

# The Effects of Broadband in Schools On Students' Performance

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## **Abstract**

This paper looks at 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 are detrimental for grades in the 9<sup>th</sup> grade national exams. For the average broadband use in schools, grades reduce 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.

**JEL:** I21, J24

# 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 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 dataset to propose a method to assess the effect of Internet and broadband on students' grades in schools.

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 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 Internet in schools on students' performance.<sup>1</sup> Moreover, these studies provide mixed results on whether ICTs indeed help students. Thus our understanding of how broadband can help learning is still limited.

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<sup>1</sup>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.

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 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 the 9<sup>th</sup> 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 for a good instrument providing us confidence in the results obtained.

Our estimates indicate that more broadband use is detrimental for students' test scores. We find that, on average, grades declined about 0.78 of a standard deviation, between 2005 and 2009, due to broadband use. This finding is robust across gender (although boys seem to be slightly more affected) and subjects (though 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 Internet in more detail, we conduct a survey to understand how 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).<sup>2</sup> The impact of other characteristics, such as teacher training and computer use, remains either non-significant or exhibits mixed results (e.g., Angrist and Lavy, 2002; Webbink, 2005; Barrera-Osorio and Linden, 2009).

Most studies look at students' test scores in 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' demand. 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 4<sup>th</sup> graders. Goolsbee and Guryan (2006) study the impact of subsidizing schools' Internet access in the U.S. and find no evidence that Internet in classroom has an effect on students' performance, as measured by the Stanford Assessment Test (SAT). Leuven et al. (2007)

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<sup>2</sup>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.

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-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 non-significant or negative results is provided by Machin et al. (2007) who use changes in investment rules in the UK 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 investment in ICTs (for example, availability of computers or 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, lack of granularity is more likely to produce a non-result. Also, when ICTs are already available to almost all subjects in the sample (which is increasingly true where most schools have 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 also 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 9<sup>th</sup> 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 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 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 ISDN (FCT, 2001). In 2004, the same Ministry launched another major initiative, this time aimed at replacing all the existing ISDN connections by broadband ADSL.

By 2006, 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 Central Office (CO) of Portugal Telecom (PT), the 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 on whether they wanted a broadband or not. 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 while 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

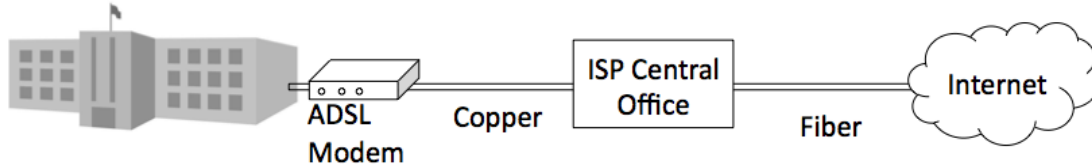


Figure 1: Broadband schools' connection to the Internet. Schools connect through a copper line to the ISP's central office. From there, the ISP ensures connectivity to the Internet backbone through fiber.

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.<sup>3</sup> 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 provides always an easy way to obtain and use information.<sup>4</sup> Differences in skills and in the attitude of teachers towards the Internet translate into significant differences on how much students use the Internet in the classroom.

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<sup>3</sup>Some of the teachers interviewed referred that students engage more in discussions and are more motivated when Internet is used in class.

<sup>4</sup>One of the teachers interviewed pointed out that he had a hard time to explain to students that Wikipedia is not a reliable source of information and that they should always check their sources.



School-specific Internet access policies may also explain part of the differences in the patterns of Internet use across schools. While 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 web sites (mainly adult content sites), while other schools block access to a whole range of sites considered inappropriate in the school context.<sup>5</sup> 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, 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 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 towards the use of ICTs in the classroom, school's Internet access policies and time spent at school after classes are some of the factors that contribute to such a variation.

