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ICT Use at home for school-related tasks: what is the effect on a student's achievement? Empirical evidence from OECD PISA data

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ABSTRACT

In this paper, we have employed data from the OECD's Programme for International Student Assessment (PISA, 2012 edition) on the EU-15 countries in order to investigate the effect of using ICT at home on achievement. By employing Propensity Score Matching, we provide robust evidence that in most countries there is a negative association between using computers intensely for homework and achieving lower test scores across all subjects. Such negative effect affects the achievement of both low- and high-performing students and is robust to a specification that consider unobservable self-sorting of students across schools. Our findings suggest that a more cautious approach should be taken with regards to the wide-spread use of digital innovation as a means to support students' out-of-school work.

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1. Introduction, motivation and research questions

The role of information and communications technologies (ICT), used here to refer to desktop computers, laptops and tablets with or without Internet connection, has gradually expanded in all education-related processes. Today, there is an urgent need to assess how effective ICT is at improving educational outcomes. As highlighted in literature reviews covering empirical studies conducted since the 1980s, the question of evaluating whether ICT has a positive effect on school-leaving rates and test scores is not new. Cheung and Slavin (2013) reviewed 74 studies, finding that educational technology applications generally produced a positive, albeit modest, effect on exam scores. Furthermore, they established that part of the impact of ICT can be linked to two major issues: (i) the role played by student characteristics, and (ii) how ICT tools are specifically designed, developed and implemented.

Recent papers provide empirical evidence showing that these two issues matter significantly when investigating the relationship between ICT and any measure of instructional output (Wittwer and Senkbeil 2008; De Witte and Rogge 2014; Comi et al. 2017). According to Biagi and Loi (2013), macro-level or institutional factors (such as technological infrastructure and training policies for ICT teachers) and meso-level or school characteristics (the attitude of principals/teachers towards ICT and school ICT resources, for example) are likely to affect student computer use within school. However, micro-level features of the actual students (gender, attitudes, ability, age, motivation, etc.) or their family (such as socio-economic background, family structure, ICT equipment at home and parental attitude towards ICT) will, instead, affect how they use computers at home. Combined with the many possible connections between ICT and the learning process, all these factors mean

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Supplemental data for this article can be accessed https://doi.org/10.1080/09645292.2020.1822787 that the evaluation of the impact of ICT on academic achievement is, inevitably, a complex empirical undertaking.

One of the emerging areas of interest concerns the availability and use of ICT at home. This area focuses on investigating whether students who are technologically more active out of school also achieve better school results. It is crucial to understand this effect in order to explore how, and if, technology can help to improve efficiency and fairness in educational outcomes, as well as how in-school versus out-of-school usage shapes student results. Despite the importance of this subject matter, robust research into the topic is still limited. Our study fills this void in the literature by examining the relationship between the use of ICT at home for school-related tasks and student proficiency within the European context. Thus, the aims of our study depart from the goals of traditional literature concerned with how ICT affects student results. Instead, it specifically focuses on investigating how students use computers at home – an issue that is very important in determining particular aspects of the educational production function.

Our paper responds to two research questions:

(a) Is there an association between ICT used at home for school-related purposes and test scores in reading, mathematics and science within a selected group of EU countries and is this correlation uniform or heterogenous across these countries?
(b) Is the impact of such ICT usage uniform across the whole student population (within countries) or does it differ for low- and high-achieving students?

This research uses data from the Organisation for Economic Co-operation and Development (OECD) Programme for International Student Assessment (PISA) 2012 database to investigate whether there is an association between how students use ICT and their test scores in reading, mathematics and science. Our sample contains twelve European Union (EU) countries: Austria, Belgium, Denmark, Finland, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain and Sweden.[1] While the concept of ICT usage[2] covers a range of possible threads, we are primarily interested here in describing the specific role of ICT used at home for educational purposes. The main variable of interest in the PISA dataset is the composite indicator *homsch* or ICT use at home for school-related tasks.

By suggesting that there is a robust relationship between computer (ICT) use and test scores, this paper contributes to the existing literature in a number of ways. Firstly, when exploring the average association of ICT usage on test scores, we also examined whether this potential relationship varies, substantially or otherwise, from country to country. To do this, we retrieved information from many sources of available data beyond single-country analyses based on existing datasets such as PISA and TIMSS (Trends in International Mathematics and Science Study). The institutional reports prepared by the OECD (see, for example, OECD 2015) evidently discuss the results from a cross-national perspective. However, they only provide descriptive analyses. Secondly, we explicitly addressed potential threats to the validity of this study by applying a propensity score matching (PSM) econometric approach. Thirdly, we examined the potentially different ways in which ICT usage is linked to the three subjects tested in PISA: reading, mathematics and science. Most published academic papers focus on only one subject, with a keen preference for mathematics. Our empirical analyses were based on the educated guess that not all subjects benefit equally from the use of computers at home, where an overall picture of such differences is a valuable outcome per se. Fourthly, while it is often argued that ICT usage may produce different effects depending on the level of achievement of individual students, only a few studies cover both the average effect of computer use on student performance and its impact on high- vs low-achieving students (Falck, Mang, and Woessmann 2018). Lastly, this study is one of the few empirical studies that reveal the role played by computer use at home on student results within the European context. Therefore, it can add to comparable literature focusing primarily on the USA (Fairlie and Robinson 2013; Vigdor, Ladd, and Martinez 2014).

When measuring the impact of the variable related to ICT used at home for school-related tasks, our main findings highlight a degree of heterogeneity within the results across countries. When ICT is used for school-related tasks, there is no substantially difference between high-achieving and low-achieving students. Frequent home usage of ICT is detrimental to everyone's results, as measured through OECD PISA test scores in all subjects and for most countries.

The remainder of the paper is organised as follows. The results from a selected list of relevant papers are reviewed in Section 2 in order to outline the gaps addressed in this study. Data are then reported and discussed in Section 3. Our methodological approach and empirical strategy are described in Section 4, reporting the main results. The key findings are discussed in Section 5, which also includes concluding remarks.

2. Literature review

In this section, we critically discuss evidence on the relationship between student ICT use at home for educational purposes and their educational results, measured, for example, by their test scores. We did not set out to prepare a comprehensive survey of the numerous studies regarding the impact of ICT on educational outcomes, as this issue has already been addressed by reviews by Punie, Zinnbauer, and Cabrera (2006), Cox and Marshall (2007) and Bulman and Fairlie (2016). Instead, we intended to ground our work on existing related studies to derive conceptual hypotheses concerning the potential educational impact of using computers at home.

Therefore, we should make a preliminary distinction between the use of computers *at home* and *at school* (Rohatgi, Scherer, and Hatlevik 2016). If the mere exposure to more ICT devices could improve educational productivity, then students who have more and easier access to computers (and related devices) at home should achieve better results (Wainer, Vieira, and Melguizo 2015). Another factor that comes into the equation when ICT is used at home is that teenagers use computers extensively in their social communication practices. It is up to both parents/teachers and schools to instil healthy ICT habits Areepattamannil and Khine (2017), which may then drive student educational achievement in a positive direction. In this review section, we focus on previous literature on the use of computers at home for educational purposes, especially for homework, which is the specific topic investigated in this paper.

One key issue concerns the precise definition of ICT use (or availability) in the context of studies about the determinants of educational results. For example, the OECD uses two indicators relating to computer availability at home to explore how they are actually used. As pointed out by Wittwer and Senkbeil (2008), students using computers are engaged in functions that exert a positive, neutral or even negative impact on their school achievement. For instance, complex Internet searches for information can stimulate their constructive behaviour and skills, while playing videogames or spending too much time online can affect their schoolwork negatively (OECD 2015). That said, the mechanisms behind these effects have yet to be robustly identified. By building upon the concept of opportunity costs to model the effect of ICT use on instruction, Falck, Mang, and Woessmann (2018) made an interesting theoretical contribution in this respect. They found that time spent on learning (during school time, but also at home) is to some extent constrained. Therefore, the choice to spend time on traditional learning activities comes at the expense of using ICT and vice versa.

