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Are Classroom Internet Use and Academic Performance Higher after Government Broadband Subsidies to Primary Schools?

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Abstract: This paper combines data from a government programme providing broadband access to primary schools in Ireland with anonymised survey microdata on schools', teachers' and pupils use of the internet to examine the links between public subsidies, classroom use of the internet and educational performance. The microdata are drawn from the 9-year-old cohort of the *Growing Up in Ireland* Study. We estimate regression models to identify the factors associated with internet use in the classroom and students' scores on standardised reading and mathematics tests, and we check whether internet use is endogenous in the test score models. We find that provision of broadband service under the government scheme is associated with more than a doubling of teachers' use of the internet in class after about a two year lag. Better computing facilities in schools are also associated with higher internet use, but advertised download speed is not statistically significant. Internet use in class is associated with significantly higher average mathematics and reading scores on standardised tests. A set of confounding factors is included, with results broadly in line with previous literature.

I INTRODUCTION

The connection of schools and other educational institutions to the internet and, more recently, specifically to the broadband network continues to be high on the agendas of politicians and policymakers around the world. This paper combines data from a government programme providing broadband access to primary schools in Ireland with survey microdata on schools', teachers' and pupils' use of the internet. In a fortunate coincidence, the implementation of Ireland's "Broadband for Schools" (BFS) programme overlapped with the collection of data on a large sample of primary school children in the *Growing Up in Ireland* national longitudinal study of children (GUI).[1] We exploit this coincidence to examine the links between public subsidies, classroom use of the internet and educational performance. Having access to matched microdata on the timing and quality of schools broadband connectivity and on many likely influences on students' educational outcomes allows us to control for many confounding factors. However, we do not have control of the "experiment" on which the study is based, so we cannot make strong causal claims.

The next section of the paper considers why broadband access might affect educational outcomes and briefly reviews some of the existing evidence on use of the internet in schools and its association with student academic performance. Section III sets out our methodological approach and the data we use, Section IV gives our results and the last section sets out some conclusions.

[1] © Department of Health and Children.

II EVIDENCE ON ACCESS TO THE INTERNET IN SCHOOLS AND THE EFFECTS OF INTERNET USE ON STUDENT PERFORMANCE

2.1 *The Policy Background*

In 2004, Ireland's Department of Education and Science and the Department of Communications, Marine and Natural Resources jointly launched the Broadband for Schools programme. This project, which was jointly funded by the government and the telecommunications sector, aimed to ensure that every primary and secondary school in Ireland had access to broadband technology by the end of 2005. Government ministers at the time stressed the positive role broadband would play in education; that it would "… significantly enhance the potential of ICT in teaching and learning" and would "pay dividends in years to come" (DCMNR, 2004). The contracts for delivering broadband to schools were in place by mid-2005 which ensured that 841 schools would be connected to the broadband network via DSL (fixed line), 1,507 by wireless and 1,577 by satellite technology (DCMNR, 2005). The cost of the programme, including set-up and running costs for about three years, was about €30 million (Department of Education and Science, 2008).

Government support for the use of ICT, and specifically broadband access, in the classroom is based on a view that it will have a positive effect on teaching and learning outcomes. The UK's Broadband Stakeholders Group (BSG, 2001) highlight five channels through which they believe broadband can positively impact education. The first is by "enhancing the learning experience"; allowing schools to access innovative educational content, which would not be accessible through a narrower bandwidth, should motivate students' desire to learn. Evidence of the positive impact of ICT on students' motivation is provided by Passey *et al.* (2003), who conducted case studies of the use of ICT in schools; the authors do note, however, that the way in which ICT was used affected pupils' motivation.

The second channel is through improved cooperation between educational institutions; for example, video-conferencing can be used in order to share scarce teacher resources. The third channel is by delivering "new potentialities", by which the BSG are referring to innovations on a larger scale such as using the internet in language classes to connect with native speakers. The fourth channel is by improving efficiencies from an administrative point of view; enabling schools to streamline reporting, collation of performance data and other administrative tasks. The fifth and final channel proposed by the BSG is "widening access to education"; the report refers specifically to the ability of broadband to widen access to educational material from external sources such as libraries and museums, and also to widen access in a geographical sense.

Similar mechanisms are mentioned in the US context. The National Broadband Plan (FCC, 2010) outlines the role that ICT can play in broadening the array of material available to students, facilitating teaching that is increasingly tailored to students' individual needs. The National Broadband Plan also notes that barriers, such as a lack of adequate infrastructure, may prevent schools from successfully embracing online learning. Such benefits are also mentioned in the European Commission's Digital Agenda, with a further emphasis placed on the ability of ICT to promote pupil engagement in science, technology and mathematics. The ability of online materials to accommodate different learning styles is frequently cited as a benefit.

Despite the near consensus among policymakers internationally in favour of extending the use of the internet and other forms of ICT in schools, the empirical evidence is not one-sided. Indeed, Livingstone (2012) notes that the lack of conclusive evidence of the positive effects of ICT on education may provide an explanation as to why schools have been reluctant to change traditional teaching practices to accommodate new technologies. In the next subsection we review some of the existing evidence.

2.2 *Empirical Evidence*

Early studies of the effects of ICT on educational outcomes found mixed evidence, and many suffered from serious methodological shortcomings, e.g., small sample sizes, failing to control for important confounding factors or lacking a control group (Kirkpatrick and Cuban, 1998). More recently, studies have been carried out using more robust approaches to account for omitted variables and possible endogeneity; these have measured the effect of ICT on education by using methods such as randomised control trials or natural experiments exploiting rule changes and discontinuity in rules. A great deal of research has been carried out on ICT effects, and although the findings are extremely varied and dependent upon specific circumstances of programmes and affected groups, there is evidence that these investments can have a positive effect. A second-level meta analysis by Tamim *et al.* (2011) finds statistically significant low to moderate positive mean effects of ICT on achievement, using a dataset made up of 25 meta analyses that refer to 1,055 primary studies.

Of course, while ICT generally may have benefits for teaching and learning, that does not mean every possible ICT investment is worthwhile. In this paper we focus on broadband connectivity: a technology that is currently being highlighted by policymakers and which is receiving significant investment in many countries. For broadband use per se, the evidence of positive effects on educational outcomes remains equivocal.

Goolsbee and Guryan (2006) look at the effect of the E-Rate programme on internet connectivity and student outcomes in California public schools. The E-Rate programme provides subsidies to schools and libraries to gain access to internet and communication technologies; the subsidies range from 20 per cent-90 per cent of the cost depending on the characteristics of the school. The authors use a regression discontinuity design (RDD) to examine the effects of the subsidy on the level of internet connectivity for schools which were just above and just below the cut-off point for the subsidy, and OLS regression to test the effect of subsidies on ICT investment, and the effect of this investment on student performance,[2] in all schools in the dataset. The authors find that while the subsidies lead to a strong and statistically significant increase in the number of schools with internet access, this does not lead to an increase in pupil performance.

A more recent study by Belo *et al.* (2014) looks specifically at the effects of broadband access on educational outcomes. Following a 2004 initiative by the Portuguese government to connect all schools to the broadband network, the authors use distance between the school and the broadband provider's central office as an instrument for broadband connection quality (and thus quantity of broadband used) and find that the effects of internet usage on educational outcomes are negative for both male and female pupils. Furthermore, they find that the negative effect is stronger in schools where pupils are allowed to access websites such as YouTube. However, they do find that the effect was stronger in the 2005-2008 period compared to the 2005-2009 period which, the authors note, may indicate that the negative effects fade over time. Where empirical evidence suggests a negative effect of technology on educational outcomes (as opposed to ineffectiveness), this raises the question of whether ICT-aided educational techniques are less effective than traditional teaching methods or whether, as suggested by Underwood *et al.* (2005), the traditional assessment techniques in use are unable to capture the progress made by ICT use in the classroom.