## 4 Data

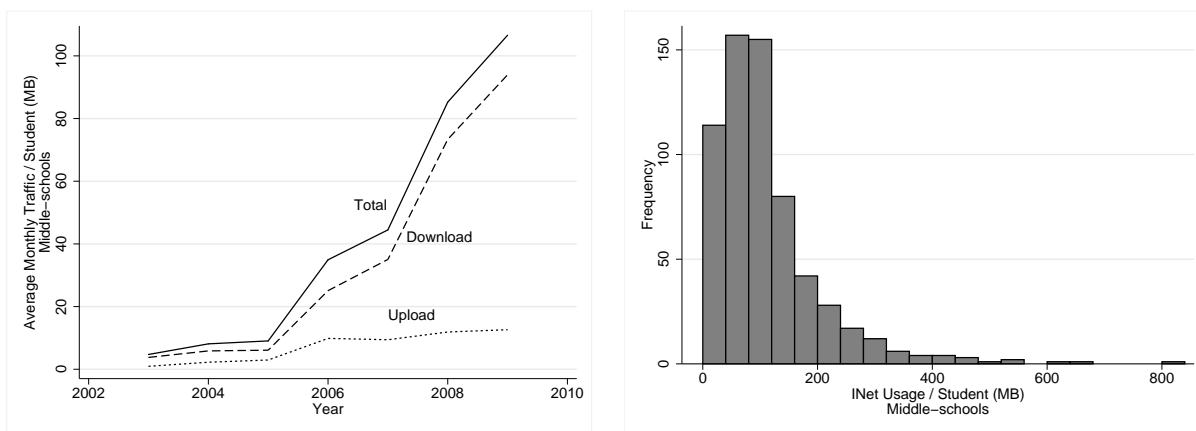
School traffic data were obtained from the monitoring tools set up by FCCN. From the ISDN project, we obtained data for all ISDN sessions between November 2002 and January 2005 for all schools in the country. From the ADSL project, we obtained monthly reports that include download and upload traffic 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.

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<sup>5</sup>Video, chat, social network and adult content sites are among the categories most often blocked. In the later section of this paper, we provide more details on these policies.

For our measure of school broadband use, we average out the total monthly traffic (upload plus download) over the entire academic period.<sup>6</sup>

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).<sup>7</sup> There is significant heterogeneity in usage (large standard deviation (95 MB)).



(a) Internet traffic between 2003 and 2009.

(b) Monthly average Internet use per student in 2009.

Figure 2: Middle school Internet traffic and monthly average Internet use per student in 2009.

Performance is measured by the school's average score at the 9<sup>th</sup> grade national exams. 9<sup>th</sup> grade is the last year of middle school and the mandatory education level in Portugal until 2009. The

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<sup>6</sup>We use as academic year the period between September and June in accordance to the academic calendar published by the Ministry of Education of Portugal.

<sup>7</sup>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.

Ministry of Education publishes anonymous disaggregated data at the exam level since 2005, including information on exam score, course, gender, age and school of the examinee. 9<sup>th</sup> 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 9<sup>th</sup> grade. Therefore, students have clear incentives to perform well in these exams.<sup>8</sup>

For ready interpretation, we normalize all grades by the standard deviation of 2005 grades. Figure 3 shows 9<sup>th</sup> grade normalized average exam scores over time.<sup>9</sup> 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.

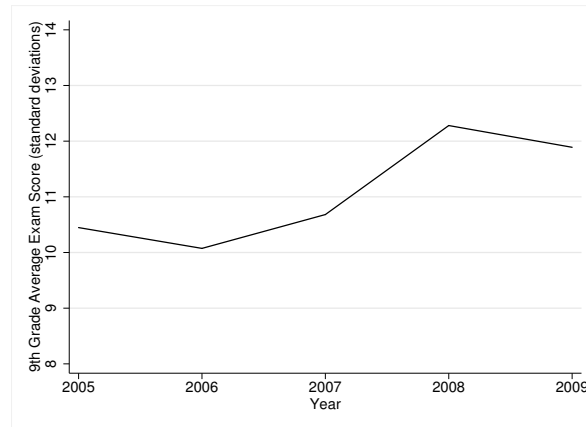


Figure 3: 9<sup>th</sup> grade average exam scores between 2005 and 2009.

Finally, we obtained GPS coordinates for all the COs of PT (Portugal Telecom), which held a market share of about 70% in the Portuguese broadband market during the years of our study (ANACOM, 2011). Furthermore, we also obtained the average monthly traffic rate per CO for residential Internet access from the PT. Regional data were provided by the Portuguese National Statistics Institute. These data include population density (2001 census data; at the civil parish

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<sup>8</sup>Even though this is a standardized exam, it is not necessarily a multiple choice response only exam. The students have to write detailed answers.

<sup>9</sup>9<sup>th</sup> grade exam scores are published in a 1-5 scale (with increments of 1).

level), average earnings and mandatory education rates<sup>10</sup> (2005) across municipalities. Table 1 presents summary statistics for these variables for schools in our sample.<sup>11</sup> School enrollment (2007) was obtained from the Ministry of Education.<sup>12</sup>

Table 1: Summary statistics.

