Grade 2005 (s.d.)	628	10.20	1.008	7.185	13.80
INet Usage 2009/Stu. (MB)	628	111.2	95.32	4.22e–04	800.5
INet Usage 2008/Stu. (MB)	628	86.70	97.42	0.123	1,766
INet Usage 2005/Stu. (MB)	556	8.004	13.50	5.25e–05	179.0
Students	628	579.3	239.2	72	1,412
Pop. Density	628	1,820	2,868	5.800	20,648
Earnings 2005	628	787.0	186.8	532.8	1,487
Mandatory Educ. (%)	628	39.14	13.73	10.38	80.05

For ready interpretation, we normalize all grades by the standard deviation of 2005 grades. Figure 3 shows ninth-grade normalized average exam scores over time.[9] Average exam scores have increased from 2005 to 2009 (14.0%), which may reflect a positive impact of broadband on students' performance. Alternative explanations for this rise include unobserved factors, such as exams becoming easier over time, particularly in 2008.

Finally, we obtained global positioning system (GPS) coordinates for all the COs of PT, which held a market share of about 70% in the Portuguese broadband market during the years of our study (ANACOM 2010). Furthermore, we also obtained the average monthly traffic rate per CO for residential Internet access from PT. Regional data were provided by the Portuguese National Statistics Institute. These data include population density (2001 census data, at the civil parish level), average earnings, and mandatory education rates[10] (in 2005) across municipalities. Table 1 presents summary statistics for these variables for schools in our sample.[11] School enrollment (in 2007) was obtained from the Ministry of Education.[12]

5. Framework

We introduce a simple model that explains how the time students spend using the Internet at school affects their performance. Let P represent students' performance. Let I represent the time they spend using the Internet at school. Let S represent the time they spend at school without using the Internet (hereafter called traditional study time at school). Let $T = I + S$ represent the total time students spend at school.

[9] Ninth-grade exam scores are published on a 1–5 scale (with increments of 1).

[10] Mandatory education was nine years of schooling during the period of analysis.

[11] Portugal has a population of 10.6 million. The country is divided into 308 municipalities, which are further divided into 4,261 civil parishes. Schools in our sample cover 204 municipalities and 547 civil parishes.

[12] We were able to obtain student enrollment only for 2007. We use the 2007 values for the whole time period because the number of students in a school is unlikely to change much from year to year.

We assume that school hours remained unchanged with the introduction of the Internet in schools.

The performance of students depends on the effectiveness of the time they spend using the Internet at school and on the effectiveness of the time they dedicate to traditional study at school. Therefore, define $P = f(I, S)$, where f is a production function. All else being equal, more of one input cannot reduce output, thus we have $f_I \geq 0$ and $f_S \geq 0$.

The effect of Internet use in school on students' performance is given by

$$\frac{dP}{dI} = f_I + f_S S_I = f_I + f_S(T_I - I_I) = f_I + f_S(0-1) = f_I - f_S.$$

At school, time on the Internet substitutes traditional study time without the Internet. The productivity of Internet time at school (f_I) trades off with the productivity of traditional study time (f_S), and thus performance can either increase or decrease with the Internet.

Furthermore, we split Internet time at school into learning time, L, and distraction time, D, and make $I = L + D$. We also have $L_I \geq 0$; that is, all else being equal, more time on the Internet does not reduce learning time. Likewise for distraction, and thus $D_I \geq 0$. These statements, together with $I = L + D$, imply $L_I \leq 1$.

Consider now that the students' performance depends on the effectiveness of the time they spend learning on the Internet at school and on the effectiveness of the time they dedicate to traditional study at school. Therefore, define $P = g(L, S)$, where g is a production function. As before, we have $g_L \geq 0$ and $g_S \geq 0$.

In this case, and using the fact that $T = S + I$ is constant, the effect of Internet use at school on students' performance is given by

$$P_I = g_L \cdot L_I - g_S.$$

The productivity of learning with the Internet (g_L) weighted by how the Internet time is devoted to learning (L_I) trades off with the productivity of traditional study time at school (g_S). Note that $g_L \cdot L_I \geq 0$ and $g_S \geq 0$, and thus again, the introduction of the Internet in schools can either increase or decrease performance. In fact,

$$\operatorname{sgn}[P_I] = \operatorname{sgn}\left[\frac{g_L}{g_S} L_I - 1\right].$$

The impact of the Internet at school on students' performance (P_I) is positive when the relative productivity of learning time on the Internet at school to the productivity of traditional study time at school (g_L/g_S), weighted by how Internet time is devoted to learning (L_I), is greater than one. One may expect that learning with the Internet may be more productive than traditional study ($g_L/g_S > 1$). Even then, our model highlights that the impact of the Internet is critically affected by how much Internet time is devoted to learning. Even if $g_L > g_S$, only if L_I is large—that is, only if students are largely using the Internet for learning purposes—we could expect their performance to improve.

Consider a constant elasticity of substitution (CES) production function

$$P = [\beta L^r + (1-\beta) S^r]^{1/r},$$

with $0 \leq \beta \leq 1$ and $r \leq 1$. Differentiating with respect to I yields

$$\operatorname{sgn}[P_I] = \operatorname{sgn}[\gamma (L/S)^{r-1} \cdot \partial L/\partial I - 1],$$

where $\gamma \equiv \beta/(1-\beta)$. In this case, $\gamma(L/S)^{r-1}$ is the relative productivity of learning time on the Internet to traditional study time. For the case of a linear production function ($r = 1$), the effect of Internet use in school is given by $\gamma L_I - 1$. Furthermore, if students devote a constant share of the time they spend on the Internet at school to learning activities, call it α ($\alpha \equiv L_I$), then the effect of Internet use in school is constant and given by

$$\frac{dP}{dI} = \gamma\alpha - 1. \tag{1}$$

In other words, the impact of the Internet on students' performance depends on how effective Internet use is relative to standard study and how much time students actually devote to learning activities.

6. Empirical Specification

6.1. Differences Model

School performance is assumed to depend on broadband use, socioeconomic factors, and school-specific unobserved factors, such as the quality of teachers and the comfort and size of the classrooms. Therefore, school performance can be expressed by the following structural equation:

$$P_{it} = \delta + \omega I_{it} + \mathbf{x}_i \boldsymbol{\beta} + \mathbf{w}_{it} \boldsymbol{\theta} + c_i + u_{it}, \tag{2}$$

where P_{it} represents the performance of school i at time t; ω is the effect of Internet use on school performance ($\gamma\alpha - 1$ in Equation (1)), our parameter of interest; I_{it} represents broadband use; $\mathbf{x}_i$ and $\mathbf{w}_{it}$ are row vectors with time-fixed and time-varying school-specific and region-specific control variables. We include, as time-invariant control variables, school size (measured by the number of students in each school in 2007), population density (in 2001), earnings (in 2005), and the percentage of people with the

mandatory level of education (in 2001) in the municipality where the school is located. As a time-varying control, we use the average Internet traffic rate per person (in Mbps per capita) at the school's closest ISP's CO. This variable is used as a proxy for home Internet use in the region where the school is located. The parameter vectors to be estimated are in $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$, c_i is an unobserved time-constant school-specific effect, and u_{it} is a random error term.

