Spillovers Effects of Wiring Schools with Broadband: the Critical Role of Children

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Abstract

Providing broadband to schools can be an effective way to foster household Internet adoption in neighboring areas. On the one hand, the infrastructure put into place to meet schools' needs can also be used to serve households. On the other hand, students get acquainted with Internet at school and signal its usefulness to adults at home who can, as a consequence, be more likely to adopt it. In this paper we model the roles that broadband use at school and broadband adoption in neighboring households play in the decision to adopt broadband at home and measure their effects empirically. We use data from Portugal between 2008 and 2009 on household broadband penetration and on how much schools use broadband. We use two different sets of instruments for the schools' broadband use to alleviate endogeneity concerns. Both approaches yield similar results which increases our confidence in our findings. We find that broadband use at school leads to higher levels of broadband penetration in neighboring households, in particular in households with children. The average broadband use in schools across our dataset increased the probability of broadband adoption by 20% in households with children, while no statistically

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significant effect is found in households without children. These results show that wiring schools with broadband is an effective policy to lower the barriers for Internet adoption at home and as such contributes to accelerate the pace of broadband diffusion.

1 Introduction

The penetration of broadband in firms and households increased significantly in most developed countries in recent times. For example, according to Horrigan (2009) 63% of adults had broadband at home in the US in 2009 compared to only 41.5% in 2000. Spillovers contribute to this increase as people share information and knowledge about how to benefit from the Internet across institutional boundaries and life situations reducing some of the uncertainty that can inhibit widespread adoption. In fact, the role of spillovers has been widely established in the literature. In the industrial context several authors, including Jaffe (1986), David (1990), Jaffe et al. (1993a), Jorgenson and Stiroh (2000), Forman et al. (2005a), Draca et al. (2006), Desmet et al. (2008) and Tambe and Hitt (2010) have shown that the mobility of people across organizations contributes to knowledge spillovers across firms and industries, specially in R&D related activities, which have then been associated to increases in firm productivity and economic growth.

In parallel, Governments have been devoting significant funds to wire schools with broadband. For example, according to Wells and Lewis (2006) the number of classrooms with Internet in the US increased from 3% in 1994 to 94% in 2005. But, are there spillovers from wiring schools with broadband? Haddon (1988), Pugh (1997), Rompaey et al. (2002), L.Holloway and Valentine (2003), Robertson et al. (2004) and Tengtrakul and Peha (2011) show that households with children in school are more likely to have Internet. However, these studies do not attempt to establish causality. Hoffman and Novak (1998), Hoffman et al. (2000), Goldfarb (2006) and Vicente and Lopez (2006) show that attending college is highly related to the adoption of computers and Internet later in life. But what is the effect of Internet use by children at school on Internet adoption at home? Are households close to schools that use more Internet more likely to adopt Internet? Schools offer a motivating and safe environment for students to explore and develop the necessary skills to appreciate the value of the Internet. At schools, access to the Internet and the acquisition of IT-related skills come together, which might lower the barriers to adopt the technology all together. Children go back and forth between school and home on a daily basis, which provides plenty of opportunity for spillovers. They can transmit knowledge to adults at home about how best to benefit from the Internet. As a consequence, adults might adopt broadband at home.

However, a number of concurrent factors shape the adoption of broadband at home, which make it harder to obtain unbiased estimates for the effect of usage at school. Adults use Internet at home for a number of reasons, in particular for leisure and work Horrigan (2009). Living in a neighborhood where more households have broadband may also increase the probability of adoption. There are also supply side spillover effects that one must consider. For example, when carriers wire schools with broadband they are likely to upgrade their networks which provide Internet access not only to schools but also to households. All these factors raise difficult empirical challenges to identify the effect of broadband use at school on household broadband adoption.

This paper aims at teasing out the effect of broadband usage in school on broadband adoption at home. For this purpose, we developed a structural model that provides insights on how spillovers from schools to households might occur and we used a very unique and detailed dataset to estimate it. We used data on actual broadband usage in schools and household broadband penetration in Portugal between 2008 and 2009. We controled for a number of regional covariates, such as income, household size and population density. We used two sets of different instruments to alleviate additional endogeneity concerns. In this respect, our paper provides a novel contribution to the literature. All empirical approaches we pursued yielded similar results, which increases our confidence in the findings reported. We found evidence that households with children are more likely to adopt Internet and that their propensity to do so increases with the children's use of Internet at school. In this context, our paper provides an important contribution as it highlights the critical role that children play as the fundamental mechanism that activates the spillovers from schools' broadband use to household broadband adoption. Once we controled for whether households have children that use Internet at school, we did not find evidence of regional-level spillover effects in the adoption of home Internet across households. These results show that wiring schools with broadband is an effective policy to lower the barriers for Internet adoption at home and to contribute to accelerate the pace of broadband diffusion.

2 Literature Review

2.1 ICTs, Productivity and Economic Growth

The impact of ICTs on economic growth and productivity has been the subject of a significant amount of research. Since Solow's paradox that studies at the national level, including Oliner and Sichel (1994), Oliner and Sichel (2000), Oliner and Sichel (2002), Oulton (2002), Gordon (2000), Gordon (2003), Wolff (2002), Jorgenson et al. (2002), van Ark (2002), Ark (2005) and Bloom et al. (2009), provide mixed findings depending on the countries considered and whether researchers look at output, labor productivity or total factor productivity. Chun and Nadiri (2002), Stiroh (2002), Basu et al. (2003) and Oulton and Srinivasan (2003) also show mixed results at the industry level, mostly notably by comparing the US and the UK during the 1980s and 1990s.

The positive effects of ICTs on economic output are clearer at the firm level. Dewan and ki Min (1997), Lehr and Lichtenberg (1998), Lehr and Lichtenberg (1999), Black and Lynch (2001), Black and Lynch (2004) and Nguyen and Atrostic (2005) find excess returns of IT and computer capital across US firms and the US Government in the late 1980s and throughout the 1990s. A number of subsequent studies, including Bresnahan et al. (2002), Brynjolfsson and Hitt (2003), Crespi et al. (2007) find that the contribution of ICTs to the output of US firms is inextricably linked to how they shape and modernize organizations.

Bresnahan and Trajtenberg (1995), Helpman and Trajtenberg (1996), Greenwood and Yorukoglu (1997) and Andolfatto and MacDonald (1998) argue that ICTs are mostly general purpose technologies. They do not provide complete or final solutions but rather enable growth in adjacent industries as they become pervasive across the economy. Understanding how ICTs diffuse is therefore critical to learn how they can contribute to economic development. Positive network externalities in the diffusion of technology, as identified by Griliches (1957), Rogers (1962) and Bass (1969), and substantial decreases in prices over time promote the widespread use of ICTs once a critical mass is attained. ICTs have been reported to provide a sense of empowerment Brown et al. (2001), Cammaerts and Audenhove (2003) and Klein (2009), which can prompt people to become active participants in both social and political matters, to contribute to manage the safety of populations Bellows et al. (2006), to advance the practice of medicine Yunkap et al. (2009) and offer significant improvements in health care in developing countries Wresch (2009).

2.2 ICTs in Schools

Investments in ICTs in schools are a significant part of the movement towards the information society. Puma et al. (2000) and Goolsbee and Guryan (2006) discuss how the Telecommunications

Act of 1996 increased the number of classrooms with Internet in the US. According to Wells and Lewis (2006) this number went from 3% in 1994 to 94% in 2005. Newberger (2001) reports that in 2000 56.9% of all children aged 6 to 17 used computers at both school and home, 22.8% used only at school and 9.9% used only at home. Rainie and Hitlin (2005) show that in 2004 87% of all children aged 12 to 17 used the Internet, 78% at school. For 20% of them school was the location where they went online most often. Korte and Husing (2006) report that in 2006 90% of the schools in most European countries had Internet access and 67% had broadband access. According to the ITU, in 2009, 73% of schools around the world had Internet access and 68% had broadband. These statistics increase to 97% and 91%, respectively, in Europe.

Kozma and McGhee (2003), Underwood et al. (2005) and Michalchik et al. (2008) argue that ICTs can improve dramatically the students' learning experience. However, there are numerous accounts showing that school investments in ICTs might not necessarily translate into increased performance, at least not in the short run. Coleman (1968), Hanushek (1986) and Hanushek et al. (1996) show that schools' resources and expenditure alone are unlikely to improve student outcomes. Cuban and Kirkpatrick (1998), Angrist and Lavy (2002) and Barrera-Osorio and Linden (2009) find no evidence that investment in ICTs translated to better learning in places such as Silicon Valley, Israel and Colombia. Both Goolsbee and Guryan (2006) and Ward (2006) find only modest evidence that e-rate subsidies might have increased students' performance in the US. Some studies find even a negative impact of investment in ICTs on education. Fuchs and Woessmann (2004), Leuven et al. (2007), Vigdor and Ladd (2010), Malamud and Pop-Eleches (2011) find that providing computers and broadband to schools might result in lower grades. Using instrumental variables and randomized experiments to overcome some limitations of these studies, recent studies such as Rouse and Krueger (2004), Banerjee et al. (2007), Machin et al. (2007), Barrow et al. (2009) and Carrillo and Ponce (2011) find positive effects of investment in ICTs and computer use in schools on students' performance. Still, Belo et al. (2013) finds that the introduction of broadband in schools in Portugal contributed to decrease the students' performance.

2.3 ICTs and Households

The adoption of ICTs at home has also been growing worldwide. Haddon (1988), Pugh (1997), Rompaey et al. (2002), L.Holloway and Valentine (2003), Robertson et al. (2004) and Tengtrakul and Peha (2011) show that having children at home is a major factor for the adoption of ICTs (computers and Internet access in particular) in countries such as the US, the UK, Belgium and Thailand. In the US, and according to the 2000 Census, 51% of the households had a computer in 2000 and 41.5% had an Internet connection. These statistics were 45.1% and 37% for households without children and 66.8% and 53.3% for households with children, respectively. According to Horrigan (2009), 63% of adults in the US had broadband in 2009. This statistic was 77% for the parents of a minor child at home.

Scholarly research has also shown that often mere access to ICTs is not enough to trigger increased nor effective use. Selwyn et al. (2004) and Selwyn (2004) argue that the way people use ITCs is to a large extent shaped by their perception of whether ICTs can help them. People need a sense of purpose to use ICTs as well as the appropriate ICT-related skills to accomplish their goals with the Internet. People need to be taught about what ICTs can do for them. Compaine (2001) shows that most non-Internet adopters indicate no relevance, no interest or no need as the most important factors for such a choice, rather than price.

A significant number of empirical studies focus on the relationships between household and/or individual characteristics and adoption. As such, they do not aim at establishing causality. Leigh and Atkinson (2001), Demoussis and Giannakopoulos (2006), Guida and Crow (2009) and Mitra

(2009) find that Internet adoption is mostly correlated to education and income. According to Chaudhuri et al. (2005) and Ono and Zavodny (2007) age, gender, race and language also explain some variance in adoption of ICTs.