VARIABLES	(1) N	(2) mean	(3) sd	(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

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

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<sup>10</sup>Mandatory education was 9 years of schooling during the period of analysis.

<sup>11</sup>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.

<sup>12</sup>We were able to obtain student enrollment only for 2007. We use the 2007 values for the whole time period as the number of students in a school is unlikely to change much from year to year.

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, 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 Internet in schools can either increase or decrease performance. In fact,

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

The impact of 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 ( $\frac{g_L}{g_S} > 1$ ). Even then, our model highlights that the impact of 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 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

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

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  $\alpha$  ( $\alpha \equiv L_I$ ), then the effect of Internet use in school is constant and given by

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

Or, in other words, the impact of 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, on socio-economical factors 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

$$P_{it} = \delta + \omega I_{it} + \mathbf{x}_i \beta + \mathbf{w}_{it} \theta + c_i + u_{it} \quad (2)$$

where  $P_{it}$  represents the performance of school  $i$  at time  $t$ ;  $\omega$  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- 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 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.  $\beta$  and  $\theta$  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 time-constant factors. Alternatively, we can write this as a differences model as

$$\Delta P_{it} = \phi + \omega \Delta I_{it} + \Delta \mathbf{w}_{it} \theta + \Delta u_{it}. \quad (3)$$

where  $\phi$  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.  $\Delta$  represents the difference between period  $t$  and 2005 (e.g.,  $\Delta P_{it} \equiv P_{it} - P_{i2005}$ ). Notice 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 06, 07, 08 and 09, all relative to 05), 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  $\mathbf{x}_i\beta$  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:

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

This is equivalent to adding an extra term  $d_{2005} \cdot \mathbf{x}_i \beta$  to our structural equation where  $d_{2005}$  is an indicator variable for year 2005.<sup>13</sup>

## 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  $\omega$ . For example, a change in the resources available to a school<sup>14</sup>, 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

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

<sup>14</sup>During the period of analysis students were awarded laptops, under a parallel Governmental program. This may have changed both broadband usage and scores.



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 Central Office (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 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.<sup>15</sup>

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.<sup>16</sup> Additionally, 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 than urban schools, Portugal is more homogeneous: most schools are within 2 Km from a CO (see Figure 4) and there is little difference in the distance to the closest CO for urban vs rural schools as can be seen in Figure 5 in Appendix B and as shown by t-tests: the average distance to CO is 1.08 Km 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 distance between the school and the town center as another control. One

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<sup>15</sup>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.

<sup>16</sup>Some central offices 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 up to the 1980s. Thus, some of the central offices are located near the post offices, and in general existed long before the schools’ foundation. For the 313 schools for which we were able to obtain information on foundation date, average foundation year is 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 can not say with certainty whether the decision to install newer COs was influenced by school locations.

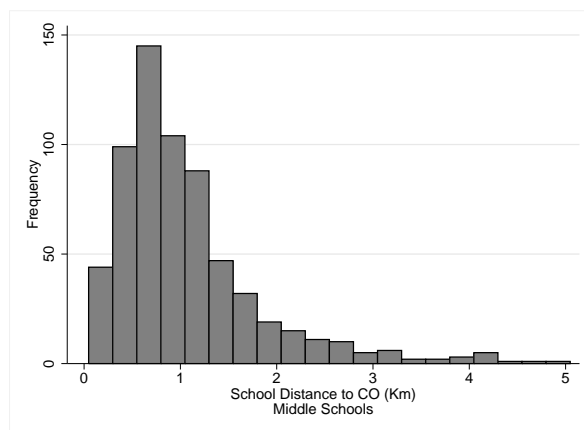


Figure 4: Middle Schools' distances to the closest CO.

may worry that a school away from CO may be more rural or be somehow different. And, despite our fixed effect specification, such schools may (or may not) receive some interventions, such as subsidized laptops or teacher training during the 05-09 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<sup>17</sup> 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 socio-economic characteristics for 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 socio-economic characteristics, population density or with grades before the deployment of broadband in schools. This strengthens our intuition that the distance to CO is independent of specific regional characteristics. Figures 5, 6 and 7 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 CO, suggesting that COs are more likely to be located closer to respective city centers.

As an additional test for the instrument, we run a regression of school's 2005 grades on school's

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<sup>17</sup>Town hall GPS coordinates were gathered from town hall addresses using the Google geocoding API. Town hall addresses were obtained from a civil parish directory at <http://www.freguesias.pt>.

Table 2: Cross-Correlations for Middle Schools.

