The Effects of Broadband in Schools: Evidence from Portugal

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Abstract

The introduction of broadband in schools provides a new resource for learning but also an opportunity for distraction. Consequently, broadband use in schools can either increase or reduce students' performance. This paper provides a model that shows how these two effects trade off. We use a rich panel of data with information on broadband use in all schools in Portugal and on students' performance in the 9th grade national exams to learn how broadband use affects performance. We use a first-differences specification to control for school-specific unobserved effects. We also use a proxy for the quality of the broadband connection as an instrument to control for unobserved time-varying effects. We show that high levels of broadband use in schools in 2008 and 2009 are detrimental for the grades of 9th grade students. For the average broadband use in schools, grades reduce about 0.76 and 0.67 of a standard deviation in 2008 and 2009, respectively. We also show evidence suggesting that broadband has a negative impact on exam scores regardless of gender, subject or school quality. We also find suggestive evidence that the way schools allow students to use the Internet affects students' performance, in particular, students in schools that block access to websites such as YouTube perform relatively better. Although test scores do not measure all the effects that broadband in schools have on the performance of students throughout life, our results show that the introduction of Internet in schools is a task that deserves careful planning.

1 Introduction

There is a generalized consensus that education plays an important role in the economic performance of countries as well as on the success of firms and of individuals in the labor market. Research has shown that higher levels of education are associated with both higher productivity at the country level (e.g., Mankiw et al., 1992) and higher wages at the individual level (e.g., Card, 1999). There is also a general belief that providing more resources to schools contributes to increase the quality of education, which raises students' performance and, consequently, productivity levels both at the individual and at the aggregate level.

However, researchers have hardly reached a consensus regarding whether better resources (including technology) in schools lead to better outcomes. For a long time research on the impact of resources in education has produced mixed results. A review of such studies provided by Hanushek (1986) suggested that there is "no strong or systematic relationship between school expenditures and student performance". In fact, teasing out the impact of resources on student performance from archival data is challenging because many unobserved factors contaminate the estimates. More recent studies, that control for such factors, show that some types of resources (e.g., class size, school hours) have a consistent positive impact on students' performance, but others do not, such as Information and Communications Technologies (ICTs) (Webbink, 2005).

ICTs are perceived by many as potential 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 are heavily subsidizing computers and now 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 & Pop-Eleches, 2010). 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 broadband use in school on students' performance. Moreover, these studies provide mixed results on whether ICTs indeed help students. Thus there is little understanding of how broadband can help learning.

In this paper, we first provide a model for how broadband use in schools contributes to students' performance. In essence, broadband use can be beneficial when students spend a considerable amount of time in productive activities, and detrimental when students engage mainly in distracting activities that substitute traditional study. We then provide empirical evidence on the impact of *actual usage* (as opposed to existence of a broadband connection in schools) of broadband in schools on students' performance drawing from the case of Portugal. Actual usage is measured by the amount of information exchanged with the Internet over ADSL connections. Performance is measured by scores obtained in national exams. We collect a panel of data on broadband use and school performance in more than 900 Portuguese schools, between 2005 and 2009. We use a first differences model to account for school-specific unobserved effects. The school performance may be endogenous to broadband use. We overcome this by instrumenting 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 for a good instrument providing us confidence in the results obtained.

For 9^{th} grade students, our estimates indicate that more broadband use is detrimental for students' test scores. We find that, on average, grades declined about 0.76 of a standard deviation between 2005 and 2008 and about 0.67 of a standard deviation between 2005 and 2009 due to broadband use. We find that there is little difference across genders (both boys and girls suffer equally) and across math vs language (grades in both Portuguese and math exams reduce equally). 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 Internet in more detail, we conduct a survey to understand how Internet is utilized in schools. In particular we focus on school policy regarding blocking or allowing applications and services such as Facebook, YouTube and file-sharing, which are likely to cause distraction. We find some evidence that schools that allow these activities perform worse and the effect of Internet is significantly more negative when schools allow YouTube use. Overall, our results suggest that merely providing broadband access does not help students. Without proper monitoring and control, broadband access in schools may be more harmful than helpful.

This paper is structured as follows. Section 2 provides a review of relevant literature. Section 3 introduces the initiatives sponsored by the Portuguese government to provide Internet to schools. Section 4 and Section 5 describe the data we used and a model of how broadband affects student's performance. Section 6 presents the model we have empirically estimated. Section 7 and Section 8 present empirical results and some suggestive evidence for the distraction hypothesis. Section 9 concludes.

2 Related work

2.1 School Resources and Students' Performance

There is a vast literature on the impact of class size, school hours, teacher training, computer use and peer group effects on students' performance. One of the first studies is Coleman's report (Coleman, 1968), which concludes that higher levels of school resources do not necessarily translate into improved test scores. A series of subsequent works have also been inconclusive in this respect. In his influential meta-analyses, Hanushek (Hanushek, 1986; Hanushek et al., 1996) also concludes that there is no systematic relationship between school expenditures and student performance.

These early results have been questioned because unobserved effects might have biased some of the conclusions. 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 that overcome the endogeneity problem find a positive impact of class size (e.g., Krueger, 1999; Angrist & Lavy, 1999), school hours (e.g., Lavy, 1999) and peer group effects (e.g., Sacerdote, 2001).[1] The impact of other characteristics, such as teacher training and computer use, either remains non-significant or exhibits mixed results (e.g., Angrist & Lavy, 2002; Webbink, 2005; Barrera-Osorio & Linden, 2009).

We note that most studies look at students' test scores in a standardized test as an outcome measure (e.g., Angrist & Lavy, 2002; Goolsbee & Guryan, 2006; Leuven et al., 2007; Machin et al., 2007). Even though test scores have some obvious limitations, most studies use test scores as a measure of student performance 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' demand. As a consequence, schools, teachers and students all have incentives to improve test scores.

2.2 ICT Investments and Students' Performance

Research on the contribution of ICTs to students' performance has also produced mixed results. Early studies on the use of computers in the classroom report positive effects on students' performance, but are often criticized either because they fail to account for endogeneity or because they report effects with small magnitudes (Cuban & Kirkpatrick, 1998; Webbink, 2005).

More recent work overcomes the endogeneity problem by exploiting exogenous sources of variation in computer use. Angrist & Lavy (2002) present the first study along these lines. They 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 8^{th} graders. Goolsbee & Guryan (2006) study the impact of subsidizing schools' Internet access and find no evidence that more classrooms with Internet has an impact 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. In 2000, Dutch schools in which more than 70% of

[1] 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 & Lavy (1999) take advantage of a maximum class size rule; Lavy (1999) taps on variations on the allocation of school hours; and Sacerdote (2001) uses random dorm assignments.

the students were considered disadvantaged were eligible to receive a subsidy to acquire computers. Using a differences-in-differences framework, they find that this subsidy had a negative impact on students' performance, especially on girls. Malamud & Pop-Eleches (2010) exploit a discontinuity in a subsidy provided in Romania in 2008. This subsidy would allow low-income families to acquire a home computer. They find that the students of families that used this subsidy (households that indeed bought a home computer) had significant lower school grades in math, English and Romanian. They also find that these students had higher scores in tests of computer skills and in self-assessment tests of computer fluency.

An exception to this recent trend of non-significant or negative results is provided by Machin et al. (2007). In 2001 the rules governing ICT investment in different regions in the UK changed.[2] This change created a quasi-experiment setting with winners and losers across regions. Machin et al. (2007) find evidence of a positive effect of ICT investment in elementary schools.

A few studies show positive effects of computer-aided learning on students' performance. Rouse & Krueger (2004) study the results of a randomized experiment on the use of a specific software designed to improve language or reading skills (FastForWord). Their results suggest that the use of this software improves some aspects of students' language skills, but this does not necessarily translate into better language acquisition and reading skills.

Banerjee et al. (2007) report the results of randomized experiments in schools in urban India aimed at improving the test scores of students lagging behind. One of such projects consisted in using a computer-assisted program aimed at improving math scores. They find that math scores increased by 0.47 of a standard deviation, but this result fades to 0.1 of a standard deviation one year after the end of the project. These results did not seem to spillover to other subjects.

Barrow et al. (2009) find that students randomly assigned to a computer-aided instruction program scored significantly higher in algebra and in pre-algebra tests, than those that were not assigned to the program. They ran the experiments between 2003 and 2005 in 17 schools (146 classes) in the U.S and hypothesized that the higher scores were due to the individualized instruction provided by the program.

[2]ICT funds are awarded to each region in proportion to population, whereas before a bidding process took place.

In summary, the impact of ICTs and school resources on student performance is an empirically challenging question. Also, most studies published so far look at the impact of investment in ICTs on student's performance and not at the impact of actual usage of ICTs. Furthermore, most of these studies look at the availability of ICTs in general rather than the use of a specific technology. This paper looks at the impact of *actual broadband* use on a real school environment. We also examine the impact of specific applications and services. We provide a credible instrument to alleviate the endogeneity concerns. Overall, we find that broadband usage over the 2005-2009 period had an adverse effect on school performance.

3 Broadband in Portuguese Schools

3.1 Broadband Provision to Schools

In Portugal most elementary and secondary schools are public schools, funded either by the Central Government or the Local Government, with limited autonomy to manage their resources. The provisioning of Internet to schools has been managed by FCCN - the Portuguese National Foundation for Scientific Computation. FCCN is a private foundation, under the tutelage of the Ministry of Science, Technology and Higher Education, that runs the National Research and Education Network (NREN). The NREN connects all schools, institutions of higher education and research labs in the country. The same institutional model is followed by a number of other European countries, each having its own NREN. NRENs interconnect forming a trans-European NREN, called the GÉANT network.

In Portugal, by the end of 1997, all private and public preparatory, middle and high schools had at least one computer connected to the Internet with at least a 64 Kbps ISDN connection. By mid 2001, all 7135 elementary schools in the country had also been connected (FCT, 2001). This initiative was complemented by programs aimed at providing technical skills to teachers on how to use the Internet (see, for example ESES, 2002). Up-front capital costs to connect all schools were covered by the Ministry. The monthly costs associated with the ISDN connection of elementary schools were supported by City Halls. The Ministry covered these costs for the reminder of the schools.