This is the classic fixed-effects specification. Specifying a separate dummy for each school in the form of c_i lets us control for school-specific unobserved time-constant factors. Alternatively, we can write this as a differences model:

$$\Delta P_{it} = \phi + \omega \Delta I_{it} + \Delta \mathbf{w}_{it}\boldsymbol{\theta} + \Delta u_{it}, \tag{3}$$

where ϕ captures the average change in exam scores over the period of analysis. For example, $\phi > 0$ captures the fact grades increased because, suppose, exams became easier, and Δ represents the difference between period t and 2005 (e.g., $\Delta P_{it} \equiv P_{it} - P_{i2005}$). Note that we use 2005 as the baseline year for comparisons because there was no broadband in schools in 2005. Our specification compares change in grades with their 2005 level. Instead of running four separate regressions (for 2006, 2007, 2008, and 2009, all relative to 2005), we estimate one regression and interact school Internet use with year dummies to estimate period-specific effects. This readily allows for comparing across different years. We also include year dummies to control for period-specific variation. Additionally, we cluster the standard errors at the municipality level to account for possible correlation among observations in the same municipality.

Note that the term $\mathbf{x}_i\boldsymbol{\beta}$ in Equation (2) gets differenced out because it corresponds to time-constant factors. However, to account for the fact that some school-specific variables in $\mathbf{x}_i$ might drive not only performance but also its rate of change, we include the baseline values of $\mathbf{x}_i$ as additional controls:

$$\Delta P_{it} = \phi + \omega_t \Delta I_{it} + \mathbf{x}_i\boldsymbol{\beta} + \Delta \mathbf{w}_{it}\boldsymbol{\theta} + \Delta u_{it}. \tag{4}$$

This is equivalent to adding an extra term $d_{2005} \cdot \mathbf{x}_i\boldsymbol{\beta}$ to our structural equation, where d_{2005} is an indicator variable for 2005.[13]

6.2. Identification

Despite the school fixed effects and observable controls in $\mathbf{x}_i$, potential unobserved *time-varying* factors may lead to both increased broadband use and better (or worse) exam scores, resulting in inconsistent estimates for ω. For example, a change in the resources available to a school,[14] changes in school organization, or its technical savviness might influence both broadband use and exam scores during the period of analysis. The school-specific dummies do not capture these time-varying unobserved effects. Time dummies help capture average dynamic effects but are not enough for identification purposes.

We exploit the heterogeneity in the quality of broadband connections across schools as an exogenous source of variation in our setup. Schools that benefit from a better connection to the Internet are more likely to use it more and, therefore, more likely to register more traffic. With ADSL technology, a greater distance between the customer's premises and the ISP's CO results in a lower maximum-transfer bitrate (e.g., Kagklis et al. 2005). Therefore, schools further away from the CO are likely to get less throughput. Such lower throughput leads to degraded performance, decreasing the attractiveness of the broadband connection at the school and thus lowering the amount of traffic exchanged over the Internet. Consequently, we use line-of-sight distance between each school and its closest CO as a proxy for the quality of the school's broadband connection.[15]

Distance is an attractive choice for an instrument because one expects that the distance between a school and its closest CO to be fairly randomly distributed; schools and COs have been around for much longer than broadband.[16] Additionally, the population in Portugal is fairly densely distributed. Therefore, unlike the United States where one would worry about rural schools being systematically farther from the CO than urban schools, Portugal is more homogeneous: most schools are within 2 km of a CO (see Figure 4), and there is little difference in the distance to the closest CO for urban versus rural schools, as can be seen in Figure B.1 in Appendix B and as shown by t-tests; the average distance to a CO is 1.08 km

[13] Our results are similar whether or not we include $\mathbf{x}_i$ as controls. We leave these controls in the differences equation for generality.

[14] During the period of analysis, students were awarded laptops under a parallel governmental program. This may have changed both broadband usage and scores.

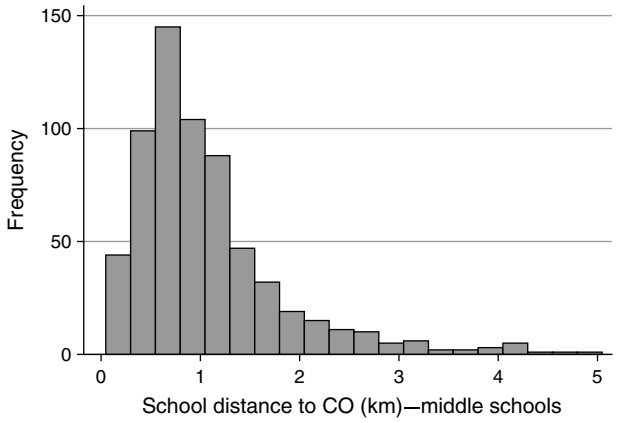
[15] Line-of-sight distance is calculated from information on the GPS coordinates of both schools and the ISP's COs. We obtain similar results when using walking distance between the schools and CO as calculated by Google Maps.

[16] Some COs are still located at the old telephone exchange premises, today's post office locations. The deployment of this telephone exchange network began at the end of the 19th century and was expanded significantly from the 1930s to the 1980s. Thus, some of the central offices are located near the post offices and, in general, existed long before the schools' foundations. For the 313 schools for which we were able to obtain information on foundation date, the average foundation year was 1986 (median: 1988; s.d.: 11), with a minimum of 1950 and maximum of 2003. There is little evidence that the COs had been installed as a function of school location or vice versa. However, we cannot say with certainty whether the decision to install newer COs was influenced by school locations.

Table 2 Cross-Correlations for Middle Schools

Variables	*Dist. Sch–CO*	*Dist. Sch–Cntr*	*Avg. Grade 2005*	*Students*	*Pop. Density*	*Earnings 2005*	*Mandatory Educ.* (%)
Dist. Cntr–Sch	0.097						
Avg. Grade 2005	−0.092	−0.053					
Students	0.034	0.015	0.161				
Pop. Density	−0.030	−0.047	0.055	0.323			
Earnings 2005	−0.023	−0.030	0.126	0.095	0.496		
Mandatory Educ. (%)	−0.106	−0.042	0.262	0.401	0.521	0.579	
Avg. CO Traffic 2005 (Mbps)	0.104	−0.008	−0.002	0.142	0.081	−0.005	0.134

Figure 4 Middle School Distances to the Closest CO



for the 299 rural schools (population density below 500 people per squared kilometer) and 1.07 for the 329 urban schools, with standard deviations of 0.89 and 0.65, respectively.

Additionally, we use the distance between the school and the town center as another control. One may worry that a school away from a CO may be more rural or be somehow different. And despite our fixed effect specification, such schools may (or may not) have received some interventions, such as subsidized laptops or teacher training during the 2005–2009 period, which would affect our results. However, we believe that the distance between schools and their town centers should pick up some of these unobserved effects. Moreover, how far a school is located from the town center should have no bearing on its Internet quality; only the distance from the CO matters. We use town hall GPS coordinates[17] as the center of the parish to which schools belong and use line of sight distance to schools.