Some studies have shown more positive (or at least mixed) results, however. Underwood *et al.* (2005) find that broadband access has a positive impact on the examination outcomes of second-level pupils but that for primary school pupils ("Key Stage 2") there is no effect. Sprietsma (2012) examines the effect of computer and internet usage, and the availability of designated computer labs, on the test scores of 15-year-old students in Brazil, using a pseudo-panel approach. Results from this analysis find that use of the

[2] Performance was measured by standardised test scores; the percentage of pupils taking more advanced courses; the proportion of pupils progressing to a system with higher standards; and the drop-out rate.

internet *by the teacher* has a positive impact on test scores in both reading and maths, and use of a computer by students has a positive effect on maths scores only. Conversely, access to a computer lab has a significant, negative effect on test scores in both subjects; the author hypothesises that this may be due to limited resources, and thus investing in a computer lab means that investments in other resources cannot be made.

To our knowledge, the associations between broadband provision, classroom internet use and educational performance of primary school children have not been studied in Ireland before. There is evidence that home use of computers and some internet applications in Ireland are associated positively with primary school test scores. Casey *et al.* (2012) find that moderate use of computers by children in the home had a significant positive association with mathematics and reading test performance. This paper also examines this association at the level of particular computer applications and finds that some were positive and others negative. Computer use in class may also interact in complex ways with its use in the home: McCoy, *et al.* (2012a) find that primary school students with internet access in school tend to use ICT more outside school, particularly for social networking purposes. This group of students also achieved among the highest scores for reading and mathematics, suggesting the use of ICT reinforces literacy and other skills.

III METHODOLOGY AND DATA

This section first sets out our approach to the analysis and then discusses the data employed.

3.1 *Analytic Strategy*

Ultimately, we are interested in whether the BFS programme leads to improved educational outcomes. Connection of a school to the internet should not, of itself, have any direct effect on educational outcomes. Instead, the introduction of better internet access may affect teaching practices and other school activities, and through these channels have an impact on the educational performance of pupils. A range of complementary infrastructures are likely to be essential intermediating factors, e.g., availability of computers in the school or classroom through which the internet may be used, rules or filtering software governing its use, and the way in which teachers use the internet in the classroom. An additional complementary factor is whether or not computer usage in the classroom promotes computer usage in the home, dependent on economic factors.

Due to data limitations, we cannot model the chain of causation explicitly. Only cross-sectional information is currently available on pupil characteristics and outcomes (although this will change when the next wave of GUI becomes available) and we do not know whether individual schools had broadband access per se, just when they received service under the BFS programme. Schools may have purchased broadband service outside the programme or might have taken it up if the programme did not exist.

Nevertheless, we can cast some light on one channel that we think might be important, the association between BFS and internet use in the classroom, and try to control for as many other possible confounding factors. Although we will not be able to prove causation with the data available, we can see whether the data are consistent with two hypotheses:

> H1: Ireland's Broadband for Schools Programme helped increase use of the internet in primary school classrooms.
>
> H2: Use of the internet in class led to better educational performance for children in Ireland's primary schools.

If significant associations are found, this should help indicate directions for future research.

To examine H1, we estimate a regression model of whether the internet was used in each classroom in the GUI study.[3] We express the use of the internet in class or not as a 1/0 variable (U) and use a logistic regression model. This model is estimated at the classroom level, as summarised in Equation 1 below:

$$\Pr(U_i = 1) = f(\alpha + \beta^I I_j + \beta^E E_j + \beta^F F_j + \beta^S S_j + \beta^D D_j + \beta^B B_i + \beta^T T_i) \qquad (1)$$

where f is the cumulative logistic function and teacher i is in school j and the β terms are vectors of regression coefficients. Vectors of explanatory variables are included for the time elapsed since Broadband for Schools internet connectivity was made available to the school (I), the nature of service supplied (E), advertised download speed of service (S), other complementary facilities such as computers in the school and classroom (F), demographics of the area served by the school (D), the teacher's experience and teaching style (B) and a proxy for how early in the GUI study the teacher was surveyed (T).

Two econometric models are estimated at child level to test H2: the dependent variables are measures of children's performance on standardised reading and mathematics tests given to nine-year-olds. The models are

[3] All regressions were estimated using Stata® v.12.

estimated using OLS, but we also employ a two-stage least squares (2SLS) estimator to test for endogeneity of the dependent variables. The OLS specification is summarised in Equation (2) below:

$$
\begin{aligned}
P_k = \alpha &+ \beta^S S_j + \beta^F F_j + \beta^D D_j + \beta^D B_i + \beta^G G_k + \beta^A A_k + \beta^E E_k \\
&+ \beta^C C_k + \beta^H H_k + \beta^Y Y_k + \beta^T T_k + \varepsilon_k
\end{aligned}
\tag{2}
$$

where teacher i is in school j and k refers to pupil. P represents either reading or maths test performance, depending on the model being estimated. Vectors of explanatory variables are included for advertised download speed of Broadband for Schools service (S), other complementary facilities such as computers in the school and classroom (F), demographics of the area served by the school (D), the teacher's experience and teaching style (B), study child gender (G), indicators of the child's home activity profile (A), parents' levels of educational attainment (E), household social class (C), indicators of the child's health (H), family income (Y) and a proxy for how early in the GUI study the child's household was surveyed (T). e is an error term.

One concern we have in estimating these models with OLS is that there might be unobserved factors affecting both a teacher's propensity to use the internet in class and a pupil's results on standardised tests. In other words, the use of the internet in class may not be exogenous in the reading and maths test models. In an attempt to allow for this possibility, we also estimate these models in a 2SLS framework and we test whether internet use in class (modelled in the first stage) is endogenous in the models of test performance (the second stage). The time since enabling of BFS and a dummy variable for schools that were not enabled by the time they were surveyed are used as instrumental variables. While our endogenous regressor of interest is binary, the 2SLS methodology estimates the first stage using a linear model. As discussed by Angrist and Kruger (2001), the consistency of the 2SLS estimates does not depend on the correct functional form being used in the first stage. Furthermore, as discussed by Angrist and Kruger (2001) and Angrist and Pischke (2009) amongst others, modelling the first stage as a probit or logit is not an appropriate estimation strategy.[4]

Details of the variables used in the models are provided in the next sub-section.

3.2 *Data*

This paper uses data from the extended Research Microdata File for the nine year-old cohort of the *Growing Up in Ireland* national longitudinal study

[4] We are grateful to an anonymous referee for bringing this issue to our attention.

of children (GUI). Only the first wave of the study is currently available, so the file is cross-sectional in structure. In addition, a set of variables has been added to GUI indicating when participants' schools received broadband service under the Irish government's Broadband for Schools programme and some details about the nature of services received (i.e. advertised download speed and technology used to supply broadband for each school). This additional information was provided by the Department of Education and Skills. Further details of the GUI study, with specific reference to research about influences on learning, are given in McCoy *et al.* (2012a, b).

In this section we discuss the variables included in our models, starting with the dependent variables (use of the internet in the classroom and educational test scores).

