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Spillovers from Wiring Schools with Broadband: The Critical Role of Children

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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 serve households. On the other hand, students get acquainted with the Internet at school and signal its usefulness to adults at home who, consequently, can be more likely to adopt it. In this paper, we model the roles that broadband use at school and Internet adoption in neighboring households play in the decision to adopt the Internet at home and measure their effects empirically. We use data from Portugal between 2006 and 2009 on household Internet 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. We find that broadband use at school leads to higher levels of Internet penetration in neighboring households. Broadband use in schools was responsible for a year-over-year increase of 3.5 percentage points on Internet penetration in households with children. Across our data set this effect accounts for about 17% of the increase in home Internet adoption. We also find evidence of regional spillovers in Internet adoption across households. These were roughly responsible for an increase of 2.1 percentage points in Internet penetration or 38% of the total increase in household Internet penetration between 2006 and 2009. 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 accelerating the pace of broadband diffusion.

Keywords: broadband in schools; household Internet adoption; technology spillovers; instrumental variables
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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 United States 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 studied in the literature. In the industrial context, several studies have shown that the mobility of people across organizations contributes to knowledge spillovers across firms and industries, especially in R&D related activities, which have then been associated to increases in firm productivity and economic growth (e.g., Jaffe 1986, David 1990, Jaffe et al. 1993, Jorgenson and Stiroh 2000, Forman et al. 2005a, Draca et al. 2006, Desmet et al. 2008, Tambe and Hitt 2014).

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 the Internet in the United States increased from 3% in 1994 to 94% in 2005. But, are there spillovers from wiring schools with broadband? It has been shown that households with children in school are more likely to have the Internet (e.g., Haddon 1988, Pugh 1997, Rompaey et al. 2002, Holloway and Valentine 2003, Robertson et al. 2004, Tengtrakul and Peha 2011), and that attending college is highly related to the adoption of computers and the Internet later in life (e.g., Hoffman and Novak 1998, Hoffman et al. 2000, Goldfarb 2006, Vicente and Lopez 2006). But what is the effect of Internet use by children at school on Internet adoption at home? 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 is complemented with the acquisition of Internet-technology-related skills, which together might lower the barriers to adopt the technology. In addition, 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, making it harder to obtain unbiased estimates for the effect of broadband use at school. Adults use the 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 use in school on Internet adoption at home and, in particular, at understanding the critical role that children play in this respect. For this purpose, we develop a model that provides insights on how spillovers from schools to households might occur. In addition, we use a very unique and detailed data set to estimate this model. We use data on actual broadband use in schools and household Internet penetration in Portugal between 2006 and 2009. We control for a number of covariates, such as income, household size, and population density. We use two sets of different instruments to alleviate additional endogeneity concerns. In one approach, we use the distance between schools and the Internet service provider's (ISP's) central offices to proxy the quality of broadband connectivity. In another approach we use municipality level covariates—after controlling for the corresponding household level variables—as instruments for school broadband use in the municipality. Both approaches yield similar results, which increases our confidence in our findings. As such, our paper provides a novel contribution to the empirical literature aimed at identifying spillover effects. We find evidence that households with children are more likely to adopt the Internet and that their propensity to do so increases with the children's use of broadband at school. Broadband use in schools was responsible for a year-over-year increase of 3.5 percentage points on Internet penetration in households with children. Across our data set this effect accounts for about 17% of the increase in home Internet adoption. Therefore, our paper highlights and shows empirically the important role that children play as a mechanism that activates spillovers from schools' broadband use to household Internet adoption. We also find evidence of regional spillovers in Internet adoption across households. These were roughly responsible for an increase of 2.1 percentage points in Internet penetration or 38% of the total increase in household Internet penetration between 2006 and 2009. These results show that wiring schools with broadband is an effective policy to lower the barriers for Internet adoption at home and to accelerate the pace of Internet diffusion. Although we cannot generalize from a single point in case, we believe that the diffusion mechanism described in this paper—from schools, to children, to adults—can be triggered not only in other countries but also in contexts other than ICTs. As such, our paper identifies a pathway—children—to improve knowledge acquisition and diffusion that can be used worldwide to bridge gaps.

2. Literature Review

2.1. ICTs in Schools and in Households

Investments in information and communication technologies (ICTs) in schools are a significant part of the movement toward 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 the Internet in the United States. 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 ITU (United Nations specialized agency for information and communication technologies), 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.

The adoption of ICTs at home has also been growing worldwide. Having children at home is a major factor to adopt ICTs (computers and Internet access in particular) in countries such as the United States, the United Kingdom, Belgium, and Thailand (e.g., Haddon 1988, Pugh 1997, Rompaey et al. 2002, Holloway and Valentine 2003, Robertson et al. 2004, Tengtrakul and Peha 2011). In the United States, and according to the Census, 51% of the households had a computer and 41.5% had an Internet connection in 2000. 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 United States 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 or 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. In fact, Compaine (2001) shows that most non-Internet adopters indicate no relevance, no interest, or no need as the most important factors to remain disconnected, rather than price.

A significant number of empirical studies focus on the relationships between household and/or individual characteristics and adoption. Some authors find that Internet adoption is mostly correlated to education and income Leigh and Atkinson (2001), Demoussis and Giannakopoulos (2006), Guida and Crow (2009), Mitra (2009). Age, gender, race, and language also explain some variance in the adoption of ICTs (e.g., Chaudhuri et al. 2005, Ono and Zavodny 2008). Closer to our paper, Tengtrakul and Peha (2013) showed a positive correlation between availability of ICTs in schools and Internet household adoption in Thailand.

2.2. 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 situations. Spillovers have been largely studied in the industrial context. The movement of people across organizations is seen as the most important mechanism for knowledge spillovers across firms and industries (e.g., David 1990, Jorgenson and Stiroh 2000, Draca et al. 2006, Tambe and Hitt 2014). In addition, knowledge spillovers, especially those related to R&D activities, tend to be local in nature (e.g., Jaffe 1986, Jaffe et al. 1993, Forman et al. 2005b, Desmet et al. 2008). Goolsbee and Klenow (2002) find evidence of local spillovers and network externalities in the diffusion of home computers and Ward (2012) identifies local spillovers in the adoption of the Internet, both in the United States.

People can discover new technologies on their own or they can learn from others by imitation, the latter having an effect on the speed of diffusion (e.g., Jovanovic and MacDonald 1994, Ericson and Pakes 1995, Young 1991, Chari and Hopenhayn 1991). Schools and universities also play a major role in facilitating learning as they help to overcome the "triability, observability and complexity" barriers (Rogers 2003, p. 16) that may often hinder adoption (e.g., Goldfarb 2006). In the comforting settings provided by schools and universities, students learn about what they can do with ICTs. They bring these teachings and experience home and carry them later to the workplace. This is likely to accelerate the process of diffusion of ICTs without generating overadoption by those who do not find ICT sufficiently useful.

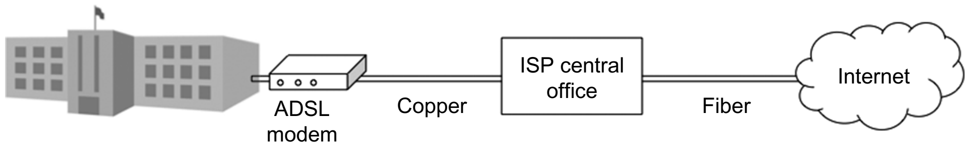
The adoption of ICTs is also a social process. Fraser and Villet (1994) argue that most of the successful projects that ensure widespread use of ICTs tend to fully engage people in the process of change instead of regarding them as naive users or mere recipients of technology. One example of such a program is the ITU "Connect a school, Connect a community," in which public-private partnerships promote broadband connectivity to 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 improved economic and social development all around.

Finally, we note that children may also play an important role in spillovers that are unrelated to ICTs. For example, Kuziemko (2014) presents a model in which children's acquisition of human capital leads adults to "learn from" or "lean on" them. The author exploits a policy change in California that required all public school instruction to be conducted in English. The author argues that the adoption rate of this policy change was random and relies on this variation to assess its impact on the language skills of adults that live with the children that were affected by this policy. She finds that English proficiency increased the most in areas with higher policy compliance. Yet, adults living with children in these areas have lower levels of English proficiency compared to other adults in the same areas.

3. Context and Data

In Portugal, most elementary and secondary schools are public schools funded by either the central government or the local government, with limited autonomy to manage their resources. The provisioning of the Internet to schools has been managed by the Portuguese National Foundation for Scientific Computation (FCCN). FCCN is a private foundation, under the tutelage of the Ministry of Science, Technology, and Higher Education, that runs the National Research

Figure 1 **Broadband Connection to the Internet at School**



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

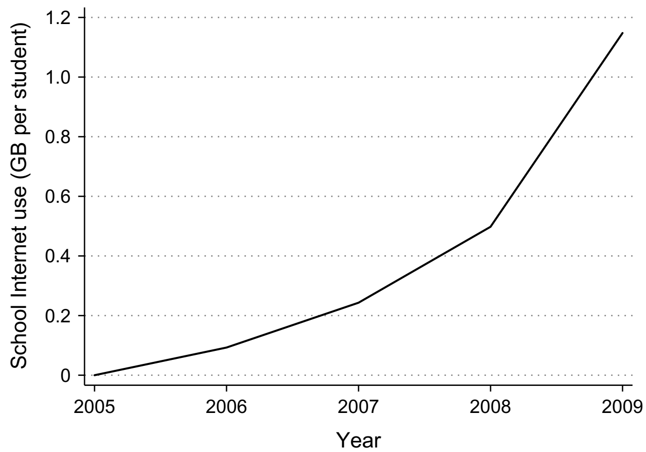
and Education Network (NREN). The NREN connects all schools, institutions of higher education, and research labs in the country. The same institutional model is followed by a number of other European countries, each having its own NREN. NRENs interconnect to form a trans-European NREN, called the GEANT network.