2.4 Spillover Effects in the Adoption of ICTs

Spillovers play a major role in accelerating the pace of the diffusion of ICTs as people share IT-related knowledge across organizational boundaries and life stituations. Spillovers have been largely studied in the industrial context. David (1990), Jorgenson and Stiroh (2000), Draca. et al. (2006) and Tambe and Hitt (2010) discuss how the movement of people across organizations contribute to substantial knowledge spillovers across firms and industries. Jaffe (1986), Jaffe et al. (1993b), Forman et al. (2005b) and Desmet et al. (2008) discuss how knowledge spillovers, specially those related to R&D activities, tend to be local in nature. Goolsbee and Klenow (2002) find evidence of local spillovers and network externalities in the diffusion of home computers and Ward (2010) identifies local spillovers in the adoption of Internet, both in US.

Jovanovic and MacDonald (1994) and Ericson and Pakes (1995) suggest that people can discover new technologies on their own or they can learn from others by imitation. The latter affects the speed of diffusion as discussed by Young (1991), Chari and Hopenhayn (1991), Lucas (1993), Jovanovic and MacDonald (1994), Andolfatto and MacDonald (1998). Goldfarb (2006) discusses how schools and universities play a major role in facilitating learning as they help overcome the "triability, observability and complexity" barriers that may often hinder adoption. In the comforting settings provided by schools and universities, students learn about what they can do with ICTs and then they bring these teachings and experience home and later to the work place. This is likely to accelerate the process of diffusion of ICTs without generating over adoption by those that do not find ICT sufficiently useful.

Far and foremost, the adoption of ICTs is also a social one. Fraser and Villet (1994) argue that most of the development projects that are successful in ensuring widespread use of ICTs tend to fully engage people in the process of change instead of regarding them as naive users or mere recipients of technology. One example of such a program is the ITU "Connect a school, Connect a community", in which public-private partnerships promote broadband connectivity for schools in developing countries around the world. Connected schools can serve not only the youth and children who attend them but also the broader communities in which they are located thus contributing to improve economic and social development all around.

3 Context and Data

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 GEANT network.

In 2004, this Ministry launched a major initiative, aimed at replacing all the existing ISDN connections in schools by broadband ADSL.[1]. This project was completed by January 2006, despite the

[1] Migration to ADSL was complemented with several other initiatives. One such initiative was ICTs training for

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).[2] 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.

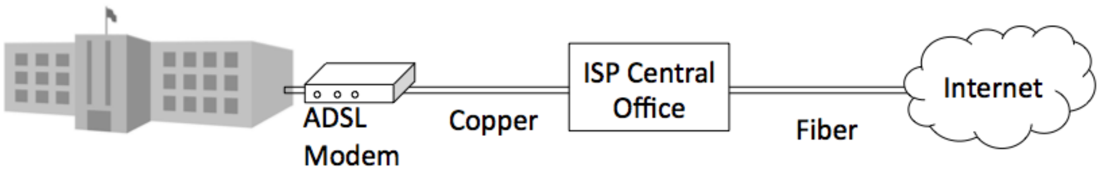

Figure 1: Broadband schools' connection to the Internet. Schools connect through a copper line to the ISP's central office. From there, the ISP ensures connectivity to the Internet backbone through fiber.

3.1 Household Level Data

Household data were obtained from a yearly survey administered to households in Portugal by the Portuguese National Statistics Institute (PNSI). PNSI administers this survey to track the use of Information and Communication Technologies (ICT) in the country. This survey is administered since 2003 but household identifiers are not available and thus we are not able to construct a true pane. Still, we know the municipality in which each household is located. Also, some of the survey questions change from one year to the next, which prevents us from using some of the data available. For example, information about whether households have children and household income are only available since 2008. Roughly 4,000 households are surveyed every year. There are about

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.

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

3.5 million households in Portugal.

Internet penetration in Portugal increased from just over 20% in 2003 to almost 50% in 2009. Broadband Internet grew as well. In 2003 it represented half of all Internet penetration, while in 2009 broadband was in virtually all households with Internet (see Figure 2).

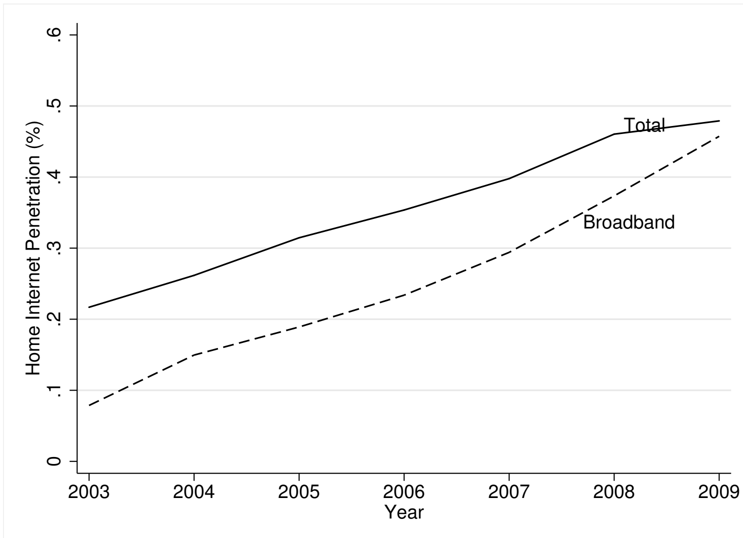

Figure 2: Home Internet penetration.

Figure 3 depicts the evolution of broadband technologies over the period of analysis. Cable and DSL have been the dominant broadband technologies for a long time but in 2006 wireless Internet started growing significantly surpassing wired broadband in 2009.[3] In this paper, we are interested in learning whether the increase in broadband household penetration has been influenced by Internet usage in nearby schools and, if so, how big is this effect.

As expected, computer and home Internet penetration rates are higher in more densely populated areas (see Table 1). Intermediate density areas exhibit a higher percentage of households with children. Also, consistent with our first hypothesis, households with children exhibit higher levels

[3]Note that the sum of ADSL, cable and wireless is higher than household broadband penetration because some households have both wired and wireless Internet. While some people use wireless Internet as their primary way to access the Internet, other people use wireless only as a secondary way to connect.

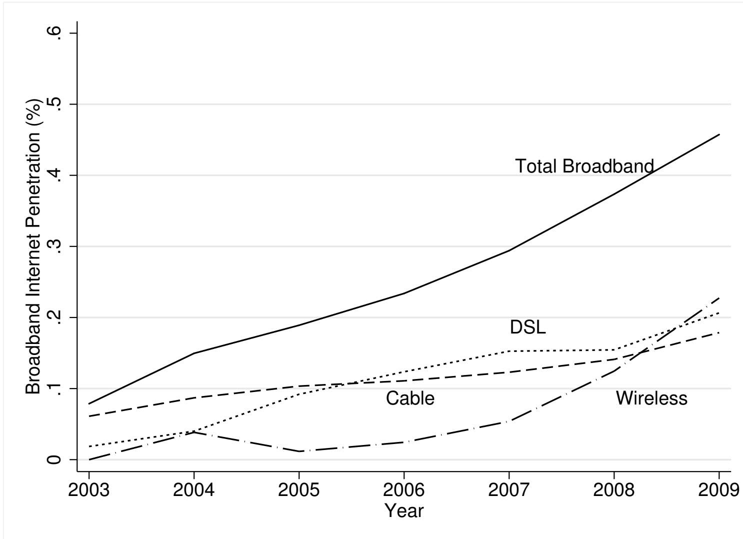

Figure 3: Household broadband Internet penetration by technology

of computer and Internet adoption as well as higher income (see Table 2).[4]

Table 1: Summary statistics by population density.

VARIABLES	(1) High Dens.	(2) Interm. Dens.	(3) Low Dens.
Home INet 2009	0.561	0.474	0.368
	(0.496)	(0.499)	(0.482)
Broadband INet	0.538	0.452	0.354
	(0.499)	(0.498)	(0.478)
Wireless INet	0.235	0.197	0.174
	(0.424)	(0.398)	(0.380)
Computer (%)	0.635	0.565	0.447
	(0.482)	(0.496)	(0.497)
Children (%)	0.302	0.322	0.258
	(0.459)	(0.467)	(0.438)
Household Income	4.834	4.290	3.777
	(2.177)	(1.983)	(1.799)
Household Size	2.789	2.892	2.713
	(1.322)	(1.329)	(1.250)
Observations	2,603	2,672	2,407

[4]The relationship between having children and computer and Internet adoption is not stated in a causal sense. In particular, selection might play an important role in this regard. For instance, households with better financial conditions might have chosen to have children and thus are also more likely to be able to afford computers and Internet access.

Table 2: Summary statistics by household type.

VARIABLES	(1) No Children	(2) Children
Home INet 2009***	0.377	0.693
	(0.485)	(0.461)
Broadband INet***	0.358	0.670
	(0.480)	(0.470)
Wireless INet***	0.149	0.331
	(0.356)	(0.471)
Computer (%)***	0.437	0.825
	(0.496)	(0.380)
Household Income***	4.091	4.844
	(2.038)	(1.953)
Household Size***	2.293	4.013
	(0.968)	(1.200)
Observations	5,413	2,269

Standard deviations in parentheses
*** p<0.01, ** p<0.05, * p<0.1

3.2 Internet Use at School

Data on school Internet traffic were obtained from monitoring tools set up by FCCN. 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 aggregate the total traffic (upload plus download) across all schools in a municipality over the entire academic period.[5]

Internet use in schools grew significantly since the introduction of ADSL in late 2005 (Figure 4). Internet use grew from nearly zero in 2005 to 1.15 GB on average per student per year in 2009. The latter statistic corresponds to watching almost ten hours of YouTube video (at 260 Kbps), browsing 3,500 webpages (at 320 KB per page), or exchanging 8,500 emails (at 130 KB per email).[6] Broadband use per student exhibits high variability across municipalities. Figure 6

[5] We use as academic year the period between July 1st and June 30th.

[6] 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.

provides an histogram for this statistic. Figure 5, shows that broadband use in schools grew more in low density areas, which is consistent with our third hypothesis. Overall, broadband use per student in school is considerable in 2008 and 2009.

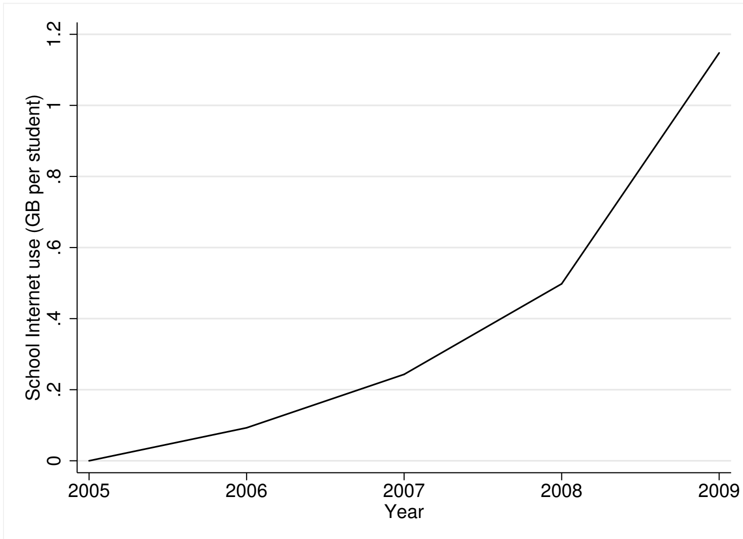

Figure 4: School Internet use per student.