3.2.1 Use of the Internet in the Classroom

The Teacher's questionnaire includes a yes/no question on use of the internet: "Do the children in the study child's class use a computer to access the internet?" For 56.9 per cent of study teachers, the answer was yes, for the remainder it was no. We use the answer to this question as a dependent variable when we estimate Equation (1) and an explanatory variable in the other models.

3.2.2 Educational Test Scores

We estimate two models based on Equation (2): one explaining pupils' mathematics test scores and the other explaining reading scores. We use the logit scores for the vocabulary component of the *Drumcondra Primary Reading Test – Revised* and part 1 of the *Drumcondra Primary Mathematics Test – Revised*, which were collected as part of the *Growing Up in Ireland* Study. Further details of these variables are given in Casey, *et al.* (2012).

3.2.3 Data on the Broadband for Schools Programme

Our main interest in estimating Equation (1) is whether the Broadband for Schools Programme is associated with increased or accelerated adoption of the internet in classrooms. We can look at this because we know the timing of programme implementation relative to the timing of the survey. Figure 1 compares the time pattern of broadband installation under Broadband for Schools (bars with dark shading) with the time pattern of surveying in the GUI study (light shading). There is a small overlap between the survey period and installation period, but most of the variation in our sample comes from the lag since installation experienced by different schools. Although our data only capture when each child's household questionnaire was completed, not the teacher's questionnaire, we construct a proxy for when the teacher was surveyed by assigning each teacher the earliest survey date reported for any of his or her students. Because teachers' surveys were distributed ahead of those of their students, we consider that this to be a reasonable proxy for when teachers' surveys might have been completed.

Figure 1: *Sample Frequency Distributions of Dates that Survey was Administered and Broadband was Supplied Under the BFS Scheme (Unit of Analysis: Classrooms)*

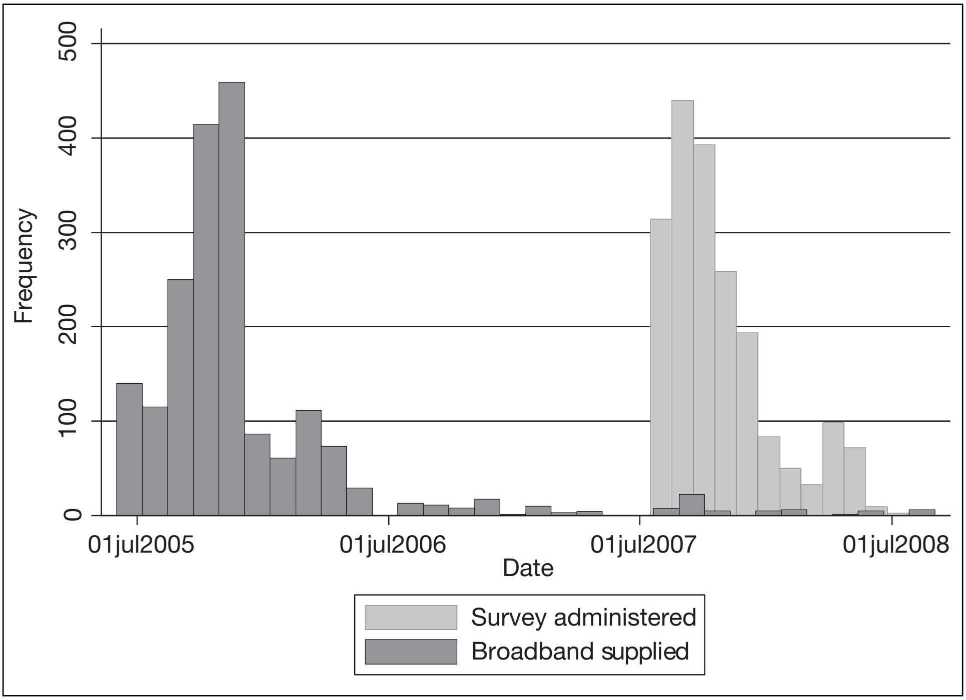
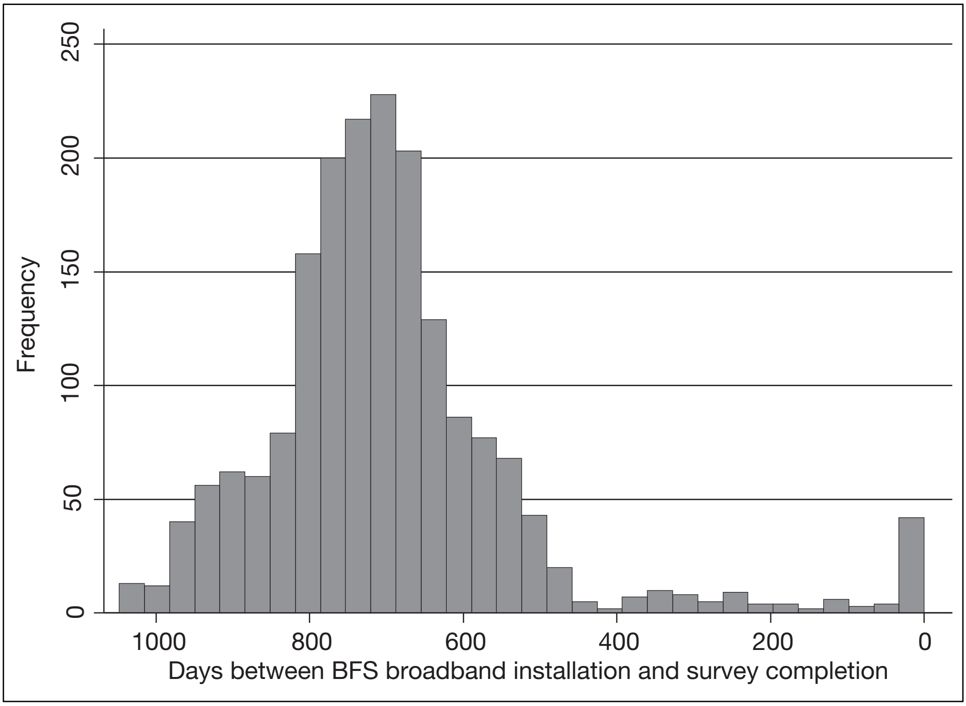


Figure 2 shows how this lag is distributed. Almost 80 per cent of classrooms in our sample were in schools that received BFS service at least 800 days before the GUI survey was administered to their teachers. Of classes, 37 were in schools that did not receive service under the scheme, either at all or by the time they were surveyed. Observations where no service was received are shown with a zero value.

We have no prior expectation about how time elapsed since service provision might affect school practices or outcomes, so we try two functional forms. The first approach includes a continuous variable for the time lag since installation, implying that this factor has a linear effect. The other treats the time lag as categorical, allowing for a more flexible relationship. Categories

Figure 2: *Sample Frequency Distribution of Time Between Broadband Installation and Survey Completion (Unit of Analysis: Classrooms)*



are chosen to allow a broadly similar number of samples in each category: 1-599 days, 600-699 days, 700-799 days, and 800+ days. Both approaches include a dummy variable for being in a school that did not receive service under the scheme.

This set of explanatory variables is included only in the internet use models; we have no reason to think that broadband provision per se should affect academic performance of children; its effects on such outcomes should be indirect as an enabling technology facilitating the use of computers and the internet.