In Table 2 we provide the correlation matrix with distance and socioeconomic characteristics for the middle schools as well as the distance between the school and the corresponding town center. Distance to the CO does not seem to be correlated with any of the socioeconomic characteristics, population density, or grades before the deployment of broadband in schools. This strengthens our intuition that the distance to the CO is independent of specific regional characteristics. Figures B.1–B.3 in Appendix B offer more details on the relationship between distance and demographic characteristics. The distance from the town center is slightly positively correlated with the distances to the CO, suggesting that the COs are more likely to be located closer to respective city centers.

As an additional test for the instrument, we run a regression of schools' 2005 grades on schools' distance to the CO (see Table 3). Without controls, distance is statistically significant, but its effect is economically trivial: an increase of one standard deviation in distance to a CO (0.77 km) is associated with a decrease of less than 0.1 of a standard deviation in grades. However, this statistical relationship disappears completely once we include the usual covariates, such as population density and mandatory education levels. (Furthermore, the coefficient reduces even further in magnitude.) The distance from the school to the center of the town was unrelated to grades in 2005 altogether. Moreover, the distance between the school and the town center is not a good proxy for Internet use at a school, as can be seen in Table B.2 in Appendix B. This provides a good falsification test and further confirms the suitability of the distance to the CO as an independent and good proxy for Internet use.

In summary, schools that perform better (or worse) are not systematically located closer or farther from the CO. These facts suggest that the distance from the CO is a viable instrument for our analysis. More details on the appropriateness of distance as an instrument are provided in Appendix B.

More importantly, note that because we use school fixed effects, we need distance to be uncorrelated with Δu_{it} in Equation (4) and not necessarily with u_{it}. In other words, our strategy allows us to control for various school unobserved effects using school fixed effects. The use of fixed effects should increase the robustness of our instrument. With distance as

[17] Town hall GPS coordinates were gathered from town hall addresses using the Google geocoding application programming interface (API). Town hall addresses were obtained from a civil parish directory at http://www.freguesias.pt, accessed November 28, 2012.

Table 3 Average Score in 2005 as a Function of Distance and Other Controls (OLS)

	Average grade—2005				
Variables	(1)	(2)	(3)	(4)	(5)
Dist. Sch–CO (km)	−0.127***		−0.0760		−0.0748
	(0.0454)		(0.0473)		(0.0477)
Dist. Sch–Cntr (km)		−0.0123		−8.84e−03	−5.55e−03
		(0.0202)		(0.0200)	(0.0211)
Students			2.99e−04	2.70e−04	2.89e−04
			(2.38e−04)	(2.37e−04)	(2.40e−04)
Pop. Density			−3.66e−05**	−3.67e−05**	−3.69e−05**
			(1.68e−05)	(1.67e−05)	(1.68e−05)
Earnings 2005			−9.30e−05	−1.41e−04	−1.11e−04
			(2.23e−04)	(2.20e−04)	(2.24e−04)
Mandatory Educ. (%)			0.0238***	0.0250***	0.0241***
			(4.90e−03)	(4.76e−03)	(4.93e−03)
Avg. CO Traffic (Mbps)			−30.88	−39.02	−31.64
			(44.43)	(42.56)	(44.40)
Constant	10.33***	10.21***	9.310***	9.254***	9.327***
	(0.0687)	(0.0515)	(0.197)	(0.193)	(0.197)
Observations	538	537	538	537	537

Note. Standard errors (in parentheses) clustered at the municipality level.
**$p < 0.05$; ***$p < 0.01$.

an instrument, we estimate a two-stage least-squares (2SLS) specification as follows:

$$\begin{aligned} \Delta P_{it} &= \phi + \omega_t \Delta I_{it} + \mathbf{x}_i\boldsymbol{\beta} + \Delta\mathbf{w}_{it}\boldsymbol{\theta} + \Delta u_{it}, \\ \Delta I_{it} &= \varrho + \eta_t Distance_i + \mathbf{x}_i\boldsymbol{\varphi} + \Delta\mathbf{w}_{it}\boldsymbol{\vartheta} + \epsilon_{it}. \end{aligned} \tag{5}$$

7. Results

7.1. Estimates Without the Instrument

We estimate Equation (4) without accounting for endogeneity concerns. However, note that we still control for school unobservable effects via first differences. The results are presented in columns (1) and (2) of Table 4, without and with covariates, respectively. They are very similar though. Broadband use is measured as average use per student in units of 100 MB. Results show a very small and statistically insignificant relationship between change in exam scores and change in broadband use. Not only are the standard errors high but the estimates are economically insignificant. Control variables are also statistically and economically insignificant, which is expected given that we are using school fixed effects. In short, OLS produces insignificant coefficients.

7.2. Correcting for Endogeneity

We estimate our instrumental variable (IV) specification as given by Equation (5). The results are presented in Table 4. Columns (3) and (4) present results without and with covariates, respectively.

The first stage of the IV specifications are presented in Table 5. Columns (1)–(4) present the first stages without covariates, and columns (5)–(8) present the first stages of the specification with all the covariates. The estimate on distance is significant and negative in all specifications. This suggests that our instrument works as expected. For 2009, an increase of 1 km in the distance between a school and the CO leads to about a 14.2 MB (16.7 MB with covariates) decrease in total usage per student. We follow Stock et al. (2002) to test whether distance to the ISP's CO is a weak instrument.[18] The *F*-statistic for the distance to the CO in the first stage of our main regression for the aggregate effect is 17.16. The Stock et al. (2002) critical value for a test of size $r = 0.1$ and significance level $\alpha = 0.05$ is 16.38. Therefore, our instrument does not belong in the set of weak instruments. We provide additional details on the effectiveness of our instrument in Appendix B. Other estimates are sensible as well. The number of students, earnings, and educational level all affect Internet usage negatively. However, the estimates are quite small. Recall that most of the control variables are pegged at 2005 levels.

Our key focus is on the results of the second stage, which are presented in columns (3) and (4) of Table 4. The key estimate of interest is how the growth in

[18] We use the size-based definition of weak instruments to test whether the correlation between our instrument and the endogenous regressor is weak, in which case the conventional first-order asymptotics no longer hold. Technically, our two-stage setup requires four instruments, one for each interaction between the distance to the CO and year. Because the Stock et al. (2002) critical values for weak instruments are not available for four instruments, and given that the only instrument we use is the distance to the CO, we use the aggregate regressions (without year interactions) as a benchmark.