Variables	Dist.	Dist.	Avg. Grade	Stud.	Pop.	Earn.	Mand.
	Sch - CO	Sch - Cntr	2005	Stud.	Dens.	2005	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

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 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 school to the center of the town is 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 school, as can be seen in Table 11 in Appendix B. This provides a good falsification test and further confirms the suitability of the distance to CO as an independent and good proxy for Internet use.

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

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

Standard errors (in parentheses) clustered at the municipality level  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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 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, notice that since we use school fixed effects, we need distance to be uncorrelated with  $\Delta u_{it}$  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 an instrument, we estimate a two stage least squares (2SLS) specification as follows:

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

## 7 Results

### 7.1 Estimates without the instrument

We estimate Equation (4) without accounting for endogeneity concerns. However, notice 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 the standard errors are high but also 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. Column (3) and column (4) present results without and with covariates

respectively.

Table 4: Change in 9<sup>th</sup> grades as a function of broadband use (IV).

VARIABLES	(1) OLS	(2) OLS	(3) IV (2nd Stg)	(4) IV (2nd Stg)
$\Delta$ INet / Student (100 MB) $\times$ 2006	-0.0507 (0.0836)	-0.0410 (0.0921)	-0.334 (0.841)	-0.0584 (0.913)
$\Delta$ INet / Student (100 MB) $\times$ 2007	0.0614 (0.0627)	0.0836 (0.0745)	-2.052 (1.392)	-1.571 (1.060)
$\Delta$ INet / Student (100 MB) $\times$ 2008	-8.94e-04 (0.0329)	-3.38e-03 (0.0377)	-0.981** (0.473)	-0.973** (0.463)
$\Delta$ INet / Student (100 MB) $\times$ 2009	0.0294 (0.0536)	0.0468 (0.0593)	-0.691* (0.398)	-0.698* (0.380)
Students ( $\times$ 1000)		0.103 (0.122)		-0.882** (0.419)
Pop. Density ( $\times$ 1000)		-0.0144 (0.0138)		-0.0131 (0.0160)
Earnings ( $\times$ 1000)		-0.0143 (0.186)		-0.404 (0.288)
Mandatory Educ. (%)		1.98e-03 (2.34e-03)		-2.42e-03 (3.35e-03)
$\Delta$ Avg. CO Traffic (Mbps)		0.521 (8.303)		3.082 (10.55)
Dist. Sch - Cntr (Km)		0.0238 (0.0144)		0.0228 (0.0210)
Constant	-0.432*** (0.0355)	-0.560*** (0.156)	-0.357 (0.217)	0.513 (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

Standard errors (in parentheses) clustered at the municipality level  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

The first stage of the IV specifications are presented in Table 5. Columns (1)-(4) present the first stages without covariates while 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 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.<sup>18</sup> 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. critical value for a test of size  $r = 0.1$  and

<sup>18</sup>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 distance to CO and year. As the Stock-Yogo critical values for weak instruments are not available for four instruments, and given that the only instrument we use is distance to CO, we use the aggregate regressions (without year interactions) as benchmark.

Table 5: Year-specific change in broadband use as a function of distance to CO.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta$ Inet	$\Delta$ Inet	$\Delta$ Inet	$\Delta$ Inet	$\Delta$ Inet	$\Delta$ Inet	$\Delta$ Inet	$\Delta$ Inet
Dist. Sch - CO (Km) $\times$ 2006	-0.0414*** (0.0154)				-0.0421*** (0.0162)			
Dist. Sch - CO (Km) $\times$ 2007		-0.0494** (0.0249)				-0.0646** (0.0269)		
Dist. Sch - CO (Km) $\times$ 2008			-0.130*** (0.0463)				-0.157*** (0.0509)	
Dist. Sch - CO (Km) $\times$ 2009				-0.142*** (0.0420)				-0.167*** (0.0401)
Students ( $\times$ 1000)					-0.443*** (0.0716)	-0.680*** (0.116)	-1.428*** (0.230)	-1.766*** (0.204)
Pop. Density ( $\times$ 1000)					-0.00406 (0.00368)	-0.00139 (0.00444)	0.00577 (0.00800)	0.00279 (0.00946)
Earnings ( $\times$ 1000)					-0.225*** (0.0670)	-0.165** (0.0804)	-0.445*** (0.166)	-0.921*** (0.212)
Mandatory Educ. (%)					0.000336 (0.00151)	-0.00488** (0.00202)	-0.00871** (0.00354)	-0.00759*** (0.00291)
$\Delta$ Avg. CO Traffic (Mbps)					-4.848 (10.93)	10.13 (8.474)	9.260 (7.095)	2.595 (5.624)
Dist. Sch - Cntr (Km)					-0.0103 (0.00649)	-0.0103 (0.00751)	0.00921 (0.0146)	0.0282 (0.0208)
Constant	0.304*** (0.0254)	0.432*** (0.0419)	0.926*** (0.0788)	1.193*** (0.0657)	0.754*** (0.102)	1.173*** (0.176)	2.453*** (0.338)	3.218*** (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