3.2.4 Other Control Variables Included in Both the Internet Use and Academic Performance Models

The advertised broadband download speed for the service provided to each school by the BFS (for those that received service) is available as a categorical variable. There are many categories in the original dataset, some of which overlap. We have aggregated them into the following set: "⩽0.5 MBit/s", "⩽1 MBit/s", "⩽2 MBit/s", "⩽3 MBit/s", "⩽5 MBit/s", and "other". The

"≤5 MBit/s" category includes "Up to 4 MBit/s", and "Up to 5 MBit/s", while the "other" category includes ">2 MBit/s" and "> 8MBit/s". Each of the remaining categories are made up of two bands from the original dataset: one giving an exact estimate of the speed and the other having an upper bound at the same point; for example, our "≤2 MBit/s" band includes the original categories "2 Mbit/s" and "Up to 2 Mbit/s". We have no information on the extent to which the advertised speed is reflected in actual speed for each school.

We also know what technology was used to deliver broadband to each school in the scheme. This may capture some unobserved element of service quality. We have consolidated the original data into three categories:

- Fixed line: fixed line broadband connections delivered using existing copper local phone circuits (digital subscriber lines or unbundled local loops) and partial private circuits (leased lines). This incorporates five categories from the original dataset: "dsl", "ull", "ppc", "DSL WAS SAT" and "Pure ULL".
- Wireless: Fixed wireless broadband service where data is transmitted to fixed locations over a terrestrial radio network.
- Satellite: Fixed wireless broadband service where data is transmitted to fixed locations over a satellite-based radio network.

The extent of complementary facilities is accessible through four variables. We can compute the number of computers per pupil in the school using two fields in the Principal's questionnaire: the number of computers available to pupils and the number of pupils. Also on that questionnaire, there is a subjective categorical statement about the quality of computer facilities in the school, coded as "poor", "fair", "good" or "excellent". From the Principal's questionnaire we know whether there is a computer room in the school, and from the Teacher's questionnaire we know whether computers were available in the classroom and, if so, how often they were used. Better quality facilities should be associated with more extensive use of the internet (although the causation may run both ways) and could lead to improved academic performance if the facilities offer significant benefits for teaching and learning processes.

In line with previous research, we include a proxy for the social mix in each school. The Delivery of Equality of Opportunity in Schools (DEIS) programme provides additional supports to about 21 per cent of Irish primary schools that are deemed to experience high concentrations of disadvantage. Schools are selected for the programme based on a set of indicators including local unemployment rates, the prevalence of public housing, and the share of children eligible for the free book grants scheme. We use a four level DEIS status indicator, which distinguishes between Urban band 1 (most disadvantaged), Urban band 2 (disadvantaged), Rural DEIS (disadvantaged) and a fourth category denoting "Not disadvantaged". There are at least two channels of influence that might be important for this factor in the present study. DEIS Urban Band 1 and Rural DEIS schools seem to use computers more often in class than other schools (McCoy *et al.,*2012b), and past research has shown that pupils in disadvantaged (particularly urban DEIS) schools tend to suffer reduced performance on standardised tests (McCoy *et al.*, 2014).

We include controls for the number of years' teaching experience possessed by each study child's teacher and the active teaching index introduced in McCoy *et al.* (2012b). It is possible that more experienced teachers are more or less likely to introduce innovative technologies and associated teaching methods, so this factor could have either a positive or negative partial effect in the internet use models. Teacher experience is expected to have a positive effect on test performance. Similarly, use of active teaching methods (e.g., hands-on activities, pair work and group work) might have a direct effect on outcomes in as much as it leads to greater engagement and more effective learning by pupils, but we also want to rule it out as a possible confounding factor for the effects of internet use. It may be that teachers adopting active teaching methods are also more open to using the internet in class, so omitting this factor could lead to bias on the internet use coefficient in the academic performance models.

Finally, we include a time index (in days) for the time elapsed between the date a given observation was surveyed and the date the earliest survey was completed (i.e., the earliest completion date = 1), allowing us to control for unobserved effects that might vary with calendar time. When we are estimating the probability of classroom internet use this variable is based on the earliest survey completion in a given classroom; in the models of exam performance it is based on when each child's household was surveyed.

3.2.5 Other Control Variables – Academic Performance Models only

A range of child-level characteristics are included, again drawn from previous research into the determinants of children's educational performance. These include the child's gender, a dummy variable for chronic illness or disability as reported by the mother and a dummy variable for learning disability as reported by the class teacher. Children with learning disabilities or chronic health problems are likely to have lower test scores on average. Parental education is often found to have an important (positive) influence on educational performance, so we include categorical variables for the highest level of education attained by the primary carer (almost invariably the mother) and the secondary carer (father). The categories are lower

Table 1: *Survey Shares for Categorical Variables (Survey Weights Applied at Each Level)*

	Sample Share (%)		*Sample Share (%)*
SCHOOL LEVEL(s) & TEACHER LEVEL(t)		Some days	53.7
		Most days	15.7
BFS broadband installed[t]		Every day	9.70
No broadband under BFS	2.06		
1-599 days before survey	16.2	CHILD LEVEL	
600-699 days before survey	25.7	*Gender of children*	
700-799 days before survey	34.8	Male	49.1
800+ days before survey	21.3	Female	50.9
BFS technology (if BFS school)[s]		*Activity clusters of children*	
Fixed line	26.0	Busy lives	14.4
Satellite broadband	41.9	Social networkers	16.3
Wireless broadband	32.0	TV and sports	26.7
		Sports and computer games	21.5
Broadband speed (if BFS school)[s]		Cultural activities	21.2
⩽0.5 MBit/s	33.0		
⩽1 MBit/s	24.7	*Mother's Education*	
⩽2 MBit/s	25.7	Lower secondary	30.3
⩽3 MBit/s	5.99	Higher secondary	36.4
⩽5 MBit/s	9.17	Post secondary	15.7
Other	1.47	Third level	17.6
School computer facilities[s]		*Father's Education*	
Poor	15.4	Lower secondary	26.3
Fair	31.3	Higher secondary	22.2
Good	37.8	Post secondary	11.4
Excellent	15.5	Third level	16.3
		No secondary carer	18.5
Computer/internet use and availability		Not reported	5.4
Computer room in school[s]	39.7		
Internet used in class[t]	56.9	*Social Class of Household*	
Computers available in class[t]	81.5	Professional managers	8.32
		Managerial and technical	33.1
School DEIS status[s]		Non manual	19.0
Urban band 1	6.59	Skilled manual	16.3
Urban band 2	5.32	Semi skilled	9.24
Rural DEIS	6.71	Unskilled	1.76
Non-disadvantaged	81.4	Unclassified	12.3
Computers used in class		Learning disability	10.6
Never or almost never	21.0	Chronic illness or disability	10.9

secondary, higher secondary, post secondary and third level (the reference category). For fathers we also include categories for "no secondary carer" and "not reported". A categorical variable for the social class of the study child's household and the log of equivalised net household income are also included, in the expectation that higher social class and income will be associated with higher average test performance.

There is evidence that a child's profile of activities undertaken out of school may affect educational performance. McCoy *et al.* (2012a) carry out a cluster analysis of Irish children's out-of-school activities, and we include the five clusters identified in their paper as explanatory variables here to allow for possible confounding effects from this source. McCoy *et al.* refer to these clusters as "TV and sports", "social networkers", "sports and computer games", "cultural activities" and "busy lives", although obviously such shorthand descriptions provide only an indicative sense of the activities undertaken and more detail is given in the paper.

Table 1 lists the sample shares for each of the categorical variables discussed above and Table 2 shows sample means for the continuous variables.