In 2004, this ministry launched a major initiative, aimed at replacing all the existing ISDN connections in schools by broadband asymmetric digital subscriber line (ADSL).[1] This project was completed by January 2006, despite the fact that only less than 15% of the schools had migrated to ADSL before July 2005 (UMIC 2007). Most schools (>95%) received a DSL modem from FCCN and an ADSL connection of at least one Mbps over the copper line that connects them to the ISP's central office (CO) from which FCCN buys connectivity to the Internet backbone (Figure 1). The remainder of the schools, where this speed could not be offered over copper, got a symmetric 256 Kbps Integrated Services Digital Network (ISDN) connection to the Internet.[2] The ministry covered all up-front capital costs to deploy broadband to schools. The broadband monthly bill was paid by City Hall for elementary schools or by the Ministry for nonelementary schools.

3.1. Internet Use at School

Data on school broadband use were obtained from the 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 (*SchInetPS*), we aggregate the total traffic (upload plus download) across all schools in a municipality over the entire academic year (July 1st to June 30th) and divide by the number of students in the municipality. The number of students per school is for 2007 and was obtained from the Ministry for Education.[3]

Figure 2 **School Internet Use per Student**



Internet use in schools grew significantly since the introduction of ADSL in late 2005 as Figure 2 shows. Internet use grew from nearly zero in 2005 to 0.5 GB and 1.15 GB on average per student per year in 2008 and 2009, respectively. In 2009, this corresponds to watching almost 10 hours of YouTube video (at 260 Kbps), browsing 3,500 webpages (at 320 KB per page), or exchanging 8,500 emails (at 130 KB

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

[2] Unfortunately, we do not know which schools obtained an ISDN connection. In any case, it is likely that schools farther away from the COs did so. Our results remain unchanged when we exclude from our analysis schools located more than four Km away from the CO (the distance beyond which ADSL is only likely to provide only very little throughput). These results are available upon request.

[3] Unfortunately, we were only able to obtain the number of students per school for 2007, which we use as fixed throughout our analysis. We note that the total number of students in the country did not change dramatically from year to year: 1,482,830 in 2005, 1,460,025 in 2006, 1,469,440 in 2007, 1,445,086 in 2008, and 1,476,408 in 2009. The changes are therefore minimal. Furthermore, the number of schools in our survey did not change much from year to year: 5,395 schools in 2005, 5,423 schools in 2006, 5,385 schools in 2007, 5,423 schools in 2008, and 5,308 schools in our survey in 2009. Again, the changes are minimal. All these figures are available from the Studies and Planning Office of the Portuguese Ministry for Education.

Figure 3 **School Internet Use per Student in 2009**

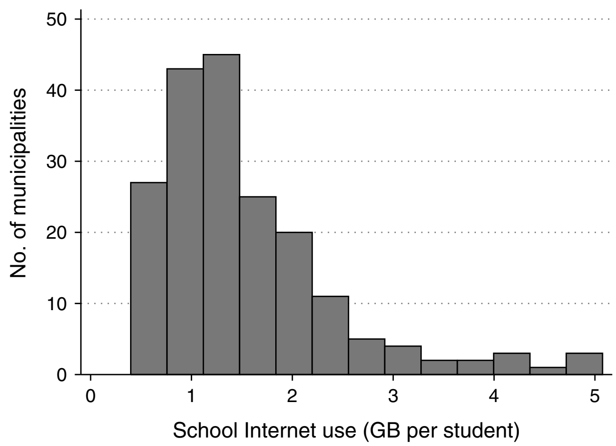
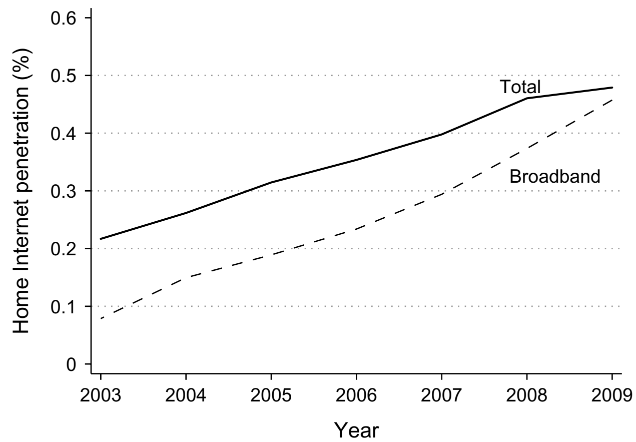


Figure 4 **Home Internet Penetration (Averages Across Municipalities)**



per email).[4] Broadband use per student exhibits high variability across municipalities. Figure 3 provides a histogram for this statistic in 2009. Overall, broadband use per student in school was considerable between 2006 and 2009. Furthermore, we observe that school Internet use is significantly right skewed. For this reason, we use its log version in the remainder of our paper.

3.2. Internet at Home and Household Characteristics

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 ICTs in the country. It is the Portuguese governmental entity responsible for reporting these statistics to the EuroStat, the European Commission, and the World Bank. Furthermore, the methodologies and sampling properties for these surveys are similar across European countries because they are used to build continent-wide rankings.

PSNI's survey is performed at the national level to a representative sample of the Portuguese population. This sample is selected from a "mother" sample originally developed in 2001 and is created by systematically selecting 539 geographical areas among the 1,408 areas in the mother sample. Systematic sampling is a sampling method in which every Nth observation from the population is selected, with N determined once the sampling size is selected. This method is similar to random sampling when the population list does not contain any hidden order.[5] A geographical area is formed by one or more contiguous statistical sections, usually belonging to the same civil parish and always to the same municipality. A statistical section corresponds to a geographical area with about 300 households. In each statistical section, households are selected systematically a priori for the survey. The survey is performed in person or by phone if after several tries the in-person interview is not possible. This survey includes sampling weights. Sampling weights represent the inverse of the likelihood with which each observation is sampled. We use these weights to compute all summary statistics presented in this paper.

This survey has been administered yearly in Portugal since 2003 during April and May so our measure of household Internet penetration pertains roughly to the end of the academic year. About 4,000 households are surveyed every year but we cannot follow them over time. There are about 3.5 million households in Portugal. Also, there are 308 municipalities in the country. However, our data cover only 215 municipalities because of the sampling strategy above. An additional 20 municipalities are dropped from our analysis because they are located in the autonomous regions of Madeira and Azores, for which we do not have information about school broadband use. Therefore, our study applies only to Continental Portugal.

Figure 4 shows that Internet penetration in Portugal increased from just over 20% in 2003 to almost 50% in 2009. These statistics are averages of the household Internet penetration rates across municipalities. Broadband Internet grew as well. In 2003 it represented half of all Internet penetration, and in 2009 it was virtually in all households with the Internet.

Table 1 shows descriptive statistics for households with and without children pooling observations for all years. As expected, households with children are larger, wealthier, located in denser areas, and exhibit

[4] Average webpage size was obtained from https://web.archive.org/web/20120324082535/http://code.google.com/speed/articles/web-metrics.html (accessed January 26, 2016). We use the average email size of one of the authors as reference, as we found no reliable information on this statistic.

[5] For more information on sampling methods, refer to https://www.statpac.com/surveys/sampling.htm (accessed January 26, 2016).

Table 1 Summary Statistics by Household Type

Variables	(1) No children	(2) Children
HomeInternet(*fraction*)	0.374	0.563
	(0.484)	(0.496)
BroadbandInet(*fraction*)	0.304	0.487
	(0.460)	(0.500)
Computer(*fraction*)	0.437	0.670
	(0.496)	(0.470)
LowDensity(*fraction*)	0.315	0.270
	(0.465)	(0.444)
MediumDensity(*fraction*)	0.312	0.343
	(0.463)	(0.475)
HighDensity(*fraction*)	0.372	0.387
	(0.483)	(0.487)
HouseholdIncome(*Eur.*)	1.022	1.109
	(0.521)	(0.481)
HouseholdSize	2.497	3.438
	(1.114)	(1.238)
Observations	10,253	3,841

Table 2 Summary Statistics by Locality Type

Variables	(1) Low density	(2) Medium density	(3) High density
HomeInternet(*fraction*)	0.339	0.414	0.504
	(0.474)	(0.493)	(0.500)
BroadbandInet(*fraction*)	0.269	0.329	0.444
	(0.443)	(0.470)	(0.497)
Computer(*fraction*)	0.392	0.501	0.587
	(0.488)	(0.500)	(0.492)
Children(*fraction*)	0.243	0.292	0.280
	(0.429)	(0.455)	(0.449)
HouseholdIncome(*Eur.*)	0.880	1.033	1.189
	(0.451)	(0.497)	(0.529)
HouseholdSize	2.649	2.861	2.746
	(1.197)	(1.260)	(1.205)
Observations	4,270	4,522	5,302

higher levels of computer and Internet penetration.[6] Table 2 shows descriptive statistics at the household level per type of locality pooling observations for all years. Computer and Internet penetration are higher in denser areas and so is income.[7] The relationship between children and computer or Internet adoption is not stated in a causal sense here. In particular, selection might play an important role in this regard. For instance, households with higher incomes may be more likely to be able to afford computers and Internet access and so might also choose to have children. In this paper we will try to tease out the impact of children on a household's propensity to adopt the Internet.