In 2004, the same Ministry launched another major initiative, this time aimed at replacing all the existing ISDN connections by broadband ADSL.[3] This project was completed by January 2006, despite the fact that only less than 15% of the schools had migrated to ADSL before July 2005 (UMIC, 2007). Most schools (>95%) received a DSL modem from FCCN and an ADSL connection of at least 1 Mbps over the copper line that connects them to the ISP's Central Office (COs) from which FCCN buys connectivity to the Internet backbone (Figure 1).[4] As before, the Ministry covered all up-front capital costs to deploy broadband to schools. City Halls foot the broadband monthly bill for elementary schools and the Ministry covers these costs for the reminder of the schools.

[Figure 1 about here.]

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 proxy for the school's overall broadband use.

3.2 Internet Use at School

We conducted preliminary informal interviews with teachers in 8 different schools to learn more about how Internet is used in schools. Some teachers are comfortable with using ICTs in the

[3]Migration to ADSL was complemented with several other initiatives. One such initiative was ICTs training for teachers. Another initiative was the subsidization of 150-Euro laptops to students. This initiative, called "e-schools", might have boosted Internet use in many schools. A third initiative was to award up to 24 laptops to each and every school. Most schools use these laptops to bring Internet to the classroom. Some schools have a dedicated room in which these laptops remain and can be used as desktops.

[4]The remainder of the schools, where this speed could not be offered over copper, got a symmetric 256 Kbps ISDN connection to the Internet.

classroom and consider the Internet a good tool to capture the students' interest and to improve the learning process.[5] Other teachers look at the Internet as just another resource that students can possibly use for learning. However, not all teachers felt that Internet always provides easy to use information.[6] Differences in skills and in the attitude of teachers towards the Internet translate into significant differences on how and how much students use the Internet in the classroom.

School-specific Internet access policies may also explain part of the differences in the pattern of Internet use across schools. While some schools provide an open wireless network that any computer can tap into, such as 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 web sites (mainly adult content sites), while other schools block access to a whole range of sites considered inappropriate in the school context.[7] All these factors influence how students use the Internet at school and, consequently, their incentive to bring their laptop to school. 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 after classes is yet another aspect that might explain variations in Internet use across schools. In some schools students usually stay at school after class time, while 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 Internet at home are likely to exhibit different usage patterns than those who do. On the one hand students that only access the Internet at school might develop a more mature approach to use it because they learned how to navigate the Internet under the teachers' supervision. Students that have Internet at home might know better how to use it for recreational purposes and carry that practice to school. However, it might also be that students

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

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

[7]Video, chat, social network and adult content sites are among the categories most often blocked. In the later section of the paper, we provide more details on the distribution of which applications and services are allowed at different schools

that use the Internet at home for recreational activities do not need to do so at school and thus indulge in learning activities while at school. All in all, there is a wide variation across schools in terms of how students use the Internet. Teacher knowledge and attitude towards the use of ICTs in the classroom, school's Internet and wireless network access policies, time spent at school after classes and the number of students that access the Internet, both at school and elsewhere, 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 out the total monthly traffic (upload plus download) over the entire academic period.[8]

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), probably because the ISDN connections could not carry more traffic. Inbound traffic is the major contributor for this increase; outbound traffic remains relatively little across most schools. Broadband use per student exhibits high variability across schools (see Figure 3 for a histogram). In 2009, students used 111 MB 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).[9] The standard deviation of broadband use in 2009 is considerably large (95 MB), which highlights the heterogeneity in usage.[10] Overall, broadband use per student in school

[8]We use as academic year the period between September and June.

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

[10]When a video is watched at school, several students might be watching it at the same time, for example in the classroom.

is considerable.

[Figure 2 about here.]

[Figure 3 about here.]

Performance is measured by the school's average score at the 9$^{\text{th}}$ grade national exams. The Ministry of Education publishes anonymous disaggregated data at the exam level since 2005, including information on exam score, course, gender, and age of the examinee. 9$^{\text{th}}$ graders are examined in two subjects, Portuguese and math, and their exam scores constitute part of their final score on these subjects and might determine whether the student graduates. Therefore, students have clear incentives to perform well in the 9$^{\text{th}}$ grade national exams.[11]

Figure 4 shows average exam scores for both the 9$^{\text{th}}$ grade normalized to a 0-100 scale.[12] 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 with time, particularly in 2008.

[Figure 4 about here.]

Finally, 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 regional dropout rates (2005; at the municipality level) across municipalities. Table 1 presents summary statistics of these variables for schools in our sample.[13]

[Table 1 about here.]

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

[12]9$^{\text{th}}$ grade exam scores are published in a 1-5 scale (with increments of 1).

[13]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 277 municipalities and 723 civil parishes.

5 Framework

We introduce a 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, otherwise hereinafter called traditional study time at school. Let $T = I + S$ represent the total time students spend at school. We assume that the total time students spend at school remains unchanged with the introduction of Internet in the school.

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

$$\frac{dp}{dI} = f_I - f_S.$$

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 when Internet is introduced in schools.

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

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

$$\frac{dp}{dI} = g_L \cdot \frac{\partial L}{\partial I} - g_S.$$

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

$$sgn\,[dp/dI] = sgn\left[\frac{g_L}{g_S}(\partial L/\partial I) - 1\right].$$

The impact of Internet at school on students' performance (dp/dI) 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 ($\partial L/\partial I$), is greater than one. One may expect that learning with the Internet may be more productive than traditional study ($\frac{g_L}{g_S} > 1$). Even then, our model highlights that the impact of Internet is critically affected by how Internet time is devoted to learning. Even if $g_L > g_S$, only if $\partial L/\partial I$ is large, that is, only if students are largely using the Internet for learning purpose, we could expect their performance to improve.

Consider a 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

$$sgn\,[dp/dI] = sgn\left[\gamma(L/S)^{r-1} \cdot \partial L/\partial I - 1\right],$$

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 $\gamma(\partial L/\partial I) - 1$. Furthermore, if students devote a constant share of the time they spend on the Internet at school to learning activities, call it α ($\alpha \equiv \partial L/\partial I$), then the effect of Internet use in school is constant and given by

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

Or, in other words, the impact of Internet depends on how effective it is relative to standard study and how much time students actually devote to learning activities.

6 Empirical Specification

6.1 First-Differences Model

School performance is assumed to depend on broadband use, on socio-economical factors, such as average earnings, population density and percentage of people with mandatory level of education, and on 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

$$p_{it} = \delta + \omega I_{it} + \mathbf{X}_i\beta + \mathbf{W}_{it}\theta + c_i + u_{it} \tag{2}$$

where p_{it} represents the performance of school i at time t; $\omega \equiv (\gamma\alpha - 1)$ is the effect of Internet use on school performance (see 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- and region-specific control variables. We include, as time-invariant control variables, school size (measured by the number of students in each school), population density, earnings in 2005, and the percentage of people with mandatory level of education in 2001 in the municipality where the school is located. As time-varying control, we use average Internet traffic rate per person (in Mbps per capita) at the school's closest ISP's Central Office (CO). This variable is used as a proxy for home Internet use in the region where the school is located. β and θ are parameter vectors; 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 allows for controlling for school-specific unobserved factors. Alternatively, we can write this as a first-differences model as

$$\Delta p_i = \phi + \omega \Delta I_i + \Delta \mathbf{W}_i \theta + \Delta u_i. \tag{3}$$

Given that we will use only two time periods, we drop time subscript t. Furthermore, we assume Internet use to be zero in 2005 and thus replace ΔI by broadband use in the last year of our period of analysis.[14] ϕ in equation (3) captures the average change in exam scores over the period of analysis. For example, a $\phi > 0$ captures the fact grades increased because, for example, exams became easier. Note that the term $\mathbf{X}_i\beta$ in equation (2) gets differenced out because it corresponds to time constant factors. However, to account for the possibility that some school-specific variables in $\mathbf{X}_i$ might also drive the change in performance and in broadband use, we include the baseline values of $\mathbf{X}_i$ as additional controls:

$$\Delta p_i = \phi + \omega \Delta I_i + \mathbf{X}_i \beta + \Delta \mathbf{W}_i \theta + \Delta u_i. \tag{4}$$

This is equivalent to adding an extra term $d_2 \cdot \mathbf{X}_i\beta$ to our structural equation where d_2 is an indicator variable such that $d_2 = 1$ for the later period in our analysis (2008 and 2009). This means the effect of $\mathbf{X}_i$ on performance is different in the later period.[15]

We use three- and four-year differences to capture the accumulated effect of broadband use on performance because differences in broadband use in schools over one single academic year are only likely to have a little impact on that year's exam scores, if at all. We estimate the first-differences specification by running separate regressions for 2005-2008 and for 2005-2009, clustering the stan-

[14] Broadband was brought to schools during the second half of 2005. Thus it is safe to assume there was no broadband use for most of 2005, and in fact Internet use in 2005 is negligible when compared to 2008 and 2009 levels. In any case, we have used the exact differences in our regressions and obtained similar results.

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

dard errors at the municipality level. We have also estimated pooled first-differences regressions with 2005-2008 and 2005-2009. Both approaches yield the same qualitative results.[16]

6.2 Identification

Despite the first-differences setting and the controls in $\mathbf{X}_i$, potential unobserved *time-varying* factors may result in increased broadband use and better (or worse) exam scores in 2008 and 2009, leading to inconsistent estimates for ω. For example, a change in the resources available to a school[17], internal organization or technical savviness, might have influenced both broadband use and exam scores during the period of analysis. The school-specific dummies do not capture these time-varying unobserved effects and therefore our estimates might become inconsistent.

We ensure identification by exploiting the variation 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 costumer's premises and the ISP's Central Office (CO) results in a lower maximum transfer bitrate. Therefore, schools further away from the CO are likely to get less throughput on their connection. 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 with 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.[18]

Distance is an attractive choice for the instrument because one expects that the distance between the schools and the CO would be fairly randomly distributed; schools and COs have been around for much longer than broadband. The population in Portugal is fairly densely distributed. Therefore, unlike the US where one would worry about rural schools being systematically farther from the CO

[16]When pooling differences, we add a 2009 year dummy and an interaction term between broadband use and the year 2009 to control for different effects in each of the differences.