Table 2: *Means and Standard Deviations of Continuous Variables in Survey (Survey Weights Applied at Each Level)*

		Mean	*St. Dev.*
School level	Computers/pupil in school	0.105	0.0729
Teacher level	Days since broadband provided under BFS	693	178
	Teaching experience of teacher (years)	12.7	11.4
	Active teaching index of teacher	2.74	0.514
	Time index of survey, teacher level (days)	101	77.3
Child level	Time index of survey, child level (days)	117	71.6
	Reading test logit score	0.00706	0.996
	Maths test logit score	–0.764	0.931
	Equivalised household annual income (€)	19,008	12,400

IV RESULTS

We first discuss the results for use of the internet in the classroom, followed by those for pupils' reading and mathematics test performance.

4.1 *Modelling the Effect of the Broadband for Schools Programme on Use of the Internet in Class*

We first estimate two logit regressions with a dependent variable indicating whether the internet was used in class or not (Table 3). The first model includes a linear variable for the number of days since service was provided under the BFS programme. The other uses a categorical representation of this variable.

The time since BFS service was provided has a positive and significant association with internet use in the linear model. Using the categorical form of this variable, coefficients suggest a positive association but it is only significant in the case of classrooms that received service at least 800 days before they were surveyed (relative to the reference case where service was provided 1-599 days ago). Such classrooms are over twice as likely to use broadband as those in the reference group. There is a strong negative association for classrooms in schools where broadband was not provided under the programme by the time they were surveyed. This category includes only about 2 per cent of the teachers in the sample, so the coefficient may not be reliable.

This result is consistent with the hypothesis that BFS encouraged classroom internet use, but implies that it took about two years to have a measurable impact in the average school. It is plausible that incorporating use of the internet in classroom activities would take time, e.g., for adaptation of lesson plans, acquisition of complementary equipment, etc.

Indeed, as expected we also find strong positive associations between some relevant facilities and classroom internet use. Having computers available in the classroom or a computer room in the school has large and significant effects. Teachers in schools where principals reported that computer facilities were fair rather than good are much less likely to use the internet in class, as are those who used the computers in class "some days" or "never or almost never" rather than "most days".

Other possible factors, including download speed, BFS technology, computers per pupil, teacher experience, the active teaching index and DEIS status are not statistically significant in these models.

4.2 *Modelling the Effect of Internet Use in Class on Students' Reading Test Performance*

Table 4 shows OLS regression results for the model of children's reading test results. Being in a classroom where the internet is used is associated with about 0.083 points higher reading test logit score. Exogeneity of the internet use variable is not rejected when tested using a 2SLS model (see Annex 2). We therefore find that use of the internet in the classroom has a positive and significant association with students' reading test scores.

Many other factors are significant in these models, with most results following the expected pattern. Positive associations are found for children with a more highly educated primary or secondary carer and those from a household with a higher social class or higher income. Negative associations are found for those with an intellectual disability or attending urban schools classified as disadvantaged.

Table 3: *Results from Logit Regressions on Internet Use in the Classroom for Teachers in the GUI Dataset*

DV: "Do the children in the study child's class use a computer to access the internet?" [1/0]	*Linear BFS Effect Model*		*Categorical BFS Effect Model*	
Variables	*Odds Ratio*	*Robust S.E.*	*Odds Ratio*	*Robust S.E.*
Days since broadband provided under BFS	1.00205	0.000640***		
No broadband under BFS	1.0206	0.699	0.295	0.169**
BFS broadband inst. 1-599 days ago			REF	
BFS broadband inst. 600-699 days ago			1.138	0.243
BFS broadband inst. 700-799 days ago			1.186	0.245
BFS broadband inst. 800+ days ago			2.47	0.725***
BFS provided DSL or ULL broadband	0.766	0.198	0.597	0.171*
BFS provided satellite broadband	0.982	0.239	0.900	0.225
BFS provided wireless broadband	REF		REF	
Broadband speed $\leqslant$0.5 MBit/s	REF		REF	
Broadband speed $\leqslant$1 MBit/s	1.221	0.352	1.152	0.343
Broadband speed $\leqslant$2 MBit/s	0.999	0.210	1.0856	0.228
Broadband speed $\leqslant$3 MBit/s	1.308	0.473	1.529	0.559
Broadband speed $\leqslant$5 MBit/s	1.226	0.454	1.488	0.560
Broadband speed other	1.977	1.34	2.27	1.48
Computers/pupil in school	2.36	2.89	3.28	4.05
School computer facilities: poor	0.805	0.175	0.827	0.178
School computer facilities: fair	0.685	0.119**	0.695	0.121**
School computer facilities: good	REF		REF	
School computer facilities: excellent	1.0326	0.207	0.996	0.205
Computer room in school	1.475	0.244**	1.469	0.243**
Computers available in class	1.746	0.316***	1.775	0.323***
Comp. use in class: never/almost never	0.172	0.0383***	0.171	0.0379***
Comp. use in class: some days	0.654	0.120**	0.639	0.117**
Comp. use in class: most days	REF		REF	
Comp. use in class: every day	0.866	0.222	0.849	0.218
Constant	0.582	0.378	2.10	1.18
Teacher experience	Not significant		Not significant	
Teacher active teaching index	Not significant		Not significant	
School DEIS status	Not significant		Not significant	
Time index of survey, teacher level	Not significant		Not significant	
N	1,412		1,412	
Pseudo R^2	0.111		0.111	
Hosmer and Lemeshow goodness of fit test	$\chi^2(1387)$=1,413 [P=0.305]		$\chi^2(1385)$=1,407 [P=0.337]	

Notes: Standard errors are robust to clustering at school level and survey weights are used, averaged at teacher level. REF = the reference category for each factor variable. The single, double and triple asterisks represent the 10 per cent, 5 per cent, and 1 per cent levels of significance respectively.

Table 4: *Results from Regression on Reading Test Performance*

DV: Reading Test Logit Score	*OLS model*	
Variables	*β*	*Robust S.E.*
Internet used in class	0.0833	0.0362**
Broadband speed ≤0.5 MBit/s	REF	
Broadband speed ≤1 MBit/s	0.0907	0.0650
Broadband speed ≤2 MBit/s	0.0274	0.0552
Broadband speed ≤3 MBit/s	–0.0375	0.0887
Broadband speed ≤5 MBit/s	0.0820	0.0712
Broadband speed other	0.209	0.104**
Computers/pupil in school	–0.256	0.464
School DEIS Urban Band 1	–0.160	0.0872*
School DEIS Urban Band 2	–0.206	0.0748***
School DEIS Rural DEIS	0.0422	0.107
School non-disadvantaged	REF	
Teacher experience	0.00226	0.0016
Teacher active teaching index	–0.0430	0.0333
Activity cluster: busy lives	–0.0225	0.0470
Activity cluster: social networkers	0.190	0.0478***
Activity cluster: TV and sports	REF	
Activity cluster: sports and computer games	0.106	0.0437**
Activity cluster: cultural activities	0.169	0.0414***
Boy	–0.0626	0.0316**
Girl	REF	
Primary carer education lower secondary	–0.372	0.0486***
Primary carer education higher secondary	–0.209	0.0401***
Primary carer education post-secondary	–0.169	0.0458***
Primary carer education third level	REF	
Secondary carer education lower secondary	–0.320	0.0509***
Secondary carer education higher secondary	–0.124	0.0471***
Secondary carer education post-secondary	–0.21	0.0501***
Secondary carer education third level	REF	
No Secondary carer	–0.182	0.0655***
Secondary carer education not reported	–0.323	0.0771***
SC Professional workers	REF	
SC Managerial & technical	–0.027	0.0458
SC Non-manual	–0.117	0.0544**
SC Skilled manual	–0.214	0.0617***
SC Semi-skilled	–0.0661	0.0675
SC Unskilled	–0.165	0.112
SC Unclassified	–0.128	0.0892
(Log) Household net equivalised income	0.123	0.0376***
Intellectual disability	–1.04	0.0475***
Chronic illness or disability	–0.0670	0.0488
Time index of survey, child level	–0.000526	0.000247**
Constant	–0.541	0.405

Table 4: *Results from Regression on Reading Test Performance (Contd.)*

DV: Reading Test Logit Score	*OLS Model*	
Variables	β	*Robust S.E.*
Quality of school computer facilities	Not significant	
Computer room in school	Not significant	
Computers available in class	Not significant	
Frequency of computer use in class	Not significant	
N	5,651	
R^2	0.250	

Notes: Standard errors are robust to clustering at teacher level, and survey weights are used. REF = the reference category for each factor variable. The single, double and triple asterisks represent the 10 per cent, 5 per cent, and 1 per cent levels of significance respectively.