Finally, we note that the nationwide growth rate of household Internet penetration (Figure 2) did not seem to accelerate significantly in 2006 when schools obtained broadband. However, this aggregate statistic does not reveal the school-level effects that might have been at play. Our research hypothesis, that broadband use at school plays a significant role in the dynamics of household Internet adoption, must be assessed vis-à-vis what would have happened if schools had not been given broadband access. This can only be tested with more disaggregated data and taking into account offsetting factors that could have slowed down household Internet penetration, such as the economic recession that hit Portugal between summer 2007 and spring 2009. (See http://en.wikipedia.org/wiki/Great_Recession_in_Europe, accessed January 26, 2016, for more information in this respect.) Finally, we note that it is important to study the Portuguese case during the 2006–2009 window and find out whether wiring schools with broadband had any effect on household Internet penetration. According to the Internet World Stats (http://www.internetworldstats.com), worldwide Internet penetration was 39% in 2013. Therefore, today there are still many countries in the world with an Internet penetration level as low as Portugal in 2006, in particular in Africa, Asia, and South America.

4. Model and Research Hypotheses

4.1. Adults' and Children's Utility

We first present a model that provides intuition on the spillover mechanisms. It also sets the stage for our empirical strategy. We start by assuming that households have children and adults, and that adults decide whether to subscribe to the 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 the Internet at home, represented by h_c, how much they use broadband 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 the 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 $h_c + s_c + l_c \leq 1$.

[6] We follow PNSI's definition for high, medium, and low density areas. A high density area corresponds to an area with more than 500 inhabitants per square kilometer or more than 5,000 inhabitants; a medium density area is an area with between 100 and 500 inhabitants per square kilometer or between 2,000 and 5,000 inhabitants; a low density area is an area with fewer than 100 inhabitants per square kilometer or fewer than 2,000 inhabitants.

[7] Income is measured by PNSI in a scale from 1 to 5 as follows: 1—less than 400 euros/month; 2—between 400 and 999 euros/month; 3—between 1,000 and 1,499 euros/month; 4—between 1,500 and 1,999 euros/month; 5—more than 1,999 euros/month. We convert this to a euro estimate. This estimate is calculated by fitting a linear trend on the correspondence between the ordinal categories and the midpoint of the bracket interval they represent. Thus, the original ordinal values from 1 to 5 are replaced by 195, 715, 1,235, 1,755, and 2,275, respectively. This is just a linear transformation of the ordinal data that does not affect the regressions but helps in assigning a rough sense of magnitude to household income.

Similarly, let $u_c^*|_{I=0}$ represent the utility realized by children in a household without the 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 the 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, u_c^*, how much they consume the 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 simplicity, we assume that the utility of children adds linearly into the utility of adults. We also assume that the utility of adults is quadratic in Internet use at home and in other activities and quasi-linear in the outside good. The quadratic utility structure is widely used in the telecommunication fields (e.g., Miravete 2002, Economides et al. 2008, Kim et al. 2009). Therefore, adults solve the following:

$$\max_{\{h_a, l_a, x_a\}} \{u_c^* + \alpha(2h_a - h_a^2)I + \beta(2l_a - l_a^2) + x_a\} \quad (1)$$

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 y represents wealth and f represents the fixed fee paid for Internet access. The price of the outside good, x_a, is normalized to 1. The time constraint is $h_a + l_a \leq 1$. In this specification, α represents the relative productivity of using the Internet at home. Solving the adults' optimization problem yields

$$(h_a^*, l_a^*, x_a^*) = \left(\frac{\alpha I}{\alpha I + \beta}, \frac{\beta}{\alpha I + \beta}, y - If\right). \quad (2)$$

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

$$u_a^*(\beta, \alpha, I, y, f) = u_c^* + \beta + \frac{(\alpha I)^2}{\alpha I + \beta} + y - fI$$
$$\approx u_c^* + \beta + \alpha I + y - fI, \quad (3)$$

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

4.2. Decision to Adopt the Internet

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

$$u_a^*|_{I=1} - u_a^*|_{I=0} = u_c^*|_{I=1} - u_c^*|_{I=0} + \alpha - f = \delta_c + \alpha - f \geq 0. \quad (4)$$

This expression shows that adults subscribe to the Internet at home if the increased utility of doing so $(\delta_c + \alpha)$ exceeds its cost (f). Note that both δ_c and α are nonnegative because both children and adults would not use the Internet at home if this would hurt them.

Adults in a household without the Internet develop a belief about how productive the Internet will be. We assume that this belief aggregates three effects. First, adults have an a priori belief about how useful the Internet can be, represented by θ. Second, children use broadband at school (s_c) and transmit knowledge about its benefit to adults at home. Finally, adults in neighboring households that have already adopted the Internet also transmit knowledge about how to benefit from the Internet at home. As such, the adults' utility also depends on the fraction of nearby households that have already adopted the Internet, represented by k. Therefore,

$$\alpha = \theta + \alpha_s s_c + \alpha_k k. \quad (5)$$

In this specification, α_s measures the effect of knowledge spillovers from the children's broadband use at school to the adults' Internet use at home and α_k measures the effect of regional spillovers from the adoption of the Internet in neighboring households. Therefore, a household with children adopts the Internet iff $\delta_c + \alpha - f = \delta_c + \theta + \alpha_s s_c + \alpha_k k - f = \delta_c + \alpha_s s_c + \alpha_k k + u \geq 0$, where $u \equiv \theta - f$. A household without children adopts the Internet iff $\alpha - f = \theta + \alpha_k k - f = \alpha_k + u \geq 0$. Let d_c indicate whether the household has children. Then, the two expressions above can be combined and a household will adopt the Internet iff

$$d_c \delta_c + \alpha_s d_c s_c + \alpha_k k + u \geq 0. \quad (6)$$

This expression leads us to state our research hypotheses:

Hypothesis 1 (H1). *Households with children in schools with more broadband use are more likely to adopt the Internet.*

Hypothesis 2 (H2). *Households in areas with more households with the Internet are more likely to adopt the Internet.*

Hypothesis 1 pertains to the effect of children using broadband at school and represents the main spillover hypothesis we pursue in this paper. Hypotheses 2 pertains to regional spillover effects that may arise from considering the effect of Internet adoption by neighboring households.

4.3. Household Internet Penetration over Time

Let θ_c represent the minimum for the a priori usefulness that adults attach to the Internet at home that triggers adoption for households with children. This is given by $f - \alpha - \delta_c$, 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 the Internet at home is lower for households with children and is lower the greater the amount of broadband used at school.

A household with children will adopt the 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 the 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 all households (both with and without children) and thus

$$k(t+1) = \frac{N_c}{N}\int_{\theta_c(t)}^{\bar{\theta}} g(x)\,dx + \frac{N - N_c}{N}\int_{\theta_{nc}(t)}^{\bar{\theta}} g(x)\,dx, \quad (7)$$

where N represents the number of households and N_c represents the number of households with children. Assuming that θ is uniformly distributed with $g(\theta) = \gamma$, the above is a differences equation in k whose solution is given by

$$k(t) = \varphi_0 + \varphi_1 \frac{N_c}{N} + \varphi_2 \frac{N_c}{N}(\gamma\alpha_k)^t + \varphi_3 \frac{N_c}{N} S_c(t-1) + \varphi_4 (\gamma\alpha_k)^t, \quad (8)$$

with $\varphi_0 = (1 - \gamma f)/(1 - \gamma\alpha_k)$, $\varphi_1 = \gamma\delta_c/(1 - \gamma\alpha_k)$, $\varphi_2 = \gamma\delta_c/(1 - \gamma\alpha_k)(\gamma\alpha_k)^{-s}$, $\varphi_3 = \gamma\alpha_s$, $\varphi_4 = (k(s) - (1 - \gamma f)/(1 - \gamma\alpha_k))(\gamma\alpha_k)^{-s}$, $S_c(\tau) = \sum_{i=0}^{+\infty}(\gamma\alpha_k)^i s_c(\tau - i)$ and s represents the year in which schools got broadband. The full derivation of this formulation for $k(t)$ is provided in the appendix. Note that $S_c(\tau)$ is essentially the cumulative use of broadband in schools up to time τ with a $\gamma\alpha_k$ discount rate.

5. Empirical Strategy

We use a linear probability model (LPM) to estimate the effect of school broadband use on household Internet adoption. In our setting LPM is consistent and thus its coefficients can be readily interpreted as average marginal effects. An LPM is also advantageous when many of the regressors are binary or discrete with only a few values, as in our case (Wooldridge 2002, p. 454). In §§5.2 and 5.3, we will be using instrumental variables to identify our effects of interest and LPMs require fewer assumptions to do so than nonlinear models.

From Equation (6) the expression for Internet adoption for household i in municipality j at time t given that this household has not yet adopted the Internet is given by

$$1\{u_a^* \mid \{I = 1\} \geq u_a^* \mid \{I = 0\}\}_{ijt} = \alpha_0 + d_{c_i}\delta_c + \alpha_s d_{c_i} s_{c_{jt}} + \alpha_k k_{jt} + \boldsymbol{\beta}\mathbf{x}_{it} + \phi_t + \varepsilon_{it}, \quad (9)$$

where d_{c_i} is an indicator 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 that proxy θ_{it}, ϕ_t are time dummies, and ε_{it} is the error term. Note that our model, presented in §4, is agnostic about school broadband use having a direct effect on adults' utility. As such, Equation (9) does not include the term $s_{c_{jt}}$ alone but only its interaction with *Children* in $d_{c_i}s_{c_{jt}}$. Yet, we still present results controlling for (and instrumenting) $s_{c_{jt}}$ as an additional covariate in $\mathbf{x}_{it}$. The results are similar—both in terms of statistical significance and magnitude—whether we do so or not. Also, this effect turns out not to be statistically significant across all our empirical specifications.