The literature includes several studies conducted using robust econometric techniques to examine the effect of computers used at school on educational outcomes (Machin, McNally, and Silva 2007; De Witte and Rogge 2014; Fariña et al. 2015; Falck, Mang, and Woessmann 2018), although there is a much smaller body of literature dealing with how computer use at home affects students' results. Bulman and Fairlie (2016) compiled a critical review of the existing evidence in this narrow field. Firstly, they noted that there were disparities among students in terms of their access to and use of technology at home, directing attention towards the need to explore how this factor contributes to educational achievement. They proposed a theoretical framework where the use of computers at home can be beneficial – if used for homework – or negative – if used for gaming, social networking and other leisure activities. When looking at the results of previous studies, the authors warned against applying simplistic regression analysis to assess this effect, because a number of unmeasurable factors may also come into play (for instance, motivation).

The study by Wittwer and Senkbeil (2008) uses traditional statistical modelling to measure the association between the use of computers at home and student performance, in this case with a focus on mathematics. The authors employed a mixed-coefficients multinomial logit model applied to OECD PISA 2003 data for 15-year-old Germans. The results indicated that access to a computer is not associated with higher test scores in mathematics. The study also modelled different categories of students grouped according to how they used computers at home, but again there was found to be no substantial impact. Note that this study is likely to reflect a student selection bias, given that no attempt was made to set up an adequate control group. Other previous studies based on simpler methodological approaches, such as panel models, tend to find that home computers have a positive effect on educational outputs – see, for example, Fairlie, Beltran, and Das (2010), who used administrative data from two US datasets, the 2000–2003 Current Population Survey and the National Longitudinal Survey of Youth 1997.

Because of potential flaws in traditional methodologies, previous empirical studies should be based upon adequate experimental or quasi-experimental designs. The most recent literature, which uses proper methods of this kind, tends to report small or zero effects, with some evidence of potential heterogeneity among findings and more beneficial effects for disadvantaged students. These studies are usually confined to single situations and do not provide an overview of comparable outputs in an international setting. The main contribution of this paper is its attempt to fill this gap by using adequate econometric modelling (based on propensity score matching) in combination with a dataset that compares 15-year-old students from several countries, with the outputs measured using the standardised tests applied in the PISA 2012 framework.

A number of studies provide interesting insight into the topic and inspire the theoretical framework and empirical strategy adopted in this paper. Fairlie, Beltran, and Das (2010) made use of a novel dataset that matches data from the Current Population Survey (CPS) against data from the National Longitudinal Survey of Youth 1997 to demonstrate that there is a positive relationship between students that have access to computers at home and their test scores, even after controlling for their socio-economic status. The authors provide a series of hypotheses that can justify their findings, ranging from higher productivity when doing homework to generally improved IT skills. Fairlie and Robinson (2013) conducted a randomised controlled trial involving more than 1,000 students (grades 6–10) attending 15 schools across California. While they found that having a computer at home did increase students' Internet use and encouraged the use of digital material for schoolwork – certainly aided by the availability of more digital school material –, the results fell short of finding a meaningful association with any output indicators (marks, test scores, credits earned, etc.).

Another interesting study was conducted by Fariña et al. (2015). The authors used data on 15-year-old students in several countries (Chile, Portugal, Spain and Uruguay) extracted from the OECD PISA 2009 database to investigate whether using computers (at home) for reading had an impact on the students' academic scores. They were aware of endogeneity problems and therefore employed a two-stage IV regression to compute the probability of students using computers for reading books and other material online. After accounting for endogeneity, the results found no association between reading online at home and scores in reading literacy. Vigdor, Ladd, and Martinez (2014) explored a database about students in North Carolina state schools (grades 5–8) in 2000–2005. Their econometric analysis was based on within-students estimates (analysed separately by subject) and revealed that an increase in a student's access to ICT at home was associated with a small but significant decline in his or her test scores. In their conclusions, they claimed that the use of computers at home could potentially have an effect on a series of aspects that were not, however, captured by test scores. Thus, there were no data for testing this eventuality.

Fairlie and Kalil (2017) conducted a randomised controlled trial where they provided to a group of Californian students (grades 6–10) with computers for use at home with the specific aim of testing the potential effect of their use on the students' social development. They measured this construct through a questionnaire designed to capture aspects such as number of friends, how often students hung out with friends, involvement in sports teams and other clubs, etc. This analysis was groundbreaking for its novel investigation of the impact of computers at home on other areas of students' lives and not just on their academic results. Interestingly, their findings revealed that children with computers at home communicated with more friends outside school time, and the same children also spent more time in person with their friends. More broadly, there was no evidence that computers at home had any negative effects on the various dimensions of social engagement.

After looking at how computer and/or ICT access and use at home can affect educational outputs, we can conclude that the existing evidence is, at best, mixed. Nevertheless, the literature is still in its infancy and focuses on only a few countries. Our paper belongs to the relatively recent stream of studies that adopt a robust econometric methodology to study this topic, and it contributes to the literature by providing evidence on a group of EU15 countries.

3. Data, variable selection and descriptive statistics

This study used data from OECD PISA (Programme for International Student Assessment), a large-scale international survey that measures the knowledge and skills of representative samples of 15-year-old students in more than 60 education systems worldwide every three years. Since 2000, PISA has been assessing student performance in reading, mathematics and science, with one specific subject being assessed in greater depth on each occasion. The research presented in this study focused on PISA 2012 data. Of the 65 countries taking part in the 2012 wave, 34 were OECD countries, with mathematics being the subject under closer scrutiny. For the reasons outlined below, this research includes data and results from 12 of the EU15 countries.

3.1. Selection of variables for the empirical analysis

PISA uses student and school questionnaires to collect information on various aspects related to the students' home and family background, as well as to the school environment, in all PISA participating countries. PISA also offers some interesting variables in connection with ICT at student level, and these proved very useful for the purposes of our research. These variables were extrapolated from the 'ICT familiarity questionnaire', an optional survey included in PISA. Unfortunately, the survey was not administered to all participating countries, a factor that determined the selection of countries to be examined in our empirical analysis. We originally intended to analyse all EU15 countries, but we were unable to include France, the UK and Luxembourg in our study because critical ICT-related information was missing. Our final group of EU countries consisted of Austria, Belgium, Denmark, Finland, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain and Sweden.

Going into the detail of the ICT questions and variables, we worked mainly with the variables *homsch* (ICT use at home for school-related tasks), which was our main variable of interest, *ictsch* (ICT availability at school) and *entuse* (ICT entertainment use). These, and the other five, ICT variables are continuously scaled indices provided in the PISA database. The indices were computed by the OECD on the basis of questions answered by students in response to the ICT familiarity questionnaire (OECD 2014). The *ictsch* variable was built from seven items, each associated to three possible response categories: 'Yes, and I use it', 'Yes, but I don't use it' and 'No'. The distribution of item difficulties and step difficulties used to create this index account for the fact that tablets and e-book readers are not used in schools as commonly as desktop computers and Internet connections. Ten items were used to determine the 'ICT for entertainment' variable, *entuse*, covering the many ways ICT can be used for fun (from playing video games to going on social networks or browsing the Internet for fun). Lastly, seven item parameters were used to gather information on the use of ICT at home for school-related tasks, *homsch*, which is our variable of interest and refers to tasks like communicating with teachers or peers, doing homework and searching for material to include in presentations. The responses to questions about these items fell into categories ranging from 'Never or hardly ever', 'Once or twice a month', '"Once or twice a week' to 'Almost every day' and 'Every day'.

The other variables used in the analysis refer to controls for students' personal and family background, such as gender, immigrant status, family structure, pre-primary school attendance (ISCED 0), month of birth, grade retention, absenteeism, and the PISA index of economic, social and cultural status (ESCS) as a proxy for family socio-economic status (SES). At school level, we introduced the variables for school type, location, classroom size, student absenteeism as reported by the school principal, disciplinary climate at school and the school-level ESCS index as a proxy for the school's mean SES. It was crucial to control for some school-level indicators to account for the possibility of school policies, ultimately dependent on some of the observable school characteristics, having influenced the role of ICT use at home. Lastly, we applied the test scores in mathematics, reading and science to account for student achievement. We converted these scores into z-scores for the 12 countries in our study, where the mean score was 0 and the standard deviation was 1 (Brown et al. 2007). These calculations accounted for the first plausible value for each score, as the results for the other plausible values had been found to be very similar.[3] Table 1 lists the definitions and labels of these variables and their response categories.