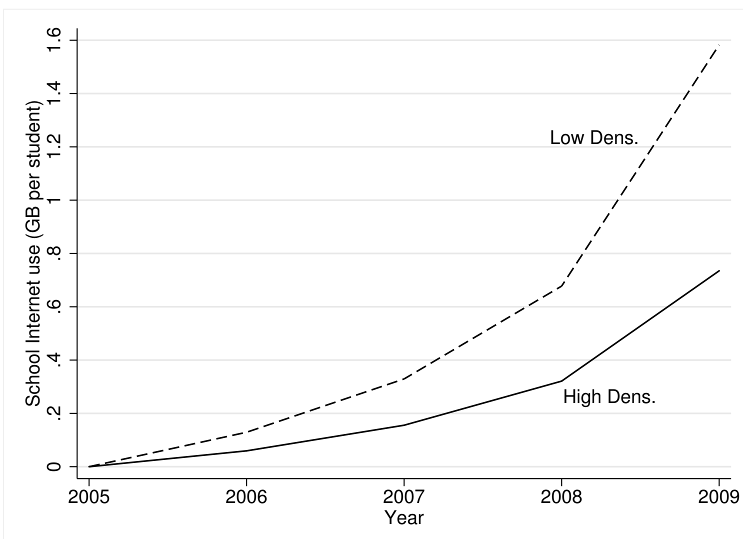

Figure 5: School Internet use per student by population density.

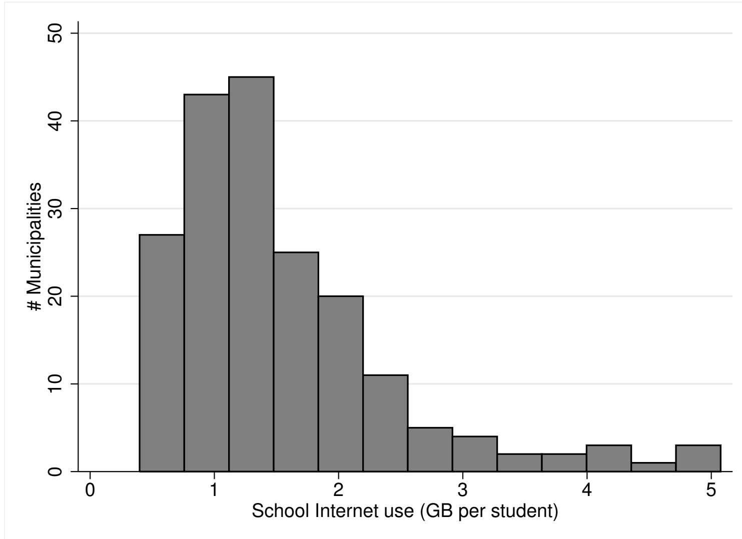

Figure 6: School Internet use per student in 2009 (GB).

3.3 Municipality Data

Finally, municipality data were provided from the Portuguese National Statistics Institute. These data include population density, average income, and population by age bracket across municipalities. Table 3 provides summary statistics for these variables as well as for household level variables.[7] Municipalities exhibit also high variability in terms of the percentage of households with children (see Figure 7).

4 Preliminary Evidence

We start by presenting the cross-section OLS regressions of school Internet traffic on home Internet penetration (see Table 4). Our dependent variable is binary and represents whether the household has Internet access or not; the independent variable, school Internet traffic, is continuous and is measured in Gigabytes (GB) per student in a given year. It shows up twice in the regressions:

[7] Portugal has a population of 10.6 million. The country is divided into 308 municipalities. Our sample covers schools in 195.

Table 3: Summary statistics for municipality data.

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Home INet 2009	7,866	0.479	0.500	0	1
Broadband INet	7,866	0.457	0.498	0	1
Wireless INet	7,864	0.227	0.419	0	1
Computer (%)	7,868	0.560	0.496	0	1
Children (%)	7,868	0.276	0.447	0	1
Household Income	7,686	4.408	2.097	1	9
Household Size	7,868	2.704	1.204	1	14
School INet / Student (GB)	5,585	1.148	0.668	0.398	5.075
Pop. Dens. (Municipality)	7,868	1,297	1,822	5.600	7,183
Avg. Income (Municipality)	7,868	13.20	3.119	8.660	23.34
Age 0 to 14 (%)	7,868	0.151	0.0213	0.0676	0.239
Age 15 to 24 (%)	7,868	0.113	0.0151	0.0793	0.179
Age 25 to 64 (%)	7,868	0.556	0.0241	0.429	0.592
Distance to CO (Km)	5,585	1.322	0.446	0.351	2.612

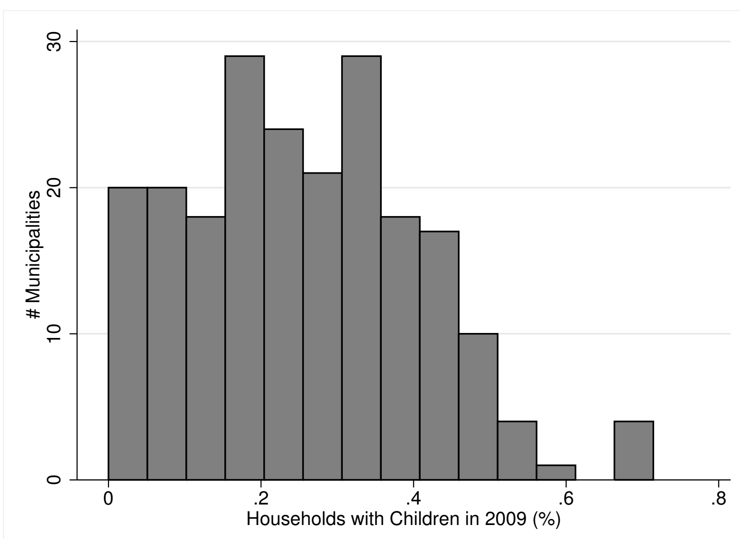

Figure 7: Households with Children in 2009 (%).

by itself (SchInetPS) and interacted with the children indicator (SchInetPS×Children). We use a set of household and municipality-level variables as additional controls. As expected, household income, household size, and population density are positively correlated with having Internet at home (column (1)). Also, having children is correlated with home Internet penetration (columns (3)-(4)). Having children at home is associated with an increase of 5% to 12% in the likelihood of having Internet at home. School Internet traffic does not seem to be correlated with home Internet penetration (columns (2)-(4)). The interesting result is that school Internet use seems to be highly correlated with the home Internet penetration for households with children. For each additional GB used by a student in a given year, the probability of having Internet for a household with children increases by 7%. This corroborates the hypothesis that there are spillover effects from schools to households and that children play a key role in the process. Additionally, it is not only availability at school that matters for the spillover effect, but it is the level of Internet usage (or quality) as well. There are, however, several alternative explanations for the observed results, such as reverse causality. These alternatives will addressed in Section 6.

Alternatively, we can perform the analysis at the municipality level. We regress the gap in Internet penetration between households with and without children on Internet use at school, that is,

$$(\bar{I}_{children} - \bar{I}_{nochildren})_{jt} \quad = \quad s_{jt} + \beta \mathbf{x}_{jt} + \varepsilon_{jt} \tag{1}$$

where $\bar{I}_{children_{jt}}$ and $\bar{I}_{nochildren_{jt}}$ are the household Internet penetration rates for households with and without children, respectively, in municipality j, s_{jt} is the schools' Internet use in this municipality at time t, $\mathbf{x}_{jt}$ includes municipality-level covariates, β is a parameter vector and ε_{jt} is a municipality-level error term. Given that we have two years of data, we can run a regression in levels, but also apply panel data techniques, such as random effects and fixed effects models to control for potential

Table 4: Internet at home as a function of school Internet traffic.

VARIABLES	(1) HomeInet	(2) HomeInet	(3) HomeInet	(4) HomeInet
SchInetPSChildren				0.0696***
				(0.0198)
SchInetPS		0.000349	0.00149	-0.0119
		(0.0102)	(0.0104)	(0.0103)
Children			0.117***	0.0515*
			(0.0172)	(0.0279)
ChildrenMuni	0.128**	0.245***	0.171***	0.157***
	(0.0499)	(0.0454)	(0.0446)	(0.0441)
HouseholdIncome	0.182***	0.180***	0.182***	0.184***
	(0.00672)	(0.00834)	(0.00806)	(0.00807)
HouseholdSize	0.0771***	0.0993***	0.0740***	0.0738***
	(0.00758)	(0.00600)	(0.00627)	(0.00624)
LocalityType	-0.0417***	-0.0306***	-0.0303***	-0.0321***
	(0.00691)	(0.00838)	(0.00816)	(0.00827)
Year2009	0.0565***	0.0357	0.0386*	0.0461**
	(0.0161)	(0.0220)	(0.0217)	(0.0214)
Constant	-0.203***	-0.281***	-0.233***	-0.216***
	(0.0288)	(0.0303)	(0.0306)	(0.0311)
Observations	11,814	8,263	8,263	8,263
R-squared	0.293	0.322	0.329	0.330

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

individual municipality effects.

Figure 8 shows a scatterplot of the Internet adoption gap between households with and without children as a function of Internet use at school. The linear fit shows a trend with a clear positive slope.

Table 5 shows the results of estimating Equation (1) in the aggregated data using an OLS (column (1)) and first differences (column (2)). We still observe evidence of spillover effects from Internet use at school on household Internet penetration at this level of data aggregation. The coefficient of interest is statistically significant in both columns and has a magnitude slighly higher than the coefficientes obtained with the disaggregated data, but more in line with the results obtained with our IV strategy in Section 7.

Using two different estimation strategies we showed encouraging evidence that children have an

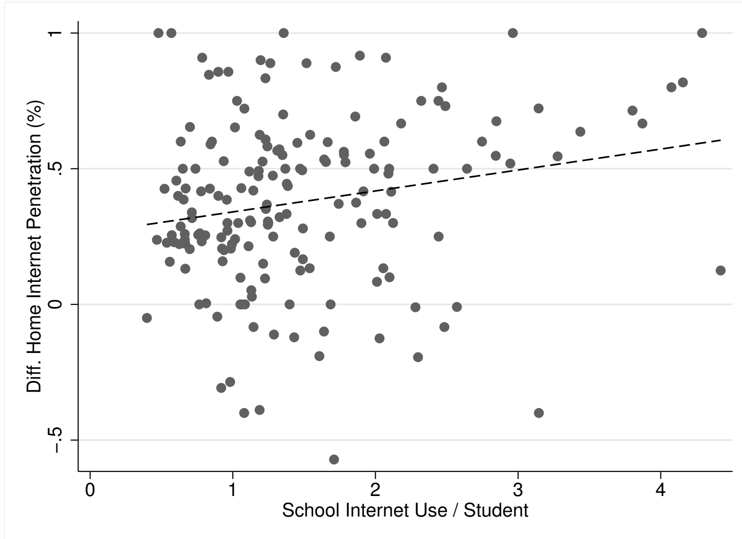

Figure 8: Internet adoption gap between households with and without children as a function of Internet use at school.

