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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 relationship between (i) the way in which students use ICT at home for school-related purposes and (ii) their test scores in reading, mathematics and science. By employing two different econometric techniques – namely, propensity score matching and instrumental variables – we can provide evidence that in most countries there is an association between using computers intensely for homework and achieving lower test scores across all subjects. No clear pattern emerges for differences between students with higher socio-economic status (SES) and their low-SES counterparts, although some models suggest that the negative effect of using ICT at home is slightly greater for high-SES students. These 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. Such an indication can potentially suggest that teachers should be trained to integrate this practice effectively into their strategies for assigning homework.

Keywords. Digital learning, educational production function (EPF), OECD-PISA, propensity score matching, instrumental variables

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1. Introduction, motivation and research questions

The current wide-spread role of Information and Communication Technology (ICT) in education demands an assessment of its effectiveness in raising educational achievement. The problem of evaluating whether ICT has a positive effect on measures of educational output (such as graduation rates and test scores) is not new, and existent literature reviews provide some insights derived from the empirical studies conducted since the 1980s. For instance, Cheung and Slavin (2013) reviewed 74 “qualified” studies and reported that using technological applications in education leads to a general, small but positive, effect on test scores. However, part of the impact of ICT on learning performance depends on two major factors: (i) the role played by the students’ own features and (ii) the specific way ICT tools are designed, developed and implemented in any (explicit) context. Several recent papers have provided empirical evidence that these two elements matter greatly when investigating the relationship between ICT and any measure of instructional output. For example, De Witte and Rogge (2015) estimated the effect of ICT on a sample of 4th-grade students in the Netherlands, using data from the international dataset Trend in International Mathematics and Science Study (TIMSS). According to these authors, the apparent differences between students who are more exposed to ICT and those who are exposed less vanish when properly controlling for student, teacher and school aspects. In the same vein, but obtaining opposite results, Wittwer and Senkbeil (2008) analysed the results of German 15-year-old students who took part in the Organisation for Economic Co-operation and Development (OECD)’s Programme for International Student Assessment (PISA). In their study, they found that computer use at home (which can be a proxy of the students’ technological background) had no effect on PISA test scores in mathematics.

With regards to the reasons whereby a student will use ICT, there may be a mix of factors influencing them at different levels. Following Biagi and Loi (2013), aspects at institutional level (such as technological infrastructure and the students’ ICT teachers’ teaching policies) and school level (the attitude taken by the school’s head/principal and teachers towards ICT and ICT resources, for example) can affect how students use ICT in school. On the contrary, the student’s personal features (gender, mental outlook, ability, age, motivation, etc.) and family aspects (such as socio-economic background, family structure, ICT equipment at home and parents’ attitude towards ICT) will condition how ICT is used at home. The degree to which ICT is used by students can have a certain impact on their academic achievement, although this is certainly influenced, at the same time, by other factors (to the same degree as explained before). Because of all these factors, alongside all the possible ways that ICT connects to the learning process, any evaluation into the impact of ICT on academic achievement is inevitably a complex task.

There is also another important topic when considering ICT use, which is connected to the diverse approaches employed by advantaged and disadvantaged students, which raises questions about equality. International studies have also shown that there is universal access to ICT at home in most developed countries, but the way ICT is used there differs between rich and poor: students from an advantaged background tend to use ICT at home for studying, whereas students from disadvantaged background tend to do so for entertainment (OECD, 2015; Zhang, 2015). This suggests that the diverse ICT-related uses outside school can compound the disparity in education results between rich and poor, if different home use is indeed associated to different outcomes.

In addition to the role that ICT plays in efficiency (i.e. maximizing average student performance), the impact of ICT on inequality in educational achievement has become a priority in educational policy agendae. Compared to the studies concerned with investigating the effects of ICT on efficiency, only a few international works have concentrated on whether ICT reduces or exacerbates disparities in education between richer and poorer students, and have examined data from only a limited number of countries (for example, Gui, Micheli and Fiore, 2014; Gürsakal, Murat and Gürsakal, 2016). Because these international studies were based upon cross-sectional research design, it is difficult to draw a causal inference on this matter.