Table 4 Change in Ninth Grade as a Function of Broadband Use (IV)

Variables	(1) OLS	(2) OLS	(3) IV (2nd stage)	(4) IV (2nd stage)
Δ *INet/Student* (100 MB) × *2006*	−0.0507	−0.0410	−0.334	−0.0584
	(0.0836)	(0.0921)	(0.841)	(0.913)
Δ *INet/Student* (100 MB) × *2007*	0.0614	0.0836	−2.052	−1.571
	(0.0627)	(0.0745)	(1.392)	(1.060)
Δ *INet/Student* (100 MB) × *2008*	−8.94e−04	−3.38e−03	−0.981**	−0.973**
	(0.0329)	(0.0377)	(0.473)	(0.463)
Δ *INet/Student* (100 MB) × *2009*	0.0294	0.0468	−0.691*	−0.698*
	(0.0536)	(0.0593)	(0.398)	(0.380)
Students (×1,000)		0.103		−0.882**
		(0.122)		(0.419)
Pop. Density (×1,000)		−0.0144		−0.0131
		(0.0138)		(0.0160)
Earnings (×1,000)		−0.0143		−0.404
		(0.186)		(0.288)
Mandatory Educ. (%)		1.98e−03		−2.42e−03
		(2.34e−03)		(3.35e−03)
Δ *Avg. CO Traffic* (Mbps)		0.521		3.082
		(8.303)		(10.55)
Dist. Sch–Cntr (km)		0.0238		0.0228
		(0.0144)		(0.0210)
Constant	−0.432***	−0.560***	−0.357	0.513
	(0.0355)	(0.156)	(0.217)	(0.606)
Observations	2,521	2,111	2,533	2,111
R-squared	0.504	0.508	0.103	0.229
Year dummies	Yes	Yes	Yes	Yes

Note. Standard errors (in parentheses) clustered at the municipality level.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

usage of broadband per student affected grades. The estimates are negative and large for all years and are statistically significant for 2008 and 2009 (at the 5% and 10% significance level, respectively, with or without covariates). Our estimates (−0.973 for 2008 and −0.698 for 2009) are now unequivocally negative, suggesting an adverse effect of broadband on performance. The average broadband use per student in 2009 was about 111 MB. Therefore, broadband growth between 2005 and 2009 resulted in an average decrease of $0.698 \times 0.111 = 0.78$ standard deviations in the average exam score. This effect amounts to 1.08 standard deviations for 2008. As a comparison, Angrist and Lavy (2002) find a negative effect 0.2 standard deviations in the performance of fourth-grade students in their IV specification, and Malamud and Pop-Eleches (2011) find that owning a computer at home decreases student performance by 0.2–0.5 of a standard deviation, as measured by math GPA. Although different interventions are not fully comparable, the adverse effect of the Internet in schools found in our paper seems to be relatively large.

In summary, our results seem to suggest that broadband use in school is generally detrimental for students' performance, at least within a few years after its introduction into the school's environment. If one believes that distracting activities on the Internet (e.g., listening to music, playing games, and watching movies) are inherently bandwidth intensive, then our instrument provides a consistent reason for the observed behavior. Schools that are closer to the CO allow higher throughput and thus make it easier for students to indulge in distracting activities, lowering their exam scores. These results are in line with a study performed by Stinebrickner and Stinebrickner (2008). Their paper instruments a student's study time by whether the student's randomly assigned roommate owns a gaming console in the room. Their findings show that the study time positively influences academic performance. We explore the distraction hypothesis in more detail in §8.

We make it clear that our results do not suggest that schools should not have broadband. There are many other benefits broadband may accrue that we do not measure, such as improving students' computer and Internet skills and providing wide access to information and knowledge that are not tested in national exams. However, our results seem to suggest that merely connecting schools to broadband may not be enough. If anything, such effects may be detrimental. Various other measures may need to be implemented in parallel to increase the productivity of investments

Table 5 Year-Specific Change in Broadband Use as a Function of Distance to CO

	Δ *INet*							
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dist. Sch–CO (km) × *2006*	−0.0414***				−0.0421***			
	(0.0154)				(0.0162)			
Dist. Sch–CO (km) × *2007*		−0.0494**				−0.0646**		
		(0.0249)				(0.0269)		
Dist. Sch–CO (km) × *2008*			−0.130***				−0.157***	
			(0.0463)				(0.0509)	
Dist. Sch–CO (km) × *2009*				−0.142***				−0.167***
				(0.0420)				(0.0401)
Students (×1,000)					−0.443***	−0.680***	−1.428***	−1.766***
					(0.0716)	(0.116)	(0.230)	(0.204)
Pop. Density (×1,000)					−0.00406	−0.00139	0.00577	0.00279
					(0.00368)	(0.00444)	(0.00800)	(0.00946)
Earnings (×1,000)					−0.225***	−0.165**	−0.445***	−0.921***
					(0.0670)	(0.0804)	(0.166)	(0.212)
Mandatory Educ. (%)					0.000336	−0.00488**	−0.00871**	−0.00759***
					(0.00151)	(0.00202)	(0.00354)	(0.00291)
Δ *Avg. CO Traffic* (Mbps)					−4.848	10.13	9.260	2.595
					(10.93)	(8.474)	(7.095)	(5.624)
Dist. Sch–Cntr (km)					−0.0103	−0.0103	0.00921	0.0282
					(0.00649)	(0.00751)	(0.0146)	(0.0208)
Constant	0.304***	0.432***	0.926***	1.193***	0.754***	1.173***	2.453***	3.218***
	(0.0254)	(0.0419)	(0.0788)	(0.0657)	(0.102)	(0.176)	(0.338)	(0.258)
Observations	629	627	637	628	527	523	534	527
R-squared	0.008	0.005	0.012	0.014	0.124	0.178	0.210	0.352
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note. Robust standard errors in parentheses.
**$p < 0.05$; ***$p < 0.01$.

in school broadband. We discuss the implications of our results in detail in §9.

7.3. Impact Across Gender

Our specification does not allow us to estimate α and γ in Equation (1) separately. However, distinct groups of students might use broadband to perform different activities that affect them differently. For example, we may expect that students who perform more distracting activities (lower α) may be more adversely affected by increased broadband use.

According to a survey administered by the Portuguese Telecom Regulator (ANACOM) of 659 students,[19] boys and girls tend to perform different sets of activities on the Internet. For example, boys are more likely to report using MySpace, watching YouTube videos and TV, listening to online radio and music, and playing online games. Girls are more likely to look for scientific information online. Most of these differences are considerable and statistically significant. Thus, according to our framework, if we characterize activities such as YouTube, chat, and games as distracting, then we should expect a stronger adverse effect of broadband use on boys' performance. We test this hypothesis by calculating separate average scores for boys and girls and by running separate regressions of performance on broadband use for each of them.

For brevity, we show the IV regressions in Appendix A. Both boys and girls seem to be affected by broadband Internet use, but boys seem to be slightly more affected both in terms of magnitude[20] and statistical significance. Although not conclusive, these estimates are in line with our hypothesis that boys should be more affected than girls given that they perform more distracting activities on the Internet (lower α).

7.4. Impact on Different Courses

The ninth-grade score combines scores in math and Portuguese. We split the data between math and Portuguese and examine how each of these scores is affected by broadband usage. The literature does not provide clear guidance for whether computer or broadband should affect math or languages. Angrist and Lavy (2002) find a negative effect in math exam scores for fourth graders. Malamud and Pop-Eleches (2011) find that families that acquire computers had

[19] From this, 652 students (332 girls and 320 boys) answered a question about activities performed on the Internet.

[20] Although not statistically different, the effect is 9% larger for boys than for girls.

significant lower school grades in math, English, and Romanian. Rouse and Krueger (2004) find that the use of specific software designed to improve language or reading skills (FastForWord) improves some aspects of students' language skills. Banerjee et al. (2007) and Carrillo et al. (2011) report that the use of computer-assisted programs improve performance in math but not in language.

We estimate Equation (5) for math and Portuguese separately. We get large, negative, and statistically significant estimates for both math and Portuguese, consistent with Malamud and Pop-Eleches (2011). Again, these results are presented in Appendix A for brevity.