We find similar results for out-of-school activities as those reported in McCoy *et al.* (2012a): children assigned to the clusters styled "social networkers", "sports and computer games" and "cultural activities" have higher average scores than the reference group "TV and sports". Separately, we test whether there might be an interaction between the effect of classroom internet use on academic performance and that of out-of-school activity variables or an alternative variable capturing the intensity of ICT outside school. For example, using the internet at school might prime children to use it more effectively at home, or vice versa. Taking the variables for out-of-school activities or home internet use in and out of the model has little impact on the classroom internet use coefficients (detailed results available on request from the authors).

We find little evidence that the broadband speed or principal-reported quality of school computer facilities has a direct effect on reading test results. Other insignificant factors include the child having a chronic illness or disability, the density of computers in the school, teacher-reported frequency of computer use in class, teacher experience and the active teaching index. The time index shows a very small negative trend during the sample period.

4.3 *Modelling the Effect of Internet Use in Class on Students' Maths Test Performance*

In Table 5, we turn to the models of mathematics test results. The OLS results are qualitatively similar to those for reading tests, but there are some interesting differences. Internet use in class is again positive but in this case is highly significant, associated with 0.13 points higher maths test logit scores. Here too, exogeneity of the internet use variable is not rejected (see Annex 2), so we conclude that use of the internet in the classroom has a positive and significant association with students' mathematics test scores.

Table 5: *Results from Regression on Mathematics Test Performance*

DV: Maths test logit score	*OLS Model*	
Variables	*β*	*Robust S.E.*
Internet used in class	0.134	0.0385***
Broadband speed ⩽0.5 MBit/s	REF	
Broadband speed ⩽1 MBit/s	–0.0146	0.0595
Broadband speed ⩽2 MBit/s	0.0636	0.0546
Broadband speed ⩽3 MBit/s	–0.0000601	0.0847
Broadband speed ⩽5 MBit/s	–0.00843	0.0724
Broadband speed other	0.249	0.131*
Computers/pupil in school	–0.141	0.390
School DEIS Urban Band 1	–0.148	0.0800*
School DEIS Urban Band 2	–0.0509	0.0777
School DEIS Rural DEIS	–0.0593	0.0817
School non-disadvantaged	REF	
Teacher experience	0.00409	0.00157***
Teacher active teaching index	–0.0311	0.0354
Activity cluster: busy lives	0.0328	0.0468
Activity cluster: social networkers	0.152	0.0441***
Activity cluster: TV and sports	REF	
Activity cluster: sports and computer games	0.0686	0.0420
Activity cluster: cultural activities	0.146	0.0404***
Boy	0.0743	0.0329**
Girl	REF	
Primary carer education lower secondary	–0.361	0.0494***
Primary carer education higher secondary	–0.116	0.0404***
Primary carer education post-secondary	–0.0776	0.0427*
Primary carer education third level	REF	
Secondary carer education lower secondary	–0.212	0.0491***
Secondary carer education higher secondary	–0.0634	0.0459
Secondary carer education post-secondary	–0.145	0.0519***
Secondary carer education third level	REF	
No Secondary carer	–0.199	0.0607***
Secondary carer education not reported	–0.22	0.0695***
SC Professional workers	REF	
SC Managerial and technical	–0.0552	0.0478
SC Non-manual	–0.119	0.0570**
SC Skilled manual	–0.162	0.0629***
SC Semi-skilled	–0.175	0.0712**
SC Unskilled	–0.0762	0.117
SC Unclassified	–0.155	0.0826*
(Log) Household net equivalised income	0.0602	0.0335*
Intellectual disability	–0.837	0.0519***
Chronic illness or disability	–0.0917	0.0477*
Time index of survey, child level	–0.000313	0.000231
Constant	–1.06	0.362***

Table 5: *Results from Regression on Mathematics Test Performance (Contd.)*

DV: Maths test logit score	*OLS Model*	
Variables	β	*Robust S.E.*
Quality of school computer facilities	Not significant	
Computer room in school	Not significant	
Computers available in class	Not significant	
Frequency of computer use in class	Not significant	
N	5,708	
R^2	0.206	

Notes: Standard errors are robust to clustering at teacher level, and survey weights are used. REF = the reference category for each factor variable. The single, double and triple asterisks represent the 10 per cent, 5 per cent, and 1 per cent levels of significance respectively.

We find no significant effects from broadband speed, quality of school computing facilities, computers/pupil, or the active teaching index.

Being in an urban disadvantaged school was not significant (in contrast to the reading models where it was). Two other differences from the reading models are that teacher experience and being male have positive and significant associations with mathematics test scores, whereas having a chronic illness or disability has a marginally significant negative association in this case.

As in the reading test model, intellectual disability, social class, income, parental education and activity clusters have the expected associations with maths test results. The time index shows no significant trend during the sample period.

4.4 *Another Exogeneity Check: Did Schools in Better- or Worse-off Areas Get BFS Service First?*

An additional potential source of endogeneity might be that schools prone to better academic performance (e.g., those in better off areas or with a stronger set of internal institutions) might have been able to gain earlier access to the Broadband for Schools programme. Although we include controls for disadvantaged schools in all models, some of this variation might still be omitted and be picked up erroneously by the coefficients on the Broadband for Schools variables.

As a cross-check, we estimate models of the time it took for schools to be given service under BFS, including only those schools (most) that were served within the sample period. Both OLS and count data (negative binomial) models are used, but the choice of estimator made no qualitative difference. To illustrate these results, an OLS version of the model is shown in Table 6.

Table 6: *Results from Regression on How Long it Took Broadband to be Installed in Schools*

DV: Days between start of programme and broadband installation in a given school	*OLS Model*	
Variables	*β*	*S.E.*
Border region	–10.2	27.8
Dublin region	REF	
Mid-East region	6.35	25.2
Midland region	13.5	31.2
Mid-West region	–17.4	26.3
South-East region	16.6	26.5
South-West region	–21.9	25.0
West region	–12	28.0
Total pupils	–0.0815	0.0387**
DEIS Urban Band 1	–21.8	21.2
DEIS Urban Band 2	–45.7	17.4***
DEIS Rural Band 1	–2.57	13.9
Non-DEIS	REF	
Principal's total years of experience	–0.201	0.673
Constant	202	26.7***
N	761	
R^2	0.0272	

Notes: Standard errors are robust to clustering at school level, and survey weights are used. REF = the reference category for each factor variable. The single, double and triple asterisks represent the 10 per cent, 5 per cent, and 1 per cent levels of significance respectively.