This research uses data from OECD PISA 2012 to investigate whether the students' use of ICT is related to their test scores in reading, mathematics and science – and, if this is the case, whether this impact varies subject by subject and/or according to the students' socio-economic backgrounds. Our sample contains twelve European Union[2] countries: Austria, Belgium, Denmark, Germany, Spain, Finland, Greece, Italy, Ireland, the Netherlands, Portugal and Sweden. Since we are aware of the methodological limits of using a cross-sectional dataset to calculate simple correlations of linear regression, we have employed an array of different statistical and econometric techniques to explore the relationship between ICT use and educational results more thoroughly, potentially allowing us to suggest that there are causal links between these two factors. While the concept of ICT use[3] can be approached from many angles, in this paper we are primarily interested in describing the role of ICT used at home for educational purposes. In our case, the variable from the PISA dataset in which we are most interested is the composite indicator *homsch*: ICT Use at Home for School-related Tasks.

Our paper specifically addresses two research questions:

a) Is ICT used at home for school-related purposes associated with test scores in reading, mathematics and science, within a selected group of EU countries? Is this effect uniform across the countries or is it instead heterogeneous?
b) Is the impact of ICT use uniform across all the student population (within countries), or are there differences for students from a disadvantaged socio-economic background (who are likely to suffer from various forms of digital divide) or for the top or low achievers?

From a methodological point of view, all the econometric analyses were carried out country by country, rather than by combining all students, schools and countries into an aggregated model.

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[2] Our first choice was to examine all EU-15 member countries, to gain a more homogeneous overview, but three of these countries (the United Kingdom, France and Luxembourg) did not take part in the optional ICT module.
[3] When dealing with ICT, it is completely relevant to define which specific aspect/s are measured, including the kinds of infrastructure and/or connections, whether ICT is available or not, the ICT level of use, the location (home versus school), how students use ICT (whether for entertainment, homework, school tasks, and whether only teachers have access) and how intense is the use (heavy users vs. low users, number and kinds of ICT activity).

This allowed us to explore the subject of interest without running the risk of ignoring structural (country-level) differences that could affect the relationship between ICT use and test scores in any number of ways, and thereby create confusion with regards to the main links between the two dimensions. At the same time, we have presented the results in both a qualitative and a quantitative manner, examining the evidence that has valid implications for many countries.

This paper updates the existent literature in a variety of ways. First, our aim is not simply to explore the "average" effect of the students' use of ICT on their test scores, but we are also particularly interested in how this potential effect varies from country to country. We, therefore, decided to use the available data to the widest effect, without limiting ourselves to single-country analyses based on existing datasets such as PISA and TIMSS. Clearly the OECD's institutional reports (see, for example, OECD 2015) present their results from a cross-national perspective and, while these reports provide a complete descriptive analysis picture, this paper employs robust statistical and econometric techniques to investigate the topic. Second, we explicitly address any threat to the validity of the study based upon the suggestion of a causal relationship between computer (ICT) use and test scores. While we are well aware that none of the methods proposed can alone be sufficient to draw the inference of causality, the triangulation of several different econometric and statistical methods can provide a much more convincing view that the results presented here do not suffer from the typical limitations of single-method studies - which form the bulk of the current literature in the field – and this can be interpreted as a series of robustness checks. Third, we have estimated whether the use of ICT is linked in any way to the various subjects tested through PISA, reading, mathematics and science. Most published academic papers focus on one subject at a time, with a strong preference for mathematics. Our empirical analyses are based upon the theoretical intuition that not all subjects benefit from ICT support to the same level – and providing an overall picture of these differences is in itself valuable. Fourth, to the best of our knowledge, this is the first study that simultaneously addresses both the question of the average effect of ICT on student performance and that of its heterogeneous impact on students from a disadvantaged background. In our study, we wish, therefore, to highlight the potential interaction between socio-economic status (SES), ICT home and school use, and academic performance. In this context, our empirical results are useful for shedding light on the elements that make up the "average" ICT effect, which is traditionally considered to be key policy information.

Our main findings highlight a degree of heterogeneity in the results across countries when measuring the impact of the variable associated to ICT used at home for school-related tasks. There is only a minor difference in the way this use of ICT affects high-achieving or low-achieving students. Overall, as measured through OECD PISA test scores, when students use ICT intensely at home, this has a detrimental impact on their school results, in all subjects and in most countries.