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

[18]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.

than urban schools, Portugal is more homogeneous: many schools are within 2 Km from a CO (see Figure 5) and there is little difference in distance of a urban school vs the rural school.

[Figure 5 about here.]

In Table 2 we provide the correlation matrix with distance and socio-economic characteristics for middle schools. Distance does not seem to be correlated with any of the socio-economic characteristics. This strengthens our intuition that distance to CO seems to be fairly independent of specific regional characteristics. Figures 6, 7 and 8 in the appendix offer more details on relationship between distance and demographic characteristics.

[Table 2 about here.]

We also test whether distance explains grades before the deployment of broadband in schools. We regress average school grades in 2005 on distance and other covariates for middle schools. Table 3 presents the results.

[Table 3 about here.]

Distance to CO is statistically and economically insignificant in Table 3 suggesting that school grades are not affected by distance.[19] Thus schools that perform better or worse are not systematically located closer or further from the CO. These facts suggest that distance from the CO is a viable instrument for our analysis. More details on the appropriateness of distance as an instrument are provided in the Appendix.

More importantly, notice that since we use the school fixed effects, we need distance to be uncorrelated with Δu_i in Equation (4) and not necessarily with u_i. In other words, our strategy allows us to control for various school unobserved effects increasing the robustness of our instrument. With distance as an instrument, we estimate a two stage least squares (2SLS) specification as follows:

[19]This coefficient on distance would yield a reduction of 0.08 of a standard deviation in grades per kilometer.

$$
\begin{aligned}
\Delta p_i &= \phi + \omega \Delta I_i + \mathbf{X}_i \beta + \Delta \mathbf{W}_i \theta + \Delta u_i \\
\Delta I_i &= \varrho + \eta Distance_i + \mathbf{X}_i \varphi + \Delta \mathbf{W}_i \vartheta + \epsilon_i
\end{aligned} \tag{5}
$$

7 Results

7.1 Estimates without the instrument

We first estimate Equation (4) without accounting for endogeneity concerns. However, notice that we still control for school unobservable effects via first differences. We use two separate time windows, 2005-2008 and 2005-2009. The results are presented in columns (1) and (2) of Table 4. Estimates with and without covariates are very similar. Broadband use is measured as average use per student taking 100 MB as the unit. Results show a very small and statistically insignificant relationship between change in exam scores and change in broadband use, both between 2005 and 2008, and between 2005 and 2009 (see Table 4). The signs also are different with a positive estimate in 2008 and a negative one on 2009. However, not only the standard errors are high, the estimates are economically insignificant. Given that we are using school fixed effects, as expected, most control variables are statistically and economically insignificant. In short, the OLS produces insignificant coefficients.

[Table 4 about here.]

7.2 Correcting for Endogeneity

The OLS estimates may be spurious due to time-varying unobserved effects. Namely, a change in the internal organization of the school or new resources that a school might have obtained during the period of analysis can influence both test scores and broadband use. To overcome this problem, we estimate our Instrumental Variable (IV) specification as given by equation (5). The results are presented in Table 5. Columns (1) and (2) present results without covariates while columns (3) and (4) present results with all covariates. We present results for both 2005-2008 and 2005-2009.

[Table 5 about here.]

The first stage of the IV specification is presented in columns (1) and (3). The estimate on distance is highly significant and negative in all specifications across both 2008 and 2009 years. This suggests that our instrument works as expected. A one kilometer increase in the distance between a school and the CO leads to about 13.0 MB (14.1 MB) decrease in total usage per student in 2008 (2009). Notice that including covariates does not change the estimate on distance which confirms our earlier analysis that distance is uncorrelated with other covariates. We provide additional details on the effectiveness of our instrument the Appendix. Other estimates are sensible as well. Number of students, earning of the municipality, and educational level at the municipalities 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 in the results of the second stage which are presented in columns (2) and (4) of Table 5. The key estimate of interest is how per capita broadband growth has affected grades. The estimates for both 2005-2008 and 2005-2009 windows are negative, large and significant (at the 5% level for 2008 and at the 10% level for 2009). The sign on the estimate is now unequivocally negative, pointing clearly the adverse effect of broadband on performance. Moreover, this effect seems to be reasonably large. The 2008 estimate (-4.86) suggests that a unit (100 MB) increase in broadband use at the student level leads to about 4.86 reduction in average grade. The average broadband use per student in schools in 2008 was about 87 MB and the average grade in 2005 was about 51. Therefore, broadband growth between 2005 and 2008 resulted in an average decrease of 8.3% in the average exam score, i.e., a decrease of about 0.76 standard deviations in 2008 scores. This effect is still negative for the 2005-2009 period, though it becomes smaller in magnitude. For 2009 broadband growth resulted in an average decrease of 7.4% in grades since 2005, which represents a decrease of 0.67 standard deviations in 2009 scores. These results may suggest that the adverse effect of broadband use can wear off with time. The estimates on other control variables seem to be similar to OLS specification. Given the school fixed effects, most of the control variables are insignificant.

In summary, for OLS specifications, we find no effect of broadband use on students' performance. However, once we instrument for broadband use, we consistently find a strong negative effect. Therefore, our results seem to suggest that broadband use in school is generally detrimental for students' performance, at least during the years right after its introduction into the school's environment. If one believes that distraction activities on the Internet (for example, listening to music, playing games and watching movies) are inherently bandwidth intensive, then our instrument provides a consistent reason for the observed behavior. Schools which are closer to the CO, allow higher throughput and thus make it easier for students to indulge in distractive activities, lowering their exam scores. We will explore the distraction hypothesis in more detail in section 8.

The deployment of broadband in schools can certainly provide significant benefits and our results do not suggest that schools should not have broadband. There are many other benefits broadband may accrue which we do not measure. However, our results seem to suggest that merely connecting schools to broadband may not be enough. Various other measures need to be implemented in parallel in order to increase the productivity of investments in school broadband. We discuss the implications of our results in detail in later sections.

7.3 Impact on Different Courses

The 9$^{\text{th}}$ grade score combines scores in math and Portuguese. Since we have information on scores in each of these courses, we now split the data between math and Portuguese and examine how these scores are affected by broadband usage. Literature does not provide a clear guidance on whether computer or broadband should affect math or languages. Angrist & Lavy (2002) find a negative effect in math exam scores for 8$^{\text{th}}$ graders. Malamud & Pop-Eleches (2010) find that families that acquire computers had significant lower school grades in math, English and Romanian. Rouse & Krueger (2004) find that use of a specific software designed to improve language or reading skills (FastForWord) improves some aspects of students' language skills. Banerjee et al. (2007) report use of computer-assisted program improve the math scores slightly.

We estimate Equation 5 for math and Portuguese separately. For brevity we do not report the first stage of IV regression. First stages yield consistent estimates as before. The results are presented in Table 6.

[Table 6 about here.]

We get large, negative and statistically significant estimates for math and Portuguese in both years. The only exception is the estimate for math in 2009 which is still negative but not statistically significant. Consistent with Malamud & Pop-Eleches (2010), our results indicate that the adverse effect of broadband is similar for math and Languages.

7.4 Impact Across Gender

We compute separate average scores for boys and girls for each school and run separate regressions of performance on broadband use. Table 7 shows the results from separate IV regressions for 9$^{\text{th}}$ graders. In all regressions broadband usage is detrimental for grades. In the 2005-2008 difference, girls seem to be more affected than boys, both statistically and in magnitude. For the 2005-2009 difference, the coefficients for boys and girls are very similar though only the former is statistically significant. Overall, these estimates are in line with the aggregate results and, essentially, show that broadband in schools affects boys and girls alike.

[Table 7 about here.]

7.5 Low Performance vs. High Performance Schools

We also study which schools suffer the most with the introduction of broadband. We split our sample of schools into quartiles based on their 9$^{\text{th}}$ grade average exam score in 2005, thus just prior to the deployment of broadband. Table 8 shows the descriptive statistics for schools in the 1$^{\text{st}}$ and 4$^{\text{th}}$ quartiles. Notice that the distance of schools from the CO for the first and fourth quartile schools in terms of test scores is economically insignificant confirming the validity of our instrument. In 2005 average grade in the 4$^{\text{th}}$ quartile is 32% higher than in the 1$^{\text{st}}$ quartile. This difference reduces to 19% and 18% in 2008 and 2009 respectively.

[Table 8 about here.]

We interact broadband use and distance with each of the quartile dummies in our IV setting. Table 9 shows the results obtained. None of the quartile interaction variables displays a statistically significant coefficient either in 2008 or 2009. Moreover, Wald tests suggest that there is no difference across these coefficients. If anything, we see that the coefficient of the 4$^{\text{th}}$ quartile is more negative, possibly indicating a slight approximation of schools in extreme quartiles. Overall, these results suggest that broadband affects exam scores across all types of schools, independently of how good they were prior to the deployment of broadband.

[Table 9 about here.]

8 Distraction Hypothesis: Additional evidence

The total amount of Internet traffic at each school is not enough to estimate α and γ in equation (1) separately. To better understand how distraction and learning with the Internet at school affect students' grades we need to acknowledge that different schools put in place different strategies to benefit from the Internet that ultimately result in different usage patterns and learning experiences. In particular, some schools restrict access to distracting websites and applications such as Facebook and YouTube (i.e., schools with higher α), while other schools allow full access to the Internet. If the impact of broadband on school performance is negative due to these distractive activities, we should see the effect of such policies on school performance and broadband use.

We designed a survey to middle schools in Portugal in order to better understand current Internet access policies and practices. The survey consisted of 27 questions and was administered over the phone to school ICT managers between December 10$^{\text{th}}$ 2010 and January 17$^{\text{th}}$ 2011.[20] A total of

[20]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 attributed to one of the ICT teachers in the school.

344 answers were obtained (response rate of 55%). Schools who completed the survey are similar to schools that did not in terms of grades, size and distance to the CO, but are different[21] in terms of Internet usage, population density, income levels and basic education levels (see Table 10[22]).

[Table 10 about here.]

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, Blocking is performed by ISP, Other Sites, No Sites or Applications are Blocked. This question seems to be the one that best proxies distraction activities with the Internet at school. The other questions in the survey covered mostly IT resources and skills. For example, we asked if schools had wireless networks on campus that students could tap into and we asked if teachers had any specific IT related training. The answers to these questions show substantial variance across schools in terms of the practices put forward to benefit from Internet connectivity.