Robust standard errors in parentheses

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

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. 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 usage of broadband per student affected grades. The estimates are negative and large for all years, and 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 4<sup>th</sup> 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 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 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 distracting activities, lowering their exam scores. These results are in line with a study performed by Stinebrickner and Stinebrickner (2008). The 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 section 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 which 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 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 Across Gender**

Our specification does not allow us to estimate  $\alpha$  and  $\gamma$  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  $\alpha$ ) may be more adversely affected with increased broadband use.

According to a survey administered by the Portuguese Telecom Regulator (ANACOM) to 659 students<sup>19</sup>; 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<sup>20</sup> 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  $\alpha$ ).

## 7.4 Impact on Different Courses

The 9<sup>th</sup> grade score combines scores in math and Portuguese. We now split the data between math and Portuguese and examine how each of these scores is affected by broadband usage. The literature does not provide a 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 4<sup>th</sup> graders. Malamud and Pop-Eleches (2011) find that families that acquire computers had significant lower school grades in math, English and Romanian. Rouse and Krueger (2004) find that use of a specific

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<sup>19</sup>From these, 652 students (332 girls and 320 boys) answered a question about activities performed on the Internet.

<sup>20</sup>Although not statistically different, the effect is 9% larger for boys than for girls.



software designed to improve language or reading skills (FastForWord) improves some aspects of students' language skills. Banerjee et al. (2007) and Carrillo and Ponce (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 9<sup>th</sup> grade average exam score in 2005, thus 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 good they were 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 engage 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  $\alpha$ ), while other schools allow full access to the Internet. We now explore whether such policies have any effect on school performance and broadband use.

In order to better understand current Internet access policies and practices, we designed and deployed a survey to middle schools in Portugal. The survey consisted of 27 questions and was

administered over the phone to school ICT managers between December 10<sup>th</sup> 2010 and January 17<sup>th</sup> 2011.<sup>21</sup> A total of 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 in terms of Internet usage, population density, income levels and basic education levels (see Table 6)<sup>22</sup>.

Table 6: Summary statistics. Surveyed vs. non-surveyed schools.

VARIABLES	(1)	(2)
	No Survey	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<0.01, ** p<0.05, * p<0.1 (t-tests eq. var.)		

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, Other Sites. 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.

We examine if these policies have an impact on school performance. Such policies possibly proxy

<sup>21</sup>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.

<sup>22</sup>We use 95% confidence interval t-tests to test whether the two groups have the same mean. The '\*' symbols correspond to significance levels in equal variance t-tests for the difference between surveyed and non-surveyed schools.

for the school attitude towards 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.

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 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.

Table 7: Summary statistics by blocking policy: *No Blocks* and *Allow YouTube*.

VARIABLES	(1)	(2)	(3)	(4)
	No Block	Block	Allow YouTube	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 vs. No Block, t-tests eq. var.)

†† p<0.05, † p<0.1 (Allow YouTube vs. Block YouTube, t-tests eq. var.)

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.<sup>23</sup>

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.<sup>24</sup> 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 8 show the results obtained.<sup>25</sup>

Notice in column 3 that Internet is still negative and significant but the *No Blocks* indicator and its interaction with 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 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 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.

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<sup>23</sup>We use the interaction between the predicted Internet use and the *No Blocks* indicator as a second instrument.

<sup>24</sup>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.

<sup>25</sup>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.