The remainder of the paper is organized as follows. The results of a selected list of relevant papers are commented on in next section §2, to highlight the gaps that we are seeking to address in this study. In section §3, we will describe our methodological approach and empirical strategy. The data (drawn from PISA 2012) are presented and examined in section §4. The main results of this study are reported in section §5, and discussed in section §6, which also includes some concluding remarks.

2. Prior literature and conceptual framework

2.1 Existing evidence on the effects of ICT use on educational results

In this section, we will critically discuss the evidence about the relationship between ICT used for educational purposes and actual educational results, such as the students' test scores. Our primary aim is not to prepare a comprehensive survey of the numerous studies on the topic (several reviews of this kind have already been carried out, although by now they are rather dated, see, for instance, Cox et al., 2003; Punie et al., 2006; Cox and Marshall, 2007), but rather to derive conceptual hypotheses on the basis of relevant existing studies. For our theoretical purposes, it is important to understand whether ICT use is a "critical" input within education. In other words, we wish to verify whether it is the case that technology (for instance, using laptops and tablets for studying, computer-assisted testing and online learning) are more productive than the traditional "chalk-and-talk" type of education. If this is the case, we should find that students who are exposed to higher use of ICT will, with all else being equal, perform better and acquire more skills educationally-wise than their counterparts who do not have the same ICT opportunities. In this vein, Smeets (2005) has presented the theory of "empowered learning environments", enhanced by using ICT, while Hermans et al. (2008) illustrated how teachers' beliefs and attitudes are directly related to how computers and ICT in general are used in practice within primary education. Operationally, when moving from the theoretical debate to empirical assessments, analysts should gather data on how students use ICT, examining how intensely the technology is actually used and comparing the effect of the various levels of intensity on educational achievement, in order to detect any potential link between the two. Since a huge number of empirical studies dealing with this topic have already been produced, they form the basis for our theoretical considerations, including our expectations concerning the correlation between the indicators of ICT use (for instance, time spent studying using a computer) and indicators of educational results (for example, standardized test scores or success in gaining admission to university or other places of higher education). It is important to remember, at this point, that most existing studies focus on the "productivity" of using ICT resources for educational purposes in terms of purely academic results. This effect can potentially also reflect on other areas education. For example, computers used at home can indicate greater curiosity in the topics studied, or greater openness towards cross-disciplinary knowledge, etc. These are all non-cognitive skills that can benefit from the students' higher exposure to ICT, and the resulting effects may not directly or immediately lead to higher test scores or other non-traditional measures of educational success. While leaving empirical explorations of this kind to future studies, in this paper we will limit our definitions and framework to the concept of ICT productivity for a specific measure of academic results, specifically the subject-based and competence-based test scores in the subjects tested through OECD PISA – reading, mathematics and science.

We will make a preliminary distinction between the use of computers *at home* (i.e. for studying or for other purposes related to education) and the use of computers *at school*, typically for purely teaching purposes. If exposure to more ICT instruments raises productivity in education, then students who have greater access to computers (and associated tools and devices) at home should produce better results. A survey conducted in Brazil among primary school children, for example, recorded positive associations of this kind (Wainer et al., 2015). The authors themselves, however, acknowledged that differences in test scores can be due, at least in part, to the families' different socio-economic backgrounds (this threat to the validity of the studies, which stems from the endogeneity of the variables for ICT use, is discussed later in this section). In addition, these studies do not cover the interaction between computers available at home and at school and could be either a complementarity aspect or a trade-off. This point is a crucial feature when incorporating ICT use within an Educational Production Function (EPF) framework. To illustrate this point more clearly, if we consider, for example, an EPF as follows:

$$y_{ij} = f\left(X_{1ij}, X_{2j};\ \varepsilon_{ij}\right) \qquad (1)$$

where y_{ij} is the educational result of the i-th student in the j-th school, X_{1ij} is the vector of student-specific features (gender, age, SES, etc.), X_{2j} contains indicators relating to the schools' features and ε_{ij} is random noise – which also includes all unobservable factors not captured through specified indicators in X_{1ij} and X_{2j}. While access to computers at home is a factor included in X_{1ij}, use of computers at school belongs to X_{2j}. Let us assume that the former variable is labelled *Comp_hom$_{ij}$* and the latter *Comp_school$_j$*: then the empirical model should consider the coefficients for both indicators, and also the potential interaction given by *Comp_hom$_{ij}$* * *Comp_school$_j$*.