We will examine if these policies have an impact on school performance. Such policies possibly proxy for the school attitude towards technology use. By explicitly capturing these in our analysis, we are controlling for these (hence) unobserved differences across schools. Though we use school fixed effects, we cannot completely rule out that the policies might be endogenous. Our focus, however, is to extend our earlier model by examining how the marginal effect of broadband is conditioned by school policies.

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 not only it may be a distracting activity, it is also bandwidth intensive. Thus the marginal effect of Internet use in schools that allow YouTube should capture the effect of distraction. We first present some summary statistics in Table 11.

[21] We use 95% confidence interval t-tests to test whether the two groups have the same mean.

[22] The '*' symbols correspond to significance levels in equal variance t-tests for the difference between surveyed and non-surveyed schools. See table footer.

[Table 11 about here.]

The differences in these characteristics between schools that block and allow these applications are not large. 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 the the interaction between Internet use and the *No Blocks* indicator in the 2005-2008 and 2005-2009 windows.[23] We also assume that the Internet usage policies in these schools have not changed from 2005 to 2008 and 2009.[24] Since 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 Section 6.1).

Table 12 shows the results obtained.[25] Schools that do not block access to any web site or application performed worse than average: 3.5% between 2005 and 2008 (column (1)), i.e., 0.32 of a standard deviation. The magnitude of the *No Block* coefficient, 1.778, corresponds to about 3.5% of 50.95 — the average grade in 2005 — and to about 0.32 of 5.579, the average grades' standard deviation in 2008. This effect wears off in 2009. After including the interaction term of *No Blocks* and Internet usage (column (3)), the effect of school policy disappears. The marginal effect is large and negative for 2008 suggesting that the effect of Internet is more negative for schools which do not block distrative activities but it is not precisely estimated, and wears off by 2009.

[Table 12 about here.]

The *No Blocks* indicator provides preliminary evidence that between 2005 and 2008 schools that

[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 might be biased downwards, and, therefore, should be interpreted as a lower-bound.

[25]Some covariates are missing for some of the middle schools that were surveyed and therefore the number of observations in these regressions falls short of 344. First stage estimates are provided in Appendix.

do not block any type of content perform worse. However, we do not find evidence that this is related to Internet use given that the estimate on the interaction terms is statistically insignificant in the regressions above. One of the reasons for this result might be that not all websites are bandwidth-intensive and thus it is hard to establish a relationship between the time students spend in distraction activities and the amount of bytes consumed. For all the web sites 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 with them without consuming many bytes. On the other hand, file-sharing applications are bandwidth intensive, but students can share files in the background as they perform other activities. Hence, as explained earlier, we 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 in the 2005-2008 and 2005-2009 windows on Internet use, our regional co-variates, the *Allow YouTube* indicator, and the interaction between Internet use and this indicator. Again, we use the interaction between the predicted Internet use and the *Allow YouTube* indicator as a second instrument. Table 13 shows the results obtained.[26] Schools that allow YouTube perform worse than the average: the magnitude of the *Allow YouTube* coefficient, 1.856, corresponds to about 3.6% decline between 2005 and 2008 and the estimate 1.975 correspond to about 3.7% decline between 2005 and 2009 (columns (1) and (2)), i.e., 0.33 of a standard deviation. Including the interaction effect shows that the Internet use in schools that allow YouTube leads to a large adverse effect on grades, especially for 2008 (column (3)). For 2009 the effect is negative and large but not precisely estimated (column (4)).

In sum, consistent with our story, we find evidence that the way schools allow students to use Internet connectivity affects students' performance and students do relatively worse in schools that enact laxer access policies that do not control the opportunities for exaggerated distraction.

[Table 13 about here.]

[26] First stage estimates are provided in Appendix.

9 Conclusion and Discussion

There is a general belief that providing schools with computers and broadband improves the quality of education and, consequently, increases productivity levels and wages. However, reliable empirical evidence of this fact has been hard to establish. Our paper lays out a model to explain why the introduction of broadband in schools might have competing effects on student performance. The trade-off comes from the fact that broadband in schools provides students and teachers with a new resource to learn that can complement traditional study but also with an opportunity for distraction whereby students indulge in unproductive activities what take time away from study.

We use a comprehensive dataset on broadband use in every middle school in Portugal to examine its impact on students' performance. We measure performance by the scores that students obtain in 9^{th} grade national exams. Despite using school fixed effects, one of the challenges we face is that school performance and broadband usage may be endogenous. We correct for potential endogeneity using the distance between the school and the ISP's Central Office as an instrument for broadband use. All tests on the robustness of our the instrument suggest that it is a credible instrument. In this regard, our paper makes a significant methodological contribution. Once we instrument for broadband usage, we find evidence that the broadband hurts student performance. Our analysis shows that on average broadband is responsible for a decline of 0.76 of a standard deviation in grades in the 2005-2008 window. This statistic becomes 0.67 in the 2005-2009 window, which might suggest that this effect might wear off over time.

We also study the effects of broadband use on math and Portuguese exam scores separately. Consistent with the aggregate results, we find negative and statistically significant estimates for math and Portuguese in both 2005-2008 and 2005-2009, the only exception being the estimate for math in 2005-2009 which is still negative but not statistically significant. Thus, our results seem to indicate that the adverse effect of broadband in schools affects math and Portuguese scores alike. We also show that both boys and girls are negatively affected by broadband use. We then split schools into quartiles based on their test scores in 2005 and observe if schools in different quartiles behave differently. We find that all types of schools are equally affected by broadband regardless of their performance in 2005. Therefore, we find that merely providing broadband to low performing schools is not sufficient to push them towards the mean.

To explore the distraction effect of Internet in more detail, we conduct a survey to understand how Internet in utilized in schools. Some schools block many applications and services which can be characterized as distractive (such as music, movies, chat, online gaming). Using these additional data, we find that schools that block access to all such activities perform better that the schools which do not. More interestingly, we focus on YouTube access, which is a bandwidth intensive application. In fact, schools which allow YouTube, typically also consume more bandwidth. Therefore, the marginal effect of Internet use should be large for such schools if one believes that YouTube causes distraction. We find strong evidence that indeed Internet use is significantly more adverse 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 increase students' performance, at least in the years right after its deployment. While 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 that promote 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. We also find that merely providing technology resources to poor performing schools is not enough to bridge the performance gap. A technology like broadband may not always be used productively, hence its availability in poor performing schools might not necessarily translate into better grades all of a sudden.

While we use a very detailed dataset, our study is not without limitations. We do not know precisely the kind of activities students engage in with the Internet. Future work should complement this paper by either monitoring Internet connections in schools at the protocol level or surveying directly teachers and students in order to gather a deeper understanding of how broadband is effectively used. Similarly, broadband may still be beneficial for students in ways that test scores do not capture, whose effects 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 must emphasize that in any country education policy today is largely shaped by schools' performance and in that regard our paper is the first of its kind to provide concrete evidence of how the introduction of broadband in schools affects student performance.

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Appendix

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 Figure 9 for ADSL theoretical limits.[27])

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 characteristics (see Table 3).

There is, however, the 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 14 shows that none of the distance thresholds is significant in 2009.[28] This shows that usage reduces with distance for schools close and far away from the CO alike. This is consistent with the hypotheses that ADSL connections have not been capped, at least not at a rate that schools do use, and that users perceive differences in the quality of the ADSL connection even across schools that are close to the CO.

[Table 14 about here.]

There is also a concern that distance to CO and regional co-variates such as population density, earnings and mandatory education are correlated. Table 2 shows that this is not the case. Furthermore, Figure 6 shows that the distance to 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 7 and 8 report.

[Figure 6(a) about here.]

[Figure 7(a) about here.]

[27] Data obtained from *http://whirlpool.net.au/wiki/?tag=DSLAM_speeds*.

[28] Regressions for 2008 yield similar results.

[Figure 8(a) about here.]

Testing for weak instrument

As mentioned by Staiger & Stock (1997), weak instruments may lead to a more severe bias than the bias introduced by OLS estimates when one of the regressors is endogenous. We follow Stock et al. (2002) to test whether distance to the ISP's CO is a weak instrument. 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. Table 15 shows the F-statistics for the distance to the CO in the first-stage of our main regressions. The Stock et al. critical value for a test of size $r = 0.2$ and significance level $\alpha = 0.05$ is 6.66. Therefore, our instrument does not belong in the set of weak instruments, for this size and significance level, for both 2008 and 2009. In fact, in 2009 we can even consider a stricter size for our test, such as $r = 0.1$ whose critical value is 16.38.

[Table 15 about here.]

Schools' descriptive statistics by restriction policy

Table 16 shows the descriptive statistics for middle schools by restriction policy. Roughly 26% of the schools report blocking Facebook. These schools are usually smaller and located in more affluent areas. Schools that block YouTube (7%) tend to be bigger and located in areas with higher levels of basic education. These schools also did slightly better in national exams than other schools in 2008 and 2009, but not in 2005. Schools that block chat applications (33%) tend to have lower grades and tend to be more distant from the central office. Schools that block online games (54%) tend to be smaller and to use more Internet on a per-student basis. Schools that block adult content (79%) and schools that block file sharing applications (49%) do not seem to be different from schools that do not.

[Table 16 about here.]

First-stage regressions by restriction policy

Tables 17 and 18 show the first stages for the regressions presented in Tables 12 and 13 in section 8. All instruments are highly significant and behave as expected. We also test the weakness of the new sets of instruments. Table 19 shows Kleibergen-Paap Wald F-statistics for each of the regressions and the corresponding minimum size of r so that each set of instruments is not considered weak at the significance level $\alpha = 0.05$. As before, setting $r = 0.2$ is enough to rule out the weakness hypothesis for 2008 when using Distance to CO as the only instrument. When using two instruments, we need to set $r = 0.25$. For 2009 we can use the stricter value of $r = 0.1$, independently of whether we are using one or two instruments.

[Table 17 about here.]

[Table 18 about here.]

[Table 19 about here.]