3.2. Descriptive evidence about ICT use and its relationship with academic performance

The descriptive statistics of the variables used in the analysis are shown in Table 2, detailed country by country. There are differences in sample size between countries, and Italy and Spain have the highest number of sampled students.[4] At first glance, the results suggest that the variables are heterogeneous from country to country. Students from Belgium, Finland, Germany, Ireland and the Netherlands have higher average PISA scores in all the tests, while students from Greece and Sweden show the lowest PISA score results in our analysed sample.

Looking at the three ICT indices, we find that there are clear differences between countries. The average values for these indices are high for Danish students, indicating that they are the top users of ICT both at school and at home, with a slightly lower use for entertainment purposes. The values of these variables for other countries are much lower, and all values are negative in the case of Ireland. Apart from this, there is no clear pattern. Students from some countries report a high use of ICT at home, yet low usage for entertainment (the Netherlands) or a high use for entertainment and low for schoolwork (Italy). The availability of ICT devices at school also differs across countries: the value of this index is negative for Germany, Ireland Spain and, more notably, Belgium and Italy. At the opposite end of the scale, the values for Denmark, Finland, the Netherlands and Sweden are all very positive.

Focusing on the correlation between the ICT variables and test scores, Table 3 shows that there is marked heterogeneity across countries. There is a negative (and significant) relationship between the availability of ICT at school and student scores in mathematics, science and reading in Ireland, Germany, the Netherlands and Portugal, but the values are less than 0.20. Although home use of ICT for school-related tasks is found to correlate positively with test scores in Austria and the Netherlands and negatively in Greece, the correlation is negligible (and not statistically significant) in most countries. In the case of ICT used for entertainment (*entuse*), there is no correlation between this variable and student test scores – either in terms of the value of its coefficient or its significance – in any country, except for Finland, where the correlation is negative. Lastly, students using ICT for entertainment also appear to use it for school-related tasks, as shown in the last column (correlation between *entuse* and *homsch*), with significantly high values for the coefficient of correlation (this relationship is more pronounced for Greece and Portugal).

These correlations can, however, be confounded by the presence of structural differences in student characteristics. In order to explore a more robust relationship between the use of ICT at home by students for educational purposes and their test scores, it is necessary to properly control for (observable) differences across students. Section 4 describes the methodological, econometric approach employed in this paper to pursue this objective.

Table 1. Variables and definitions.

	Variable	Definition
Student level	z_pv1math	Plausible value 1 (z-score), maths
	z_pv1scie	Plausible value 1 (z-score), science
	z_pv1read	Plausible value 1 (z-score), reading
	homsch	ICT Use at Home for School-related Tasks (index)
	entuse	ICT Entertainment Use (index)
	ictsch	Availability of ICT at school (index)
	gender	Student's gender: Girl (dummy)
	immigrant	Student's immigrant status: 1st generation (dummy)
	preprimary	Student's attendance at ISCED0: Yes (dummy)
	famst	Family structure: Traditional (dummy)
	month_birth	Month of birth
	mothedu	Level of studies of the mother: superior (dummy)
	ownroom	Student has his/her own room (dummy)
	books200	More than 200 books at home (dummy)
	repeat_once	Repeated some course in primary or secondary: Yes (dummy)
	truan_some	Skip some classes within school day: Yes (dummy)
	grade	Grade compared to modal grade in country (from −3 to 2)
	ESCS	Index of economic, social and cultural status (index)
	IC09Q01	Browsing the internet for schoolwork
	IC09Q02	Using email for communication with other students for schoolwork
	IC09Q03	Using email for communication with teachers for schoolwork
	IC09Q04	Downloading, upload or browse material form my school's website
	IC09Q05	Checking the school website for announcements, e.g. absence of teachers
	IC09Q06	Doing homework on the computer
	IC09Q07	Sharing school related materials with other students
School level	private	Type of school: private (dummy)
	rural	School location: rural area (dummy)
	disclima_m	Disciplinary climate (index)
	clsize_m	Classroom size
	truan	Students truancy (index)
	ESCS_m	Index of economic, social and cultural status (index)
	AUT	Austria
	BEL	Belgium
	DEU	Germany
Country level	DNK	Denmark
	ESP	Spain
	FIN	Finland
	GRC	Greece
	IRL	Ireland
	ITA	Italy
	NLD	Netherlands
	PRT	Portugal
	SWE	Sweden

4. Methodological approach and results

In this paper, we used propensity score matching (PSM) to conduct a robust analysis of the relationship between ICT used by students at home for educational purposes (*homsch*) and their test scores, as detailed below. We are aware that PSM is not a perfect method for inferring the causal effects of the variable of interest (use of computers at home) and associated output (academic achievement). Given that, in this case, we cannot apply more sophisticated quasi-experimental techniques (such as instrument variables or regression discontinuity), we calculated the most robust estimation possible with the available data.[5] Hence, all the results should be interpreted as statistically robust, but not necessarily causal. Anyway, the associations reported in this paper are informative for policy suggestions.

Table 2. Summary statistics, by country.

	AUT					BEL					DEU					DNK				
Variables	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.
z_pv1math	4,755	0.07	0.98	−3.10	3.80	8,597	0.18	1.09	−3.54	3.55	5,001	0.16	1.02	−3.30	3.17	7,481	0.01	0.87	−3.56	2.68
z_pv1scie	4,755	−0.02	0.98	−3.75	3.59	8,597	−0.01	1.07	−4.76	3.32	5,001	0.18	1.00	−3.68	2.92	7,481	−0.09	0.98	−4.21	2.96
z_pv1read	4,755	−0.10	0.97	−3.37	2.96	8,597	0.11	1.08	−4.56	3.15	5,001	0.10	0.96	−3.48	2.70	7,481	−0.02	0.90	−3.90	2.59
homsch	4,614	−0.01	0.94	−2.44	3.73	7,742	−0.04	0.96	−2.44	3.73	4,082	−0.14	0.80	−2.44	3.73	6,462	0.43	0.76	−2.44	3.73
entuse	4,629	−0.06	0.85	−3.97	4.43	7,772	0.02	0.92	−3.97	4.43	4,094	−0.07	0.82	−3.97	4.43	6,589	0.24	0.81	−3.97	4.43
ictsch	4,662	0.10	0.79	−2.80	2.83	7,813	−0.33	1.11	−2.80	2.83	4,115	−0.13	0.90	−2.80	2.83	6,721	0.81	0.69	−2.80	2.83
gender	4,755	0.50	0.50	0.00	1.00	8,597	0.50	0.50	0.00	1.00	5,001	0.49	0.50	0.00	1.00	7,481	0.50	0.50	0.00	1.00
immigrant	4,695	0.06	0.23	0.00	1.00	8,382	0.07	0.26	0.00	1.00	4,006	0.03	0.17	0.00	1.00	7,311	0.03	0.17	0.00	1.00
preprimary	4,730	0.98	0.13	0.00	1.00	8,467	0.98	0.15	0.00	1.00	4,258	0.97	0.18	0.00	1.00	7,324	0.99	0.10	0.00	1.00
famst	4,438	0.86	0.35	0.00	1.00	8,012	0.86	0.35	0.00	1.00	3,974	0.86	0.35	0.00	1.00	6,976	0.84	0.36	0.00	1.00
month_birth	4,755	6.66	3.46	1.00	12.00	8,597	6.52	3.39	1.00	12.00	5,001	6.66	3.41	1.00	12.00	7,481	6.56	3.42	1.00	12.00
repeat_once	4,514	0.07	0.25	0.00	1.00	7,375	0.21	0.41	0.00	1.00	3,679	0.08	0.28	0.00	1.00	7,061	0.03	0.16	0.00	1.00
truan_some	4,716	0.13	0.33	0.00	1.00	8,491	0.08	0.27	0.00	1.00	4,307	0.10	0.30	0.00	1.00	7,378	0.16	0.37	0.00	1.00
mothedu	4,525	0.27	0.44	0.00	1.00	7,957	0.54	0.50	0.00	1.00	3,782	0.30	0.46	0.00	1.00	6,993	0.60	0.49	0.00	1.00
ownroom	4,719	0.91	0.28	0.00	1.00	8,458	0.92	0.27	0.00	1.00	4,220	0.94	0.24	0.00	1.00	7,365	0.97	0.16	0.00	1.00
book200	4,652	0.23	0.42	0.00	1.00	8,370	0.21	0.41	0.00	1.00	4,158	0.29	0.45	0.00	1.00	7,225	0.21	0.41	0.00	1.00
ESCS	4,703	0.08	0.85	−3.41	2.60	8,412	0.15	0.91	−5.05	2.71	4,141	0.19	0.93	−3.20	3.01	7,298	0.43	0.84	−3.49	2.75
grade	4,755	−0.54	0.61	−3	2	8,483	−0.45	0.67	−3	2	5,001	0.27	0.67	−2	2	7,481	−0.17	0.40	−2	1
private	4,748	0.09	0.28	0.00	1.00	8,471	0.68	0.46	0.00	1.00	4,356	0.06	0.25	0.00	1.00	6,912	0.24	0.43	0.00	1.00
rural	4,754	0.43	0.50	0.00	1.00	8,471	0.25	0.43	0.00	1.00	4,356	0.32	0.47	0.00	1.00	6,912	0.51	0.50	0.00	1.00
disclima_m	4,734	0.20	0.47	−1.90	1.85	8,380	0.04	0.41	−2.04	1.85	4,852	−0.04	0.41	−1.90	1.01	7,466	−0.01	0.39	−2.48	1.40
clsize_m	4,698	24.34	8.63	13.00	53.00	8,327	20.12	4.09	13.00	28.00	4,356	25.25	4.79	13.00	53.00	6,896	21.18	3.38	13.00	53.00
truan	4,751	0.44	0.50	0.00	1.00	8,432	0.30	0.46	0.00	1.00	4,356	0.20	0.40	0.00	1.00	6,536	0.33	0.47	0.00	1.00
ESCS_m	4,755	0.08	0.49	−1.80	1.33	8,597	0.14	0.51	−2.35	1.54	4,991	0.18	0.53	−1.36	1.51	7,481	0.40	0.40	−0.94	1.50