Another key issue concerns the precise definition of "ICT use" (or "availability"/ "access") in the context of studies about the determinants of educational results. Referring back to the EPF in equation [1], the two indicators for computer availability at home contain the various ways in which the devices are actually used. As pointed out by Wittwer and Senkbeil (2008), the type of use computers are put to can exert a positive, neutral or even negative impact on achievement. To clarify, browsing on the internet to search for more information can stimulate a constructive mindset and increase the students' skills, but playing videogames can be detrimental in terms of their education, as can be spending too much time online (OECD, 2016). The mechanisms behind these effects have, however, yet to be robustly identified. Some studies suggest that the reality is different and, for example, Bowers and Berland (2013) give evidence about grade 10 USA students having higher grades if their use of computers "for fun" (including video gaming) is moderate. An interesting theoretical contribution in this sense was made by Falck et al. (2015), who modelled the effect of ICT use on instruction by building on the concept of opportunity cost. They suggested that time spent on learning (at school, but also at home) is subject to a constraint, so that choosing to spend a given amount of time on traditional learning processes comes at the cost of not using ICT and vice versa. This choice should be based on the relative productivity for the various possible processes: for example, searching for information over the web can be more productive than going to look for it in a library; while routine tasks (such as exercises on grammar) can be more productive if carried out in the traditional way, without computer assistance. In this framework, the authors claim that the null effect of ICT on test scores often found in the literature could be interpreted as the combination of the positive and negative underlying effects of specific computer uses. While both fascinating and reasonable, in this paper we have not broken down ICT use to this level of detail, as our main goal is to analyse the effects of using computers *at home*, although we have also included ICT availability at school as complementary information.

Keeping these introductory remarks in mind, the empirical descriptive analyses conducted on a variety of national and international datasets did not, in general, bring up any univocal answers. For example, according to several studies, there is a positive correlation between ICT use and test scores (see Sosin et al. (2004) for a study within a higher education setting in the USA, and Wainer et al. (2015) for a study on Brazilian primary school children). Others, instead, failed to find any positive effect, as in the case of Goolsbee and Guryan (2006), who studied the impact of a policy to spread ICT within Californian state primary schools between 1996 and 2000. Nevertheless, even when researchers found statistically significant correlations between ICT indicators and educational results, these may easily be considered as spurious, i.e. driven by factors such as socio-economic status (SES), family educational background and student gender, which can have an effect both on the use of ICT and on academic results. In order to avoid the problem of omitted variables, which can lead to biased results, a series of variables can be included to control for the differences across students. This is the main criticism exposed by Wittwer and Senkbeil (2008) when conducting their analysis of German students using PISA 2003 data. As they reported, "[…] none of the [previous] studies takes the multiple determination of school performance into account" (p. 1559). They rightly claim that much of the variation in students' test scores has been attributed as a matter of course to computer use, while it is, instead, generated by other factors. In their own study, they highlighted that, after controlling for a variable that measures the PISA Economic, Social and Cultural Status (ESCS)[4], there are no differences in the maths test scores between the students who used computers at home, independently of the ways in which they used their computers. Over the last decade, numerous studies have adopted an econometric approach to estimating how ICT and learning outcomes are related, with all else being equal – i.e. once the influence exerted by the other inputs to the educational production function has been factored in. Biagi and Loi (2013) explored OECD PISA 2009 data for 23 countries, and theirs are rather counter-intuitive findings. After having created a measure of breadth in ICT use, their empirical model shows a negative correlation with test scores in reading, mathematics and science – with particular reference to the variable that measures ICT use relating to the "creation of content and knowledge" (e.g. drill and practice in learning, for instance, a foreign language or mathematics, or homework completed on a school computer). This study is highly important to the present paper, because our results are linked to the picture outlined, and the intuitions reported there are in part used to explain some of our findings.

[4] The PISA index of ESCS was derived from five indices: highest occupational status of parents, highest educational level of parents (in years of education according to the International Standard Classification of Education), family wealth, cultural possessions and home educational resources (OECD, 2014). The rationale for using these components is that socio-economic status is usually measured based on education, occupational status, and income.