Figures

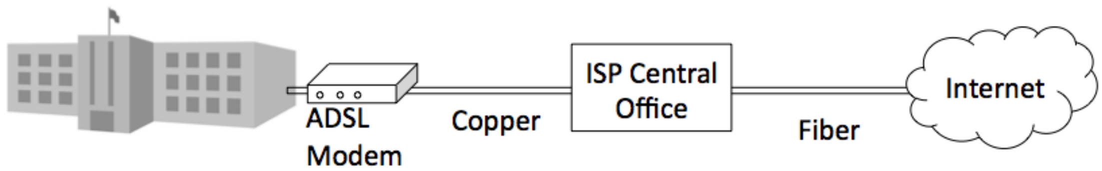


Figure 1: Broadband schools' connection to the Internet. Schools connect through a copper line to the ISP's central office. From there, the ISP ensures connectivity to the Internet backbone through fiber.

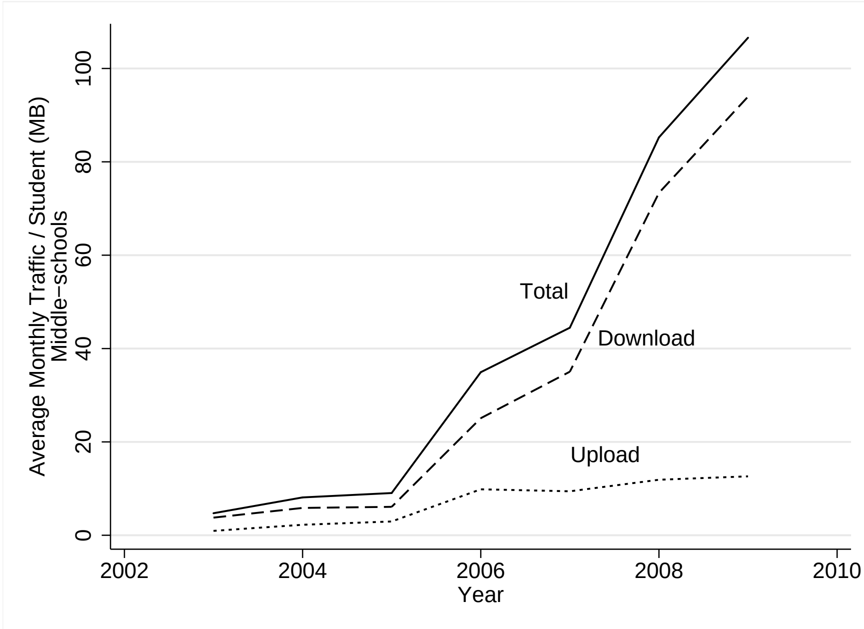


Figure 2: Middle school Internet traffic between 2003 and 2009.

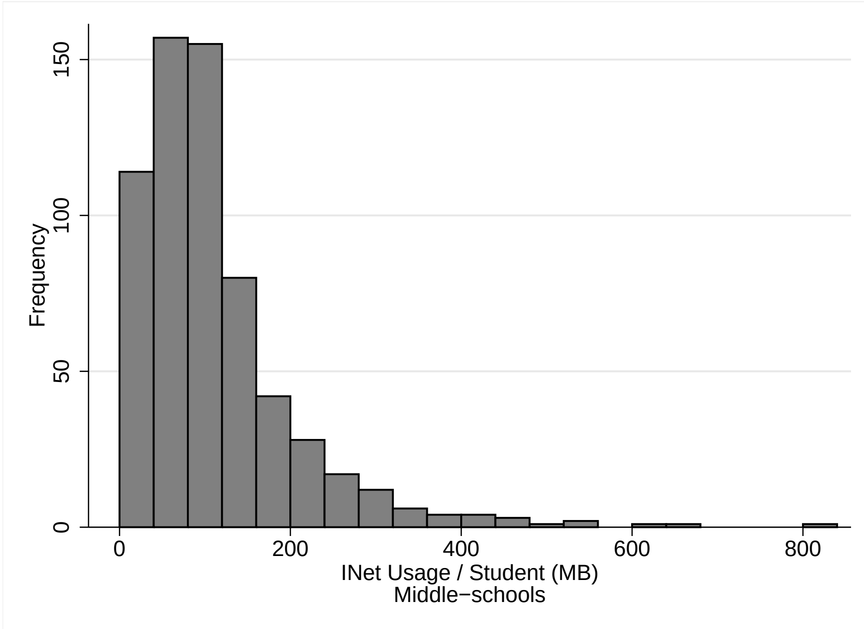


Figure 3: Middle school monthly average Internet use per student in 2009.

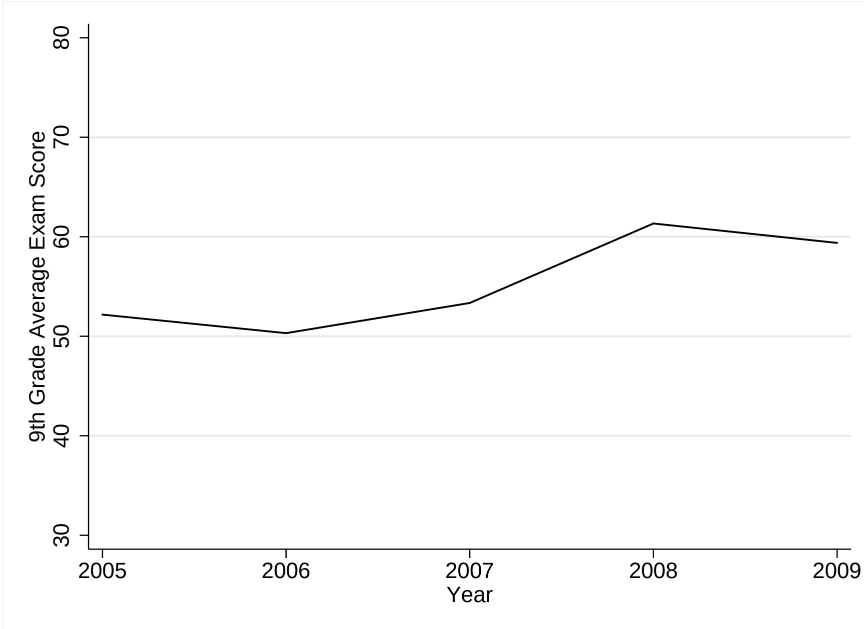


Figure 4: 9^{th} grade average exam scores between 2002 and 2009.

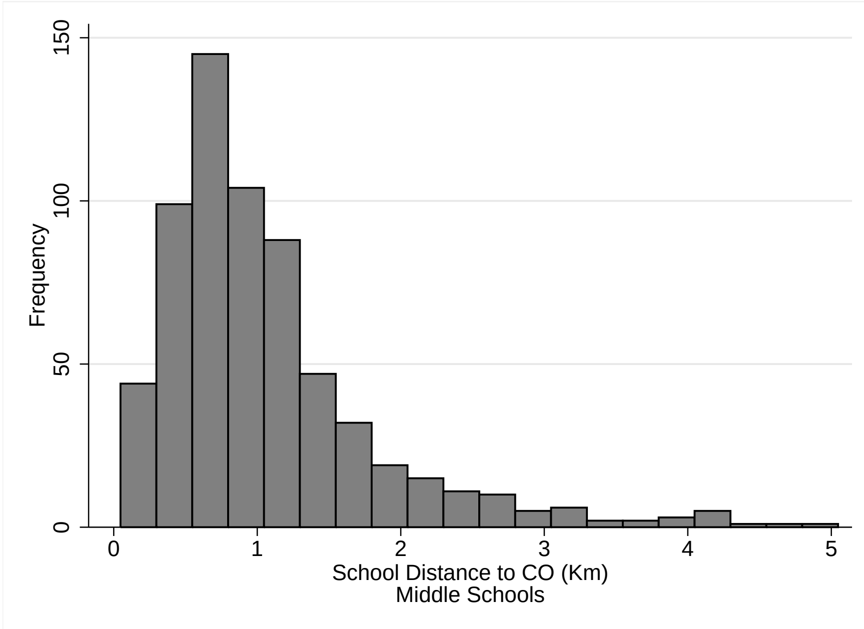
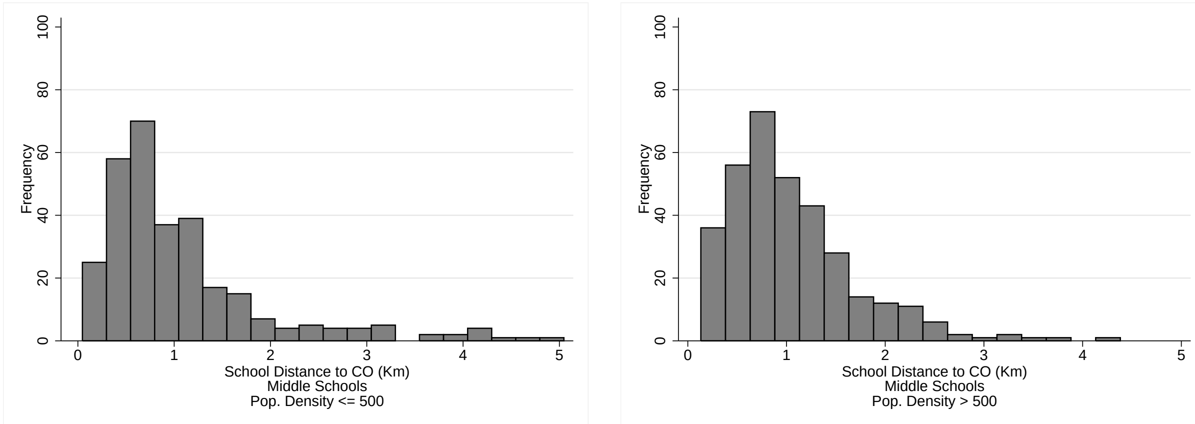


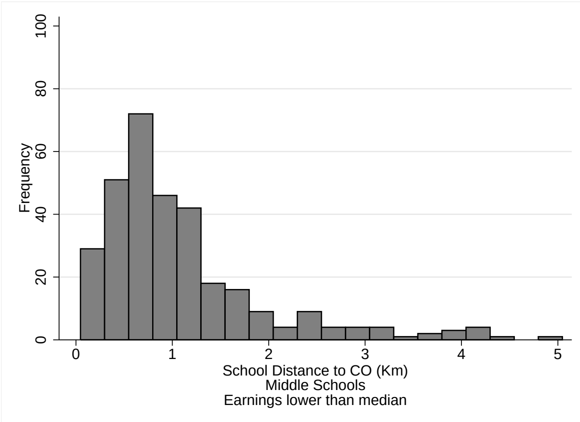
Figure 5: Middle Schools' distances to the closest CO.