7.5. Impact Across School Quality

We also study which schools suffer the most with the introduction of broadband. We split our sample of schools into quartiles based on their ninth-grade average exam score in 2005, just prior to the deployment of broadband. We interact broadband use and distance with each of the quartile dummies in our IV setting. None of the quartile interaction variables displays a statistically significant coefficient. Moreover, Wald tests suggest that there is no difference across these coefficients. (Regression results are available from the authors upon request.) Overall, these results suggest that broadband affects exam scores across all types of schools, independently of how well the schools scored prior to the deployment of broadband.

8. Distraction Hypothesis: Additional Evidence

To better understand how distraction and learning with the Internet at school affects grades, we need to understand what activities students perform on the Internet. The choice of these activities is directly affected by school policies on Internet use. In particular, some schools restrict access to distracting websites and applications such as Facebook and YouTube (i.e., schools with higher α), but other schools allow full access to the Internet. We now explore whether such policies have any effect on school performance and broadband use.

To better understand current Internet access policies and practices, we designed a survey and deployed it to middle schools in Portugal. The survey consisted of 27 questions and was administered over the phone to school ICT managers between December 10, 2010, and January 17, 2011.[21] A total of 344 answers were obtained (a response rate of 55%). The schools that completed the survey were similar to the schools that did not in terms of grades, size, and distance to the CO, but they were different in terms of Internet usage, population density, income levels, and basic education levels (see Table 6).[22]

Table 6 Summary Statistics for Nonsurveyed vs. Surveyed Schools

Variables	(1) No survey	(2) Survey
Avg. Grade 2005 (s.d.)**	10.28 (1.026)	10.13 (0.990)
INet Usage 2009/Stu. (MB)***	100.2 (81.41)	120.2 (104.7)
INet Usage 2008/Stu. (MB)**	77.30 (65.81)	94.46 (116.8)
Students	589.0 (231.9)	571.2 (245.1)
*Pop. Density****	2,142 (3,211)	1,553 (2,523)
*Earnings 2005***	802.8 (183.0)	773.9 (189.2)
Mandatory Educ. (%)***	40.84 (13.74)	37.74 (13.59)
Dist. Sch–CO (km)*	1.025 (0.716)	1.111 (0.815)
Dist. Sch–Cntr (km)**	1.182 (1.234)	1.441 (2.135)
Observations	284	344

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$ (t-tests equal variance).

Among other questions, the survey asked whether the school blocks access to specific websites or applications. Respondents indicated a subset of the following options as sites or applications blocked in the school: YouTube, Facebook, Hi5, MySpace, chat applications, online games, other video sites, file-sharing applications, and other sites. This question seems to be the one that best proxies distracting activities with the Internet at school. The other questions in the survey covered mostly IT resources and skills.

We examine if these policies have an impact on school performance. Such policies possibly proxy for the school attitude toward technology use. By explicitly capturing them in our analysis, we control for these unobserved differences across schools. Our focus is to extend our earlier model by examining how the marginal effect of broadband is conditioned by school policies. We must point out that our results are suggestive because schools that block applications may be different from schools that do not in ways that are not observed and that may have an impact on the productivity of Internet use (leading to potential selection). Furthermore, our survey data are available only for one year and school policies might have changed over time.

[21] The role of ICT manager is well defined in each school and corresponds to the person that is responsible for the maintenance of the school's computers and network. This role is usually assigned to one of the ICT teachers in the school.

[22] We use 95% confidence interval t-tests to test whether the two groups have the same mean. The asterisk (*) symbols correspond to significance levels in equal variance t-tests for the difference between surveyed and nonsurveyed schools.

Table 7 Summary Statistics by Blocking Policy: No Blocks and Allow YouTube

Variables	(1) No block	(2) Block	(3) Allow YouTube	(4) Block YouTube
Avg. Grade 2005 (s.d.)**	10.36 (0.847)	10.09 (1.005)	10.12 (0.977)	10.24 (1.132)
INet Usage 2009/Stu. (MB)	120.4 (104.0)	120.2 (104.8)	121.6 (106.8)	103.1 (68.87)
INet Usage 2008/Stu. (MB)	83.41 (65.83)	96.05 (122.7)	95.65 (120.3)	77.54 (48.49)
Students††	607.4 (255.4)	565.2 (242.6)	563.6 (246.0)	662.7 (207.5)
Pop. Density	1,766 (2,028)	1,526 (2,595)	1,553 (2,561)	1,636 (2,031)
Earnings 2005†	766.9 (168.1)	775.8 (192.7)	769.8 (182.7)	833.0 (254.5)
Mandatory Educ. (%)††	39.54 (12.51)	37.46 (13.71)	37.38 (13.47)	42.33 (13.90)
Dist. Sch–Cntr (km)	1.164 (0.883)	1.102 (0.802)	1.103 (0.807)	1.209 (0.893)
Observations	48	298	320	26

**$p < 0.05$ (block versus no block, t-tests equal variance); †$p < 0.1$; ††$p < 0.05$ (allow YouTube versus Block YouTube, t-tests equal variance).

Schools seem to be quite heterogeneous in terms of what content and activities they allow. We will focus on two measures. First, we examine if the schools that block all activities perform differently. Second, we examine the role of YouTube. We focus on YouTube in particular because it may be a distracting activity and is bandwidth intensive. Thus, the marginal effect of Internet use in schools that allow YouTube should capture the effect of distraction.

We first present summary statistics in Table 7. The differences in school policies seem to be independent of school characteristics. The average 2005 grades across schools are quite similar. Still, schools in slightly higher income and more educated regions are more likely to block YouTube. The Internet use in schools that allow YouTube is substantially higher as expected.

Our hypothesis is that Internet use is more harmful in schools that do not restrict access to distracting websites or applications. To test this hypothesis, we add the indicator *No Blocks* to our IV setup along with its interaction with Internet use.[23]

For readability purposes, we pool the 2008 and 2009 differences. We also assume that the Internet usage policies in these schools have not changed over time.[24] Because we are assuming *No Blocks* to be a time-fixed school characteristic, it would be differenced out along with the other time-fixed covariates. By including it in the differences equation, we are allowing it to drive the *change* in school performance, along with all other time-constant covariates (see §6.1). Table 8 shows the results obtained.[25]

Note in column (3) of Table 8 that the Internet is still negative and significant but the *No Blocks* indicator and its interaction with the Internet provides no evidence that the schools that do not block any type of content perform any worse. One of the reasons for this result might be that not all websites are bandwidth intensive, and hence Internet usage does not capture the distractive activities that students might perform. Also, the behavior of students in schools that block *all* activities may not be too different from schools that block *some* activities.

From all the websites and applications considered in our survey, YouTube seems to be the one for which a linear relationship between Internet use and distraction time is more likely to hold. Social network sites, chat applications, and online games are relatively low-bandwidth intensive, so students can spend a lot of time on them without consuming many bytes. File-sharing applications might also be bandwidth intensive, but students can share files in the background as they perform other activities. Hence, we focus on YouTube use and build an indicator called *Allow YouTube* to identify laxer schools in terms of Internet access policies.