These recent studies, however, are threatened by the occurrence of spurious correlation (i.e. unobserved underlying variables driving the correlation between test scores and ICT use), making it necessary to develop additional (statistically and econometrically) robust studies where endogeneity is taken into account, achieved through various econometric techniques (experimental design, matching procedures, change in policy, instrumental variables, etc.). This endogeneity problem is, however, taken explicitly into account in only a few studies. Angrist and Lavy (2002) adopted an Instrumental Variables (IV) strategy to evaluate a policy of bringing computers into Israeli primary schools on a wide-spread basis, and they did not find evidence of any relevant effect on the children's test scores – in actual fact, they found a negative impact on test scores in mathematics. Machin et al. (2007) explored a change in UK policy with regards to allocating resources to ICT equipment in English schools, and used an IV methodology to demonstrate that higher investment in ICT led to better test scores in reading and science (but not in mathematics). Spiezia (2010) focused on OECD PISA 2006 data for 33 countries, and adopted an "endogenous treatment model", where the frequency of computer use is modelled on the basis of specific observable characteristics belonging to students. The results considered the impact of ICT use on science test scores, pointing to a positive effect. Nevertheless, while computer use at home and at school both had a positive effect, this was higher for home computer use. De Witte and Rogge (2014) used TIMSS 2011 data for Dutch 4th-graders, employing a matching technique. Their variable of interest was the lack of ICT at school, used to analyse whether students attending institutions with better/worse ICT equipment perform better/worse than their counterparts. Their findings revealed that, after factoring in the students' and schools' features properly, the differences in test scores between students who attend schools with different IT equipment vanish. Fariña et al. (2015) used PISA 2009 tests for Spanish and Chilean 15-year old students to analyse the effect of using computers for reading on digital reading scores. They used a two-step procedure to control for endogeneity of computer use: in the first step, they constructed an explanatory model for computer use, and in the second step they used the predicted values to estimate how computer use affects digital reading test scores. The results revealed that, when endogeneity is taken into account, using computers for reading has no correlation on digital reading scores. Falck et al. (2015) analysed 8th-grade and 4th-grade students, using TIMSS 2011 data, and they found that the self-selection of students into specific schools and classrooms was the main methodological threat. They, therefore, proposed an identification strategy based on a within-student, between-subject variation in test scores. While the average effect of using computers at school turned out to be zero, there were significant differences between the different ways computers were used, with positive effects linked to the intensity of using computers to process and analyse data, and negative effects linked to using computers for practising skills and procedures.

Some studies conducted in the USA focused specifically on computers used at home, and their objective was to detect whether there were any associations or effects linked to educational outputs – the exact research question we are investigating in our paper. In an earlier study, Fairlie (2005) found evidence that teenagers who can access a computer at home are more likely to be regularly enrolled at school (i.e. less likely to drop out). This research is based on a probit model applied to the Current Population Survey of 2001 in the USA, and the estimated effect of home computers on school enrolment is about 1.5% after controlling for the students' features and background. In a study that made use of a new dataset that matched the Current Population Survey (CPS) with the USA National Longitudinal Survey of Youth 1997, Fairlie et al. (2010) conducted an econometric analysis, based on a two-stage least squares regression analysis, demonstrating that there is a positive relationship between a computer being available at home and test scores, even after controlling for the students' socio-economic status. The authors provided a wide range of hypotheses to justify such positive and statistically significant effect on educational performance of having a computer available at home: from the effect of higher productivity when completing homework to the effect of raising general IT skills. The most credible study, which was based on an experimental strategy, was that carried out by Fairlie and Robinson (2013). The experiment involved five school districts in California, targeting the middle school students (grades 6-10). While having a home computer did increase the student's use of the internet and helped in creating digital teaching processes, the results from the statistical analysis were unable to find any meaningful association with any indicator of output (grades, test scores, credits earned, etc.). As in all the experimental studies, this also suffered from the problem of external validity.