	ESP					FIN					GRC					IRL				
	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.
z_pv1math	25,313	−0.15	0.93	−4.25	3.32	8,829	0.22	0.91	−3.49	2.88	5,125	−0.48	0.93	−3.40	2.51	5,016	0.03	0.90	−3.49	3.42
z_pv1scie	25,313	−0.11	0.91	−5.15	3.35	8,829	0.42	0.99	−4.02	3.49	5,125	−0.42	0.94	−4.36	2.72	5,016	0.16	0.97	−2.44	3.73
z_pv1read	25,313	−0.11	0.97	−4.47	3.45	8,829	0.28	1.00	−4.48	3.48	5,125	−0.23	1.04	−5.24	3.17	5,016	0.26	0.91	−3.97	4.43
homsch	23,803	0.07	0.90	−2.44	3.73	8,450	−0.76	0.85	−2.44	3.73	4,951	0.00	1.18	−2.44	3.73	4,889	−0.60	0.92	−1.61	4.11
entuse	24,090	0.02	0.84	−3.97	4.43	8,504	0.16	0.72	−3.97	4.43	4,993	0.16	1.25	−3.97	4.43	4,913	−0.30	0.85	0.00	1.00
ictsch	24,411	−0.15	0.94	−2.80	2.83	8,513	0.28	0.77	−2.80	2.83	5,007	0.17	1.05	−2.80	2.83	4,935	−0.08	0.84	−2.80	2.83
gender	25,313	0.49	0.50	0.00	1.00	8,829	0.49	0.50	0.00	1.00	5,125	0.50	0.50	0.00	1.00	5,016	0.49	0.50	0.00	1.00
immigrant	24,824	0.08	0.28	0.00	1.00	8,676	0.02	0.14	0.00	1.00	5,032	0.06	0.24	0.00	1.00	4,914	0.09	0.28	0.00	1.00
preprimary	24,934	0.94	0.24	0.00	1.00	8,694	0.98	0.16	0.00	1.00	5,089	0.95	0.21	0.00	1.00	4,960	0.86	0.34	1.00	12.00
famst	23,797	0.89	0.31	0.00	1.00	8,081	0.83	0.37	0.00	1.00	4,834	0.90	0.30	0.00	1.00	4,594	0.89	0.32	0.00	1.00
month_birth	25,313	6.56	3.46	1.00	12.00	8,829	6.50	3.39	1.00	12.00	5,125	6.49	3.34	1.00	12.00	5,016	6.61	3.42	0.00	1.00
repeat_once	22,451	0.25	0.43	0.00	1.00	8,442	0.03	0.16	0.00	1.00	4,956	0.02	0.15	0.00	1.00	4,601	0.03	0.18	−3.42	2.56
truan_some	25,113	0.32	0.47	0.00	1.00	8,649	0.16	0.36	0.00	1.00	5,095	0.42	0.49	0.00	1.00	4,984	0.12	0.33	0.00	1.00
mothedu	24,515	0.36	0.48	0.00	1.00	8,482	0.72	0.45	0.00	1.00	5,028	0.41	0.49	0.00	1.00	4,901	0.43	0.50	0.00	1.00