Recall that δ_c represents the change in the children's utility due to Internet use at home. We assume that this difference does not change with broadband use at school. If this is the case, then the spillover effect of the children's broadband use at school on the adults' propensity to adopt the Internet is captured by α_s. If, however, broadband use at school and at home are substitutes, then more broadband 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, broadband use at school and at home are complements, then more broadband 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 broadband 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 α_s. In the appendix, we provide some empirical evidence suggesting that the children's use of broadband at school and at home seem to be substitutes and thus a positive α_s should be interpreted as a lower bound for the spillover effect of the children's use of broadband in school on the utility that adults derive from using the Internet at home. In any case, if one rather believes that broadband use at school and at home are complements, then α_s captures the aggregate effect of spillovers from the children's use of broadband at school to Internet use at home by children and adults all together.

We need to consider two sources of endogeneity to estimate Equation (9). On the one hand, the children's use of broadband at school may be endogenous in our setting. Unobserved time varying effects, such as the deployment of new Internet backbone infrastructure, might drive both broadband use at school and household Internet adoption, which may bias our estimates for the parameters of interest in Equation (9). On the other hand, a household's decision to adopt the Internet is also a function of whether neighboring

Table 3 Summary Statistics for Municipality-Level Data (2009)

Variables	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
HomeInternet(*fraction*)	215	0.477	0.153	0	1
Children(*fraction*)	215	0.275	0.118	0	0.714
HouseholdIncome	215	951.7	216.0	195	1,582
HouseholdSize	215	2.702	0.322	1.500	4.071
SchoolInet/Student (GB)	191	1.148	0.669	0.398	5.075
Pop.Dens. (*municipality*)	215	1,297	1,826	5.600	7,183
Population (*municipality*)	215	129,090	133,666	2,616	479,884

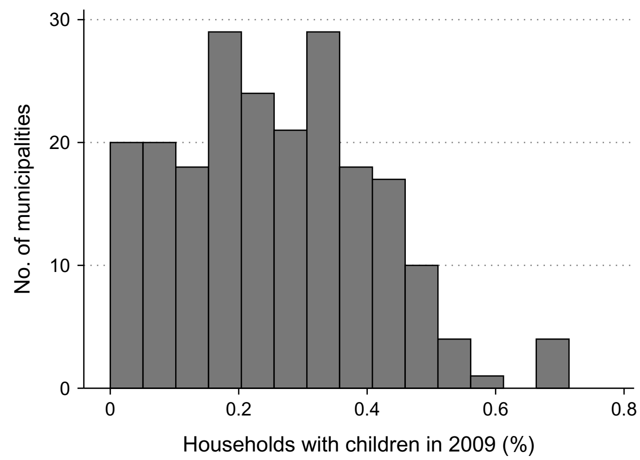
households have adopted the Internet. Unobserved effects that drive one household to adopt the Internet are likely to also drive neighboring households to do so and thus k_{jt} may be endogenous in this equation. In fact, k_{jt} is an aggregate of the household-level decisions of adopting the Internet, and thus endogenous. This is an instance of the reflection problem (Manski 1993).

We address the above-mentioned concerns in several ways. First, we add municipality dummies to Equation (9). These dummies capture the effect of time-fixed unobserved municipality traits. Second, and as an alternative, we use the dynamics of household Internet penetration over time established in §4.3 to derive appropriate instrumental variables. We use two sets of instruments in our paper. First, we use municipality-level covariates to instrument broadband use at school. This strategy has been used before by Goolsbee and Klenow (2002) and Ward (2012). We compute municipality-level covariates by averaging out over households and over schools in the same municipality. Table 3 shows the statistics obtained for 2009. For example, on average, municipalities have 27.5% of households with children. Figure 5 shows that this statistic varies significantly across municipalities, which helps in identifying spillover effects from broadband use in schools. Second, and following Belo et al. (2014), we use the distance between schools and COs as an exogenous measure of the quality of the school's broadband connection. The following subsections provide additional details on these identification strategies.

5.1. Using Municipality Fixed Effects

A first approach to control for, at least, potential endogeneity in school broadband use is to use municipality-level fixed effects. This strategy allows us to control for any municipality-specific unobservables that may be correlated both with the likelihood of having the Internet at home and with school broadband use. Note that when we include municipality dummies, our municipality-level controls are likely to drop because of multicollinearity. Also, with this strategy, we are unable to measure regional spillover effects.

Figure 5 Households with Children in 2009 (Fraction)



5.2. Instrumenting Broadband Use in School with Municipality-Level Covariates

A second approach is to estimate Equation (9) using municipality-level covariates ($\mathbf{m}_{jt}$), such as income and population density, as instruments for broadband use at school, that is,

$$s_{c_{jt}} = \psi + \boldsymbol{\varphi}\mathbf{m}_{jt} + \phi_t + \eta_{jt}. \tag{10}$$

Municipality-level covariates predict school broadband use, as our first-stage regressions will show. However, they cannot be used as instruments if correlated with unobserved household-level covariates. Still, if we include the corresponding household-level covariates in our regressions ($\mathbf{x}_{it}$), any bias due to these unobserved covariates would be captured by the household-level covariates, leaving the municipality-level coefficients unbiased. Therefore, this approach is valid as long as we assume that $E(\varepsilon_{it} \mid \mathbf{x}_{it}, \mathbf{m}_{jt}) = E(\varepsilon_{it} \mid \mathbf{x}_{it})$, where ε_{it} is the error term in Equation (9). Goolsbee and Klenow (2002) provide more details about this approach. Potential household-level unobservables may bias the coefficients of the household covariates but not those of the municipality-level covariates. For example, if technology savvy people tend to locate in high-income areas, then including household income in our regressions readily captures the correlation between technology savvyness and income. If there is no correlation between income and technology savvyness left to explain through the municipality-level income, the latter can be used as an instrument.

Finally, note that k_{jt} in Equation (9) also depends on the use of broadband in school through $(N_c/N)S_{c_{jt-1}}$. Thus, our municipality level covariates, interacted with N_c/N, will also be used as instruments in Equation (9).

5.3. Instrumenting Broadband Use in School with Broadband Quality

In a third 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 CO of the ISP providing broadband access results in a lower maximum transfer bitrate. Therefore, schools further away from the CO are likely to obtain lower throughput on their broadband 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 the line-of-sight distance between a school and its closest CO as a proxy for the quality of the schools' broadband connection. Line-of-sight distance is calculated from information on the GPS coordinates of both schools and COs. See Prieger and Hu (2008) for another example in which the distance to the CO is used to proxy Internet quality. Therefore, we have the following:

$$s_{c_{lt}} = \varphi_0 + \varphi_1 dist_l + \eta_{lt} + \phi_t + \xi_{lt}, \tag{11}$$

where $s_{c_{lt}}$ is the broadband usage at school l at time t, $dist_l$ is the distance between school l and its closest CO, η_{lt} are other school characteristics, ϕ_t are time dummies, and ξ_{lt} is the error term. The predicted broadband use across schools in the same municipality is added, using the number of students in each school as weights, to determine the predicted broadband use in schools in each municipality, that is, $\hat{s}_{c_{jt}} = \sum_{l\in j} \hat{s}_{c_{lt}} N\_Students_l / \sum_{l\in j} N\_Students_l$, where $l \in j$ indicates that school l is located in municipality j. This covariate can then be used as an instrument for broadband use in school in Equation (9). The exogeneity of this instrument has been thoroughly discussed in previous work (see Belo et al. 2014 for more information and robustness checks that essentially show that the distance between schools and COs is fairly random across schools and municipalities). In particular, the distance between schools and COs is uncorrelated with household Internet penetration (−0.025), computers at home (−0.004), and major socioeconomic covariates, such as locality type (−0.027) and income (−0.111).[8]

Yet, we note that the distance between schools and COs can be an invalid instrument if households close to schools located near a CO are themselves also close to a CO. Unfortunately, our data do not allow us to test this because we do not have household GPS coordinates. As an alternative, we use the population-weighted average distance between the civil parish center where each household is located and the closest CO as a proxy for the average distance between households and the closest CO, which allows us to control for the quality of the Internet infrastructure available to households. In Portugal, people are concentrated around civil parish centers, which renders them as good candidates to proxy household location.

We use town hall GPS coordinates, 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, accessed July 19, 2012), as the center of the parish and computed line of sight distance to the closest CO. Table 4 shows regressions of Internet household penetration as a function of both the distance between schools and the closest CO and the distance between town center and the closest CO. We run these regressions without controls (columns (1) and (2)), with municipality-level controls (columns (3) and (4)), and with household-level controls (columns (5) and (6)). These regressions show that the distance between school and CO is statistically significant when the distance between town center and CO is not included in our regressions. However, this effect disappears once we control for the distance between the town hall and the CO. Moreover, as expected, the distance between town hall and CO is statistically significant and negative. This is an indication that the distance between town hall and CO seems to allow for controlling for the quality of the household Internet connection as we argued above, thus alleviating outstanding endogeneity concerns regarding using distance between schools and COs as an instrumental variable in our setup.