So far, we can conclude that existing evidence about the effects of using and accessing computers and/or ICT on educational output is mixed, at best. While some studies have found that there is a positive impact on test scores, others fail to detect any statistically significant influence, and in some cases even found a negative correlation. In addition, most of the methodologically reliable studies cited in this section only study the use of ICT in school, and are unable to provide any insights into the impact of using this technology at home. Our paper, on the other hand, is inserted in the relatively recent stream of studies that adopt a robust econometric methodology to infer the causal effect of using ICT at home to support learning. In our study, we use two different techniques: the first based on Propensity Score Matching (PSM) and the second on Instrumental Variables (IV) – details are provided in the section on Methodology. In this sense, our study innovates the existent literature in that it provides an internal robustness check of the findings, based on different techniques being adopted simultaneously. Moreover, our study extends the current evidence on ICT and computers at home, and their effect on learning achievement, to a cross-country comparison. This is the first systematic attempt to provide evidence on the topic at European level that can be generalized.

2.2 Inequality in ICT and student outcomes

When carrying out an empirical analysis of the determinants of academic results, it is important not merely to "control for" the students' socio-economic background. In our context, we must also examine the differences in the way affluent and disadvantaged students use ICT. Since access to computers and internet at home is today nearly universal for students in most economically developed countries (OECD, 2015), the focus in studies on inequality in ICT has shifted from the "digital divide" (i.e. inequality between the "haves" and "have-nots", differentiated by the binary measures of access to and use of the new technologies) to "digital inequality" (to include different usages and skill levels, and the purposes for which the technology is used). This digital inequality is often associated with race, class, gender, geographic location and other traditional kinds of offline social stratification.

A recent OECD report (2015) highlighted the socio-economic differences in access to computers and the internet at home, but more than 95% of disadvantaged students (i.e. the bottom quartile of the SES distribution) in high-income countries, including Belgium, Denmark, Finland, Germany, Iceland and Norway, can access computers at home. More significant differences between advantaged and disadvantaged students in the PISA 2012 participating countries emerged when observing ICT-related activity at home. Disadvantaged students tend to use ICT for entertainment (e.g. playing video games and chatting on social media) rather than for learning (e.g. reading news items or carrying out research on the internet) (OECD, 2015; Zhang, 2015). These findings suggest that disadvantaged students tend not to use ICT to improve their academic capital and this can compound or exacerbate inequalities in education.

Compared to studies that look at the effects of ICT access on student learning outcomes, there is a relative lack of research on the degree to which ICT (being either access to ICT or the different usages thereof) reduces or aggravates inequalities in education, examined though the diverse effects of ICT on student learning outcomes, relative to the students' different socio-economic backgrounds (Gui, Micheli and Fiore, 2014). Prior research employed two different approaches to examine the effect of ICT on academic results for disadvantaged students. First, several studies targeted only low-income students, using regression (Jackson et al., 2006), a randomized experiment (Li, Atkins and Stanton, 2006) or quasi-experimental methods such as a regression discontinuity design (Malamud and Pop-Eleches, 2011). These studies focused mainly on the simple access to ICT rather than on types of use or skills involved. Findings from these studies are mixed, being both positive (Jackson et al., 2006; Li et al., 2006) and negative (Malamud and Pop-Eleches, 2011). These works do not reveal any specific pattern to differentiate disadvantaged students from the rest of the student population, given that only that particular subgroup was examined. In a second, alternative stream of the literature, other studies examined the whole sample of students, then adding terms of interaction between ICT variables and SES. The estimation methods employed varied from regression (Attewell and Battle, 1999; Gui et al., 2014) to quasi-experimental designs (Vigdor and Ladd, 2014). The findings from these studies, however, were also inconclusive. In some studies, it was found that advantaged students benefit more from using ICT than disadvantaged students (Attewell and Battle, 1999), suggesting that ICT use heightens socio-economic achievement inequality. Other studies pointed to a stronger negative relationship between ICT and student outcomes for disadvantaged students. Using administrative data on North Carolina state school students in the United States and student-level fixed effect models, Vigdor and Ladd (2014) found that computer technology introduced at home is associated with a modest but statistically significant and persistent negative impact on student test scores in reading and mathematics. Moreover, they found that providing universal access to home computers and high-speed internet access is liable to widen the achievement gap in mathematics and reading, instead of reducing it. With the increase in large-scale international data on student achievement, several studies have covered the link between ICT access/home use and inequality in achievement in greater detail. Since these studies have tended to focus on different aspects of ICT and have analyzed one or two country-level cases, it is somewhat difficult to make a comparison between the findings across the studies. These works have shown that the association between ICT access/home use and inequality in achievement can possibly vary across countries. Using the cross-sectional Italian PISA 2009 data and multi-level linear regression models, Gui et al. (2014) found that when students use the internet for their schoolwork, the impact on their learning does not differ on the basis of their social background. Using PISA 2012 on the sample of data for Turkey, Gürsakal et al. (2016) found that having access to computer resources at home has a significant and positive association with the students' scores in mathematics, but that time of computer use had a negative and significant association with the students' score in mathematics. They also found that availability of computer resources at home affects the students differently, depending on their ability.