As before, we use our IV setup to regress change in average grade on Internet use, our regional covariates, the *Allow YouTube* indicator, and the interaction between Internet use and this indicator.[26] Columns (4) and (5) in Table 8 show the results obtained. Schools that allow YouTube perform worse: the magnitude of the *Allow YouTube* coefficient in column (4) corresponds to a decrease in grades of about 0.39 of a standard deviation. Most importantly, including the interaction effect now shows that the Internet use in schools that allow YouTube leads to a large adverse effect on grades (column (5)): a decrease of 0.73 standard deviations per 100 MB compared to a decrease of 0.53 standard deviations in the baseline case. Put another way, the effect of the Internet is significantly worse when schools allow YouTube. This is consistent with our argument that when the Internet is being used for bandwidth-intensive distracting activities, it leads to an adverse effect on student performance.

In sum, we find suggestive evidence that the way schools allow students to use the Internet connectivity affects students' performance. Students perform

[23] We use the interaction between the predicted Internet use and the *No Blocks* indicator as a second instrument.

[24] Several schools reported that they have been blocking more sites over time, taking advantage of a filtering service provided by the ISP for this purpose. Thus, our estimates are conservative and should be interpreted as a lower bound.

[25] Some covariates are missing for some of the schools that were surveyed, and therefore the number of observations in these regressions falls short of 344 per year. First-stage estimates are available upon request.

[26] First-stage estimates are available upon request.

Table 8 Change in Ninth-Grade Performance as a Function of Broadband Use and Site Blocking Policy (IV)

Variables	(1) Baseline	(2) No block	(3) No block	(4) Allow YouTube	(5) Allow YouTube
Δ *INet usage/Student* (100 MB)	−0.526**	−0.550**	−0.543**	−0.507**	0.221
	(0.228)	(0.223)	(0.226)	(0.216)	(0.454)
Δ *INet* × *No Blocks*			−0.100		
			(0.209)		
No Blocks		−0.187	−0.0920		
		(0.142)	(0.191)		
Δ *INet* × *Allow YouTube*					−0.726*
					(0.390)
Allow YouTube				−0.392**	0.159
				(0.154)	(0.366)
Students (×1,000)	−1.047**	−1.089**	−1.104**	−1.072**	−1.057**
	(0.511)	(0.505)	(0.516)	(0.491)	(0.497)
Pop. Density (×1,000)	0.0176	0.0188	0.0191	0.0218	0.0202
	(0.0203)	(0.0205)	(0.0206)	(0.0211)	(0.0211)
Earnings (×1,000)	−0.644	−0.687	−0.704*	−0.694	−0.680
	(0.418)	(0.420)	(0.422)	(0.436)	(0.423)
Mandatory Educ. (%)	−0.00369	−0.00346	−0.00344	−0.00366	−0.00248
	(0.00530)	(0.00540)	(0.00541)	(0.00517)	(0.00530)
Δ *Avg. CO Traffic* (Mbps)	−14.04	−13.30	−13.27	−16.01	−15.14
	(14.07)	(14.13)	(14.31)	(12.84)	(13.07)
Dist. Sch–Cntr (km)	0.0443**	0.0444**	0.0451**	0.0459**	0.0463**
	(0.0189)	(0.0187)	(0.0182)	(0.0188)	(0.0184)
Constant	3.256***	3.353***	3.367***	3.648***	3.022***
	(0.789)	(0.775)	(0.786)	(0.809)	(0.932)
Observations	575	575	575	575	575
Year dummies	Yes	Yes	Yes	Yes	Yes

Note. Standard errors (in parentheses) clustered at the municipality level.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

relatively worse in schools with laxer access policies that do not control the opportunities for exaggerated distraction.

9. Conclusion and Discussion

Using a comprehensive data set on broadband use in every middle school in Portugal, we find evidence that broadband hurts student performance. Our analysis shows that, on average, broadband is responsible for a decline of 0.78 of a standard deviation in grades in the 2005–2009 window. Our paper contributes to the general empirical question of how technology, such as the Internet, impacts student performance. A novel contribution of our paper is that we measure Internet use in terms of bandwidth consumed. We also construct a plausible instrument to tease out the effect of broadband. We believe our measurements and choice of instrument make unique contributions to the literature. We also find that all types of schools (low versus high performing) are equally affected by broadband regardless of their performance in 2005. A technology like broadband may not always be used productively; hence, its availability in poor-performing schools might not necessarily translate into better grades or close the gap.

We conducted a survey to explore the distraction effect of the Internet in more detail. Some schools block access to many applications and services that can be characterized as distracting (such as music, movies, chat, and online gaming). More interestingly, we focus on YouTube access, which is a bandwidth intensive application. In fact, schools that allow YouTube typically also consume more bandwidth. We find some evidence that indeed Internet use has a significantly more adverse affect in schools that allow access to YouTube.

Our study, applied to the case of Portugal, shows that the introduction of broadband in schools does not necessarily contribute to an increase students' performance, at least in the few years after its deployment. Although we do not have direct measurement, our results suggest that the introduction of broadband in the school environment must be complemented with policies aimed at effectively embedding the Internet in the education system and promoting productive use of the Internet in ways that complement traditional study. This may be particularly true for students in early high school who, without proper monitoring, may be more likely to engage in distracting activities. Recall that broadband was provided to all schools

as a central policy decision, possibly without giving enough time to schools to think and plan ahead how best to benefit from the new technology. Benefiting from the Internet requires active engagement from schools, teachers, and students to bring everyone on board to correctly exploit the new opportunities.

Although we use a very detailed data set, our study is not without limitations. The quality of the students' ADSL connection at home might be correlated with that of their connection at school for students that live close to the school. Although we control for the household Internet traffic in the CO closest to the school to avoid confounding the effects of the Internet at home and school, our estimate may still pick up some of the former. In addition, we do not know precisely the kind of activities that students perform on the Internet.

It is also possible that teachers become less effective when they have a better Internet connection, contributing to lower student grades. Similarly, broadband may still be beneficial for students in ways that test scores do not capture, the effects of which our study cannot appreciate. For example, broadband deployment in schools allows students to be exposed to new sets of technologies that they will most likely use later both in their professional careers to increase their productivity and in their personal lives to facilitate, for example, communication with friends and family. However, these kinds of benefits are extremely difficult to measure, and our study fails to take them into account. Nevertheless, we emphasize that in any country, education policy today is largely shaped by schools' performance and everyone in the educational system (students, teachers, schools, parents, and educators) has clear incentives to improve students' performance. In this regard, our paper is the first of its kind to provide concrete evidence of how the introduction of broadband in schools affects student performance.

Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2013.1770.