Table 5: Internet adoption gap between househols with and without children as a function of Internet use at school.

VARIABLES	(1) OLS	(2) First Differences
SchInetPS	0.0946***	0.122**
	(0.0308)	(0.0573)
ChildrenMuni	0.163	0.452**
	(0.208)	(0.214)
HouseholdIncomeMuni	-0.0157	-0.0218
	(0.0171)	(0.0239)
HouseholdSizeMuni	-0.212***	-0.218*
	(0.0752)	(0.118)
LocalityTypeMuni	-0.00798	0.446
	(0.0403)	(0.626)
Pop	-5.46e-07*	-1.71e-06
	(3.25e-07)	(8.36e-06)
PopDensMuni	-5.09e-05**	0.000527
	(2.34e-05)	(0.000432)
AvEarnk	0.0498***	
	(0.0117)	
Constant	0.300	
	(0.251)	
Observations	344	156
R-squared	0.143	0.091

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

important role in determining household Internet use, and more so in areas where school Internet use is higher. However, the exact reasons why this happens have not been layed out. Next we ouline a model to explore the mechanisms that may originate school to home Internet spillovers.

5 Model and Research Hypotheses

5.1 Adults' and children's utility

Households have children and adults. Adults decide whether to subscribe Internet at home. Let I be a dummy variable indicating whether they do so. The children's utility, represented by u_c, is a function of how much they use Internet at home, represented by h_c, how much they use Internet in school, represented by s_c, and how much they engage in other activities, represented by l_c. Let $u_c^*|_{I=1}$ represent the utility realized by children in a household with Internet, that is, $max_{\{h_c,s_c,l_c\}}\ u_c(h_c, s_c, l_c)$ subject to a time constraint of the form $h_c + s_c + l_c \leq 1$. Similarly, let $u_c^*|_{I=0}$ represent the utility realized by children in a household without Internet, that is, $max_{\{s_c,l_c\}}\ u_c(0, s_c, l_c)$ subject to $s_c + l_c \leq 1$. Let $\delta_c = u_c^*|_{I=1} - u_c^*|_{I=0}$ represent the increased utility for children from Internet at home. The utility realized by children, represented by u_c^*, is given by $I \cdot u_c^*|_{I=1} + (1 - I) \cdot u_c^*|_{I=0}$.

The utility of adults in a household is a function of the children's utility, how much they consume Internet at home, represented by h_a, how much they engage in other activities, represented by l_a, and how much they consume an outside good, represented by x_a. For sake of simplicity, we assume that the utility of children adds linearly into the utility directly enjoyed by adults and that the latter is quadractic in Internet use at home, h_a, and in other activities, l_a, and is quasi-linear in the outside good. Therefore, adults solve:

$$max_{\{h_a,l_a,x_a\}}\ u_c^* + \alpha(2h_a - h_a^2)I + \beta(2l_a - l_a^2) + x_a$$

subject to both money and time constraints and to the fact that $h_a = 0$ if $I = 0$. The money constraint is $x_a + fI \leq y$, where we normalize the price of the outside good to 1. y represents wealth and f represents the fixed fee households pay for Internet access. The time constraint is $h_a + l_a \leq 1$. In this specification, α represents the relative productivity to using Internet at home. Solving the adults' optimization problem yields:

$$(h_a^*, l_a^*, x_a^*) = \left(\frac{\alpha I}{\alpha I + \beta}, \frac{\beta}{\alpha I + \beta}, y - If\right)$$

Adults split their money between the outside good and Internet access at home and split their time between using Internet at home and other activities according to their relative contribution to utility. The adult's indirect utility function is

$$u_a^*(\beta, \alpha, I, y, f) = u_c^* + \beta + \frac{(\alpha I)^2}{\alpha I + \beta} + y - fI \approx u_c^* + \beta + \alpha I + y - fI$$

where the approximation is introduced for sake of simplicity and valid for large enough α. This approximate will render our reduced form equations linear in the effects of interest and thus facilitates estimation.

5.2 Decision to Adopt Internet

Adults adopt Internet at home iff $u_a^*|_{I=1} \geq u_a^*|_{I=0}$, that is, iff

$$0 \leq u_a^*|_{I=1} - u_a^*|_{I=0} = u_c^*|_{I=1} - u_c^*|_{I=0} + \alpha - f = \delta_c + \delta_a - f$$

where $\delta_c \equiv u_c^*|_{I=1} - u_c^*|_{I=0}$ and $\delta_a \equiv \alpha$ represent the benefit of Internet at home for children and adults, respectively. This expression shows that adults subscribe to Internet at home if the increased utility of doing so supersedes its cost. Note that both δ_c and δ_a are positive because both children and adults would not use Internet at home if this would hurt them. Note that in the general case δ_c depends on s_c because using Internet at school may have an effect on the utility that children derive from using Internet at home. Note also that $\delta_c = 0$ for households without children.

Adults in a household without Internet develop a belief about how productive Internet will be. This belief aggregates three effects. First, adults have an a priori belief about how useful Internet can be, represented by θ. Second, children use Internet at school and transmit knowledge about how to benefit from it to adults at home and thus the adults' belief of how useful Internet will be is also a function of s_c. Finally, adults in neighboring households that have already adopted Internet also transmit knowledge about how to benefit from Internet at home and thus the adults' belief of how useful Internet will be is also a function of the fraction of nearby households that have already adopted the Internet, represented by k. As such, let

$$\alpha = \theta + \alpha_s s_c + \alpha_k k$$

In this specification, α_s measures the effect of knowledge spillovers from the children's Internet use at school to the adults' Internet use at home and α_k measures the effect of regional spillovers in the adoption of Internet across households.

Let θ_c represent the minimum level for the a priori usefulness that adults attach to Internet at home that triggers adoption for households with children. This is given by $\delta_a = f - \delta_c$, which leads to $\theta_c = f - \alpha_s s_c - \alpha_k k - \delta_c$. Let θ_{nc} represent the same threshold for households without children. For these households, $\delta_c = 0$ and $s_c = 0$ and therefore this threshold becomes $\theta_{nc} = f - \alpha_k k$. Thus, the minimum level of θ above which adults decide to adopt Internet at home is lower for households with children and is lower the greater the amount of Internet used at school.

5.3 Household Internet Penetration over Time

A household with children will adopt Internet at time t iff $\theta > \theta_c(t) = f - \delta_c - \alpha_s s_c(t) - \alpha_k k(t)$. Likewise, a household without children will adopt Internet at time t iff $\theta > \theta_{nc}(t) = f - \alpha_k k(t)$. Let $g(\cdot)$ represent the pdf for the distribution of θ over its support $[\underline{\theta}, \bar{\theta}]$ across households and thus

$$k(t) = \frac{N_c}{N} \int_{\theta_c(t)}^{\bar{\theta}} g(x)dx + \frac{N - N_c}{N} \int_{\theta_{nc}(t)}^{\bar{\theta}} g(x)dx$$

Now the dynamics of the system will depend on the interplay between θ and k. In fact everything will depend on our assumption for the functional form of $g(\theta)$. We assume that θ are distributed uniformly, i.e., that $g(\theta) = \gamma$ and that $G(\cdot)$ represents the cdf of θ.

$$k(t) = \frac{N_c}{N}[1 - G(\theta_c(t))] + \frac{N - N_c}{N}[1 - G(\theta_{nc}(t))]$$

$$k(t) = \frac{N_c}{N}[1 - \gamma\theta_c(t)] + \frac{N - N_c}{N}[1 - \gamma\theta_{nc}(t)]$$

$$k(t) = \frac{N_c}{N}[1 - \gamma(f - \alpha_s s_c - \alpha_k k - \delta_c)] + \frac{N - N_c}{N}[1 - \gamma(f - \alpha_k k)]$$

$$k(t) = 1 - \gamma f + \frac{N_c}{N}\gamma(\alpha_s s_c + \delta_c) + \gamma\alpha_k k \tag{2}$$

To solve this equation we define $k(t+1)$ as a function of $k(t)$:

$$k(t+1) = 1 - \gamma f + \frac{N_c}{N}\gamma(\alpha_s s_c(t) + \delta_c) + \gamma\alpha_k k(t)$$

$$\dot{k}(t) = k(t+1) - k(t) = 1 - \gamma f + \frac{N_c}{N}\gamma(\alpha_s s_c(t) + \delta_c) + (\gamma\alpha_k - 1)k(t)$$

Defining $A \equiv (1 - \gamma\alpha_k)$, $B \equiv \gamma\alpha_s \frac{N_c}{N} s_c(t)$, and $C \equiv \frac{N_c}{N}\gamma\delta_c + 1 - \gamma f$ we get:

$$\dot{k}(t) = C + B(t) - Ak(t)$$

The solution for this differential equation is of the form $k(t) = C/A - C/Ae^{-At} + k_0 e^{-At} + e^{-At}\int_0^t e^{A\tau}B(\tau)d\tau$.

Thus, we get

$$k(t) = \frac{C}{A} + e^{-At}[k_{s0} - \frac{C}{A} + \frac{N_c}{N}\gamma\alpha_s \int_0^t e^{A\tau}s_c(\tau)d\tau]$$

$$k(t) = e^{-(1-\gamma\alpha_k)t}[k_{s0} + \frac{1-\gamma f - \frac{N_c}{N}\gamma\delta_c}{1-\gamma\alpha_k}] + e^{-(1-\gamma\alpha_k)t}\frac{N_c}{N}\gamma\alpha_s\int_0^t e^{(1-\gamma\alpha_k)\tau}s_c(\tau)d\tau + \frac{1-\gamma f + \frac{N_c}{N}\gamma\delta_c}{1-\gamma\alpha_k} \quad (3)$$

k_{s0} represents the level of household Internet penetration before the introduction of Internet in schools. Its expression can be derived if we are willing to assume a time for the introduction of the Internet in a region. From equation (2) we can see that the fraction of households willing to buy Internet when there are no neighbors with Internet is $k_{s0} = 1 - \gamma f + N_c/N\gamma\delta_c$, and from equation (3) we see that this value plateaus at $(1-\gamma f + N_c/N\gamma\delta_c)/(1-\gamma\alpha_k)$. What is important is that its value changes linearly across regions with the percentage of households that have children. We use the latter expression for k_{s0} and rewrite the expression for k as

$$k(t) = \varphi_1 + \varphi_2 e^{-(1-\gamma\alpha_k)t} + \varphi_3\frac{N_c}{N} + \varphi_4\frac{N_c}{N}e^{-(1-\gamma\alpha_k)t} + \varphi_5\frac{N_c}{N}\int_0^t e^{-(1-\gamma\alpha_k)(t-\tau)}s_c(\tau)d\tau$$

where $\varphi_1 \equiv \frac{1-\gamma f}{1-\gamma\alpha_k}$, $\varphi_2 \equiv 1-\gamma f - \frac{1-\gamma f}{1-\gamma\alpha_k} = \frac{\gamma^2\alpha_k f - \gamma\alpha_k}{1-\gamma\alpha_k}$, $\varphi_3 \equiv \frac{\gamma\delta_c}{1-\gamma\alpha_k}$, $\varphi_4 \equiv \gamma\delta_c - \frac{\gamma\delta_c}{1-\gamma\alpha_k} = \frac{-\gamma^2\alpha_k\delta_c}{1-\gamma\alpha_k}$, $\varphi_5 \equiv \gamma\alpha_s$

k changes in non-linear fashion with time, which means that the fraction of households with children, N_c/N, and children's Internet use at school, s_c, will have different effects on the likelihood of adoption at different time periods. This poses a challenge to our estimation. We solve this issue by interacting our variables of interest with year dummies, therefore estimating separate spillover effects for each year. This is possible because we only have access to two years of consecutive data. An additional problem to our estimation is that school Internet use enters the expression as a compound of all previous years. We could apply the same strategy and use year dummies to account for having different effects in different years, but since in this case we have information since 2006, the first year schools got Internet, we use the sum of school Internet use assuming a discount rate of 0.1 a year:[8]

$$k(t) = \varphi_1 + \varphi_2 \cdot d_{09} + \varphi_3 \frac{N_c}{N} + \varphi_4 \frac{N_c}{N} \cdot d_{09} + \varphi_5 \frac{N_c}{N} S_c(t) \tag{4}$$

where $S_c(t) \equiv \int_0^t e^{-(1-\gamma\alpha_k)(t-\tau)} s_c(\tau) d\tau$.