We find no evidence that region systematically affects whether schools received service earlier. There is also no significant association with the principal's years of experience. Urban DEIS Band 2 schools receive service about 6-7 weeks earlier on average than non-disadvantaged schools, but other disadvantaged schools do not. Larger schools have had service for slightly longer: on average, having 100 more pupils in a school is associated with getting service about 8-9 days earlier. This might suggest larger schools are slightly better placed to manage the liaison with suppliers during the installation process, perhaps because they are more likely to have designated ICT coordinators. We also try controlling for the social class mix of the local area (based on the average from Census Small Area Population Statistics for the electoral division in which each school is located) and the principal's experience in the current school rather than total experience, but they are not significant either.

V DISCUSSION AND CONCLUSIONS

BFS provision is associated with more than a doubling in the average teacher's probability of using the internet in class with about a two year lag. Not surprisingly, having better computer-related facilities in a school also shows a positive relationship with internet use. However, advertised connection speed showed no significant effects.

Given that we have only cross-sectional survey data and some important variables are omitted, we cannot conclude with certainty that the BFS programme caused higher internet adoption. In particular, the lack of information on whether individual schools had broadband access (apart from BFS-provided services) is an important data gap. However, the direction, timing and scale of the effect seem consistent with the expectation that public supports for broadband supply to schools would lead to more use of the internet.

Our second set of models shows that use of the internet in class was associated with significantly higher average mathematics and reading scores. These models control for many factors thought to affect pupils' exam performances, and the observed associations with confounding factors such as income, social class, parental education, intellectual disability and out-of-school activities are broadly consistent with theory and previous research. To get a sense of the size of these effects, note that the internet use coefficient in the OLS mathematics model is similar to the partial effect of a child's mother having completed a third level education rather than upper secondary. The internet use coefficients are also roughly similar to the effect on test scores of having a 1-2 per cent higher net equivalised household income. We also tested whether internet use in class might be endogenous in the models of exam performance, but the data rejected endogeneity.

The existence and strength of this association suggests that further research to establish causation and to further explore the mechanisms through which school broadband subsidies affect outcomes might be worthwhile. We found no evidence for Ireland of the negative effects of broadband in schools reported by Belo *et al.* (2014) for Portugal, which might be due to different limits placed on internet use or the sites to which access is typically permitted in the two cases. In Ireland the filtering system in place can mean that only a limited number of websites can be accessed via the school's internet connection; access restrictions are dependent on the level of filtering for which schools have signed up.[5] The data available to us does not

[5] http://www.ncte.ie/Technology/SchoolsBroadband/FAQs/#Q15

permit deeper investigation of this dimension. Our findings also contrast with the insignificant effects observed by Underwood *et al.* (2005) in UK primary schools.

It would be useful to know whether programmes such as this produce societal benefits worth more than their costs. In other domains, such as health services, much more research has been carried out on valuation of treatment effects than has occurred to date in education or most other public policy areas. The available data on the effects of broadband in schools fall far short of what would be needed to quantify the full benefits or even to attribute them confidently among the many factors affecting student performance. However, we can attempt a crude illustration of how the scale of the effects found in this paper and the costs associated with the programme compare to some results from international research.

A paper by researchers in the UK (Nicoletti and Rabe, 2013) found that an average increase of £1,000 (about €1,166 in 2010)[6] on yearly per pupil expenditure would increase average test scores at age 16 by about 2 per cent of a standard deviation; the authors note that their findings are "statistically significant but very small". As a working assumption, suppose only one cohort of children benefited from the BFS programme. This is an extremely conservative assumption, but it might be taken as a lower bound since we simply do not have information about how BFS affected children in cohorts other than the one studied by GUI. Ireland's primary schools had about 60,000 children in each cohort in 2007-8 (Department of Education and Science, 2007/8). Our internet adoption (Hypothesis 1) model implies that about 31 per cent more students had internet in their classrooms than otherwise might have been expected two years after installation of broadband, 31 per cent of 60,000 gives 18,600 beneficiaries. As mentioned earlier, BFS cost about €30 million over three years to implement, or about €1,600 for each child assumed to have benefited in this crude example. Using the Nicoletti and Rabe estimates, spending this amount on each affected student would be expected to yield an increase in test scores of about 3 per cent of a standard deviation. In contrast, our results imply an increase of about 8-14 per cent of a standard deviation.[7] To get that much effect based on the UK cost estimates would require €4,660-8,160. It is also likely other cohorts received some benefit from BFS, implying a lower cost per beneficiary.

This gap is encouraging, but we must emphasise that we have no data on the cost effectiveness of Irish educational programmes with which to make a

[6] Based on the average 2011 daily exchange rate in 2011 from the European Central Bank, URL: https://www.ecb.europa.eu/stats/exchange/eurofxref/html/index.en.html

[7] Standard deviations for test logit scores in our dataset are shown in Table 2.

like-for-like comparison with the effects observed in this paper. As well as focusing on another country, the Nicoletti and Rabe estimates relate to children in secondary school. There is some research internationally on the impact of per pupil spending on educational outcomes, but it has found mixed results and seems to be very context-specific. A larger effect of expenditure per pupil was found by Hægeland *et al.* (2012) for Norway, but these results are also based on overall spending rather than individual components, indeed the authors note that "… school inputs are multidimensional and it is hard to pin down the [causal] effects of each of them". Murillo and Román (2011), looking at the effects of resources in Latin American schools, find that schools' infrastructure and teaching resources do have a positive effect, but their results vary significantly from country to country. As this study specifically relates to primary schools in Latin America it is difficult to draw conclusions from this for other countries where the economic and institutional context may be very different. More recently, DeWitte *et al.* (2014) find that the effect of spending on student performance in the Netherlands is ambiguous. The international evidence does not provide a good benchmark for comparison to an Irish programme, and we do not believe it is possible to draw robust conclusions about the cost-effectiveness of the BFS programme without better information on the societal value of improvements to academic performance and the marginal cost of measures to make such improvements in Ireland.

Our work suffers from other limitations that could be addressed in future with better data. One inevitable concern in this sort of research is possible omitted variables. For example, maybe the most advanced teachers are more effective than their peers in a range of domains but also use the internet more. Perhaps richer schools (or schools in richer areas, with more scope for fund raising) adopted the internet earlier outside BFS and thus gained an advantage not captured in our data. We have tried to control for both of these phenomena, but it is hard to be certain that no relevant unobserved heterogeneity remains.

There is potential for future research. One obvious extension would be to examine the speed and nature of internet adoption in classrooms following enabling of broadband or supply of complementary infrastructure in individual schools. In addition, the next wave of the GUI study covers the same pupils at age 13, so longitudinal analysis and examination of broadband use early in the secondary school years should be possible. In 2012 the Irish government announced it was to ensure that all secondary schools would be connected to high speed broadband (100Mbps) by 2014 (DCENR, 2012). The capital costs of this project, estimated to be in the order of €11 million, will be funded by the Department of Communications, Energy and Natural Resources who will also provide funding to cover current costs up to €10 million for the years 2013-2015; the remainder of the current costs up to 2015 are expected to be approximately €20 million, and will be funded by the Department of Education and Skills (Department of Education and Skills, 2012). With suitable access to data, the effects of these investments might be examined to provide guidance to future policymakers.