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Appendix A. Impact Across Gender and Course

Table A.1 presents the aggregate estimates across gender and course. Columns (2) and (3) show the estimates for boys and girls, respectively. Broadband in schools seems to affect boys and girls similarly. Results suggest that the average broadband use of 111 MB per month per student in 2009 leads to

Table A.1 Change in Ninth-Grade Performance as a Function of Broadband Use by Gender and Course

Variables	(1) All	(2) Male	(3) Female	(4) Portuguese	(5) Math
Δ *INet Usage/Student* (100 MB)	−0.866**	−0.936**	−0.895*	−0.779**	−0.982**
	(0.378)	(0.472)	(0.487)	(0.392)	(0.494)
Students (×1,000)	−0.887**	−0.628	−1.240**	−0.807*	−0.989*
	(0.405)	(0.502)	(0.509)	(0.443)	(0.519)
Pop. Density (×1,000)	−0.0137	−0.0247	−0.00356	−0.0124	−0.0160
	(0.0160)	(0.0218)	(0.0155)	(0.0159)	(0.0211)
Earnings (×1,000)	−0.448	−0.302	−0.714**	−0.447*	−0.477
	(0.289)	(0.439)	(0.292)	(0.265)	(0.416)
Mandatory Educ. (%)	−0.00156	−0.00209	−0.000629	−0.00283	−0.000444
	(0.00312)	(0.00392)	(0.00411)	(0.00370)	(0.00423)
Δ *Avg. CO Traffic* (Mbps)	1.985	5.215	−0.125	11.69	−7.005
	(10.32)	(11.92)	(12.55)	(9.593)	(14.61)
Dist. Sch–Cntr (km)	0.0235	0.0331	0.0133	0.0148	0.0320
	(0.0205)	(0.0238)	(0.0243)	(0.0202)	(0.0243)
Constant	0.724	0.555	1.063	−0.474	1.974***
	(0.546)	(0.711)	(0.663)	(0.557)	(0.716)
Observations	2,111	2,087	2,087	2,111	2,111
R-squared	0.283	0.155	0.272	0.372	0.470
Year dummies	Yes	Yes	Yes	Yes	Yes

Note. Standard errors (in parentheses) clustered at the municipality level.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

a decrease of about one standard deviation in the average exam scores of boys (column (2)), only slightly more than girls (column (3)). The effect for boys is 5% larger, although not statistically different. In terms of courses, we also get large, negative, and statistically significant estimates for both Portuguese and math (columns (4) and (5), respectively). Although not statistically different, the adverse effect is 29% larger for math than for Portuguese.

Appendix B. Robustness Tests for Distance as an Instrument

The distance between a school and the CO that serves it is a good instrument because the speed of the ADSL connection reduces with the length of the copper wire (see Tanenbaum 2002, Chap. 2). Our first-stage regressions show that this is the case. Also, grades in 2005 seem to be unaffected by distance, after controlling for region and school-specific