5.4 Decision to Adopt Internet Revisited

We plug back $k(t)$ given by equation (2) into the adults' decision to adopt Internet at home and find that a household with children adopts Internet iff

$$\begin{aligned}
0 \leq u_a^*|_{I=1} - u_a^*|_{I=0} &= \delta_c + \delta_a - f = \delta_c + \theta + \alpha_s s_c + \alpha_k k - f \qquad (5)\\
&= \delta_c + \alpha_s s_c + \alpha_k \varphi_3 \frac{N_c}{N} + \alpha_k \varphi_4 \frac{N_c}{N} \cdot d_{09} + \alpha_k \varphi_5 \frac{N_c}{N} S_c(t) + \alpha_k \varphi_2 \cdot d_{09} + \theta + \alpha_k \varphi_1 - f\\
&= \delta_c + \phi_1 s_c + \phi_2 \frac{N_c}{N} S_c(t) + \phi_3 \frac{N_c}{N} + \phi_4 \frac{N_c}{N} \cdot d_{09} + \phi_5 d_{09} + u
\end{aligned}$$

where $\phi_1 \equiv \alpha_s$, $\phi_2 \equiv \alpha_k \varphi_5$, $\phi_3 \equiv \alpha_k \varphi_3$, $\phi_4 \equiv \alpha_k \varphi_4$, $\phi_5 \equiv \alpha_k \varphi_2$, and $u \equiv \theta + \alpha_k \varphi_1 - f$. For a household without children this becomes:

[8] We have tried a range of different discount rates, from 0 to 1, and it turns out that all the results remain qualitatively the same. These results are available upon request.

$$
\begin{aligned}
0 \le u_a^*|_{I=1} - u_a^*|_{I=0} &= \delta_c + \delta_a - f = \theta + \alpha_k k - f \qquad (6)\\
&= \phi_2 \frac{N_c}{N} S_c(t) + \phi_3 \frac{N_c}{N} + \phi_4 \frac{N_c}{N} \cdot d_{09} + \phi_5 d_{09} + u
\end{aligned}
$$

Note that Internet use at school appears twice for households with children. The first occurrence is associated with the spillover effect from children to adults. The second occurrence, which also shows up in households without children, is associated with the spillovers from neighboring households. The latter is proportional to the percentage of households with children, N_c/N. These expressions lead to additional research hypotheses:

H1: Households with children in schools with more Internet usage are more likely to adopt Internet.

H2: Households in areas with more children are more likely to adopt Internet.

H3: Households in areas with more children in schools with more Internet usage are more likely to adopt Internet.

Hypothesis *H1* still pertains to the effect of children in the household where they leave and represents our main spillover effect hypothesis in this paper. Hypotheses *H2* and *H3* pertain to regional spillovers and arise from considering the effect of neighboring households.

6 Empirical Specification

We use a Linear Probability Model (LPM) to estimate the effect of school Internet use on household Internet adoption. LPM requires fewer assumptions to obtain consistency than a binary response model. Also, its coefficients can be readily interpreted as average marginal effects. Moreover, LPM has also advantages when many of the regressors are binary or discrete with only a few values, as in our case (Wooldridge, 2002, pp. 454). Nevertheless, we have run probit models for all the regressions reported in this paper and obtain similar results.

From equations (5) and (6), the probability of adoption for household i in municipality j at time t given that this household has not yet adopted Internet is given by

$$\begin{aligned} P(u_a^*|I=1 \geq u_a^*|I=0)_{ijt} &= d_{c_i} \cdot \delta_c + d_{c_i} \cdot \phi_1 s_{c_{jt}} + \phi_2 \frac{N_{c_{jt}}}{N} S_{c_{jt}} + \\ &\quad + \phi_3 \frac{N_{c_{jt}}}{N} + \phi_4 \frac{N_{c_{jt}}}{N} \cdot d_{09} + \phi_5 d_{09} + \beta \mathbf{x}_{it} + \nu_j + \varepsilon_{it} \qquad (7) \end{aligned}$$

where d_{c_i} is an indicator variable for whether household i has children, $s_{c_{jt}}$ represents Internet use in schools in municipality j at time t, $\mathbf{x}_{it}$ is a vector of observed household covariates, and thus we decompose θ_{it} in equations (5) and (6) into a vector of observed covariates and an unobserved term, ε_{it}, and finally ν_j embodies time-fixed unobserved municipality effects.

Equation (7) allows for testing all our research hypotheses. ϕ_1 allows for testing hypothesis *H1*, that households with children in schools with more Internet usage are more likely to adopt Internet. This captures the spillover effect from Internet usage at school to adults' usage of Internet at home. ϕ_3 and ϕ_4 allow for testing hypothesis *H2* that households in areas with more children are more likely to adopt Internet. Finally, ϕ_2 allows for testing hypothesis *H3* that households in areas with more children who use more Internet at school are more likely to adopt Internet.

Recall that δ_c represents the change in the children's utility due to Internet use at home. In estimating equation (7) we will assume that this difference does not change with how much children use Internet at school, which is a strong assumption. If this is the case, then the spillover effect of the children's Internet use at school on the adults' propensity to adopt Internet at home is captured by ϕ_1. If, however, Internet use at school and at home are substitutes, then more Internet use at school reduces δ_c and thus assuming that the latter does not depend on s_c underestimates the spillover effect from children to adults. If, on the other hand, Internet use at school and at home are complements, then more Internet use at school increases δ_c and thus assuming that the latter is constant overestimates the spillover effect from children to adults.

In short, it is hard to separate the effect of the children's use of Internet at school on their own utility of Internet use at home, captured by δ_c, and on the adults' utility of Internet use at home, captured by ϕ_1. In the appendix we provide some evidence that the children's use of Internet at school and at home seem to be substitutes and thus a positive ϕ_1 should be interpreted as a lower bound for the spillover effect of the children's use of Internet in school on the utility that adults derive from using Internet at home. In any case, if one rather believes that Internet use at school and at home are complements, then ϕ_1 captures the aggregate effect of spillovers from the children's use of Internet at school to Internet use at home by both children and adults all together.

We start by estimating a pooled regression for 2008 and 2009, the years for which we have information about children in the households. We include household income, size and locality type. We cluster standard errors at the municipality level. We do not include municipality-level dummies in these regressions because this would preclude us from estimating regional spillover effects leading to test hypotheses *H2* and *H3*. However, we have performed similar regressions with municipality-level dummies and obtained results similar to the ones reported throughout this paper for all specifications used. These results are available upon request.

Although the pooled regressions control already for some household-level effects, we are still concerned that the children's use of Internet at school is endogenous in our setting. Unobserved time varying covariates, such as the deployment of new Internet backbone infrastructure, might drive both Internet use at school and household Internet adoption, which would bias our estimates for the parameters of interest in equation (7). We use two sets of instruments to overcome this concern. First, we use municipality level covariates to instrument Internet use at school. This strategy has been already used by Goolsbee and Klenow (2002) and Ward (2010). Second, and following Belo et al. (2013), we use an exogenous measure of quality of the school's Internet connection. Below, we provide additional details for each of these strategies.

6.1 Instrumenting with Municipality-level Covariates

In one approach, we instrument school Internet traffic with municipality-level covariates, such as household income and population density. These covariates predict well school Internet traffic as shown in our first stage regressions in Table 9 in the appendix.[9] However, they might not be valid instruments if correlated with unobserved household-level covariates. However, if we include the corresponding household-level covariates in our regressions, any bias due to these unobserved covariates would be captured by the household-level covariates, leaving the municipality-level coefficients unbiased. This is valid as long as we assume that $E(\varepsilon_{it}|\mathbf{x}_{it}, \mathbf{w}_{jt}) = E(\varepsilon_{it}|\mathbf{x}_{it})$, where $\mathbf{w}_{jt}$ is a vector of municipality-level covariates (see Goolsbee and Klenow, 2002, for more details). Potential household-level unobservables would bias household covariates but not municipality-level covariates. For example, if technology savvy people tend to locate in high-income areas then including household income in our regressions would capture all correlation between technology savvyness and income.

[9] Although in theory municipality-level household income would be a valid intrument in this case as discussed ahead in the paragraph, overidentification tests show that this variable should not be an excluded instrument and should be added to the main regression. This means that municipality-level income is a relevant predictor of household level internet adoption even after controlling for household-level income. Therefore, in all the results presented below we use only population density as the municipality-level instrument. Apart from overidentification tests, all the results remain qualitatively the same if we use municipality-level household income as instrument.

6.2 Instrumenting with Broadband Quality

In a second approach, we exploit the variation in the quality of the schools' broadband connections 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 a school and the Central Office (CO) of the ISP providing Internet access results in a lower maximum transfer bitrate. Therefore, schools further away from the CO are likely to obtain lower throughput on their Internet 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 a weighted average of the line-of-sight distance between schools and their closest CO as a proxy for the quality of the schools' broadband connection in a municipality. The weights are the number of students in each school. Line-of-sight distance is calculated from information on the GPS coordinates of both schools and ISP's COs. The appropriateness of this instrument has been thoroughly discussed in previous work, see Belo et al. (2013) for more information and robustness checks that essentially show that the distance between schools and COs is fairly random.

Finally, we note that we need at least two excluded instruments to ensure identification when estimating equation (7) because school Internet use shows up twice on its right hand side. Thus, we use the interaction between our instruments and the indicator variable *Children* as an additional instrument in both IV strategies described above.