Table 8: Change in 9<sup>th</sup> 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
$\Delta$ INet Usage / Student (100 MB)	-0.526** (0.228)	-0.550** (0.223)	-0.543** (0.226)	-0.507** (0.216)	0.221 (0.454)
$\Delta$ INet $\times$ No Blocks			-0.100 (0.209)		
No Blocks		-0.187 (0.142)	-0.0920 (0.191)		
$\Delta$ INet $\times$ Allow YouTube					-0.726* (0.390)
Allow YouTube				-0.392** (0.154)	0.159 (0.366)
Students ( $\times$ 1000)	-1.047** (0.511)	-1.089** (0.505)	-1.104** (0.516)	-1.072** (0.491)	-1.057** (0.497)
Pop. Density ( $\times$ 1000)	0.0176 (0.0203)	0.0188 (0.0205)	0.0191 (0.0206)	0.0218 (0.0211)	0.0202 (0.0211)
Earnings ( $\times$ 1000)	-0.644 (0.418)	-0.687 (0.420)	-0.704* (0.422)	-0.694 (0.436)	-0.680 (0.423)
Mandatory Educ. (%)	-0.00369 (0.00530)	-0.00346 (0.00540)	-0.00344 (0.00541)	-0.00366 (0.00517)	-0.00248 (0.00530)
$\Delta$ Avg. CO Traffic (Mbps)	-14.04 (14.07)	-13.30 (14.13)	-13.27 (14.31)	-16.01 (12.84)	-15.14 (13.07)
Dist. Sch - Cntr (Km)	0.0443** (0.0189)	0.0444** (0.0187)	0.0451** (0.0182)	0.0459** (0.0188)	0.0463** (0.0184)
Constant	3.256*** (0.789)	3.353*** (0.775)	3.367*** (0.786)	3.648*** (0.809)	3.022*** (0.932)
Observations	575	575	575	575	575
Year Dummies	Yes	Yes	Yes	Yes	Yes

Standard errors (in parentheses) clustered at the municipality level  
\*\*\* p<0.01, \*\* p<0.05, \* p<0.1

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<sup>26</sup>. 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 Internet is significantly worse when schools allow YouTube. This is consistent with our argument that when Internet is being used for bandwidth intensive distracting activities, it leads to adverse effect on student performance.

<sup>26</sup>First stage estimates are available upon request.

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

## 9 Conclusion and Discussion

Using a comprehensive dataset 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 vs 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 conduct a survey to explore the distraction effect of Internet in more detail. Some schools block access to many applications and services, which can be characterized as distractive (such as music, movies, chat, online gaming). More interestingly, we focus on YouTube access, which is a bandwidth intensive application. In fact, schools which allow YouTube, typically also consume more bandwidth. We find some 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 few years 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 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.

While we use a very detailed dataset, 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 Internet at home and Internet at 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 with the Internet.

It is also possible that teachers become less effective when they have a better Internet connection, contributing in addition to lowering students' grades. 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 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.

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## A Impact Across Gender and Course

Table 9 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/month per student in 2009 leads to 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 math and Portuguese (columns (4) and (5)). Although not statistically different, the adverse effect is 29% larger for math than for Portuguese.

Table 9: Change in 9<sup>th</sup> grade performance as a function of broadband use by gender and by course.

VARIABLES	(1) All	(2) Male	(3) Female	(4) Port.	(5) Math
$\Delta$ INet Usage / Student (100 MB)	-0.866** (0.378)	-0.936** (0.472)	-0.895* (0.487)	-0.779** (0.392)	-0.982** (0.494)
Students ( $\times$ 1000)	-0.887** (0.405)	-0.628 (0.502)	-1.240** (0.509)	-0.807* (0.443)	-0.989* (0.519)
Pop. Density ( $\times$ 1000)	-0.0137 (0.0160)	-0.0247 (0.0218)	-0.00356 (0.0155)	-0.0124 (0.0159)	-0.0160 (0.0211)
Earnings ( $\times$ 1000)	-0.448 (0.289)	-0.302 (0.439)	-0.714** (0.292)	-0.447* (0.265)	-0.477 (0.416)
Mandatory Educ. (%)	-0.00156 (0.00312)	-0.00209 (0.00392)	-0.000629 (0.00411)	-0.00283 (0.00370)	-0.000444 (0.00423)
$\Delta$ Avg. CO Traffic (Mbps)	1.985 (10.32)	5.215 (11.92)	-0.125 (12.55)	11.69 (9.593)	-7.005 (14.61)
Dist. Sch - Cntr (Km)	0.0235 (0.0205)	0.0331 (0.0238)	0.0133 (0.0243)	0.0148 (0.0202)	0.0320 (0.0243)
Constant	0.724 (0.546)	0.555 (0.711)	1.063 (0.663)	-0.474 (0.557)	1.974*** (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

Standard errors (in parentheses) clustered at the municipality level

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

## 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, chapter 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 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 10 shows that none of the distance thresholds is significant in 2009.<sup>27</sup> 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 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 5 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 6 and 7 report.