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ANNEX

RESULTS OF 2SLS REGRESSIONS

To check for the possibility that internet use in class is endogenous in regressions explaining test scores, we estimate 2SLS versions of these models and carry out endogeneity tests using the "estat endogenous" post-estimation command in Stata 13, which applies the robust score test from Wooldridge (1995). Results from the first stages of the 2SLS models (see Table A1) indicate that our instrument has adequate strength; e.g., the coefficient on the instrument is highly significant and the F-statistic from the first stage is 10.9 in the Reading model and 10.8 in the Mathematics model. Based on the assumption that the results from 2SLS are consistent, we test whether or not internet use in class is endogenous and thus whether we need to use an instrumental variables estimation strategy. The results from these test do not reject exogeneity of the internet use variable in either the reading ($F(1,1390) = 0.0468$ [p=0.829]) or mathematics ($F(1,1396) = 0.0952$ [p=0.758]) models, which suggests that the results from the OLS models are valid and the less efficient 2SLS estimator is not necessary.

Table A1: *Results from First Stage (Use of the Internet in the Classroom) in 2SLS Regressions on Reading and Maths Test Performance*

DV: "Do the children in the study child's class use a computer to access the internet?" [1/0]	*Reading*		*Mathematics*	
Variables	*β*	*Robust S.E.*	*β*	*Robust S.E.*
Days since broadband provided under BFS	0.000420	0.00010***	0.000406	0.0000998***
No broadband under BFS	–0.00306	0.113	–0.0216	0.111
Broadband speed ≤0.5 MBit/s	REF		REF	
Broadband speed ≤1 MBit/s	0.00675	0.0501	0.0122	0.0498
Broadband speed ≤2 MBit/s	–0.0348	0.0470	–0.0358	0.0470
Broadband speed ≤3 MBit/s	–0.0312	0.0611	–0.0337	0.0611
Broadband speed ≤5 MBit/s	–0.0319	0.0533	–0.0322	0.0534
Broadband speed other	0.0809	0.125	0.0801	0.125
Computers/pupil in school	0.128	0.285	0.124	0.285
School computer facilities: poor	–0.0592	0.0428	–0.0628	0.0426
School computer facilities: fair	–0.0368	0.0317	–0.0363	0.0315
School computer facilities: good	REF		REF	
School computer facilities: excellent	0.00227	0.0352	2.41E-05	0.0350
Computer room in school	0.0669	0.0281**	0.0657	0.0279**
Computers available in class	0.104	0.0346***	0.110	0.0344***
Comp. use in class: never/almost never	–0.464	0.0416***	–0.458	0.0414***
Comp. use in class: some days	–0.131	0.0334***	–0.130	0.0333***
Comp. use in class: most days	REF		REF	

Table A1: *Results from First Stage (Use of the Internet in the Classroom) in 2SLS Regressions on Reading and Maths Test Performance (Contd.)*

DV: "Do the children in the study child's class use a computer to access the internet?" [1/0]	*Reading*		*Mathematics*	
Variables	*β*	*Robust S.E.*	*β*	*Robust S.E.*
Comp. use in class: every day	–0.0445	0.0510	–0.0445	0.0510
Teacher experience	–0.00226	0.00118*	–0.00233	0.00118**
Teacher active teaching index	–0.0476	0.0277*	–0.0472	0.0277*
Student intellectual disability	–0.0487	0.0304	–0.0433	0.0301
Constant	0.664	0.215***	0.628	0.213***
School DEIS status	Not significant		Not significant	
Student activity clusters	Not significant		Not significant	
Student chronic illness	Not significant		Not significant	
Parental education	Not significant		Not significant	
Parental social class	Not significant		Not significant	
Household net equivalised income	Not significant		Not significant	
Time index of survey, child level	Not significant		Not significant	
N	5,558		5,615	
R^2	0.170		0.169	

The second stage regression results for both models are shown in Table A2.

Table A2: *Results From Second Stage (Test Scores) in 2SLS Regressions on Reading and Maths Test Performance*

DV: Test logit scores	*Reading*		*Mathematics*	
Variables	*β*	*Robust S.E.*	*β*	*Robust S.E.*
Internet used in class (predicted value from first stage)	0.107	0.306	0.486	0.336
Broadband speed ⩽0.5 MBit/s	REF		REF	
Broadband speed ⩽1 MBit/s	0.0821	0.0716	–0.0449	0.0685
Broadband speed ⩽2 MBit/s	0.0240	0.0564	0.0553	0.0583
Broadband speed ⩽3 MBit/s	–0.0292	0.0904	0.0304	0.0893
Broadband speed ⩽5 MBit/s	0.0784	0.0725	–0.0258	0.0769
Broadband speed other	0.124	0.144	0.103	0.179
Computers/pupil in school	–0.323	0.483	–0.263	0.418
School DEIS Urban Band 1	–0.145	0.0897	–0.123	0.0834
School DEIS Urban Band 2	–0.197	0.0772**	–0.0725	0.0740
School DEIS Rural DEIS	0.0476	0.107	–0.0201	0.0952
School non-disadvantaged	REF		REF	
Teacher experience	0.00231	0.00175	0.0049	0.00183***
Teacher active teaching index	–0.0436	0.0369	–0.0146	0.0415
Activity cluster: busy lives	–0.0164	0.0485	0.0347	0.0471

Table A2: *Results From Second Stage (Test Scores) in 2SLS Regressions on Reading and Maths Test Performance (Contd.)*

DV: Test logit scores	*Reading*		*Mathematics*	
Variables	*β*	*Robust S.E.*	*β*	*Robust S.E.*
Activity cluster: social networkers	0.190	0.0500***	0.145	0.0462***
Activity cluster: TV and sports	REF		REF	
Activity cluster: sports and computer games	0.106	0.0450**	0.0621	0.0439
Activity cluster: cultural activities	0.175	0.0416***	0.151	0.0406***
Boy	–0.0612	0.0321*	0.0567	0.0344*
Girl	REF		REF	
Primary carer edu lower secondary	–0.374	0.0497***	–0.342	0.0516***
Primary carer edu higher secondary	–0.212	0.0402***	–0.106	0.0422**
Primary carer edu post-secondary	–0.173	0.0460***	–0.0787	0.0434*
Primary carer edu third level	REF		REF	
Second. carer edu lower secondary	–0.316	0.0516***	–0.211	0.0511***
Second. carer edu higher secondary	–0.122	0.0478***	–0.0661	0.0478
Second. carer edu post-secondary	–0.199	0.0504***	–0.122	0.0550**
Second. carer edu third level	REF		REF	
No Secondary carer	–0.177	0.0671***	–0.194	0.0621***
Second. carer edu not reported	–0.322	0.0783***	–0.222	0.0709***
SC Professional workers	REF		REF	
SC Managerial and technical	–0.0324	0.0461	–0.0642	0.0488
SC Non-manual	–0.125	0.0568**	–0.119	0.0608**
SC Skilled manual	–0.221	0.0628***	–0.170	0.0652***
SC Semi-skilled	–0.0703	0.0706	–0.177	0.0764**
SC Unskilled	–0.160	0.117	–0.139	0.118
SC Unclassified	–0.138	0.0897	–0.180	0.0824**
(Log) Household net equivalised income	0.124	0.0384***	0.0615	0.0333*
Intellectual disability	–1.04	0.0501***	–0.815	0.0546***
Chronic illness or disability	–0.076	0.0487	–0.0924	0.0468**
Time index of survey, child level	–0.000532	0.000255**	–0.000380	0.000252
Constant	–0.557	0.491	–1.32	0.458***
Quality of school computer facilities	Not significant		Not significant	
Computer room in school	Not significant		Not significant	
Computers available in class	Not significant		Not significant	
Frequency of computer use in class	Not significant		Not significant	
N	5,558		5,615	
R^2	0.249		0.175	