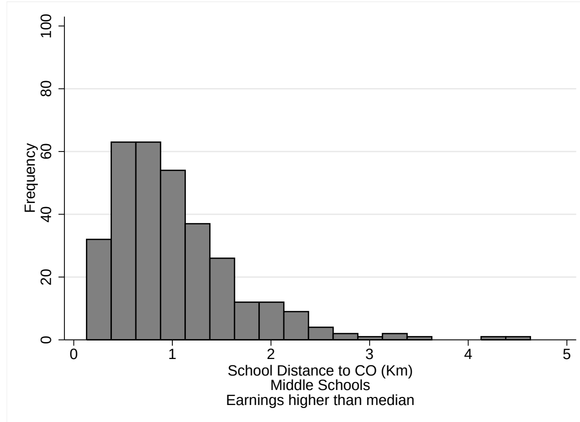
(a) Pop. Density ≤ 500.

(b) Pop. Density > 500.

Figure 6: Middle School distances to the closest CO by Population Density.

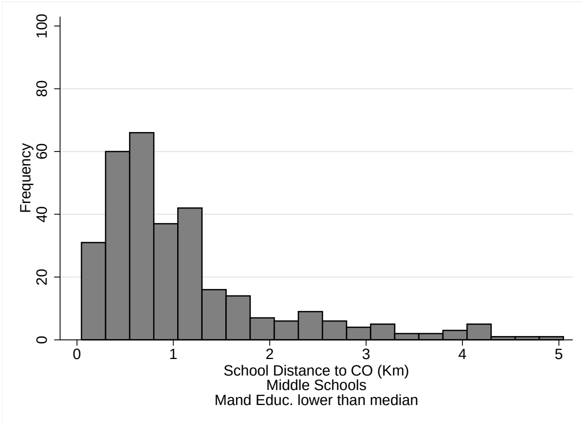


(a) Earnings lower than median

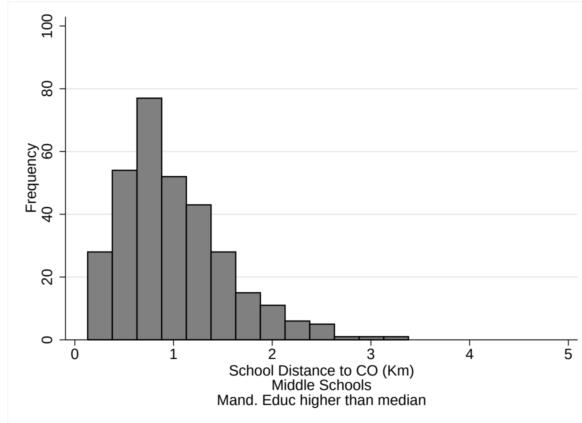


(b) Earnings higher than median

Figure 7: Middle School distances to the closest CO by Earnings.



(a) Mand Educ. lower than median



(b) Mand Educ. higher than median

Figure 8: Middle School distances to the closest CO by Educ Level.

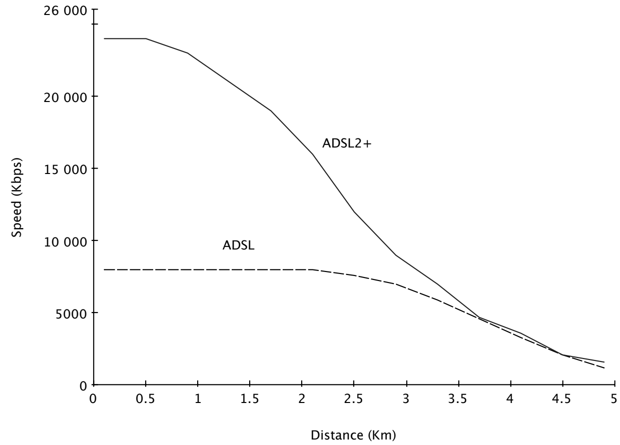


Figure 9: Bandwidth versus distance for ADSL and ADSL2+, assuming a downstream attenuation of 13.81 dB and an attainable rate of 8,000 kbps and 22,500 kbps for ADSL and ADSL2+, respectively.

Tables

Table 1: Summary statistics.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Avg. Grade 2009 (0-100)	628	57.89	5.669	39.39	75.94
Avg. Grade 2008 (0-100)	628	59.77	5.579	39.44	79.29
Avg. Grade 2005 (0-100)	628	50.95	5.035	35.88	68.94
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
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

Table 2: Cross-Correlations for Middle Schools.

Variables	Distance (Km)	Students	Pop. Density	Earn. 2005	Mand. Educ. (%)
Students	0.034				
Pop. Density	-0.030	0.323			
Earnings	-0.023	0.095	0.496		
Mandatory Educ. (%)	-0.106	0.401	0.521	0.579	
Avg. CO Traffic 2005 (Mbps)	0.121	0.090	-0.047	-0.124	0.011

Table 3: Average score in 2005 as a function of distance and other controls (OLS).

	(1)
VARIABLES	Avg. Grade 2005
Distance (Km)	-0.379
	(0.236)
Students (x 1000)	1.494
	(1.191)
Pop. Density (x 1000)	-0.183**
	(0.0838)
Earnings (x 1000)	-0.464
	(1.116)
Mandatory Educ. (%)	0.119***
	(0.0245)
Avg. CO Traffic (Mbps)	-154.2
	(221.9)
Constant	46.50***
	(0.984)
Observations	538
R-squared	0.098

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Changes in 9th grade performance as a function of broadband use (OLS).

VARIABLES	(1) 2008	(2) 2009
INet Usage / Student (100 MB)	0.0459	-0.130
	(0.174)	(0.334)
Students (x 1000)	0.505	-0.573
	(0.898)	(1.067)
Pop. Density (x 1000)	-0.155	-0.0264
	(0.0983)	(0.0897)
Earnings (x 1000)	1.230	-2.940**
	(1.638)	(1.195)
Mandatory Educ. (%)	0.0289	-8.66e-03
	(0.0179)	(0.0186)
Δ Avg. CO Traffic (Mbps)	-1.546	-21.56
	(69.77)	(38.88)
Constant	6.686***	10.26***
	(1.374)	(1.326)
Observations	534	527
R-squared	0.012	0.020

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: Change in 9th grades as a function of broadband use (IV).

	2008				2009			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
VARIABLES	1st Stg	2nd Stg	1st Stg	2nd Stg	1st Stg	2nd Stg	1st Stg	2nd Stg
INet Usage		-4.859**		-4.999**		-3.415*		-3.400*
		(2.367)		(2.268)		(1.993)		(1.770)
Students (x 1000)			-1.522***	-7.402**			-1.856***	-6.794*
			(0.244)	(3.044)			(0.220)	(3.502)
Pop. Density (x 1000)			4.52e-03	-0.134			1.11e-03	-0.0230
			(8.60e-03)	(0.116)			(9.55e-03)	(0.105)
Earnings (x 1000)			-0.493***	-1.616			-0.968***	-6.347***
			(0.176)	(2.297)			(0.238)	(2.324)
Mandatory Educ. (%)			-9.60e-03**	-9.52e-03			-8.51e-03***	-0.0297
			(3.72e-03)	(0.0255)			(3.04e-03)	(0.0246)
Δ CO Traffic			9.153	14.18			2.577	-24.06
			(8.009)	(87.43)			(5.883)	(48.53)
Distance (Km)	-0.130**		-0.161***		-0.141***		-0.166***	
	(0.0501)		(0.0544)		(0.0453)		(0.0379)	
Constant	0.994***	13.00***	2.669***	19.37***	1.259***	10.72***	3.455***	21.02***
	(0.0891)	(1.929)	(0.353)	(5.064)	(0.0834)	(2.204)	(0.285)	(5.913)
Observations	640	640	534	534	631	631	527	527
R-squared	0.011		0.222		0.013		0.368	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Performance in math and Portuguese and Broadband use (IV)

	(1)	(2)	(3)	(4)
	2008		2009	
VARIABLES	Port.	Math	Port.	Math
INet Usage / Student (100 MB)	-4.290**	-5.823**	-4.021**	-3.000
	(2.164)	(2.825)	(1.684)	(2.413)
Students (x 1000)	-6.927**	-8.005**	-6.934**	-7.017
	(3.145)	(3.764)	(3.261)	(4.767)
Pop. Density (x 1000)	-0.121	-0.154	-0.0370	-0.0152
	(0.113)	(0.140)	(0.0951)	(0.146)
Earnings (x 1000)	-1.920	-1.517	-5.642***	-7.358**
	(2.097)	(2.878)	(2.051)	(3.368)
Mandatory Educ. (%)	-0.0116	-9.15e-03	-0.0343	-0.0278
	(0.0267)	(0.0323)	(0.0280)	(0.0324)
Δ Avg. CO Traffic (Mbps)	29.52	4.658	33.87	-79.49
	(77.49)	(113.4)	(45.22)	(66.66)
Constant	13.34***	25.68***	11.68**	31.05***
	(4.968)	(6.331)	(5.560)	(8.056)
Observations	534	534	527	527

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Estimates for Boys and Girls.

	(1)	(2)	(3)	(4)
	2008		2009	
VARIABLES	Male	Female	Male	Female
INet Usage / Student (100 MB)	-3.959	-5.921**	-3.201*	-3.234
	(2.417)	(2.714)	(1.895)	(2.276)
Students (x 1000)	-3.567	-10.66***	-4.934	-8.278*
	(3.411)	(3.568)	(3.728)	(4.358)
Pop. Density (x 1000)	-0.192	-0.0970	-0.0726	0.0186
	(0.130)	(0.129)	(0.134)	(0.0968)
Earnings (x 1000)	1.669	-4.937*	-5.453*	-7.034***
	(2.643)	(2.624)	(3.269)	(2.520)
Mandatory Educ. (%)	-0.0122	-1.76e-03	-0.0290	-0.0335
	(0.0301)	(0.0316)	(0.0279)	(0.0301)
Δ Avg. CO Traffic (Mbps)	16.93	-14.38	-4.354	-30.81
	(90.58)	(116.5)	(49.70)	(56.05)
Constant	12.96**	25.25***	18.17***	23.27***
	(5.672)	(5.914)	(6.655)	(7.379)
Observations	528	528	521	521

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Descriptive statistics for schools in the 1st and 4th Quartiles in 2005.