Figure B.1 **Middle School Distances to the Closest CO by Population Density**

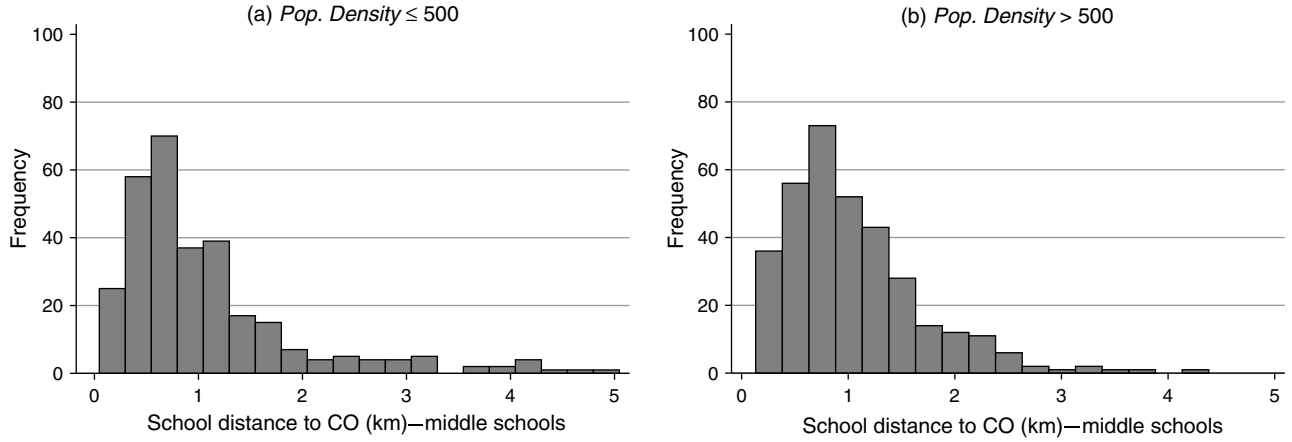

Figure B.2 **Middle School Distances to the Closest CO by Earnings**

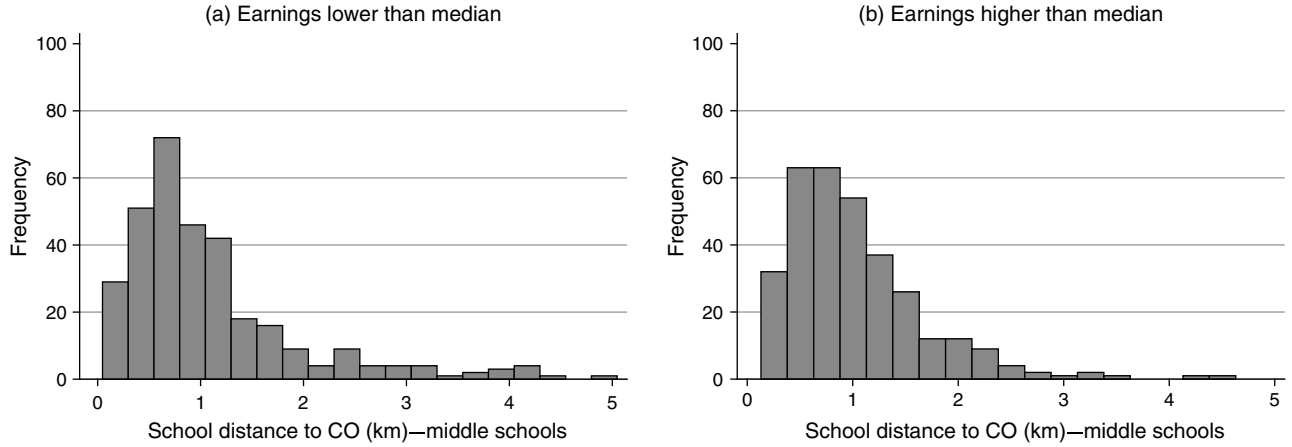

Figure B.3 **Middle School Distances to the Closest CO by Education Level**

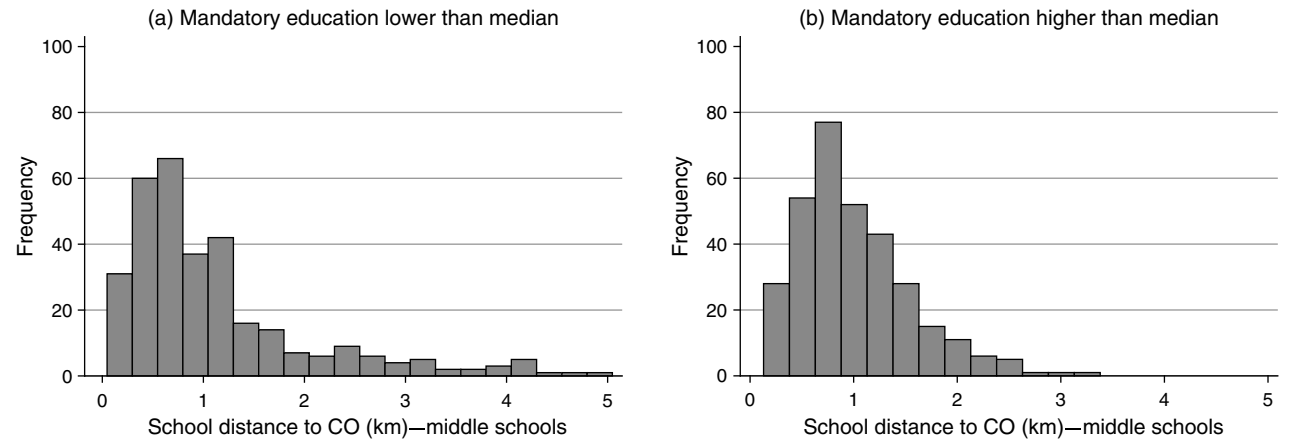

Table B.1 Distance Threshold Regressions for Schools with Ninth-Grade Students

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dist. Sch–CO (km)	−0.106***	−0.131***	−0.129**	−0.101***	−0.108***	−0.216**	−0.0447
	(0.0214)	(0.0384)	(0.0506)	(0.0378)	(0.0260)	(0.0989)	(0.0954)
Sq. Dist. Sch–CO (km)							−0.0172
							(0.0212)
Students (×1,000)	−1.077***	−1.086***	−1.078***	−1.080***	−1.078***	−1.092***	−1.087***
	(0.127)	(0.133)	(0.130)	(0.130)	(0.130)	(0.132)	(0.128)
Pop. Density (×1,000)	0.000769	0.000661	0.000900	0.000804	0.000802	0.000850	0.000923
	(0.00562)	(0.00571)	(0.00562)	(0.00570)	(0.00568)	(0.00548)	(0.00573)
Earnings (×1,000)	−0.442***	−0.445***	−0.441***	−0.442***	−0.442***	−0.449***	−0.443***
	(0.110)	(0.112)	(0.111)	(0.111)	(0.111)	(0.111)	(0.111)
Mandatory Educ. (%)	−0.00520**	−0.00530**	−0.00517**	−0.00529**	−0.00524**	−0.00520**	−0.00549***
	(0.00202)	(0.00208)	(0.00207)	(0.00207)	(0.00206)	(0.00203)	(0.00206)
Δ *Avg. CO Traffic* (Mbps)	4.731	4.986	4.709	4.915	4.754	4.808	5.124
	(5.160)	(5.131)	(5.122)	(5.055)	(5.138)	(5.069)	(5.109)
Dist. Sch–Cntr (km)	0.00424	0.00347	0.00434	0.00395	0.00418	0.00351	0.00334
	(0.0103)	(0.0106)	(0.0105)	(0.0105)	(0.0104)	(0.0105)	(0.0105)
Dist. Sch–CO >0.5 km	−0.00748					0.0246	
	(0.0749)					(0.0734)	
Dist. Sch–CO >1 km		0.0513				0.0958	
		(0.0600)				(0.0803)	
Dist. Sch–CO >2 km			0.0676			0.141	
			(0.113)			(0.128)	
Dist. Sch–CO >3 km				−0.0434		0.0972	
				(0.119)		(0.148)	
2007	0.110***	0.110***	0.110***	0.110***	0.110***	0.110***	0.110***
	(0.0180)	(0.0178)	(0.0178)	(0.0178)	(0.0178)	(0.0180)	(0.0179)
2008	0.513***	0.513***	0.513***	0.513***	0.513***	0.513***	0.513***
	(0.0406)	(0.0403)	(0.0404)	(0.0405)	(0.0403)	(0.0407)	(0.0406)
2009	0.734***	0.733***	0.734***	0.734***	0.734***	0.734***	0.733***
	(0.0516)	(0.0515)	(0.0517)	(0.0514)	(0.0516)	(0.0515)	(0.0514)
Constant	1.566***	1.579***	1.575***	1.562***	1.565***	1.616***	1.543***
	(0.177)	(0.175)	(0.172)	(0.169)	(0.168)	(0.195)	(0.177)
Observations	2,111	2,111	2,111	2,111	2,111	2,111	2,111
R-squared	0.318	0.318	0.318	0.318	0.318	0.319	0.318

Notes. Robust standard errors in parentheses.
**$p < 0.05$; ***$p < 0.01$.

Table B.2 Internet Use as a Function of Distance and Other Controls (OLS)

Variables	(1)	(2)	(3)	(4)	(5)
Dist. Sch–CO (km)	−0.0944***		−0.117***		−0.119***
	(0.0296)		(0.0285)		(0.0284)
Dist. Sch–Cntr (km)		0.00183		0.00161	0.00544
		(0.0126)		(0.0124)	(0.0104)
Students (×1,000)			−1.124***	−1.165***	−1.136***
			(0.140)	(0.150)	(0.143)
Pop. Density (×1,000)			0.00523	0.00521	0.00556
			(0.00516)	(0.00600)	(0.00551)
Earnings (×1,000)			−0.395***	−0.470***	−0.408***
			(0.120)	(0.117)	(0.121)
Mandatory Educ. (%)			−0.00638***	−0.00462**	−0.00637***
			(0.00233)	(0.00226)	(0.00235)
Δ *Avg. CO Traffic* (Mbps)			3.418	−0.624	3.220
			(5.785)	(6.403)	(5.816)
2007	0.120***	0.121***	0.111***	0.115***	0.112***
	(0.0167)	(0.0170)	(0.0193)	(0.0200)	(0.0196)

Table B.2 (Continued)

Variables	(1)	(2)	(3)	(4)	(5)
2008	0.559***	0.554***	0.547***	0.553***	0.546***
	(0.0368)	(0.0363)	(0.0437)	(0.0460)	(0.0444)
2009	0.830***	0.826***	0.790***	0.800***	0.787***
	(0.0469)	(0.0465)	(0.0601)	(0.0620)	(0.0606)
Constant	0.362***	0.259***	1.590***	1.483***	1.607***
	(0.0399)	(0.0280)	(0.176)	(0.165)	(0.185)
Observations	2,312	2,264	1,913	1,885	1,885
R-squared	0.169	0.161	0.322	0.309	0.321

Note. Standard errors (in parentheses) clustered at the municipality level.
$^{**}p < 0.05$; $^{***}p < 0.01$.

characteristics (see Table 3). There is, however, concern that end users may not be able to appreciate differences in the quality of ADSL connections for short distances between schools and COs, rendering our instrument invalid for schools that are very close to the CO. Also, ADSL speeds may have been capped by the provider, which would render the quality of ADSL connections similar for all schools close to the CO. We test these hypotheses by introducing distance threshold dummies in the first-stage regression. Table B.1 shows that none of the distance thresholds are significant in 2009.[27] This shows that usage reduces with distance for schools close and far away from the CO alike. This is consistent with the hypothesis that ADSL connections have not been capped, at least not at a rate that schools use, and that users perceive differences in the quality of the ADSL connection even across schools that are close to the CO.

There is also a concern that distance to the CO and regional covariates such as population density, earnings, and mandatory education are correlated. Table 2 shows that this is not the case. Furthermore, Figure B.1 shows that the distance to the CO for schools in both high- and low-density areas ranges from a few meters to as much as 5 km—likewise for earnings and mandatory education, as Figures B.2 and B.3 report.

[27] Regressions for 2008 yielded similar results.

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