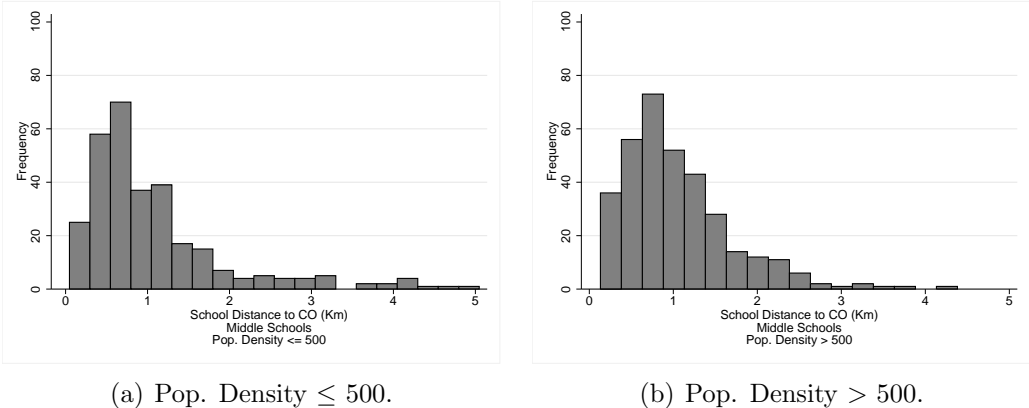


Figure 5: Middle School distances to the closest CO by Population Density.

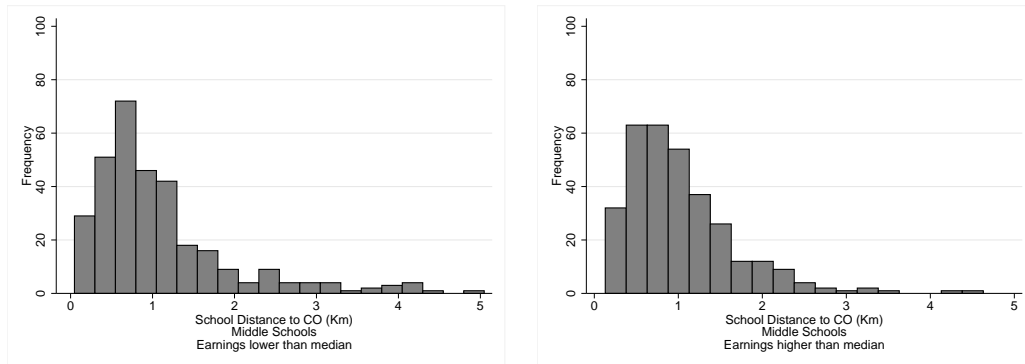
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<sup>27</sup>Regressions for 2008 yield similar results.

Table 10: Distance threshold regressions for schools with 9<sup>th</sup> grade students.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dist. Sch - CO (Km)	-0.106*** (0.0214)	-0.131*** (0.0384)	-0.129** (0.0506)	-0.101*** (0.0378)	-0.108*** (0.0260)	-0.216** (0.0989)	-0.0447 (0.0954)
Sq. Dist. Sch - CO (Km)							-0.0172 (0.0212)
Students (× 1000)	-1.077*** (0.127)	-1.086*** (0.133)	-1.078*** (0.130)	-1.080*** (0.130)	-1.078*** (0.130)	-1.092*** (0.132)	-1.087*** (0.128)
Pop. Density (× 1000)	0.000769 (0.00562)	0.000661 (0.00571)	0.000900 (0.00562)	0.000804 (0.00570)	0.000802 (0.00568)	0.000850 (0.00548)	0.000923 (0.00573)
Earnings (× 1000)	-0.442*** (0.110)	-0.445*** (0.112)	-0.441*** (0.111)	-0.442*** (0.111)	-0.442*** (0.111)	-0.449*** (0.111)	-0.443*** (0.111)
Mandatory Educ. (%)	-0.00520** (0.00202)	-0.00530** (0.00208)	-0.00517** (0.00207)	-0.00529** (0.00207)	-0.00524** (0.00206)	-0.00520** (0.00203)	-0.00549*** (0.00206)
Δ Avg. CO Traffic (Mbps)	4.731 (5.160)	4.986 (5.131)	4.709 (5.122)	4.915 (5.055)	4.754 (5.138)	4.808 (5.069)	5.124 (5.109)
Dist. Sch - Cntr (Km)	0.00424 (0.0103)	0.00347 (0.0106)	0.00434 (0.0105)	0.00395 (0.0105)	0.00418 (0.0104)	0.00351 (0.0105)	0.00334 (0.0105)
Dist. Sch - CO > 0.5 Km	-0.00748 (0.0749)					0.0246 (0.0734)	
Dist. Sch - CO > 1 Km		0.0513 (0.0600)				0.0958 (0.0803)	
Dist. Sch - CO > 2 Km			0.0676 (0.113)			0.141 (0.128)	
Dist. Sch - CO > 3 Km				-0.0434 (0.119)		0.0972 (0.148)	
2007	0.110*** (0.0180)	0.110*** (0.0178)	0.110*** (0.0178)	0.110*** (0.0178)	0.110*** (0.0178)	0.110*** (0.0180)	0.110*** (0.0179)
2008	0.513*** (0.0406)	0.513*** (0.0403)	0.513*** (0.0404)	0.513*** (0.0405)	0.513*** (0.0403)	0.513*** (0.0407)	0.513*** (0.0406)
2009	0.734*** (0.0516)	0.733*** (0.0515)	0.734*** (0.0517)	0.734*** (0.0514)	0.734*** (0.0516)	0.734*** (0.0515)	0.733*** (0.0514)
Constant	1.566*** (0.177)	1.579*** (0.175)	1.575*** (0.172)	1.562*** (0.169)	1.565*** (0.168)	1.616*** (0.195)	1.543*** (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