ownroom	25,036	0.87	0.33	0.00	1.00	8,689	0.94	0.24	0.00	1.00	5,045	0.74	0.44	0.00	1.00	4,951	0.90	0.31	0.00	1.00
book200	24,932	0.23	0.42	0.00	1.00	8,658	0.21	0.41	0.00	1.00	5,060	0.19	0.39	0.00	1.00	4,961	0.22	0.41	0.00	1.00
ESCS	25,121	−0.19	1.03	−5.30	2.73	8,685	0.36	0.77	−4.22	2.58	5,091	−0.06	1.00	−3.84	3.27	4,973	0.13	0.85	0.00	1.00
grade	25,313	−0.44	0.67	−3	1	8,829	−0.15	0.39	−2	2	5,125	−0.07	0.33	−3	0	5,016	0.49	0.75	−2	2
private	25,287	0.33	0.47	0.00	1.00	8,756	0.03	0.18	0.00	1.00	5,118	0.06	0.24	0.00	1.00	5,016	0.58	0.49	−1.07	1.11
rural	25,087	0.28	0.45	0.00	1.00	8,756	0.38	0.48	0.00	1.00	5,117	0.28	0.45	0.00	1.00	5,016	0.49	0.50	13.00	28.00
disclima_m	25,309	−0.04	0.43	−1.50	1.52	8,779	−0.32	0.30	−1.11	1.52	5,123	−0.24	0.37	−1.35	0.78	5,016	0.13	0.43	0.00	1.00
clsize_m	22,276	25.46	5.31	13.00	48.00	8,711	19.87	3.16	13.00	28.00	5,125	25.67	8.04	13.00	53.00	4,594	24.90	3.44	−0.88	1.12
truan	24,519	0.20	0.40	0.00	1.00	8,756	0.48	0.50	0.00	1.00	5,125	0.31	0.46	0.00	1.00	4,566	0.47	0.50	0.00	1.00
ESCS_m	25,313	−0.18	0.54	−2.36	1.42	8,829	0.32	0.28	−1.92	1.36	5,125	−0.07	0.56	−2.17	1.41	5,016	0.13	0.41	−0.88	1.12
			ITA					NLD					PRT					SWE		
	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.	N	Mean	S.D.	Min.	Max.
z_pv1math	31,073	−0.15	0.98	−4.14	3.32	4,460	0.25	0.97	−3.15	3.39	5,722	−0.13	1.00	−3.72	3.07	4,736	−0.22	0.97	−3.56	2.92
z_pv1scie	31,073	−0.14	0.98	−4.24	3.18	4,460	0.16	1.00	−3.57	3.33	5,722	−0.19	0.94	−3.33	2.64	4,736	−0.24	1.06	−3.99	3.06
z_pv1read	31,073	−0.09	1.02	−4.92	3.93	4,460	0.13	0.98	−4.71	2.72	5,722	−0.11	0.99	−4.19	2.56	4,736	−0.16	1.13	−4.69	3.47
homsch	28,688	−0.10	1.04	−2.44	3.73	4,239	0.44	0.70	−2.44	3.73	5,532	0.30	0.94	−2.44	3.73	4,326	−0.09	1.01	−2.44	3.73
entuse	29,007	0.11	0.99	−3.97	4.43	4,245	−0.01	0.69	−3.97	4.43	5,570	0.20	1.04	−3.97	4.43	4,385	0.08	0.97	−3.97	4.43
ictsch	29,509	−0.38	1.18	−2.80	2.83	4,250	0.41	0.67	−2.80	2.83	5,581	0.15	0.82	−2.80	2.83	4,438	0.35	0.78	−2.80	2.83
gender	31,073	0.48	0.50	0.00	1.00	4,460	0.49	0.50	0.00	1.00	5,722	0.49	0.50	0.00	1.00	4,736	0.50	0.50	0.00	1.00
immigrant	30,276	0.05	0.23	0.00	1.00	4,360	0.03	0.16	0.00	1.00	5,563	0.04	0.19	0.00	1.00	4,612	0.06	0.24	0.00	1.00
preprimary	30,810	0.96	0.20	0.00	1.00	4,389	0.98	0.15	0.00	1.00	5,575	0.85	0.36	0.00	1.00	4,625	0.92	0.27	0.00	1.00
famst	29,719	0.90	0.30	0.00	1.00	4,227	0.88	0.32	0.00	1.00	5,193	0.86	0.35	0.00	1.00	4,289	0.90	0.30	0.00	1.00
month_birth	31,073	6.53	3.39	1.00	12.00	4,460	6.71	3.43	1.00	12.00	5,722	6.62	3.46	1.00	12.00	4,736	6.28	3.35	1.00	12.00
repeat_once	27,902	0.04	0.19	0.00	1.00	4,029	0.22	0.42	0.00	1.00	4,219	0.14	0.35	0.00	1.00	4,489	0.02	0.14	0.00	1.00
truan_some	30,829	0.35	0.48	0.00	1.00	4,401	0.11	0.31	0.00	1.00	5,630	0.29	0.45	0.00	1.00	4,624	0.20	0.40	0.00	1.00
mothedu	30,257	0.29	0.45	0.00	1.00	4,256	0.46	0.50	0.00	1.00	5,503	0.22	0.42	0.00	1.00	4,414	0.62	0.49	0.00	1.00
ownroom	30,816	0.68	0.47	0.00	1.00	4,386	0.98	0.14	0.00	1.00	5,606	0.80	0.40	0.00	1.00	4,638	0.96	0.20	0.00	1.00
book200	30,602	0.20	0.40	0.00	1.00	4,358	0.20	0.40	0.00	1.00	5,600	0.14	0.35	0.00	1.00	4,590	0.26	0.44	0.00	1.00
ESCS	30,873	−0.05	0.97	−4.70	2.70	4,376	0.23	0.78	−3.49	2.59	5,623	−0.48	1.19	−3.87	2.70	4,616	0.28	0.82	−3.23	2.92
grade	31,073	−0.19	0.51	−3	2	4,460	0.47	0.57	−1	2	5,209	−0.52	0.75	−3	1	4,736	−0.02	0.25	−2	1
private	29,250	0.05	0.23	0.00	1.00	4,033	0.68	0.47	0.00	1.00	5,667	0.10	0.30	0.00	1.00	4,736	0.14	0.35	0.00	1.00
rural	29,018	0.18	0.38	0.00	1.00	4,033	0.18	0.38	0.00	1.00	5,667	0.41	0.49	0.00	1.00	4,736	0.38	0.48	0.00	1.00
disclima_m	31,062	−0.04	0.46	−1.90	1.85	4,333	−0.16	0.35	−1.23	1.21	5,722	0.01	0.36	−1.11	1.85	4,733	−0.21	0.36	−1.39	1.52
clsize_m	28,932	25.76	9.22	13.00	53.00	4,003	25.18	3.76	13.00	28.00	5,505	24.06	5.47	13.00	53.00	4,736	23.57	3.76	13.00	33.00
truan	27,513	0.35	0.48	0.00	1.00	4,033	0.25	0.44	0.00	1.00	5,529	0.33	0.47	0.00	1.00	4,683	0.29	0.45	0.00	1.00
ESCS_m	31,073	−0.05	0.52	−2.58	1.58	4,460	0.23	0.36	−0.78	1.21	5,722	−0.48	0.69	−1.63	1.47	4,735	0.27	0.34	−1.62	1.31

Table 3. Correlation of ICT variables and test scores, by country.

	PV1MATHS			PV1SCIENCE			PV1READ			
	ictsch	homsch	entuse	ictsch	homsch	entuse	ictsch	homsch	entuse	homsch/entuse
AUT	−0.0385***	0.134***	−0.061***	−0.0473***	0.136***	−0.060***	−0.0458***	0.154***	−0.122***	0.2626***
BEL	−0.0198***	0.085***	−0.046***	−0.0253***	0.048***	−0.046***	−0.0799***	0.047***	−0.060***	0.3089***
DEU	−0.1458***	0.007	−0.097***	−0.1552***	0.006	−0.101***	−0.1506***	0.025	−0.159***	0.3178***
DNK	−0.1375***	0.036***	−0.005	−0.1201***	0.049***	0.009	−0.1634***	0.045***	−0.068***	0.3365***
ESP	−0.0598***	−0.011***	0.051***	−0.0778***	−0.019***	0.064***	−0.0696***	−0.004	0.029***	0.3417***
FIN	−0.0572***	0.005	−0.110***	−0.0534***	−0.021	−0.113***	−0.0316***	0.013	−0.135***	0.2277***
GRC	−0.1095***	−0.132***	0.005	−0.1263***	−0.148***	0.016	−0.1344***	−0.181***	0.001	0.4796***
IRL	−0.1521***	−0.021	−0.009	−0.1612***	−0.012	−0.015	−0.1792***	−0.019	−0.038***	0.3735***
ITA	−0.0888***	0.021***	0.026***	−0.1044***	0.004***	0.025***	−0.1521***	0.007	0.004	0.3512***
NLD	−0.1644***	0.192***	0.023	−0.1537***	0.207***	0.040***	−0.1985***	0.213***	−0.001	0.3105***
PRT	−0.1412***	0.013	0.030***	−0.1497***	0.006	0.031***	−0.1998***	−0.013	−0.019	0.4142***
SWE	−0.0827***	−0.010	−0.065***	−0.0991***	−0.014	−0.028***	−0.0832***	0.025***	−0.100***	0.3505***

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

4.1. Propensity score matching: methodology

The PSM methodology was implemented as a four-step process. Firstly, the student sample was split into two groups. In other works in the educational field, this division was made based on a clear 'treatment' related to the research question, such as attendance of a state vs a private school (Dronkers and Avram 2010; Mancebón et al. 2018); nuclear families vs non-nuclear families (Santín and Sicilia 2016); level of openness in inquiry teaching (Jiang and McComas 2015); academic and vocational tracks as reflecting students' educational expectations (Lee 2014); perceived competition among schools (Agasisti and Murtinu 2012), etc. In our case, this was not a straightforward choice, as we were analysing a continuous variable (the *homsch* index) rather than two real groups 'treated' in completely different ways. Therefore, we decided to create a treatment or experimental group (EG), defined as the top users of ICT at home, and a control group (CG), containing all the other students. We divided students into the two groups on the basis of their responses to the PISA survey question about how often they used ICT at home. Students were defined as 'treated' if they belonged to the first quartile (25%) of the distribution of the variable of interest (*homsch*). Note that the students in the control and treatment groups could potentially behave very similarly in terms of their use of computers at home (our variable of interest), in which case the treatment could turn out to be too artificial and be unable to distinguish between individuals. We check whether this problem arises in our work. Table A1 and Figure A2 in the Appendix show that this is actually not the case here, as there is a clear difference between the values of the *homsch* indicator for the treatment and control groups across all the countries under analysis. In addition, we also performed some robustness tests to analyse whether results change when adopting different threshold for defining the treatment; as the results are very similar, we do not report them here – but are available on request from the authors.

Secondly, we then calculated the selection equation, which was used to calculate the propensity score, i.e. a regression that calculates the probability of a student belonging to the experimental or control group, given his/her observable characteristics. In terms of variable selection, we included all the variables that can simultaneously influence the ICT variable and student test scores (Caliendo and Kopeinig 2008), these being the characteristics at student and school level described in Table 1 and reported above.