6.3 Using a three-stage least squares approach

In the estimation strategy that we follow in the main text, we replace k by its components in the main equation, so that we can test all the hypotheses stated in the model with a single equation estimated by 2SLS. An alternative to this approach is to jointly estimate both household level and municipality level Internet penetration equations using a three-stage least squares (3SLS) framework. From equations (5), (6) and (4) we get following system of equations:

$$
\begin{aligned}
P(u_a^*|I = 1 \geq u_a^*|I = 0)_{ijt} &= d_{c_i} \cdot \delta_c + d_{c_i} \cdot \phi_1 s_{c_{jt}} + \phi_5 d_{09} + \beta \mathbf{x}_{it} + \alpha_k k_{jt} + \varepsilon_{it} \qquad (8) \\
k_{jt} &= \varphi_1 + \varphi_2 \cdot d_{09} + \varphi_3 \frac{N_c}{N} + \varphi_4 \frac{N_c}{N} \cdot d_{09} + \varphi_5 \frac{N_c}{N} S_{c_{jt}} + \xi_{jt} \qquad (9)
\end{aligned}
$$

Using a 3SLS approach has some advantages and disadvantages when compared with the single equation 2SLS estimation. On the plus side, the 3SLS procedure should be more efficient because, aside from other technical issues[10], the actual values of municipality level Internet penetration, k, are used. On the negative side, municipality level instruments cannot be used at the municipality level (equation (8)) because of the nature of the dependent variable, that exists only at the municipality level. Thus, distance to CO is the only instrument available for this equation. This will be evident in the results section.

7 Results

7.1 OLS Results

Table 6 shows cross-section OLS results from our regressions of household Internet penetration on school Internet traffic. Column (1) in this table shows that household income, household size and population density are positively correlated with Internet at home, as one could expect. Column

[10]The 3SLS uses an optimal weighting matrix that ensures efficiency. Additionally, we use bootstrapped standard errors because clustered standard errors are not allowed in the Stata 3SLS procedure.

(2) shows that households with children are more likely to have Internet, and that households with children in schools with more Internet use are also more likely to adopt Internet, in support of hypothesis *H1*. Column (3) shows that households in areas with more children that use more Internet at home are more likely to adopt Internet, in support of hypothesis *H3*. However, Column (4) shows that this effect is captured by whether households locate in areas with more children, in support of hypotheses *H2*, and not necessarily associated to how much Internet these children use at school.

Finally, Column (5) includes all effects at once. In this case, we see no support for hypotheses *H2* and *H3*. Still, hypothesis *H1* remains statistically significant. In particular, there is still evidence in the fuller version of our model of a positive spillover effect from the use of Internet at school on household Internet penetration. Therefore, this spillover effect seems to dominate any regional-level spillover effect across households that might potential be at play in our data. Column (5) in this table also shows that households with children are more like to adopt Internet although the statistical significance of this result partially shifts to the covariate that interacts whether households have children with how much they use Internet at school, providing yet additional evidence that it is in fact the use of Internet at school by children that supports the spillover effect.

The results above must be interpreted with caution in the sense that they provide indications of correlation between household Internet penetration and Internet use at school. Still, they provide evidence that children mediate the observed positive correlation between these two covariates.

7.2 IV Results

Several alternative explanations for the results observed in Table 6 might be at play. One such alternative is reverse causality. Suppose that households with children are more likely to adopt

Table 6: Internet at home as a function of school Internet traffic.

VARIABLES	(1) HomeInet	(2) HomeInet	(3) HomeInet	(4) HomeInet	(5) HomeInet
Children (δ_c)		0.0617**			0.0594**
		(0.0270)			(0.0282)
SchInetPS $\times$ Children (ϕ_1)		0.0678***			0.0613***
		(0.0188)			(0.0206)
SumSchInetPS (ϕ_2)			0.0384***	0.0214	0.00407
			(0.00830)	(0.0134)	(0.0148)
ChildrenMuni (%) (ϕ_3)				0.125	0.0955
				(0.0783)	(0.0771)
ChildrenMuni $\times$ Year2009 (%) (ϕ_4)				0.00720	0.0225
				(0.0951)	(0.0951)
Year2009 (ϕ_5)	0.0675***	0.0447**	0.0168	0.0257	0.0347
	(0.0168)	(0.0197)	(0.0211)	(0.0268)	(0.0263)
HouseholdIncome	0.174***	0.174***	0.170***	0.171***	0.176***
	(0.00670)	(0.00838)	(0.00860)	(0.00874)	(0.00853)
HouseholdSize	0.0814***	0.0764***	0.102***	0.101***	0.0757***
	(0.00799)	(0.00623)	(0.00608)	(0.00607)	(0.00628)
LocalityType	-0.0319***	-0.0267***	-0.0320***	-0.0261***	-0.0261***
	(0.00714)	(0.00822)	(0.00844)	(0.00862)	(0.00841)
HouseIncomeMuni	0.0592***	0.0608***	0.0585***	0.0529***	0.0525***
	(0.0141)	(0.0132)	(0.0136)	(0.0133)	(0.0132)
Constant	-0.332***	-0.337***	-0.368***	-0.389***	-0.341***
	(0.0480)	(0.0480)	(0.0485)	(0.0518)	(0.0505)
Observations	11,814	8,263	8,263	8,263	8,263
R-squared	0.294	0.331	0.324	0.324	0.332

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

Internet either because adults in these households are younger and/or more technology savvy or just because children ask for it. This can potentially make children go to school and use more Internet there when compared to children without Internet at home. School Internet use would increase because students have Internet at home and not the other way around. We proceed with the IV approaches proposed in the previous section to try to overcome these endogeneity concerns.

Table 7 shows the second stage results using instruments. First stage results behave as expected and are shown in the appendix. Column (1) replicates the OLS results for sake of comparison. Column (2), shows the results when instrumenting with municipality-level variables. The effect of the children's Internet use at school is still positive and significant at the 1% level. Additionally, the direct effect of having children at home disappears. This provides additional evidence that spillover effects from the children's use of Internet at school on the adults' decision to adopt Internet at home are indeed at play. It is not enough to have children at home. Children must be using Internet at school for the effect to be observed. The effect is larger the more the children use Internet at school. The magnitude of this effect increases after instrumentation, which is consistent with the fact that Internet usage at school and at home are substitutes. If these are substitutes, children that use more Internet at home are likely to use less at school, but once we instrument the schools' Internet use we smooth this effect.

The coefficient of 0.118 for the spillover effect (ϕ_1) means that 1 GB more in Internet use per student at school increases the probability of adoption for a household with children in 11.8%. At the average Internet use per student of 1.6 GB in 2008, this corresponds to an 19% in the probability of Internet adoption in households with children (or 4.7% in the overall population).

Columns (3) in Table 7 shows the second stage results using distance between schools and COs as instruments. These results are similar to the municipality level IV results. The effect of having

Table 7: Home Internet penetration as a function of school Internet traffic.

VARIABLES	(1) OLS	(2) Muni IV	(3) Dist IV	(4) Muni IV + Dist IV
Children (δ_c)	0.0594**	0.00666	-0.0783	-0.0186
	(0.0282)	(0.0559)	(0.0674)	(0.0526)
SchInetPS $\times$ Children (ϕ_1)	0.0613***	0.118**	0.206***	0.144***
	(0.0206)	(0.0526)	(0.0665)	(0.0496)
SumSchInetPS (ϕ_2)	0.00407	0.0707	-0.0539	0.0157
	(0.0148)	(0.0810)	(0.0785)	(0.0596)
ChildrenMuni (%) (ϕ_3)	0.0955	-0.0426	0.243	0.0817
	(0.0771)	(0.197)	(0.187)	(0.152)
ChildrenMuni $\times$ Year2009 (%) (ϕ_4)	0.0225	-0.166	0.0879	-0.0470
	(0.0951)	(0.196)	(0.211)	(0.160)
Year2009 (ϕ_5)	0.0347	0.0276	0.0520*	0.0376
	(0.0263)	(0.0311)	(0.0277)	(0.0283)
HouseholdIncome	0.176***	0.174***	0.180***	0.177***
	(0.00853)	(0.00936)	(0.00899)	(0.00897)
HouseholdSize	0.0757***	0.0747***	0.0756***	0.0751***
	(0.00628)	(0.00635)	(0.00640)	(0.00631)
LocalityType	-0.0261***	-0.0514**	-0.0222	-0.0373**
	(0.00841)	(0.0237)	(0.0238)	(0.0179)
HouseIncomeMuni	0.0525***	0.0589***	0.0518***	0.0555***
	(0.0132)	(0.0156)	(0.0147)	(0.0142)
Constant	-0.341***	-0.286***	-0.358***	-0.320***
	(0.0505)	(0.0743)	(0.0698)	(0.0629)
Observations	8,263	8,263	8,263	8,263
R-squared	0.332	0.326	0.326	0.329
Underident. Test (Kleibergen-Paap rk LM p-val)	.	3.40e-06	0.0258	2.26e-05
Weak Ident. Test (Kleibergen-Paap rk Wald F-stat)	.	23.42	2.350	13.24
Overident. Test (Hansen J P-value)	.	.	.	0.164

Robust standard errors in parentheses

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

children at home is not, per si, statistically significant. Its interaction with how much the children use Internet at school, which captures our main spillover effect, is statistically significant at the 1% level and positive. However its magnitude almost doubles when compared to the coefficient obtained using only municipality variables. However, its standard error is high enough that we cannot rule out the hypothesis that the coefficients are the same. Additionally, as can be seen by the Kleinbergen-Paap F-statistic, distance to CO seems to be a weak instrument when used by itself. Thus it is expected that these estimates are less precise. Column (4) shows the second stage results using all the IVs simultaneously. All identification test statistics are reasonable, assuring us that this specification is adequate. The main spillover effect is now highly significant and its magnitude similar to the results using only the municipality level instruments. In this case at the average Internet use per student of 1.6 GB, school internet use is associated with a 23% increase in the probability of Internet adoption in households with children (or 5.75% in the overall population).

In sum, using distance between schools and COs as an instrument yields results similar to using municipality-level covariates as instruments and therefore we observe that two different identification strategies lead to similar findings. This increases our confidence in our results and provide additional support to our claim that indeed spillover effects from wiring schools with broadband play a role in the dynamics of household Internet penetration.

7.3 3SLS results

Table 8 shows the results of the 3SLS estimation using as instruments distance to CO (columns (1) and (2)) and distance plus municipality level variables (columns (3) and (4)). Both sets of instruments yield similar results. We get statistical significance for the household level effect (columns (2) and (4)) but not for the municipality level effect (columns (1) and (3)). Although distance is a suitable instrument for school Internet use[11], the latter does not seem to significantly affect Internet penetration at the municipality level (φ_5) after controlling for other municipality level variables (columns (1) and (3)). This is consistent with the IV results. The fraction of households with children, household average income and locality are statistically significant and exhibit the expected directions. The effect of school internet use at the household level (ϕ_1) (columns (2) and (4)) is statistically significant and has a magnitude similar to the effect obtained with the IV results. In these regressions home Internet penetration at the municipality level is significant, indicating that after controlling for all observable covariates there are still unobseved factors at the municipality level determining household level penetration and being captured by this variable. Note that the significance of this coefficient should not be interpreted as evidence for a regional level spillover, as this is the role of φ_5 in columns (1) and (3); this variable is used here simply as an additional control.

8 Conclusion

This paper looks at the spillover effect of providing Internet to schools on household Internet penetration. We posit that when a Government wires schools with broadband it also contributes to increase the penetration rate of household Internet. We posit that children are the main drivers of this process. Children are exposed to Internet at school and transmit knowledge about how to benefit from it to adults at home. As a result, the adults' propensity to adopt Internet at home increases. We develop a structural model that provides insights on how this process might occur. In this model, we propose that the adults' productivity of using Internet at home Internet is a function of this knowledge transmitted by children as well as from knowledge transmitted from

[11]To save space we do not include further robustness checkcs such as single-equation first stage results for the municipality-level equation. These are available upon request.