Variable	1st Quart.	4th Quart.	Diff.
Avg. Grade 2005 (0-100)	44.78	59.26	-14.48***
Avg. Grade 2008 (0-100)	55.89	66.51	-10.61***
Avg. Grade 2009 (0-100)	54.31	64.22	-9.92***
Students	549.6	582.9	-33.36
Pop. Density	2017.7	2221.0	-203.3
Earnings	786.43	833.14	-46.71**
Mandatory Educ. (%)	36.49	44.46	-7.97***
Distance (Km)	1.10	0.95	0.15*

*** p<0.01, ** p<0.05, * p<0.1 (t-tests eq. var.)

Table 9: Change in 9th grade performance as a function of broadband use (2008 and 2009).

VARIABLES	(1) 2008	(2) 2009
INet Usage * 1st Q.	-3.053	-3.998
	(2.418)	(4.869)
INet Usage * 2nd Q.	-8.136	0.267
	(11.13)	(3.743)
INet Usage * 3rd Q.	-1.428	-3.744
	(3.860)	(2.677)
INet Usage * 4th Q.	-16.06	-5.661
	(12.04)	(5.889)
Students (x 1000)	-10.56*	-5.873
	(6.365)	(4.080)
Pop. Density (x 1000)	-0.303*	-0.131
	(0.163)	(0.118)
Earnings (x 1000)	-3.936	-7.834**
	(4.419)	(3.498)
Mandatory Educ. (%)	0.0392	0.0236
	(0.0476)	(0.0323)
Δ Avg. CO Traffic (Mbps)	-4.030	-67.83
	(116.8)	(49.64)
Constant	22.20***	23.73**
	(6.580)	(9.586)
Quartile Dummies	Yes	Yes
Observations	534	527

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Summary statistics. Surveyed vs. non-surveyed schools.

VARIABLES	(1) No Survey	(2) Survey
Avg. Grade 2005 (0-100)**	51.36	50.60
	(5.122)	(4.943)
INet Usage 2009 / Stu. (MB)***	100.2	120.2
	(81.41)	(104.7)
INet Usage 2008 / Stu. (MB)**	77.30	94.46
	(65.81)	(116.8)
Students	589.0	571.2
	(231.9)	(245.1)
Pop. Density**	2,142	1,553
	(3,211)	(2,523)
Earnings 2005**	802.8	773.9
	(183.0)	(189.2)
Mandatory Educ. (%)***	40.84	37.74
	(13.74)	(13.59)
Distance (Km)*	1.025	1.111
	(0.716)	(0.815)
Observations	284	344

*** $p<0.01$, ** $p<0.05$, * $p<0.1$ (t-tests eq. var.)

Table 11: Summary statistics by blocking policy: *No Bocks* and *Allow YouTube*.

VARIABLES	(1) No Block	(2) Block	(3) Allow YouTube	(4) Block YouTube
Avg. Grade 2005 (0-100)	51.76	50.41	50.55	51.33
	(4.231)	(5.030)	(4.887)	(5.670)
INet Usage 2009 / Stu. (MB)	120.4	120.2	121.8	100.0
	(104.0)	(105.0)	(106.9)	(68.50)
INet Usage 2008 / Stu. (MB)	83.41	96.25	95.83	76.95
	(65.83)	(123.1)	(120.4)	(49.40)
Students	607.4	565.3	563.6	668.5
	(255.4)	(243.4)	(246.4)	(209.6)
Pop. Density	1,766	1,519	1,557	1,508
	(2,028)	(2,596)	(2,564)	(1,965)
Earnings 2005	766.9	775.1	770.0	824.3
	(168.1)	(192.7)	(182.9)	(255.8)
Mandatory Educ. (%)	39.54	37.45	37.36	42.59
	(12.51)	(13.75)	(13.49)	(14.13)
Distance (Km)	1.164	1.102	1.103	1.215
	(0.883)	(0.805)	(0.808)	(0.911)
Observations	48	296	319	25

Table 12: Change in 9^{th} grade performance as a function of broadband use and site blocking policy (IV).

VARIABLES	(1) 2008	(2) 2009	(3) 2008	(4) 2009
INet Usage / Student (100 MB)	-3.271**	-2.528*	-3.094*	-2.534*
	(1.626)	(1.456)	(1.632)	(1.466)
INet * No Blocks			-3.026	0.0885
			(2.087)	(0.936)
No Blocks	-1.778**	-0.215	0.722	-0.319
	(0.804)	(0.822)	(1.713)	(1.038)
Students (x 1000)	-5.050*	-6.752*	-5.409*	-6.732*
	(2.680)	(3.864)	(2.822)	(3.875)
Pop. Density (x 1000)	0.0293	0.171	0.0411	0.171
	(0.119)	(0.123)	(0.119)	(0.124)
Earnings (x 1000)	-1.015	-6.206**	-1.535	-6.186**
	(2.872)	(2.478)	(2.821)	(2.483)
Mandatory Educ. (%)	-0.0300	-0.0160	-0.0283	-0.0160
	(0.0325)	(0.0307)	(0.0327)	(0.0307)
Δ Avg. CO Traffic (Mbps)	-37.91	-73.88	-32.48	-73.80
	(97.24)	(69.75)	(102.4)	(69.75)
Constant	17.21***	19.68***	17.55***	19.66***
	(4.251)	(5.777)	(4.399)	(5.778)
Observations	289	286	289	286

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Change in 9th grade performance as a function of broadband use and YouTube block policy (IV).

VARIABLES	(1) 2008	(2) 2009	(3) 2008	(4) 2009
INet Usage / Student (100 MB)	-2.967*	-2.422*	4.009	-0.778
	(1.596)	(1.413)	(2.853)	(3.133)
INet * Allow YouTube			-6.975***	-1.572
			(2.445)	(2.566)
Allow YouTube	-1.856**	-1.975**	3.161	-0.505
	(0.935)	(0.975)	(2.000)	(2.826)
Students (x 1000)	-4.801*	-6.838*	-4.701*	-6.629*
	(2.739)	(3.780)	(2.687)	(3.819)
Pop. Density (x 1000)	0.0360	0.192	0.0219	0.186
	(0.121)	(0.128)	(0.120)	(0.129)
Earnings (x 1000)	-0.925	-6.400**	-1.081	-6.205**
	(2.893)	(2.489)	(2.770)	(2.531)
Mandatory Educ. (%)	-0.0319	-0.0159	-0.0196	-0.0129
	(0.0314)	(0.0303)	(0.0323)	(0.0310)
Δ Avg. CO Traffic (Mbps)	-60.79	-81.78	-73.92	-78.84
	(89.26)	(65.28)	(86.19)	(66.57)
Constant	18.28***	21.54***	12.92***	19.60***
	(4.470)	(6.035)	(4.788)	(7.270)
Observations	289	286	289	286

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Distance threshold regressions for schools with 9th grade students.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Distance (Km)	-16.56***	-19.53***	-17.66**	-16.80***	-16.63***	-30.40*
	(4.315)	(5.775)	(7.259)	(5.467)	(4.094)	(16.27)
Students	-0.186***	-0.187***	-0.186***	-0.186***	-0.186***	-0.187***
	(0.0203)	(0.0209)	(0.0207)	(0.0206)	(0.0207)	(0.0208)
Pop. Density	1.10e-04	9.33e-05	1.17e-04	1.11e-04	1.11e-04	1.14e-04
	(9.80e-04)	(9.83e-04)	(9.81e-04)	(9.82e-04)	(9.82e-04)	(9.75e-04)
Earnings 2005	-0.0968***	-0.0972***	-0.0967***	-0.0968***	-0.0968***	-0.0979***
	(0.0217)	(0.0220)	(0.0220)	(0.0220)	(0.0220)	(0.0219)
Mandatory Educ. (%)	-0.850***	-0.858***	-0.849***	-0.850***	-0.851***	-0.844***
	(0.314)	(0.299)	(0.303)	(0.304)	(0.300)	(0.316)
Δ Avg. CO Traffic (Mbps)	257.1	286.5	254.3	254.6	257.7	250.8
	(585.4)	(585.6)	(581.3)	(587.6)	(580.9)	(587.1)
Dist. > 0.5 Km	-0.299					3.706
	(11.31)					(11.98)
Dist. > 1 Km		6.324				12.54
		(9.041)				(12.64)
Dist. > 2 Km			3.340			13.28
			(16.60)			(20.54)
Dist. > 3 Km				1.077		20.05
				(24.22)		(32.02)
Constant	345.6***	347.1***	346.1***	345.6***	345.5***	351.7***
	(27.18)	(26.58)	(26.53)	(26.37)	(26.17)	(28.62)
Observations	527	527	527	527	527	527
R-squared	0.368	0.369	0.368	0.368	0.368	0.369

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 15: F-statistics for the *Distance to CO* on first-stage regressions.

Regression	F-statistic
2005-2008	8.766
2005-2009	19.340

Table 16: Summary statistics by blocking policy (Middle Schools).