5.4. Instrumenting the Household Internet Penetration

Equation (8) shows that the percentage of households with the Internet depends on the percentage of households with children, N_c/N, and on its interaction with time and the lagged cumulative use of broadband in school, $(N_c/N)(\gamma\alpha_k)^t$ and $(N_c/N)S_{cjt-1}$, respectively. Preliminary results at the municipality level in Appendix A show that, in fact, children at home and children using broadband at school may be positively correlated with home Internet adoption. Furthermore, these covariates are not included in Equation (9). Therefore, using the percentage of households with children in a municipality and its interaction with the cumulative use of broadband in schools in that municipality seem to be good candidates to instrument k_{jt} in this equation. We assume that N_c/N is exogenous in our setup. This seems a

[8] Correlation coefficients at the municipality level are shown in parenthesis for the year 2009.

Table 4 Home Internet Adoption as a Function of the Distances Between Town Hall and Central Office and Between School and Central Office

Variables	Dep. var.: *HouseholdInternet* (1)	(2)	(3) Muni. ctrls.	(4) Muni. ctrls.	(5) Muni. + House ctrls.	(6) Muni. + House ctrls.
DistanceSchool–CO	−0.079***	−0.035	−0.028	0.00058	−0.021*	−0.0069
	(0.020)	(0.023)	(0.018)	(0.019)	(0.012)	(0.013)
DistanceTown Center–CO		−0.064***		−0.052***		−0.021**
		(0.017)		(0.014)		(0.0087)
Household-level variables						
Children					0.14***	0.14***
					(0.010)	(0.010)
HouseholdIncome					0.56***	0.56***
					(0.0087)	(0.0089)
DummyMediumDensity					−0.020*	−0.023*
					(0.012)	(0.012)
DummyHighDensity					−0.033**	−0.032**
					(0.015)	(0.015)
Municipality-level variables						
AverageIncome			0.012***	0.0090**	0.00015	−0.00098
			(0.0036)	(0.0037)	(0.0022)	(0.0020)
Householdsw/Children(fraction)			0.37***	0.38***	0.11***	0.11***
			(0.039)	(0.039)	(0.032)	(0.032)
Population			2.3e–07***	2.5e–07***	6.8e–08	7.4e–08
			(8.6e–08)	(7.3e–08)	(5.8e–08)	(4.7e–08)
Constant	0.45***	0.47***	0.10*	0.15***	−0.38***	−0.37***
	(0.031)	(0.031)	(0.055)	(0.058)	(0.036)	(0.034)
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,094	13,932	14,094	13,932	14,094	13,932
R-squared	0.014	0.018	0.035	0.037	0.355	0.355

Note. Municipality-level clustered standard errors in parentheses.
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

reasonable assumption because it is unlikely that the fraction of households with children in a municipality is related to the likelihood of having the Internet at home after controlling for several household-level characteristics, such as income, population density, and whether the household itself has children. Hence, we use N_c/N and its interaction with time as instruments for k_{jt} in Equation (9). However, the use of broadband at school may be endogenous. Thus, we do not use $(N_c/N)S_{cjt-1}$ as an instrument for k_{jt} in this equation.

5.5. Estimating Household and Municipality Internet Penetration Together

In yet another approach, we consider a system of two equations, one for the household's Internet penetration and another one for the municipality's Internet penetration:

$$P(u_a^* \mid I = 1 \geq u_a^* \mid I = 0)_{ijt} = \alpha + d_{c_i}\delta_c + \alpha_s d_{c_i} s_{c_{jt}} + \boldsymbol{\beta}\mathbf{x}_{it} + \alpha_k k_{jt} + \phi_t + \varepsilon_{it}, \quad (12)$$

$$k_{jt} = \varphi_0 + \varphi_1 \frac{N_c}{N} + \varphi_2 \frac{N_c}{N}(\gamma\alpha_k)^t + \varphi_3 \frac{N_c}{N} S_{c_{jt-1}} + \varphi_4(\gamma\alpha_k)^t + \mu_{jt}, \quad (13)$$

which we can estimate jointly using three-stage least squares (3SLS) to account for potential correlation between ε_{it} and μ_{jt}, improving efficiency.[9] In line with the approach followed when using 2SLS, we also add the main effect of broadband use in school to this specification. A plain 3SLS specification for the two equations above uses N_c/N, $(N_c/N)(\gamma\alpha_k)^t$ and $(N_c/N)S_{c_{jt-1}}$ as instruments for k_{jt} in Equation (13). In one of our 3SLS specifications, we use, in addition, the municipality-level covariates and their interaction with d_{c_i} to instrument $s_{c_{jt}}$ and $d_{c_i}s_{c_{jt}}$, respectively, as discussed in §5.2. In another 3SLS specification, we also add the predicted use of broadband in school in the municipality, $\hat{s}_{c_{jt}}$, and its interaction with d_{c_i} as instruments, as discussed in §5.3. In both cases, we also need to instrument the interaction between N_c/N and the cumulative lag of broadband use in school in Equation (13). We do so with the interaction between N_c/N and the distance between schools and COs. We do not use the interaction between N_c/N and municipality-level covariates in $\mathbf{m}_{jt}$ because the

[9] As pointed out by an anonymous reviewer, 3SLS improves estimation efficiency but does not strengthen the consistency argument when compared to the single-equation strategy.

latter are likely to be correlated with the error term in Equation (13).

For estimation purposes, throughout our paper, we substitute $(\gamma\alpha_k)^t$ by time dummies, which provides for more flexibility. Likewise, we also substitute the terms N_c/N and $(N_c/N)(\gamma\alpha_k)^t$ by interactions between N_c/N and time dummies. Note, however, that $(\gamma\alpha_k)^t$ is also included in $S_{c_{jt-1}}$. In the paper, we present results for $\gamma\alpha_k = 0.9$. Our results remain unchanged with different discount rates. The latter are available upon request.

6. Results

6.1. OLS and Municipality Fixed Effects Results

Table 5 shows results from our regressions of household Internet penetration on school broadband traffic (Equation (9)) pooling data from 2006 to 2009. Ordinary least squares (OLS) results in column (1) show that household income and household size are positively correlated with the Internet at home, as one could expect. OLS results in column (2) show that households with children in schools with more broadband use are more likely to adopt the Internet, in support of H1. In addition, column (3) shows that this result holds after controlling for municipality fixed effects. This provides significant evidence of a positive correlation between broadband use at school and household Internet adoption for households with children (*SchInetPS* × *Children*) even after controlling for household income and size, population density, regional spillovers, and municipality fixed effects. Columns (1) and (2) also show that households in areas with more households with the Internet are more likely to adopt the Internet (*HomeInternet*(*fraction*)(α_k)), in support of H2.

However, these results must still be interpreted with caution because they provide only indications of correlation between household Internet penetration and broadband use at school. The specification with municipality dummies already controls for unobserved time-fixed municipality effects, but this may not be enough to provide identification. In any case, these results provide some evidence that children mediate the observed positive correlation between these two covariates.

6.2. 2SLS Results

Several alternative explanations for the results observed in Table 5 might be at play. For example, households with children may be more likely to adopt the Internet because adults in these households are younger and/or more technology savvy. This can potentially make their children use more broadband compared to children without the Internet at home. School broadband use would increase because children have the Internet at home and not the other way around. We proceed with the identification strategies proposed in the previous section to try to identify the spillover effect from broadband use in school to household Internet adoption. These strategies lessen our concerns with reverse causality and unobserved effects.

Table 5 Internet at Home as a Function of School Internet Traffic

	Dep. var.: *HouseholdInternet*		
Variables	(1)	(2)	(3)
Household-level variables			
SchInetPSLn × *Children* (ϕ_1)		0.040***	0.046***
		(0.0072)	(0.0074)
Children (δ_c)		0.14***	0.16***
		(0.014)	(0.014)
HouseholdIncome	0.47***	0.47***	0.50***
	(0.010)	(0.0099)	(0.0095)
HouseholdSize	0.055***	0.038***	0.038***
	(0.0044)	(0.0042)	(0.0043)
MediumDensity (*fraction*)	−0.049***	−0.051***	0.0055
	(0.0098)	(0.0096)	(0.028)
HighDensity(*fraction*)	−0.058***	−0.060***	0.016
	(0.011)	(0.011)	(0.037)
Municipality-level variables			
HomeInternet(*fraction*) (α_k)	0.62***	0.59***	
	(0.018)	(0.019)	
SchInetPSLn	0.0077	−0.00083	
	(0.0057)	(0.0061)	
Population	−5.0e−08	−4.4e−08	
	(3.0e−08)	(2.9e−08)	
DistanceTownCenter–CO	0.0038	0.0030	
	(0.0050)	(0.0050)	
Constant	−0.55***	−0.53***	−0.45***
	(0.021)	(0.021)	(0.030)
Year dummies	Yes	Yes	Yes
Muni. dummies	No	No	Yes
Observations	13,932	13,932	14,094
R-squared	0.385	0.394	0.380

Note. Municipality-level clustered standard errors in parentheses.
$^{***}p < 0.01$.

Table 6 shows the second-stage results from estimating Equation (9) using instruments.[10] First-stage results behave as expected and are shown in the appendix. Column (1) shows results using the predicted broadband school use in a municipality, $\hat{s}_{c_{jt}}$, as an instrumental variable. Column (2) shows results using locality type as an instrument for school broadband use.[11] Column (3) shows results using both

[10] Results in Table 6 are obtained without weights. As discussed in Solon et al. (2015) and Wooldridge (2002, p. 596), the standard unweighted estimator is consistent if stratification is based solely on exogenous variables, which is our case. Wooldridge (1999) shows that in these cases weighting is unnecessary and may even be harmful for precision. In any case, results using weights are statistically similar to the ones reported in this table as shown by Hausman tests. The coefficients obtained for *SchInetPSLn* × *Children* are as follows (p-values for Hausman tests in parenthesis): 0.041*** (0.0706) for Dist IV, 0.048** (0.3455) for Muni IV and 0.041*** (0.0991) for Muni IV + Dist IV.