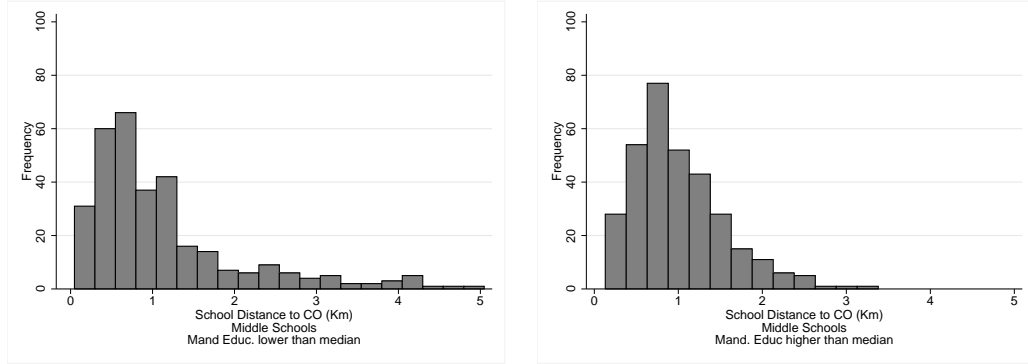
Robust standard errors in parentheses  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1



(a) Earnings lower than median

(b) Earnings higher than median

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



(a) Mand Educ. lower than median

(b) Mand Educ. higher than median

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

Table 11: Internet use as a function of distance and other controls (OLS).

VARIABLES	(1) Inet Use	(2) Inet Use	(3) Inet Use	(4) Inet Use	(5) Inet Use
Dist. Sch - CO (Km)	-0.0944*** (0.0296)		-0.117*** (0.0285)		-0.119*** (0.0284)
Dist. Sch - Cntr (Km)		0.00183 (0.0126)		0.00161 (0.0124)	0.00544 (0.0104)
Students ( $\times 1000$ )			-1.124*** (0.140)	-1.165*** (0.150)	-1.136*** (0.143)
Pop. Density ( $\times 1000$ )			0.00523 (0.00516)	0.00521 (0.00600)	0.00556 (0.00551)
Earnings ( $\times 1000$ )			-0.395*** (0.120)	-0.470*** (0.117)	-0.408*** (0.121)
Mandatory Educ. (%)			-0.00638*** (0.00233)	-0.00462** (0.00226)	-0.00637*** (0.00235)
$\Delta$ Avg. CO Traffic (Mbps)			3.418 (5.785)	-0.624 (6.403)	3.220 (5.816)
2007	0.120*** (0.0167)	0.121*** (0.0170)	0.111*** (0.0193)	0.115*** (0.0200)	0.112*** (0.0196)
2008	0.559*** (0.0368)	0.554*** (0.0363)	0.547*** (0.0437)	0.553*** (0.0460)	0.546*** (0.0444)
2009	0.830*** (0.0469)	0.826*** (0.0465)	0.790*** (0.0601)	0.800*** (0.0620)	0.787*** (0.0606)
Constant	0.362*** (0.0399)	0.259*** (0.0280)	1.590*** (0.176)	1.483*** (0.165)	1.607*** (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

Standard errors (in parentheses) clustered at the municipality level  
 \*\*\* p<0.01, \*\* p<0.05, \* p<0.1