Thirdly, we balanced both samples (treatment and control groups) of students with the propensity score indicator. According to the so-called balancing property, observations with the same propensity score must have the same distribution of the observed covariates after being matched.

Finally, we went ahead with the matching. To do this, we calculated the differences in test scores between the two (experimental and control) groups of students by matching 'treated' students with their 'non-treated' counterparts, i.e. students with the most similar propensity scores. As shown in Figure A1 of the Appendix, the students' observable characteristics are well balanced after calculating the propensity scores; note the level of bias reduction which is substantial and crucial for the validity of the empirical strategy. Table A1 (also in the Appendix) confirms that there are no statistical differences between the treated and control students, once the propensity score procedure has been implemented.

All the estimations were carried out by clustering standard errors by school in order to account for the possibility that the use of computers at home for schooling purposes was actually influenced by policies or recommendations formulated at school level. Nonetheless, the potential role of school factors deserves further attention. While the main baseline results presented in this paper (Section 4.2) refer to the model described above, we also produced a number of additional analyses and robustness checks that explored different versions, specifications and assumptions related to our treatment variable in order to examine the potential role of unobservable factors at school level (Section 4.3). In fact, we decided to run a stratified PSM, with clustering by schools (Arpino and Cannas 2016). This is quite a novel estimation approach within the family of PSM. However, the application of this technique can lead to a reduction in the bias caused by unmeasured cluster-level variables when the matching takes place between similar individuals. In this way, we would only be matching students within the same school, ensuring that they have been educated within the same environment. We used the preferential within-cluster (schools) approach.

4.2. Baseline results

Before moving on to the results of propensity score matching, we investigated whether there were differences across countries that might justify separate analyses by country or whether it made more sense to run the analysis on the pooled data. For this purpose, we employed a simple OLS model where the test scores were regressed against the set of covariates described above, including country dummies that interact with the treatment variable (*homsch*). The regression also included school fixed effects in order to control for unobservable structural differences in school quality. Table 4 reports the results. Almost all these interactions are statistically significant. This proves that it was necessary to conduct analyses separately by country. Note that, although the coefficients were negative in some cases and positive in others, they are not regarded as robust, as they do not explicitly consider differences between treatment and control groups. The robust analysis was conducted later using propensity score matching.

Another preliminary analysis consisted of taking the seven items making up *homsch* separately. The results are shown in Table A2 of the Appendix. The evidence shows that some components appear to be positively correlated with test scores (for example, IC09Q01 – browsing the Internet for schoolwork), while others correlate negatively (for example, IC09Q02 – using email for communicating with other students for schoolwork). Like the framework proposed by Falck, Mang, and Woessmann (2018), some operations could be productive, whereas others are not. In this paper, however, we focus on the overall average coefficients. In the remainder of the analysis, therefore, we employed the synthetic *homsch* indicator instead of its components.

Table 5 reports the first (baseline) results of the propensity score matching estimation. This table shows the difference in average z-scores (standardised scores) for mathematics, science and reading for the EG (top users, treatment group) and the CG (non-top users, control group) across countries. We replicated all the PSM calculations for two additional subsamples, the top performers (second column) and the bottom performers (third column). These subsamples were defined according to whether they belonged to the first or the last quartile of the test score distribution. The aim was to test whether the association between the use of ICT at home and performance could differ across the entire distribution, as well as for the best- and worse-scoring students (see the second research question in the Introduction).

For simplicity's sake, we start by discussing the results for mathematics and then set out the differences that emerged for science and reading. For the total sample, we found no significant differences between the two groups for Austria, Denmark, the Netherlands, Portugal and Sweden, that is, the use of ICT at home has no associations with student scores. Contrary to the findings for other countries, the results show that frequent ICT use does affect students' mathematics marks at Belgian schools. When focusing on top and bottom performers, the results change slightly. Only in Denmark (followed closely by Sweden) was there found to be no relationship between ICT and test scores in both the top- and the bottom-performing groups, meaning that the use of ICT at home does not play a major part in explaining the differing association of ICT with scores across the distribution of student performance. In another group of countries, there was a larger average negative coefficient for top and bottom performers. These are Finland, Greece, Ireland, Italy, Spain and, above all, Germany, the country with the highest negative value for this association. *The implication is that the use of ICT at home for school-related tasks results in the average student achieving lower scores and that this negative association is more pronounced for low achievers* and, even more so at the other end of the scale, for high achievers. In Portugal, the relationship was significant for both top and bottom performers, being worse for low-achieving students. The exact opposite occurs in the Netherlands, where ICT use for homework appears to benefit the low achievers. In Belgium, ICT at home for schoolwork is beneficial, above all, for low-achieving students, but also for the top and

Table 4. OLS regression of test scores for all countries, school and country fixed effects, interaction of *homsch* with country fixed effects.

Variables	(1) Mathematics	(2) Science	(3) Reading
gender	−0.266***	−0.130***	0.282***
	(0.0102)	(0.0105)	(0.00978)
immigrant	−0.159***	−0.196***	−0.209***
	(0.0230)	(0.0241)	(0.0248)
preprimary_no	0.110***	0.0986***	0.0636***
	(0.0244)	(0.0260)	(0.0241)
famst	−0.00249	−0.0103	−0.0271*
	(0.0158)	(0.0155)	(0.0150)
month_birth	−0.0141***	−0.0114***	−0.0117***
	(0.00148)	(0.00143)	(0.00132)
repeat_once	−0.546***	−0.462***	−0.522***
	(0.0200)	(0.0209)	(0.0197)
truan_someclass	−0.179***	−0.176***	−0.135***
	(0.0130)	(0.0127)	(0.0126)
mothedu	−0.108***	−0.113***	−0.0793***
	(0.0126)	(0.0124)	(0.0119)
ownroom	0.0473***	0.0514***	0.00314
	(0.0160)	(0.0156)	(0.0147)
book200	0.288***	0.310***	0.264***
	(0.0141)	(0.0137)	(0.0123)
usesch	−0.0904***	−0.0942***	−0.100***
	(0.00708)	(0.00700)	(0.00677)
escs	0.114***	0.118***	0.0985***
	(0.00698)	(0.00701)	(0.00663)
private	0.0278	−0.00794	0.0199
	(0.0247)	(0.0252)	(0.0242)
rural	0.0146	0.00336	−0.0361
	(0.0236)	(0.0242)	(0.0231)
disclima_m	0.253***	0.218***	0.220***
	(0.0229)	(0.0226)	(0.0220)
clsize_m	0.00397***	0.00483***	0.00516***
	(0.00143)	(0.00147)	(0.00140)
truan	−0.133***	−0.137***	−0.124***
	(0.0241)	(0.0238)	(0.0228)
escs_m	0.514***	0.471***	0.474***
	(0.0229)	(0.0230)	(0.0208)
Homsch*AUT	0.0819***	0.0773***	0.0785***
	(0.0217)	(0.0206)	(0.0214)
Homsch*BEL	0.0748***	0.0274*	0.0236
	(0.0185)	(0.0158)	(0.0166)
Homsch*DEU	−0.0840***	−0.0919***	−0.0458**
	(0.0284)	(0.0255)	(0.0231)
Homsch*DNK	−0.114***	−0.111***	−0.0940***
	(0.0227)	(0.0288)	(0.0279)
Homsch*ESP	−0.0291**	−0.0272*	−0.0247*
	(0.0130)	(0.0151)	(0.0148)
Homsch*FIN	−0.0836***	−0.238***	−0.123***
	(0.0170)	(0.0185)	(0.0191)
Homsch*GRC	−0.0756***	−0.0814***	−0.106***
	(0.0136)	(0.0142)	(0.0130)
Homsch*IRL	0.0826***	−0.00291	−0.0589***
	(0.0171)	(0.0182)	(0.0175)
Homsch*ITA	−0.00283	−0.0125	−0.0145
	(0.01000)	(0.0107)	(0.0101)
Homsch*NLD	0.255***	0.224***	0.181***
	(0.0362)	(0.0352)	(0.0309)
	(1)	(2)	(3)
VARIABLES	Mathematics	Science	Reading
Homsch*PRT	0.140***	0.0925***	0.0991***
	(0.0224)	(0.0212)	(0.0234)
Homsch*SWE	−0.0130	−0.00857	0.0393

(*Continued*)

Table 4. Continued.