[11] Municipality income would also likely be a valid instrument under this approach, as discussed in §5.2. However,

Table 6 **Home Internet Penetration as a Function of School Internet Traffic (Second-Stage Results)**

	Dep. var.: *HouseholdInternet*		
	(1)	(2)	(3)
Variables	Dist IV	Muni IV	Muni IV + Dist IV
Household-level variables			
SchInetPSLn × *Children* (ϕ_1)	0.051***	0.058**	0.051***
	(0.0096)	(0.025)	(0.0099)
Children (δ_c)	0.16***	0.17***	0.16***
	(0.016)	(0.029)	(0.016)
HouseholdIncome	0.49***	0.49***	0.49***
	(0.010)	(0.011)	(0.010)
HouseholdSize	0.036***	0.035***	0.036***
	(0.0043)	(0.0051)	(0.0044)
MediumDensity(*fraction*)	−0.030**	−0.013	−0.024
	(0.013)	(0.021)	(0.015)
HighDensity(*fraction*)	−0.026	0.011	−0.013
	(0.022)	(0.037)	(0.026)
Municipality-level variables			
HomeInternet(*fraction*) (α_k)	0.37***	0.38***	0.38***
	(0.065)	(0.074)	(0.068)
SchInetPSLn	0.033	0.10	0.059
	(0.036)	(0.064)	(0.041)
Population	3.2e−08	9.0e−08	5.2e−08
	(4.3e−08)	(7.5e−08)	(5.1e−08)
DistanceTownCenter–CO	−0.011*	−0.017	−0.013*
	(0.0064)	(0.010)	(0.0074)
Constant	−0.40***	−0.24	−0.34***
	(0.078)	(0.15)	(0.093)
Year dummies	Yes	Yes	Yes
Observations	13,932	13,932	13,932
R-squared	0.389	0.382	0.387
Underid. (KP rk LM p-value)	0.0067	0.00016	0.00024
Weak id. (KP rk Wald F-stat.)	3.06	5.54	5.21
Overid. (Hansen J P-value)	0.28	0.73	0.53

Notes. Municipality-level clustered standard errors in parentheses. Underid., underidentification test; Weak id., weak identification test; Overid., overidentification test; KP rk LM p-value, Kleibergen–Paap rk LM p-value (stata output); KP rk Wald F-stat., Kleibergen–Paap rk Wald F-statistic (stata output).
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

$\hat{s}_{c_{jt}}$ and locality type as instruments for school broadband use. In all cases, the municipality Internet penetration rate, k_{jt}, is instrumented with the interaction between the percentage of households with children in the municipality and time dummies, as discussed in §5.4.

The effect of the children's broadband use at school is still positive and highly statistically significant in all these specifications in support of H1. The magnitude of the effect increases slightly after instrumenting it. This is consistent with broadband use at school and at home being substitutes, in which case children that use more Internet at home are likely to use less broadband at school, but once we instrument the schools' broadband use we smooth out this effect. The coefficient of 0.051 in column (3) means that doubling broadband use per student at school increases the likelihood of Internet adoption for a household with children by 5.1 percentage points. School broadband use roughly doubled every year from 2006 to 2009 (0.1 GB/student in 2006, 0.24 GB/student in 2007, 0.5 GB/student in 2008, and 1.15 GB/student in 2009), which corresponds to a year-over-year increase of about 3.5 ($0.051 * \ln(2)$) percentage points in the probability of Internet adoption in households with children because of school spillover effects. Internet household penetration increased from 31% in 2006 to 48% in 2009. Given that on average 27.5% of the households have children and that Internet penetration increased roughly 5.6 percentage points every year from 2006 to 2009 ($(0.48 - 0.31)/3$), the spillover effect from broadband use at school amounts to 17% ($(0.035 * 0.275)/0.056$) of the total increase in household Internet penetration during the period of analysis.

The effect of regional spillovers remains positive and also highly statistically significant, in support of H2, though its magnitude almost halves after instrumentation. The coefficient of 0.38 in column (3) means that if all the neighbors of a household adopt the Internet then the likelihood of Internet adoption of the focal household increases by 38 percentage points. Therefore, regional spillovers were responsible for a year-over-year increase of 2.1 percentage points ($0.056 * 0.38 = 0.021$) in Internet adoption between 2006 and 2009. Thus, the effect of school Internet spillovers is 50% stronger than that of regional spillovers for households with children. For households without children, only the regional spillovers are at play. On aggregate, school broadband spillovers together with regional spillovers were responsible for an increase of three percentage points ($0.27 * 0.035 + 0.021$) in household Internet penetration, i.e., about 54% of total increase in household Internet penetration over the period of analysis.

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

6.3. 3SLS Results

Table 7 shows our 3SLS results from estimating Equations (12) and (13) simultaneously. Columns (1) and

overidentification tests fail when we add it as an instrument. This means that municipality income is a relevant predictor of household Internet adoption even after controlling for household income. Therefore, in all the results presented in our paper, we only use municipality population density as an instrument. Still, we note that all results reported in this paper remain qualitatively unchanged if we add municipality income as an instrument (and thus ignore the outcome of the overidentification test). These results are available upon request.

Table 7 Results Using Three-Stage Least Squares

Variables	(1) Dist IV (Muni. level reg.)	(2) Dist IV (House level reg.)	(3) Dist IV (Muni. level reg.)	(4) Muni IV + Dist IV (House level reg.)
	Dep. var.: *HouseholdInternet*			
Household-level variables				
SchlnetPSLn × *Children* (ϕ_1)		0.052***		0.052***
		(0.0096)		(0.0091)
Children (δ_c)		0.16***		0.16***
		(0.014)		(0.013)
HouseholdIncome		0.47***		0.47***
		(0.0066)		(0.0080)
HouseholdSize		0.037***		0.037***
		(0.0036)		(0.0030)
MediumDensity(fraction)		−0.043***		−0.042***
		(0.0086)		(0.0090)
HighDensity(fraction)		−0.056***		−0.055***
		(0.011)		(0.011)
Municipality-level variables				
HomeInternet(fraction) (α_k)		0.34***		0.31***
		(0.064)		(0.064)
SchlnetPSLn		−0.010		−0.0091
		(0.010)		(0.0086)
Population	3.4e−07***	3.7e−08	3.4e−07***	4.6e−08
	(7.4e−09)	(4.0e−08)	(7.8e−09)	(3.8e−08)
DistanceTownCenter–CO	−0.064***	−0.014*	−0.064***	−0.015**
	(0.0024)	(0.0075)	(0.0031)	(0.0072)
LnLSumSchlnetPSChildrenMuni	0.0013		0.0013	
	(0.0034)		(0.0029)	
ChildrenMuni2006	0.16***		0.16***	
	(0.027)		(0.028)	
ChildrenMuni2007	−0.00088		−0.00078	
	(0.030)		(0.027)	
ChildrenMuni2008	0.42***		0.42***	
	(0.032)		(0.028)	
ChildrenMuni2009	0.64***		0.64***	
	(0.020)		(0.018)	
Constant	0.33***	−0.46***	0.33***	−0.45***
	(0.019)	(0.034)	(0.018)	(0.031)
Year dummies	Yes	Yes	Yes	Yes
Observations	13,450	13,450	13,450	13,450
R-squared	0.337	0.382	0.337	0.381

Note. Bootstrapped standard errors in parentheses.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

(2) show results using the approach described in §5.2, that is, using municipality population density and its interaction with children to instrument broadband use at school and its interaction with children (in column (2)). Columns (3) and (4) show results using the approach described in §5.3, that is, using municipality population density, the predicted broadband school usage in the municipality and their interactions with children to instrument broadband use at school and its interaction with children (in column (4)). In both cases we use the interaction between N_c/N and the predicted use of broadband in school in a municipality to instrument the interaction between N_c/N and the cumulative use of broadband in schools in Equation (13) (in columns (1) and (3)).

The results obtained are very similar to the ones obtained in the previous section. The spillovers from broadband use at school are positive and highly statistically significant, in support of H1. Doubling Internet use in schools increases the probability of broadband adoption by roughly five percentage points in households with children. The regional spillover effects also remain positive and highly statistically significant, in support of H2. They may have contributed to roughly a third of the increase in household Internet adoption from 2006 to 2009.

7. Conclusion

This paper examines the spillover effect from wiring schools with broadband on household Internet penetration. We posit that when a government wires schools with broadband it also contributes to increasing the penetration rate of household Internet. We also hypothesize that children are the main drivers of this process. Children are exposed to broadband at school and transmit knowledge about how to benefit from it to adults at home. As a result, the adults' propensity to adopt the Internet at home might increase. We develop a model that provides insights on how this process might occur. In this model, we propose that the adults' productivity of using the Internet at home is a function of the knowledge transmitted by children as well as of the knowledge transmitted by neighboring households that have already adopted the Internet. This model highlights that households with children are more likely to adopt the Internet, in particular when the children use more broadband at school. This model also accounts for regional spillover effects, that is, households in areas with higher home Internet penetration are also more likely to adopt the Internet.

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 Portuguese National Statistics Institute. We focus on the penetration of household Internet between 2006 and 2009. We find evidence that households with children are more likely to adopt the Internet and that their propensity to do so increases with the children's use of broadband at school. We also find empirical evidence of regional spillover effects from neighboring households.