Table 8: Three-Stage Least Square regressions.

VARIABLES	(1) Dist IV HomeInternetMuni	(2) HomeInternet	(3) Muni + Dist IV HomeInternetMuni	(4) HomeInternet
SchInetPS × Children (ϕ_1)		0.174***		0.138***
		(0.0426)		(0.0293)
Children (δ_c)		-0.0427		-0.00773
		(0.0442)		(0.0292)
HouseholdIncome		0.180***		0.179***
		(0.00580)		(0.00517)
HouseholdSize		0.0725***		0.0727***
		(0.00542)		(0.00546)
LocalityType		-0.0318***		-0.0281***
		(0.00672)		(0.00745)
HomeInternetMuni (k)		0.242***		0.245***
		(0.0358)		(0.0363)
SumSchInetPS × ChildrenMuni (%) (ϕ_2)	0.0172		0.0143	
	(0.0195)		(0.0175)	
ChildrenMuni (%) (ϕ_3)	0.316***		0.322***	
	(0.0441)		(0.0388)	
ChildrenMuni × Year2009 (%) (ϕ_4)	0.0190		0.0249	
	(0.0538)		(0.0517)	
HouseIncomeMuni	0.228***		0.228***	
	(0.00271)		(0.00280)	
LocalityTypeMuni	-0.0226***		-0.0217***	
	(0.00689)		(0.00602)	
Year2009 (ϕ_5)	0.0333***	0.0285	0.0337***	0.0304*
	(0.00517)	(0.0177)	(0.00549)	(0.0175)
Constant	-0.183***	-0.269***	-0.185***	-0.279***
	(0.0174)	(0.0275)	(0.0130)	(0.0349)
Observations	8,263	8,263	8,263	8,263
R-squared	0.673	0.342	0.673	0.345

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

neighboring households that have already adopted Internet. This model highlights that households with children are more likely to adopt Internet, in particular when the children use more Internet at school, and households in areas with more children are also more likely to adopt Internet, also in particular when the children use more Internet at school.

We estimate this model using empirical data from Portugal where all schools were given broadband in early 2006. We use data on actual broadband use at school and on household Internet penetration as reported by the National Statistics Institute. We focus on how Internet use affected the penetration of household broadband between 2008 and 2009, the two years for which data about whether households have children are available. We find evidence that households with children are more likely to adopt Internet and that their propensity to do so increases with the children's use of Internet at school.

These results are obtained after instrumenting for the use of Internet at school to alleviate potential endogeneity concerns. In this respect, our paper makes an important contribution because we provide results using two different identification strategies. In one approach, we use municipality level covariates as instruments. In another approach, we use the quality of the broadband Internet connection at school as an instrument. Both strategies yield similar results, which increases our confidence in our findings. In both cases, we show that children are the fundamental drivers of the observed spillover effects. Once we control for whether households have children that use Internet at school, we do not find evidence of regional-level spillover effects in the adoption of home Internet across households.

This paper does not come without limitations. First, the nature of our data does not allow us to follow households over time, which raises challenges for our identification strategy. Still, we run several robustness checks on our instruments that lessen endogeneity concerns. Furthermore, we aggregate data at the municipality level, since we can follow municipalities, and report results for how the household Internet penetration changes as a function of Internet use at school. These results still show evidence of a positive spillover effect from Internet use at school. Second, while we find that the adults' utility from using Internet at home increases with the children's use of Internet at school, we do not know what type of activities adults' perform on the Internet at home. Arguably, these spillover effects might push adults' to using Internet at home in unproductive ways for society.

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Appendix

A Appropriateness of Distance as an Instrument to School Internet Use

Although distance between schools and COs might be unrelated to the distance between households and COs, one might still worry that the quality of Internet at school might be correlated with the quality of Internet at home because most likely children go to school close to where they live and the quality of Internet connectivity might be similar within the same region, which would render this instrument invalid and bias our estimates upwards. In fact, the Internet backbone infrastructure that provides ADSL access to schools also provides ADSL access to households and thus there might be some concern with correlation in the quality of Internet access across all ADSL connections in the same region. Column (1) in Table 10 shows that the distance between schools and COs explains home wired Internet penetration. While this does not necessarily render our instrument invalid, it casts doubts on its appropriateness.

Still, Figure 3 shows that only 20% of the households subscribe to Internet via ADSL. This figure also shows that a large number of households subscribe to Internet over cable and the quality of Internet over cable is highly insensitive to the distance between the customer's premise and the CO of the ISP providing access. Furthermore, this figure also shows that after 2007 a significant number of households subscribe to wireless broadband Internet. Wireless broadband in Portugal is provided to households not only by the provider that wired schools with ADSL but also by other telecommunication providers that combined have a significant share of the wireless market. These

Table 9: Internet penetration as a function of school Internet traffic (IV first and second stages).

VARIABLES	(1) OLS HomeInet	(2) Muni IV 1st Stage (ϕ_1)	(3) Muni IV 1st Stage (ϕ_2)	(4) Muni IV HomeInet	(5) Dist IV 1st Stage (ϕ_1)	(6) Dist IV 1st Stage (ϕ_2)	(7) Dist IV HomeInet	(8) Muni IV + Dist IV 1st Stage (ϕ_1)	(9) Muni IV + Dist IV 1st Stage (ϕ_2)	(10) Muni IV + Dist IV HomeInet
Children (δ_c)	0.0594**	0.287***	-0.178***	0.00666	1.296***	0.0410*	-0.0783	0.505***	-0.190**	-0.0186
	(0.0282)	(0.0911)	(0.0566)	(0.0559)	(0.0664)	(0.0233)	(0.0674)	(0.128)	(0.0766)	(0.0526)
SchInetPS × Children (ϕ_1)	0.0613***			0.118**			0.206***			0.144***
	(0.0206)			(0.0526)			(0.0665)			(0.0496)
SumSchInetPS (ϕ_2)	0.00407			0.0707			-0.0539			0.0157
	(0.0148)			(0.0810)			(0.0785)			(0.0596)
ChildrenMuni (%) (ϕ_3)	0.0955	-0.319***	2.168***	-0.0426	-0.250***	2.187***	0.243	-0.324***	2.176***	0.0817
	(0.0771)	(0.0680)	(0.235)	(0.197)	(0.0736)	(0.245)	(0.187)	(0.0685)	(0.242)	(0.152)
ChildrenMuni × Year2009 (%) (ϕ_4)	0.0225	0.496***	2.384***	-0.166	0.512***	2.388***	0.0879	0.499***	2.382***	-0.0470
	(0.0951)	(0.0931)	(0.309)	(0.196)	(0.0979)	(0.310)	(0.211)	(0.0927)	(0.308)	(0.160)
Year2009 (ϕ_5)	0.0347	-0.0502***	0.167***	0.0276	-0.0561***	0.159**	0.0520*	-0.0502**	0.168***	0.0376
	(0.0263)	(0.0193)	(0.0639)	(0.0311)	(0.0204)	(0.0635)	(0.0277)	(0.0196)	(0.0639)	(0.0283)
HouseholdIncome	0.176***	-0.0133**	0.0266**	0.174***	-0.0191***	0.0312***	0.180***	-0.0139**	0.0263**	0.177***
	(0.00853)	(0.00589)	(0.0105)	(0.00936)	(0.00547)	(0.00974)	(0.00899)	(0.00593)	(0.0106)	(0.00897)
HouseholdSize	0.0757***	0.00318	0.0135	0.0747***	0.00637	0.0121	0.0756***	0.00373	0.0137	0.0751***
	(0.00628)	(0.00352)	(0.00888)	(0.00635)	(0.00397)	(0.00869)	(0.00640)	(0.00343)	(0.00865)	(0.00631)
LocalityType	-0.0261***	-0.00457	-0.00378	-0.0514**	0.0751***	0.243***	-0.0222	-0.00503	-0.00444	-0.0373**
	(0.00841)	(0.00682)	(0.00357)	(0.0237)	(0.0143)	(0.0451)	(0.0238)	(0.00682)	(0.00352)	(0.0179)
HouseIncomeMuni	0.0525***	-0.0338*	-0.0430	0.0589***	-0.0287	-0.0526	0.0518***	-0.0304	-0.0299	0.0555***
	(0.0132)	(0.0188)	(0.0670)	(0.0156)	(0.0198)	(0.0678)	(0.0147)	(0.0194)	(0.0693)	(0.0142)
LocalityTypeMuni		-0.000451	0.314***					0.00344	0.265***	
		(0.00956)	(0.0466)					(0.00934)	(0.0492)	
HouseIncomeMuniChildren		-0.0360***	-0.00443					-0.0333***	-0.00417	
		(0.0119)	(0.0119)					(0.0120)	(0.0117)	
LocalityTypeMuniChildren		0.413***	0.0933***					0.349***	0.0954***	
		(0.0472)	(0.0202)					(0.0528)	(0.0254)	
DistanceIV					0.161***	-0.272*		0.0123*	-0.248*	
					(0.0276)	(0.140)		(0.00709)	(0.139)	
DistanceIVChildren					-0.955***	-0.157***		-0.292**	0.0199	
					(0.129)	(0.0498)		(0.118)	(0.0621)	
Constant	-0.341***	0.0962*	-0.778***	-0.286***	-0.137*	-0.540**	-0.358***	0.0781	-0.632**	-0.320***
	(0.0505)	(0.0506)	(0.244)	(0.0743)	(0.0698)	(0.236)	(0.0698)	(0.0493)	(0.251)	(0.0629)
Observations	8,263	8,265	8,265	8,263	8,265	8,265	8,263	8,265	8,265	8,263
R-squared	0.332	0.767	0.681	0.326	0.739	0.677	0.326	0.770	0.685	0.329
Underident. Test (Kleibergen-Paap rk LM p-val)				3.40e-06			0.0258			2.26e-05
Weak Ident. Test (Kleibergen-Paap rk Wald F-stat)				23.42			2.350			13.24
Overident. Test (Hansen J P-value)				.			.			0.164

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

Table 10: Internet at home as a function of distance to CO and other controls.

VARIABLES	(1) HomeInet	(2) WirelessInet
Dist2COkm	-0.0432***	-2.13e-03
	(0.0137)	(0.0110)
Children	0.101***	0.0605***
	(0.0189)	(0.0120)
ChildrenMuni	0.157***	1.60e-03
	(0.0494)	(0.0407)
HouseholdIncome	0.184***	0.0661***
	(8.02e-03)	(7.48e-03)
HouseholdSize	0.0732***	0.0395***
	(6.32e-03)	(4.69e-03)
LocalityType	-0.0275***	6.55e-03
	(8.54e-03)	(6.67e-03)
Year2009	0.0508***	0.0190
	(0.0184)	(0.0156)
Constant	-0.174***	-0.178***
	(0.0330)	(0.0249)
Observations	8,263	8,261
R-squared	0.320	0.145

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

providers use a different backbone infrastructure to connect their cell towers across the country and thus there is little reason to believe that the quality of wireless broadband correlates to the quality of fixed broadband, once one controls for municipality-level covariates such as income and population density. In particular, there is little reason to believe that the distance between schools and COs is at all correlated with wireless broadband penetration. In fact, Column (2) in Table 10 shows that the distance between schools and their closest CO does not explain household wireless Internet penetration. As a robustness check, we present our main IV results in Table 11 using wireless broadband penetration at home as our dependent variable when using the distance between schools and COs as an instrument to the quality of the schools' broadband connection. Altough the magnitues of the main effect are slightly smaller in this case, all the results are qualitatively the same as when using home Internet as the dependent variable, which provides even more confidence in our results.