Variables	(1) Mathematics	(2) Science	(3) Reading
	(0.0228)	(0.0247)	(0.0247)
Constant	0.188***	0.0911*	−0.00732
	(0.0494)	(0.0517)	(0.0485)
Observations	79,480	79,480	79,480
R-squared	0.337	0.306	0.331

Standard errors in parentheses***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

average performers. In Austria, ICT use at home for school-related activities benefits top performers and penalises low performers.

To recap, student academic performance suffers in most of the analysed countries if they use ICT at home for school tasks, and the top performers are those most badly affected with respect to mathematics. There are some, albeit less common, positive correlations, and the use of ICT for homework was found to be positively associated with student achievement in only two countries (Belgium and the Netherlands).

Most of the above points with regard to the results in mathematics also hold true for science and reading, apart from minor differences in Sweden and Denmark (see the top performers in science and reading) and Belgium (see the low performers). Overall, we can conclude that the relationship between *homsch* and test scores is not heterogenous across subjects, which is an interesting result *per se*, as wide considerations for policy purposes can be formulated.

The results of PSM highlight that there appears to be a negative association between ICT used at home by students for schoolwork and test scores, with no countries showing a clear, robust and consistent positive relationship, although, in most countries, it is difficult to find common patterns across countries, subjects and student groups.

4.3. Additional results and robustness checks

We are aware that the baseline results reported in section 4.2 can have some methodological limitations which are intrinsically related to the use of Propensity Score Matching. For example, some unobservable features related to the choice of a specific school can have a role in explaining a different use of ICT at home for schoolwork, and/or an impact on test scores. With the aim of exploring this eventuality, we employ a more recent and econometrically valid technique belonging to the PSM family. Specifically, we decided to run a stratified PSM, with clustering by schools (Arpino and Cannas 2016). The application of this technique can lead to a reduction in the bias caused by unmeasured cluster-level variables when the matching takes place between similar individuals. In this way, we would only be matching students *within the same school*, ensuring that they have been educated within the same environment; thus, we used the preferential within-cluster (in our case, schools) approach. In practical terms, this analysis compares the potential effect of the treatment within schools only. It therefore accounts merely for students at the same school, thereby removing potential (unobservable) confounding effects related to students self-sorting into schools. The results are shown in Table 6. In this case, we focus on the association between frequent users of computers at home (high levels of *homsch*) vs all other students, and infrequent users (low levels of *homsch*) vs all other students. The idea was to check whether there are differences relating to students from the same schools making more or less use of ICT at home, if all school characteristics are kept constant.

The findings confirm the key results outlined in Section 4.2. *Broadly speaking, in most countries, with the exception of Belgium and Sweden, a more frequent use of computers at home for schoolwork is associated with lower levels of performance in all subjects*. Interestingly, in some countries, the students who said that they did not use computers much or at all at home for school purposes achieved

Table 5. Propensity Score Matching (PSM): difference in z-scores [top users of *homsch* versus other students, after PSM] by country.

	All students			Top performers			Low performers		
	Mathematics	Science	Reading	Mathematics	Science	Reading	Mathematics	Science	Reading
AUT	0.037	0.046	0.001	0.162***	0.094**	0.053	−0.078**	0.028	0.055
	0.73	*0.92*	*0.02*	*3.36*	*1.89*	*1.14*	*−1.67*	*0.59*	*1.2*
BEL	0.105***	0.028	0.011	0.157***	0.022	−0.03	0.198***	0.084**	0.11***
	2.58	*0.72*	*0.3*	*4.11*	*0.59*	*−0.84*	*5.16*	*2.26*	*3.08*
DEU	−0.228***	−0.269***	−0.201***	−0.362***	−0.376***	−0.333***	−0.185***	−0.278***	−0.201***
	−3.7	*−4.57*	*−3.57*	*−6.32*	*−6.8*	*−6.31*	*−3.17*	*−5.02*	*−3.68*
DNK	0.013	0.038	0.032	0.03	0.102**	0.061*	−0.032	−0.028	−0.014
	0.33	*0.87*	*0.8*	*0.78*	*2.29*	*1.5*	*−0.84*	*−0.63*	*−0.36*
ESP	−0.095***	−0.1***	−0.075***	−0.231***	−0.185***	−0.187***	−0.202***	−0.151***	−0.139***
	−4.25	*−4.61*	*−3.24*	*−10.56*	*−8.59*	*−8.21*	*−9.13*	*−6.99*	*−6.14*
FIN	−0.092***	−0.123***	−0.139***	−0.148***	−0.223***	−0.153***	−0.14***	−0.108***	−0.155***
	−2.96	*−3.6*	*−4.09*	*−4.85*	*−6.73*	*−4.56*	*−4.42*	*−3.14*	*−4.4*
GRC	−0.099**	−0.099**	−0.082*	−0.272***	−0.273***	−0.344***	−0.21***	−0.303***	−0.236***
	−2.05	*−2.08*	*−1.56*	*−6.11*	*−6.14*	*−7.46*	*−4.55*	*−6.86*	*−4.9*
IRL	−0.117***	−0.135***	−0.149***	−0.118***	−0.145***	−0.199***	−0.24***	−0.275***	−0.244***
	−2.31	*−2.48*	*−2.89*	*−2.42*	*−2.81*	*−4.04*	*−5.19*	*−5.57*	*−5.11*
ITA	−0.111***	−0.114***	−0.106***	−0.206***	−0.219***	−0.28***	−0.122***	−0.124***	−0.11***
	−5.21	*−5.38*	*−4.89*	*−10.01*	*−10.63*	*−13.69*	*−5.66*	*−5.93*	*−5.13*
NLD	0.025	0.096**	0.075*	0.26***	0.345***	0.284***	0.314***	0.293***	0.289***
	0.51	*1.9*	*1.5*	*5.21*	*6.97*	*5.76*	*6.85*	*5.97*	*6.04*
PRT	−0.038	−0.014	−0.054	−0.079**	−0.028	0.03	−0.125***	−0.11	−0.058*
	−0.8	*−0.33*	*−1.18*	*−1.81*	*−0.66*	*0.72*	*−2.83*	*−2.62*	*−1.33*
SWE	−0.044	−0.061	0.002	−0.071	−0.127*	−0.046	−0.088*	−0.113**	−0.009
	−0.72	*−0.92*	*0.03*	*−1.17*	*−1.92*	*−0.7*	*−1.56*	*−1.87*	*−0.13*

Robust standard errors (clustered by school) in italics.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 6. Propensity Score Matching (PSM), clustered by school: difference in z-scores [top users of *homsch* versus other students, after PSM] by country.

	All students Mathematics	Science	Reading
AUT	0.046	0.006	0.020
	0.031	*0.030*	*0.030*
BEL	0.060***	0.003	0.001
	0.023	*0.02*	*0.022*
DEU	−0.120***	−0.104***	−0.092***
	0.036	*0.036*	*0.032*
DNK	0.008	0.018	−0.001
	0.033	*0.037*	*0.033*
ESP	−0.034**	−0.051***	−0.039***
	0.013	*0.013*	*0.014*
FIN	−0.117 ***	−0.184***	−0.182 ***
	0.035	*0.039*	*0.038*
GRC	−0.113***	−0.112***	−0.128***
	0.029	*0.029*	*0.031*
IRL	−0.131**	−0.097**	−0.109***
	0.046	*0.050*	*0.045*
ITA	−0.031**	−0.057***	−0.051***
	0.013	*0.013*	*0.013*
NLD	0.124***	0.163***	0.111***
	0.038	*0.041*	*0.038*
PRT	0.002	0.007	−0.040
	0.030	*0.030*	*0.030*
SWE	−0.160***	−0.158***	−0.119***
	0.036	*0.039*	*0.040*

Robust standard errors (clustered by school) in italics.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

lower test scores than the other students (see Belgium, Denmark, Greece and Sweden), potentially suggesting that even a little ICT support can be detrimental to their academic results.