VARIABLES	(1) Facebook No Block	(2) Facebook Block	(3) YouTube No Block	(4) YouTube Block	(5) Chat No Block	(6) Chat Block	(7) Games No Block	(8) Games Block	(9) Adult No Block	(10) Adult Block	(11) F. Sharing No Block	(12) F. Sharing Block
Avg. Grade 2009 (0-100)	57.89	57.64	57.68	59.68	58.22	57.04	58.60	57.16	58.50	57.64	58.08	57.55
	(5.543)	(5.774)	(5.495)	(6.623)	(5.129)	(6.381)	(5.475)	(5.630)	(5.013)	(5.740)	(5.455)	(5.745)
Avg. Grade 2008 (0-100)	59.34	60.11	59.36	61.89	59.54	59.54	59.74	59.37	59.45	59.57	59.51	59.57
	(5.300)	(6.099)	(5.463)	(5.869)	(5.424)	(5.742)	(5.172)	(5.815)	(5.013)	(5.662)	(5.475)	(5.591)
Avg. Grade 2005 (0-100)	50.50	50.88	50.55	51.33	50.65	50.50	50.66	50.56	51.50	50.36	50.64	50.57
	(4.759)	(5.438)	(4.887)	(5.670)	(4.688)	(5.435)	(5.030)	(4.880)	(4.551)	(5.023)	(4.743)	(5.155)
INet Usage 2009 / Stu. (MB)	123.1	112.4	121.8	100.0	126.1	108.5	108.2	130.5	113.0	122.2	118.7	121.8
	(108.5)	(93.39)	(106.9)	(68.50)	(105.1)	(103.2)	(81.38)	(120.3)	(101.2)	(105.7)	(102.9)	(106.8)
INet Usage 2008 / Stu. (MB)	98.28	83.82	95.83	76.95	101.1	81.25	83.61	103.7	81.57	97.93	95.15	93.74
	(132.0)	(55.37)	(120.4)	(49.40)	(135.0)	(65.62)	(67.19)	(145.9)	(66.19)	(126.9)	(146.2)	(75.54)
Students	587.1	527.0	563.6	668.5	572.8	568.0	603.9	543.5	600.3	563.4	585.6	556.3
	(244.2)	(243.6)	(246.4)	(209.6)	(250.6)	(234.8)	(258.3)	(230.5)	(252.2)	(243.1)	(253.2)	(236.2)
Pop. Density	1,537	1,600	1,557	1,508	1,545	1,569	1,622	1,495	1,677	1,520	1,841	1,255
	(2,187)	(3,297)	(2,564)	(1,965)	(2,420)	(2,727)	(2,502)	(2,546)	(2,185)	(2,609)	(2,786)	(2,187)
Earnings 2005	760.6	810.9	770.0	824.3	771.8	778.2	772.6	775.1	793.9	768.5	778.1	769.6
	(176.1)	(218.4)	(182.9)	(255.8)	(196.6)	(174.3)	(176.1)	(200.2)	(184.1)	(190.6)	(196.7)	(181.6)
Mandatory Educ. (%)	37.94	37.20	37.36	42.59	37.83	37.57	38.49	37.10	38.91	37.43	38.22	37.25
	(13.41)	(14.13)	(13.49)	(14.13)	(13.39)	(14.03)	(13.53)	(13.64)	(11.59)	(14.08)	(13.60)	(13.60)
Distance (Km)	1.147	1.012	1.103	1.215	1.047	1.239	1.144	1.083	1.138	1.104	1.157	1.063
	(0.815)	(0.813)	(0.808)	(0.911)	(0.772)	(0.883)	(0.874)	(0.763)	(0.831)	(0.812)	(0.880)	(0.741)
Observations	253	91	319	25	229	115	158	186	73	271	175	169

Table 17: Change in 9th grade performance as a function of broadband use and site blocking policy (IV).

	2008					2009				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
VARIABLES	1st Stg	2nd Stg	1st Stg	1st Stg	2nd Stg	1st Stg	2nd Stg	1st Stg	1st Stg	2nd Stg
INet Usage / Student (100 MB)		-3.271**			-3.094*		-2.528*			-2.534*
		(1.626)			(1.632)		(1.456)			(1.466)
INet * No Blocks					-3.026					0.0885
					(2.087)					(0.936)
No Blocks	-0.0132	-1.778**	0.233	0.194	0.722	0.124	-0.215	-0.0341	-0.151	-0.319
	(0.103)	(0.804)	(0.235)	(0.129)	(1.713)	(0.142)	(0.822)	(0.294)	(0.248)	(1.038)
Students (x 1000)	-1.877***	-5.050*	-1.967***	3.40e-03	-5.409*	-2.188***	-6.752*	-2.140***	0.0382	-6.732*
	(0.389)	(2.680)	(0.464)	(0.0356)	(2.822)	(0.327)	(3.864)	(0.354)	(0.0623)	(3.875)
Pop. Density (x 1000)	0.0218	0.0293	0.0221	4.39e-03	0.0411	0.0122	0.171	0.0122	4.38e-03	0.171
	(0.0171)	(0.119)	(0.0177)	(3.33e-03)	(0.119)	(0.0198)	(0.123)	(0.0195)	(4.52e-03)	(0.124)
Earnings (x 1000)	-0.560**	-1.015	-0.577**	-0.163**	-1.535	-1.147***	-6.206**	-1.132***	-0.170	-6.186**
	(0.275)	(2.872)	(0.280)	(0.0656)	(2.821)	(0.356)	(2.478)	(0.356)	(0.117)	(2.483)
Mandatory Educ. (%)	-0.0110**	-0.0300	-0.0112*	3.78e-04	-0.0283	-7.61e-03	-0.0160	-7.58e-03	-1.69e-04	-0.0160
	(5.54e-03)	(0.0325)	(5.66e-03)	(1.11e-03)	(0.0327)	(4.79e-03)	(0.0307)	(4.78e-03)	(1.89e-03)	(0.0307)
Δ Avg. CO Traffic (Mbps)	5.835	-37.91	7.504	-2.143	-32.48	-1.037	-73.88	-1.537	-5.244	-73.80
	(13.68)	(97.24)	(13.88)	(4.867)	(102.4)	(10.15)	(69.75)	(10.15)	(6.245)	(69.75)
Distance (Km)	-0.236***		-0.245***	0.0103		-0.247***		-0.243***	0.0219	
	(0.0850)		(0.0925)	(0.0136)		(0.0523)		(0.0553)	(0.0248)	
$\widehat{INet}$ * No Blocks			-0.295	0.757***				0.133	1.128***	
			(0.301)	(0.153)				(0.271)	(0.229)	
Constant	3.121***	17.21***	3.197***	0.0989**	17.55***	3.906***	19.68***	3.863***	0.111*	19.66***
	(0.562)	(4.251)	(0.626)	(0.0384)	(4.399)	(0.414)	(5.777)	(0.441)	(0.0564)	(5.778)
Observations	289	289	289	289	289	286	286	286	286	286

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 18: Change in 9th grade performance as a function of broadband use and YouTube block policy (IV).

	2008					2009				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
VARIABLES	1st Stg	2nd Stg	1st Stg	1st Stg	2nd Stg	1st Stg	2nd Stg	1st Stg	1st Stg	2nd Stg
INet Usage / Student (100 MB)		-2.967*			4.009		-2.422*			-0.778
		(1.596)			(2.853)		(1.413)			(3.133)
INet * Allow YouTube					-6.975***					-1.572
					(2.445)					(2.566)
Allow YouTube	-0.0434	-1.856**	-0.289	-0.0795	3.161	-0.0588	-1.975**	-0.361*	-0.0537	-0.505
	(0.0809)	(0.935)	(0.237)	(0.205)	(2.000)	(0.102)	(0.975)	(0.209)	(0.167)	(2.826)
Students (x 1000)	-1.884***	-4.801*	-1.239***	0.111	-4.701*	-2.194***	-6.838*	-1.473***	0.0512	-6.629*
	(0.392)	(2.739)	(0.426)	(0.198)	(2.687)	(0.331)	(3.780)	(0.476)	(0.234)	(3.819)
Pop. Density (x 1000)	0.0222	0.0360	0.0150	-2.15e-03	0.0219	0.0134	0.192	9.93e-03	-6.89e-04	0.186
	(0.0173)	(0.121)	(0.0159)	(0.0156)	(0.120)	(0.0199)	(0.128)	(0.0198)	(0.0200)	(0.129)
Earnings (x 1000)	-0.566**	-0.925	-0.391	-0.0496	-1.081	-1.172***	-6.400**	-0.823**	-0.0294	-6.205**
	(0.276)	(2.893)	(0.304)	(0.290)	(2.770)	(0.358)	(2.489)	(0.356)	(0.290)	(2.531)
Mandatory Educ. (%)	-0.0111**	-0.0319	-7.30e-03	2.26e-03	-0.0196	-7.34e-03	-0.0159	-4.92e-03	1.64e-03	-0.0129
	(5.59e-03)	(0.0314)	(4.75e-03)	(3.86e-03)	(0.0323)	(4.84e-03)	(0.0303)	(5.16e-03)	(4.93e-03)	(0.0310)
Δ Avg. CO Traffic (Mbps)	5.434	-60.79	0.473	-11.70	-73.92	-0.746	-81.78	-2.635	-4.703	-78.84
	(13.60)	(89.26)	(14.16)	(12.03)	(86.19)	(10.01)	(65.28)	(9.938)	(9.454)	(66.57)
Distance (Km)	-0.237***		-0.150**	0.0301		-0.244***		-0.157**	0.0132	
	(0.0855)		(0.0695)	(0.0485)		(0.0530)		(0.0759)	(0.0590)	
$\widehat{INet}$ * Allow YouTube			0.355	1.092***				0.342	1.049***	
			(0.340)	(0.274)				(0.254)	(0.168)	
Constant	3.170***	18.28***	2.350***	-0.120	12.92***	3.983***	21.54***	3.007***	-0.0674	19.60***
	(0.579)	(4.470)	(0.564)	(0.198)	(4.788)	(0.432)	(6.035)	(0.653)	(0.212)	(7.270)
Observations	289	289	289	289	289	286	286	286	286	286

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 19: Kleibergen-Paap statistics for the first-stage regressions.

Regression	Year	Instruments	Kleibergen-Paap Wald F-statistic	$r =$
No Block	2005-2008	Distance to CO	7.718	0.20
		Distance to CO $\widehat{INet}$ * No Blocks	3.824	0.25
	2005-2009	Distance to CO	22.422	0.10
		Distance to CO $\widehat{INet}$ * No Blocks	11.835	0.10
Allow YouTube	2005-2008	Distance to CO	7.666	0.20
		Distance to CO $\widehat{INet}$ * Allow YouTube	3.850	0.25
	2005-2009	Distance to CO	21.298	0.10
		Distance to CO $\widehat{INet}$ * Allow YouTube	9.442	0.10