Table 11: Internet penetration as a function of school Internet traffic (IV first and second stages).

VARIABLES	(1) OLS W. Inet	(2) Muni IV 1st Stage (ϕ_1)	(3) Muni IV 1st Stage (ϕ_2)	(4) Muni IV W. Inet	(5) Dist IV 1st Stage (ϕ_1)	(6) Dist IV 1st Stage (ϕ_2)	(7) Dist IV W. Inet	(8) Muni IV + Dist IV 1st Stage (ϕ_1)	(9) Muni IV + Dist IV 1st Stage (ϕ_2)	(10) Muni IV + Dist IV W. Inet
Children (δ_c)	-0.000514	0.287***	-0.178***	-0.00651	1.296***	0.0410*	-0.0582	0.505***	-0.190**	-0.0185
	(0.0198)	(0.0911)	(0.0566)	(0.0334)	(0.0664)	(0.0233)	(0.0434)	(0.128)	(0.0766)	(0.0321)
SchInetPS × Children (ϕ_1)	0.0843***			0.0923***			0.147***			0.105***
	(0.0186)			(0.0329)			(0.0431)			(0.0310)
SumSchInetPS (ϕ_2)	0.000990			0.0948*			0.0842			0.0864*
	(0.0106)			(0.0549)			(0.0728)			(0.0448)
ChildrenMuni (%) (ϕ_3)	-0.0968	-0.319***	2.168***	-0.301**	-0.250***	2.187***	-0.271	-0.324***	2.176***	-0.281**
	(0.0651)	(0.0680)	(0.235)	(0.127)	(0.0736)	(0.245)	(0.173)	(0.0685)	(0.242)	(0.112)
ChildrenMuni × Year2009 (%) (ϕ_4)	0.160**	0.496***	2.384***	-0.0679	0.512***	2.388***	-0.0702	0.499***	2.382***	-0.0541
	(0.0804)	(0.0931)	(0.309)	(0.164)	(0.0979)	(0.310)	(0.193)	(0.0927)	(0.308)	(0.141)
Year2009 (ϕ_5)	-0.0330	-0.0502***	0.167***	-0.0471*	-0.0561***	0.159**	-0.0423	-0.0502**	0.168***	-0.0451*
	(0.0235)	(0.0193)	(0.0639)	(0.0253)	(0.0204)	(0.0635)	(0.0274)	(0.0196)	(0.0639)	(0.0251)
HouseholdIncome	0.0614***	-0.0133**	0.0266**	0.0585***	-0.0191***	0.0312***	0.0598***	-0.0139**	0.0263**	0.0590***
	(0.00720)	(0.00589)	(0.0105)	(0.00759)	(0.00547)	(0.00974)	(0.00763)	(0.00593)	(0.0106)	(0.00747)
HouseholdSize	0.0421***	0.00318	0.0135	0.0410***	0.00637	0.0121	0.0408***	0.00373	0.0137	0.0410***
	(0.00482)	(0.00352)	(0.00888)	(0.00476)	(0.00397)	(0.00869)	(0.00490)	(0.00343)	(0.00865)	(0.00477)
LocalityType	0.00193	-0.00457	-0.00378	-0.0270*	0.0751***	0.243***	-0.0289	-0.00503	-0.00444	-0.0256*
	(0.00760)	(0.00682)	(0.00357)	(0.0145)	(0.0143)	(0.0451)	(0.0236)	(0.00682)	(0.00352)	(0.0132)
HouseIncomeMuni	0.0108	-0.0338*	-0.0430	0.0180	-0.0287	-0.0526	0.0186	-0.0304	-0.0299	0.0177
	(0.0129)	(0.0188)	(0.0670)	(0.0146)	(0.0198)	(0.0678)	(0.0149)	(0.0194)	(0.0693)	(0.0142)
LocalityTypeMuni		-0.000451	0.314***					0.00344	0.265***	
		(0.00956)	(0.0466)					(0.00934)	(0.0492)	
HouseIncomeMuniChildren		-0.0360***	-0.00443					-0.0333***	-0.00417	
		(0.0119)	(0.0119)					(0.0120)	(0.0117)	
LocalityTypeMuniChildren		0.413***	0.0933***					0.349***	0.0954***	
		(0.0472)	(0.0202)					(0.0528)	(0.0254)	
DistanceIV					0.161***	-0.272*		0.0123*	-0.248*	
					(0.0276)	(0.140)		(0.00709)	(0.139)	
DistanceIVChildren					-0.955***	-0.157***		-0.292**	0.0199	
					(0.129)	(0.0498)		(0.118)	(0.0621)	
Constant	-0.167***	0.0962*	-0.778***	-0.101**	-0.137*	-0.540**	-0.0997	0.0781	-0.632**	-0.105**
	(0.0430)	(0.0506)	(0.244)	(0.0480)	(0.0698)	(0.236)	(0.0667)	(0.0493)	(0.251)	(0.0471)
Observations	8,261	8,265	8,265	8,261	8,265	8,265	8,261	8,265	8,265	8,261
R-squared	0.157	0.767	0.681	0.146	0.739	0.677	0.143	0.770	0.685	0.146
Underident. Test (Kleibergen-Paap rk LM p-val)				3.41e-06			0.0259			2.27e-05
Weak Ident. Test (Kleibergen-Paap rk Wald F-stat)				23.41			2.349			13.23
Overident. Test (Hansen J P-value)				.			.			0.328

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

B Substitutability between Internet at Home and at School

In the paper we allude to the fact that Internet use at school and at home are substitutes, that is, having Internet at home decreases the marginal utility of having Internet at school for children. This may happen because when children use the Internet at one place they do not need to use it as much in another place. Although this seem a plausible assumption right from the outset, it might also be the case that Internet use at school and at home are complements. For example, children might take more advantage of Internet at school if it is also available at home and vice-versa.

We use data from the Programme for International Student Assessment (PISA) administered by the OECD in 2009 to assess which case is more plausible. PISA is used by the OECD to assess how well school prepares students for life after school. The survey is targeted at 15 year-olds and includes a number of questions about how students use ICTs. Among other questions, students are asked whether they have Internet at home and at school, how frequently they use it to perform certain activities at home and at school. 92% of the students surveyed in Portugal have Internet at home and 91% use it. 97% of students indicate they have Internet at school but only 65% of them indicate they use it.

We start by looking at how frequently students perform the activities they were asked about at school and compute differences in these frequencies between the students that use and do use Internet at home. Similarly, we also look at how frequently students perform the activities they were asked about at home and compute differences in these frequencies between the students that use and do not use Internet at school.

Another way to test whether school and home Internet use are either substitutes or complements for children is to regress the reported school Internet use on whether the students has Internet

Table 12: PISA: School activities by Home Internet Use.

	No HomeInetUse/s.d.	HomeInetUse/s.d.	diff./s.e.
At School - Chat	1.491	1.398	0.093^{**}
	(0.816)	(0.811)	(0.036)
At School - Email	1.883	1.732	0.151^{***}
	(0.963)	(1.004)	(0.045)
At School - Browse for school	2.446	2.240	0.206^{***}
	(0.897)	(0.981)	(0.044)
At School - Download from website	1.694	1.597	0.098^{**}
	(0.880)	(0.917)	(0.041)
At School - Post on website	1.513	1.412	0.100^{***}
	(0.818)	(0.788)	(0.035)
At School - Simulations	1.515	1.381	0.134^{***}
	(0.841)	(0.787)	(0.036)
At School - Practice and Drilling	1.619	1.520	0.099^{***}
	(0.820)	(0.839)	(0.038)
At School - Homework	1.894	1.590	0.304^{***}
	(0.931)	(0.879)	(0.040)
At School - Group Work	2.253	1.925	0.328^{***}
	(0.957)	(0.926)	(0.042)
Observations	6215		

Table 13: PISA: Home activities by School Internet Use.

	No SchInetUse/s.d.	SchInetUse/s.d.	diff./s.e.
At Home - One Player Games	2.487	2.620	-0.134^{***}
	(1.064)	(1.058)	(0.028)
At Home - Collaborative Games	1.985	2.099	-0.114^{***}
	(1.156)	(1.182)	(0.031)
At Home - Homework	2.320	2.479	-0.158^{***}
	(0.922)	(0.961)	(0.025)
At Home - Use email	3.219	3.172	0.048^{*}
	(0.913)	(0.982)	(0.025)
At Home - Chat on line	2.938	2.922	0.016
	(1.197)	(1.196)	(0.032)
At Home - Browse for fun	3.372	3.281	0.091^{***}
	(0.805)	(0.906)	(0.023)
At Home - Download music	2.878	2.814	0.064^{**}
	(1.091)	(1.124)	(0.030)
At Home - Website	2.145	2.164	-0.019
	(1.175)	(1.181)	(0.031)
At Home - Online forums	1.912	1.946	-0.033
	(1.125)	(1.138)	(0.030)
Observations	6230		

at home or not. For this purpose, we compute a binary variable, called SchInetUse, for whether the student uses Internet at school. Note that this approach makes sense only for students that have Internet at school, so we drop from these regressions all observations for students that do not. Analogously, we regress Internet use at home on whether Internet is used at school, for which we compute a binary variable, called HomeInetUse, to indicate whether the student has Internet at home. Similarly, this regression makes sense only for students who have Internet at home. Table 14 shows the results obtained. Standard errors are clustered at the school level in Columns (1) and (3) and school dummies are included in Columns (2) and (4). Students with Internet at home are less likely to use Internet at school (Columns (1) and (2)), which is consistent with the substitution hypothesis. We see no effect of school Internet use on home Internet use (Columns (3) and (4)), which suggests independence. One must interpret the latter result carefully because that are only very few students that report not having Internet at school.

In sum, the PISA data suggest that substitution and/or independence are more plausible than complementarity between Internet use at school and at home. This finding adds support to our claim that in this paper we identify a lower bound for the spillover effect from the children's use of Internet at school to the adults' adoption of Internet at home.

Table 14: PISA: School and Internet use as function of availability

	(1)	(2)	(3)	(4)
	SchInetUse	SchInetUse	HomeInetUse	HomeInetUse
HomeInet	-0.181***	-0.122***		
	(0.0196)	(0.0199)		
SchInet			0.00582	0.00464
			(0.0109)	(0.0104)
Constant	0.837***	0.833***	0.981***	0.995***
	(0.0178)	(0.0157)	(0.0108)	(0.0104)
School Dummies	No	Yes	No	Yes
Observations	6030	6030	5753	5753

Standard errors in parentheses; clustered at the school level in columns (1) and (3).
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$