To sum up, these additional results corroborated the findings reported by the main, baseline analyses. The robust associations between the use of computers for educational purposes are unlikely to be driven by unobservable factors that caused self-sorting to occur from school to school. The models described in this section appear to confirm real differences between students even within the same school. In other words, excessive or insufficient (or inadequate) use of technology to help with homework can result in achieving lower test scores in all the subjects tested by PISA.

5. Discussion of main findings and concluding remarks

In this paper, we used propensity score matching to shed light onto the relationship between: (i) the use of ICT at home for school-related tasks, and (ii) the academic outcomes achieved by 15-year-old students as measured through the student scores in the OECD-PISA's standardised tests for reading, mathematics and science. Our analyses examined the group of EU15 countries, although only 12 could then be included in the empirical study because there were no comparable data for three countries (France, Luxembourg and the UK). This research is innovative in that it moves beyond purely descriptive comparisons of ICT use and test scores in different countries (typical of the OECD reports) and establish a robust link between our variable of interest (*homsch* or ICT use at home for school-related tasks) and academic results. For this purpose, we employed a propensity score matching (PSM) technique; *the findings reveal that the intensive use of ICT at home for homework had a negative impact on all subjects in most countries*.

Thus, the broader picture that emerges in response to our first research question is quite clear and tends to indicate that, according to the results measured based on subject-specific test scores, more frequent use of ICT at home, even when explicitly connected to school-related tasks, is detrimental to academic achievement. This result is fairly consistent with previous evidence that emerged for the USA reported by Vigdor, Ladd, and Martinez (2014). Wainer, Vieira, and Melguizo (2015) also suggested that the achievement gains of owning a computer are small for primary school students in Brazil. Our results round out the existing evidence in the European context, with a focus on secondary school students. Our findings are opposed to results reported by Spiezia (2010). However, we focused on European countries (rather than all OECD member states) and had a more recent reference period, when ICT usage is likely to have been significantly more widespread.

The impact of the use of ICT at home on student results is found to be generally negative across the entire distribution of students' ability. In response to our second research question, we found no differences between low-performing and high-performing students, although the best students appear to be most (negatively) affected in a few countries. Falck, Mang, and Woessmann (2018) set out to demonstrate that the impact of ICT on student results is heterogeneous, because computers are used for an array of different purposes. Our results, however, contribute to this debate by showing that the there is a negative impact of ICT for schoolwork on test scores, irrespective of the students' level of academic proficiency.

Although exploring the specific reasons that cause the negative correlation between *homsch* and test scores is well beyond the scope of this paper, some potential hypotheses can be formulated here. Firstly, the computers and/or the software used might not be adequate for the purposes of schooling. If, for instance, computers are too old or too slow to perform the required functions, the amount of time spent on task performance is not a good proxy for ICT use at home for schoolwork, as its use is unlikely to lead to significant gains in productivity. A second, potential and possibly complementary, explanation is that students follow their teachers' instructions on how to use computers at home, which, however, fall short of ensuring that computer use is productive enough to bring about observable gains in knowledge and skills. In this setting, ICT use could potentially be a productive investment, but the students are not taught how to make the most of their ICT use. This issue could be interpreted as a teaching failure. If teachers do not update their teaching methods to introduce more extensive use of ICT tools, their mere use would not be conducive to frequent users performing better than less frequent users. As stated in the literature, teachers play a vital role in ensuring that digital learning has a real positive effect (Jager and Lokman 2000; Comi et al. 2017). This eventuality also raises the question of whether teachers are up to introducing ICT productively into the formal educational system. This is a crucial issue, as the positive gains in skills should stem from the interaction between students and teachers, thereby improving human capital. If skills on both sides are mismatched, then both could lose out in practice. Thirdly, students could, possibly, be incorrectly using ICT at home for school purposes. Students can get distracted by all the other functions on their computers (web browsing, listening to music, watching films and chatting on social media). Therefore, they over-report the amount of time they spend doing homework on their computers, providing a flawed picture of how long they really spent on schoolwork. If students do not have the expertise or are not mature enough to know how to exercise restraint when using their computers for school purposes and do not receive proper guidance from their teachers (as suggested above), then parental intervention would be necessary. Without such intermediation, students may struggle and spend too much time doing homework on computers without any real gain in extra skills and knowledge. Fourthly, another possibility is that the educational outcomes of students who use ICT at home more frequently for school purposes do improve, albeit with respect to aspects not accounted for by test scores, for example, a range of non-cognitive skills. From this viewpoint, a fuller assessment of student skills and competencies – beyond mere subject-specific knowledge – could be important in order to provide a better description of ICT effects.

Irrespective of the real channel(s) of influence, policy implications can be derived. The most important is that the sweeping endorsement of ICT as a homework assistant, without clear and precise ideas about how it should actually be used, can be harmful. The academic performance of students, who already use technology extensively in their daily life, may suffer if they are left alone to do their homework using technology without oversight from teachers and/or parents. Thus, ICT-assisted homework must be based on a strong family-school relationship, and protocols about the correct use of technological resources should be encouraged and developed. Another implication is that attention must be paid to the quality of the tools and material provided. School principals and teachers should not take the quality of material for granted and should, instead, carefully review how ICT material can generate benefits in advancing knowledge. Discussions about the adequacy of ICT support materials must become central to educational planning at school and classroom level. As the evidence suggests that schools are increasingly likely to use ICT in teaching, the process of constantly assessing the effectiveness of the deployed tools should gradually be adopted within school culture. This last point opens up the issue of the use of technology during school time to debate. Indeed, the achievement of positive outcomes by promoting the effective use of computers at home may hinge on how the students are trained at school. The decisions taken by principals and teachers should concern not only the amount of ICT use by students, but how to split this use between school and home, that is, they should address how technology can be used most productively to improve educational outcomes in specific subjects and circumstances.

Our results call for future research to corroborate their external validity, as our study has several limitations. Firstly, our estimates deal with only a limited number of countries and for a specific time frame as captured by OECD PISA 2012. The analysis could be repeated to include a wider group of countries and, especially, to look at other education systems very unlike Europe's (Asian countries, the United States and Australia) where the student-technology relationship may be substantially different. Secondly, similar limitations hold with respect to the specific cohort of students. The rate of ICT usage – and also its specific uses – varies very rapidly over time. It would be interesting to test whether the associations between ICT used at home and the student test scores are constant over time and/or whether they instead change. A replication of the analyses for OECD PISA 2009, 2015 and 2018 (the cohorts before and after our PISA 2012) would be a possible first move in this direction. The third limitation is that our study covers OECD-PISA data only, i.e. students who are 15 years old. The negative correlation between the use of ICT at home and test scores could be closely linked to this specific age and moment of school life. A particularly interesting extension of this paper, subject to data availability, would be to research the same relationship between ICT and academic achievement for cohorts at earlier stages in their education path. As pointed out by Cunha and Heckman (2007), educational production technology is defined by cumulative effects, especially in the early stages of life. From this viewpoint, it could well be the case that ICT support for homework is more productive in primary school, and its effectiveness is revealed at later school stages and only benefits the children who received adequate exposure at a younger age.

Notes

1. Other potentially interesting EU countries were excluded because systematic and relevant data for many variables of interest were missing (see Section 3.1).
2. When dealing with ICT, it is important to specify the aspect/s being measured. These factors can include infrastructure or connection type, computer availability or unavailability, the level of ICT usage, the location (home vs school), what students do with ICT (entertainment, homework, in-school tasks, access limited to teachers) and the frequency of usage (high vs low, type and number of ICT-related functions).
3. In line with the following comment from the OECD (2009, 129): 'On average, analysing one plausible value instead of five plausible values provides unbiased population estimates, as well as unbiased sampling variances on these estimates'.
4. The number of missing values varies across countries and between variables. As this number is not very high, we decided against applying sophisticated methods to impute values where they were missing. Therefore, we have only used the information effectively provided by students.
5. It is worth recalling that Oster (2019) proposed an alternative method for the analysis that somehow considers the potential for unobservable bias (for example, related with self-sorting of students across schools). Unfortunately, this method is not suitable for our empirical inquiry, as it is only really applicable to linear models. Besides, we utilised interaction terms in some of our specifications (see Section 4.2), which is another ground for not using this method. Therefore, the various robustness tests conducted against our baseline results assures that relevant, potential unobservable biases associated with school choice has been properly considered.

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