These results are obtained after instrumenting for the use of broadband at school to alleviate potential endogeneity concerns. Our paper makes an important contribution to identify these spillover effects because we provide results using two different sets of instruments. In one approach, we use municipality-level covariates as instruments. In another approach, we use the quality of the broadband connection at school as an instrument. The latter is measured by the distance between schools and central offices. In both strategies we also instrument the penetration of the Internet in neighboring households to alleviate reflection problems. Both identification 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 from broadband use at school. Broadband use in schools increased the probability of Internet adoption by 3.5 percentage points every year in households with children. Across all households, this effect accounts for about 17% of the increase in home Internet adoption between 2006 and 2009. Regional spillovers accounted for an increase of about 2.1 percentage points, or 38%, of the growth in Internet household penetration between 2006 and 2009.

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 could follow municipalities. Therefore, we aggregated data at the municipality level and reported results for how the household Internet penetration changed as a function of broadband use at school. These aggregated results also show evidence of a positive spillover effect from broadband use at school. Second, although we find that the adults' utility from using the Internet at home increases with the children's use of broadband 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 use the Internet at home in unproductive ways for them and for society as a whole.

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Appendix A. Preliminary Evidence at the Municipality Level

In this section we show additional evidence at the municipality level that broadband use at school may increase the likelihood that households with children adopt the Internet. Recall that we are unable to follow households over time. However, we can follow municipalities. Therefore, we can regress the gap in Internet penetration between households with and without children on broadband use at school at the municipality level, that is,

$$(\bar{I}_{\text{children}} - \bar{I}_{\text{nochildren}})_{jt} = \alpha + \beta s_{jt} + \gamma \mathbf{m}_{jt} + \varepsilon_{jt}, \qquad \text{(A1)}$$

where $\bar{I}_{\text{children}_{jt}}$ and $\bar{I}_{\text{nochildren}_{jt}}$ are the household Internet penetration rates for households with and without children at time t, respectively, in municipality j; s_{jt} is the use of broadband at school in municipality j at time t; $\mathbf{m}_{jt}$ includes municipality-level covariates; β and γ are parameters; and ε_{jt} is a municipality-level error term. Table A.1 shows the results obtained from estimating this equation using OLS (column (1)) and municipality-level fixed effects (column (2)).[12] We observe a positive correlation between

[12] We use analytic weights to account for differences in variance across municipalities.

Table A.1 **Correlation Between the Gap in Internet Adoption Between Households With and Without Children and Internet Use at School**

Variables	(1) OLS	(2) Fixed effects
SchInetPSLn	0.0363*	0.115*
	(0.0190)	(0.0660)
ChildrenMuni	−0.0492	−0.0313
	(0.106)	(0.121)
HouseholdIncomeMuni	−0.107*	−0.133
	(0.0610)	(0.104)
HouseholdSizeMuni	−0.0452	0.0257
	(0.0314)	(0.0609)
Year2007	−0.0178	−0.0931
	(0.0405)	(0.0779)
Year2008	0.215***	0.0876
	(0.0517)	(0.122)
Year2009	0.245***	0.0451
	(0.0616)	(0.175)
Constant	0.332***	0.353
	(0.108)	(0.246)
Observations	693	693
R-squared	0.292	0.329

Notes. Municipality-level clustered standard errors in parentheses. Underid., underidentification test; Weak id., weak identification test; Overid., overidentification test; KP rk LM p-value, Kleibergen–Paap rk LM p-value (stata output); KP rk Wald F-stat., Kleibergen–Paap rk Wald F-statistic (stata output).
$^{*}p < 0.1$; $^{***}p < 0.01$.

broadband use at school and the gap in Internet penetration between households with and without children, which provides evidence consistent with the idea that children going to school and using broadband there may increase household Internet penetration.

Appendix B. First-Stage Regressions for Instrumental Variable Estimates

This appendix provides first-stage results for the IV strategies used in this paper. Table B.1 shows the first stages for the IV regression using the predicted broadband school use in a municipality as an instrument. Columns (2), (3), and (4) show the first-stage results for the interaction between school broadband use and children (*SchInetPS* × *Children*), for school broadband use alone (*SchInetPS*), and for neighborhood household Internet penetration (*HomeInternet*(*fraction*)(α_k)), respectively. Similarly, Table B.2 shows the first-stage results for the IV regressions using locality type as an instrument (columns (2)–(5)) and both locality type and the predicted broadband school use in a municipality as instruments (columns (6)–(9)). Columns (2) and (6) show the first-stage results for the interaction between school broadband use and children, columns (3) and (7) for school broadband use alone, and columns (4) and (8) for neighborhood household Internet penetration, respectively. All instruments behave as expected across all specifications.

Table B.1 **Internet Penetration as a Function of School Internet Traffic Controlling for Distance to Town Center (IV First and Second Stages)**

Variables	(1) OLS *HomeInet*	(2) Dist IV First stage (α_s)	(3) Dist IV First stage (*SchInetPSLn*)	(4) Dist IV First stage (α_k)	(5) Dist IV *HomeInet*
Household-level variables					
SchInetPSLn × *Children* (ϕ_1)	0.040***				0.051***
	(0.0072)				(0.0096)
Children (δ_c)	0.14***	3.28***	0.011	−0.0039	0.16***
	(0.014)	(0.17)	(0.040)	(0.014)	(0.016)
HouseholdIncome	0.47***	0.018**	0.013	0.063***	0.49***
	(0.0099)	(0.0071)	(0.013)	(0.0078)	(0.010)
HouseholdSize	0.038***	0.028***	0.0032	−0.0053***	0.036***
	(0.0042)	(0.0041)	(0.0054)	(0.0016)	(0.0043)
MediumDensity(*fraction*)	−0.051***	−0.024	−0.16**	0.013	−0.030**
	(0.0096)	(0.021)	(0.072)	(0.015)	(0.013)
HighDensity(*fraction*)	−0.060***	−0.068**	−0.36***	0.022	−0.026
	(0.011)	(0.028)	(0.094)	(0.021)	(0.022)
Municipality-level variables					
HomeInternet(*fraction*) (α_k)	0.59***				0.37***
	(0.019)				(0.065)
SchInetPSLn	−0.00083				0.033
	(0.0061)				(0.036)
Population	−4.4e−08	−1.9e−07***	−6.5e−07**	1.7e−07***	3.2e−08
	(2.9e−08)	(7.2e−08)	(3.0e−07)	(4.4e−08)	(4.3e−08)
DistanceTownCenter–CO	0.0030	0.013	0.070	−0.055***	−0.011*
	(0.0050)	(0.015)	(0.053)	(0.011)	(0.0064)

Table B.1 (Continued)

Variables	(1) OLS *HomeInet*	(2) Dist IV First stage (α_s)	(3) Dist IV First stage (*SchInetPSLn*)	(4) Dist IV First stage (α_k)	(5) Dist IV *HomeInet*
Instruments					
$\widehat{SchInetPSLn} \times Children$		1.33***	0.0048	−0.0016	
		(0.048)	(0.012)	(0.0042)	
$\widehat{SchInetPSLn}$		−0.25***	0.26***	−0.049**	
		(0.023)	(0.080)	(0.019)	
ChildrenMuni × *Year2006* (%)		−0.55***	0.26	0.10	
		(0.12)	(0.25)	(0.074)	
ChildrenMuni × *Year2007* (%)		−0.25*	−0.35	0.035	
		(0.13)	(0.22)	(0.075)	
ChildrenMuni × *Year2008* (%)		−0.077	0.16	0.45***	
		(0.082)	(0.20)	(0.079)	
ChildrenMuni × *Year2009* (%)		0.15**	−0.17	0.63***	
		(0.063)	(0.19)	(0.058)	
Constant	−0.53***	−1.03***	−1.41***	0.095	−0.40***
	(0.021)	(0.091)	(0.31)	(0.076)	(0.078)
Observations	13,932	13,932	13,932	13,932	13,932
R-squared	0.394	0.829	0.872	0.396	0.389
Year dummies	Yes	Yes	Yes	Yes	Yes
Underid. (KP rk LM p-value)					0.0067
Weak id. (KP rk Wald F-stat.)					3.06
Overid. (Hansen J P-value)					0.28

Notes. Municipality-level clustered standard errors in parentheses. Underid., underidentification test; Weak id., weak identification test; Overid., overidentification test; KP rk LM p-value, Kleibergen–Paap rk LM p-value (stata output); KP rk Wald F-stat., Kleibergen–Paap rk Wald F-statistic (stata output).
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Appendix C. Substitutability Between the 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 the Internet at home decreases the marginal utility of having the Internet at school for children. This may happen because when children use the Internet in one place, they do not need to use it as much in another place. Although this seems 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 the 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 Organisation for Economic Co-operation and Development (OECD) in 2009 to assess which case is more plausible. PISA is used by the OECD to assess how well schools prepare 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 the Internet at home and at school and how frequently they use it to perform certain activities at home and at school. A total of 92% of the students surveyed in Portugal have the Internet at home and 91% use it. A total of 97% of students indicate they have the 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 not use the Internet at home (Table C.1). 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 the Internet at school (Table C.2). Students that do not use the Internet at home report performing all of the activities more frequently at school. Similarly, students that do not use the Internet at school report performing most of the surveyed activities more frequently at home. Important exceptions are using the Internet for playing games and homework. However, in general, these tables provide support for the hypothesis that Internet use at home and at school are substitutes.

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 students have the Internet at home. For this purpose, we compute a binary variable, called *SchInetUse*, for whether the student uses the Internet at school. Note that this approach makes sense only for students that have the 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 the Internet is used at school, for which we compute a binary variable, called *HomeInetUse*, to indicate whether the student has the Internet at home. Similarly, this regression makes sense only for students who have the Internet at home.

Table C.3 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 the Internet at home are less likely to use the Internet at school (columns (1) and (2)), which is consistent with substitution between the Internet at home and at schools. 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

Table B.2 Internet Penetration as a Function of School Internet Traffic Controlling for Distance to Town Center (IV First and Second Stages)

Variables	(1) OLS *HomeInet*	(2) Muni IV First stage (α_s)	(3) Muni IV First stage (*SchInetPSLn*)	(4) Muni IV First stage (α_k)	(5) Muni IV *HomeInet*	(6) Muni IV + Dist IV First stage (α_s)	(7) Muni IV + Dist IV First stage (*SchInetPSLn*)	(8) Muni IV + Dist IV First stage (α_k)	(9) Muni IV + Dist IV *HomeInet*
Household-level variables									
SchInetPSLn × *Children* (ϕ_1)	0.040***				0.058**				0.051***
	(0.0072)				(0.025)				(0.0099)
Children (δ_c)	0.14***	−0.33***	−0.037	0.022***	0.17***	3.23***	−0.0034	0.00026	0.16***
	(0.014)	(0.12)	(0.028)	(0.0080)	(0.029)	(0.17)	(0.040)	(0.014)	(0.016)
HouseholdIncome	0.47***	0.044***	0.00080	0.064***	0.49***	0.018**	0.0070	0.063***	0.49***
	(0.0099)	(0.010)	(0.013)	(0.0079)	(0.011)	(0.0071)	(0.012)	(0.0078)	(0.010)
HouseholdSize	0.038***	0.091***	0.0058	−0.0057***	0.035***	0.021***	0.0045	−0.0051***	0.036***
	(0.0042)	(0.0049)	(0.0054)	(0.0016)	(0.0051)	(0.0043)	(0.0053)	(0.0016)	(0.0044)
MediumDensity (*fraction*)	−0.051***	0.031	0.054	−0.014	−0.013	0.028	0.049	−0.014	−0.024
	(0.0096)	(0.023)	(0.062)	(0.017)	(0.021)	(0.020)	(0.063)	(0.016)	(0.015)
HighDensity(*fraction*)	−0.060***	0.035	0.016	−0.025***	0.011	0.020	0.013	−0.025***	−0.013
	(0.011)	(0.027)	(0.027)	(0.0072)	(0.037)	(0.020)	(0.026)	(0.0071)	(0.026)
Municipality-level variables									
HomeInternet(*fraction*) (α_k)	0.59***				0.38***				0.38***
	(0.019)				(0.074)				(0.068)
SchInetPSLn	−0.00083				0.10				0.059
	(0.0061)				(0.064)				(0.041)
Population	−4.4e−08	−1.4e−07	−5.6e−07*	1.6e−07***	9.0e−08	−1.3e−07*	−4.8e−07	1.4e−07***	5.2e−08
	(2.9e−08)	(1.1e−07)	(3.2e−07)	(4.9e−08)	(7.5e−08)	(8.0e−08)	(2.9e−07)	(5.0e−08)	(5.1e−08)
DistanceTownCenter–CO	0.0030	0.013	0.079	−0.056***	−0.017	0.010	0.069	−0.054***	−0.013*
	(0.0050)	(0.016)	(0.054)	(0.011)	(0.010)	(0.015)	(0.052)	(0.011)	(0.0074)

Table B.2 (Continued)

Variables	(1) OLS *HomeInet*	(2) Muni IV First stage (α_s)	(3) Muni IV First stage (*SchInetPSLn*)	(4) Muni IV First stage (α_k)	(5) Muni IV *HomeInet*	(6) Muni IV + Dist IV First stage (α_s)	(7) Muni IV + Dist IV First stage (*SchInetPSLn*)	(8) Muni IV + Dist IV First stage (α_k)	(9) Muni IV + Dist IV *HomeInet*
Instruments									
LocalityType × *Children*		−0.33***	0.015	−0.0095**		0.24***	0.017	−0.012***	
		(0.050)	(0.013)	(0.0037)		(0.055)	(0.014)	(0.0038)	
LocalityType		−0.017	−0.32***	0.049***		−0.12***	−0.24***	0.034**	
		(0.017)	(0.053)	(0.014)		(0.017)	(0.061)	(0.015)	
ChildrenMuni × *Year2006* (%)		−1.24***	0.25	0.10		−0.41***	0.27	0.097	
		(0.11)	(0.26)	(0.073)		(0.11)	(0.26)	(0.074)	
ChildrenMuni × *Year2007* (%)		−0.56***	−0.27	0.018		−0.13	−0.32	0.025	
		(0.11)	(0.22)	(0.077)		(0.13)	(0.22)	(0.075)	
ChildrenMuni × *Year2008* (%)		0.26***	0.13	0.45***		−0.021	0.18	0.45***	
		(0.081)	(0.21)	(0.078)		(0.083)	(0.20)	(0.079)	
ChildrenMuni × *Year2009* (%)		0.91***	−0.24	0.64***		0.17***	−0.16	0.63***	
		(0.068)	(0.20)	(0.058)		(0.063)	(0.19)	(0.058)	
$\widehat{SchInet}PSLn$ × *Children*						1.47***	0.012	−0.0085*	
						(0.052)	(0.014)	(0.0044)	
$\widehat{SchInet}PSLn$						−0.29***	0.21**	−0.041**	
						(0.023)	(0.084)	(0.020)	
Constant	−0.53***	−0.36***	−1.95***	0.21***	−0.24	−1.01***	−1.29***	0.081	−0.34***
	(0.021)	(0.041)	(0.13)	(0.036)	(0.15)	(0.088)	(0.30)	(0.074)	(0.093)
Observations	13,932	13,932	13,932	13,932	13,932	13,932	13,932	13,932	13,932
R-squared	0.394	0.599	0.870	0.392	0.382	0.839	0.874	0.398	0.387
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Underid. (KP rk LM *p*-value)					0.00016				0.00024
Weak id. (KP rk Wald *F*-stat.)					5.54				5.21
Overid. (Hansen J *P*-value)					0.73				0.53

Notes. Municipality-level clustered standard errors in parentheses. Underid., underidentification test; Weak id., weak identification test; Overid., overidentification test; KP rk LM *p*-value, Kleibergen–Paap rk LM *p*-value (stata output); KP rk Wald *F*-stat., Kleibergen–Paap rk Wald *F*-statistic (stata output).
$^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table C.1 **PISA: School Activities by Home Internet Use**

	NoHomeInetUse (SD)	*HomeInetUse* (SD)	Diff. (SE)
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		6,215	

Notes. SD, standard deviation; SE, standard error.
$^{**}p<0.05$; $^{***}p<0.01$.

there are only very few students who do not use the 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 the Internet at school to the adults' adoption of the Internet at home.

Appendix D. Household Internet Penetration over Time

Section 4.3 introduces a differences equation to specify the dynamics of k over time. In particular,

$$\begin{aligned} k(t+1) &= \frac{N_c}{N}\int_{\theta_c(t)}^{\bar{\theta}} g(x)\,dx + \frac{N-N_c}{N}\int_{\theta_{nc(t)}}^{\bar{\theta}} g(x)\,dx \\ &= 1-\gamma f+\gamma N_c/N\delta_c+\gamma\alpha_s N_c/Ns_c(t). \end{aligned}$$

Table C.2 **PISA: Home Activities by School Internet Use**

	NoSchlnetUse (SD)	*SchlnetUse* (SD)	Diff. (SE)
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 online	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		6,230	

Notes. SD, standard deviation; SE, standard error.
$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$.

Table C.3 PISA: School and Internet Use as Function of Availability

	(1) *SchInetUse*	(2) *SchInetUse*	(3) *HomeInetUse*	(4) *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	6,030	6,030	5,753	5,753

Note. Standard errors in parentheses; clustered at the school level in columns (1) and (3).
$^{***}p < 0.01$.

Therefore, we can write $c_1 k(t) + c_0 k(t-1) = x(t)$, with $c_1 = 1$, $c_0 = -\gamma\alpha_k$ and $x(t+1) = 1 - \gamma f + \gamma N_c/N\delta_c + \gamma\alpha_s N_c/Ns_c(t)$. We can solve this differences equation using the following theorem: if $c_1 y_t + c_0 y_{t-1} = x_t$, then $y_t = A(-c_0/c_1)^t + c_1^{-1}\sum_{i=0}^{+\infty}(-c_0/c_1)^i x_{t-i}$ when $|c_0| < |c_1|$. Substituting, we get

$$k(t) = A(\gamma\alpha_k)^t + \frac{1-\gamma f + \gamma Nc/N\delta_c}{1-\gamma\alpha_k} + (\gamma\alpha_k N_c/N)\sum_{i=0}^{+\infty} s_c(t-1-i)(\gamma\alpha_k)^I,$$

where A is a constant. Assume that schools obtain broadband at time s and that household Internet penetration at s is exogenously known and given by $k(s)$. Using the equation above, we have $k(s) = A(\gamma\alpha_k)^s + (1-\gamma f + \gamma Nc/N\delta_c)/(1-\gamma\alpha_k)$. Thus, $A = (k(s) - (1-\gamma f + \gamma Nc/N\delta_c)/(1-\gamma\alpha_k))(\gamma\alpha_k)^{-s}$. Substituting, we obtain

$$k(t) = k(s)(\gamma\alpha_k)^{t-s} + (1-(\gamma\alpha_k)^{t-s})\frac{1-\gamma f + \gamma N_c/N\delta_c}{1-\gamma\alpha_k} + \gamma\alpha_k N_c/NS_c(t-1).$$

The expressions for φ_0 through φ_5 reported in the paper follow immediately.

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