However, as mentioned above, prior research on inequality in ICT suggests that it is important to investigate the types of ICT activity students carry out (i.e. ICT for school-related tasks vs. entertainment) in order to gain a thorough understanding of the effect of ICT on the gap in achievement between advantaged and disadvantaged students. Patterns of inequality can arise in how students are empowered by using available ICT tools in different ways. This concept explains why, in this paper, we have focused primarily on ICT used at home for specific school-related purposes. Because prior international research mainly made use of cross-sectional correlational research design, it is important to apply quasi-experimental design in order to assess the causal effect of ICT on inequality in achievement within international contexts; and the precise aim of this paper is to fill this gap.

3. Data, choice of variables and descriptive evidence

This study used data from OECD PISA, a triennial large-scale international survey to measure the knowledge and skills of representative samples of 15-year-old students from more than 60 education systems worldwide. Since 2000, PISA has been assessing student performance in reading, mathematics and science, with each survey assessing one subject in greater depth. The research presented in this study focused on PISA 2012. The survey involved 65 countries, 34 being OECD countries, and this time it focused on mathematics. For the reasons illustrated in the subsequent sections, this research includes data and results from 12 countries in the EU-15 group.

3.1 Selection of variables for the empirical analysis

PISA employed student and school questionnaires to collect information on various aspects of the students' home environments and their family and school backgrounds, for all PISA participating countries. PISA also offers some interesting variables related to ICT, at student level, which are very useful for the purposes of our research. These variables came from the optional "Information Communication Technology (ICT) questionnaire". This section was, unfortunately, not taken in all participating countries, and our choice of countries to include in the empirical analysis was dictated by the availability of these variables. We had initially intended to analyse all EU-15 countries, but since the ICT information was missing for France, United Kingdom and Luxembourg, they could not be included in our study. We, therefore, came down to 12 countries belonging to the EU: Austria, Belgium, Germany, Denmark, Spain, Finland, Greece, Ireland, Italy, the Netherlands, Portugal and Sweden.

Going into the detail of the ICT questions and variables, we have mainly worked with the variables *homsch* (ICT Use at Home for School-related Tasks), which is our main variable of interest, *ictsch* (Availability of ICT at School) and *entuse* (ICT Use for Entertainment). All these variables (along with other five ICT variables) are continuous scaled indices provided in the PISA database. They were computed by the OECD, on the basis of several questions answered by the students as part of the ICT literacy questionnaire (OECD, 2014). The variable *ictsch* was created using seven items, with three response options, “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 took into account the fact that tablets and e-book readers are not used at school as commonly as desktop computers or internet connection. Ten items were used to create the variable ICT for entertainment, *entuse*, which covered a wide range of the different possible ways of using ICT for fun (from playing video games to social networks and browsing the internet for fun). Seven item parameters were then used to gather information on home ICT for school related tasks, *homsch* (such as communicating with teachers or school mates, doing homework or researching material for presentations). The answers to the questions concerning these items were “Never or hardly ever”, “Once or twice a month”, “Once or twice a week”, “Almost every day” and “Every day”.

All these items were scaled using Item Response Theory (IRT) scaling methodology. The ranges of these indices vary from -4.20 to 4.50, and include differences. Lower values are always associated with a null or minimum use of ICT, while values closer to 4 denote the contrary. As well as introducing these three variables, we also created quartiles of students to identify the top home users of ICT for school purposes (the top 25% with higher values for the *homsch* variable) and the lower users (the bottom 25% with lower values for the *homsch* variable). These groups of interest have the function of studying the students’ different behaviour in terms of how they use ICT, and for detecting the potential associations between these uses and their academic results. Our measure for ICT use at home has an intrinsic limitation in that the value is self-reported by students. Two problems can potentially impinge on the credibility of an indicator of this type. First, students can give the wrong information either on purpose or through a genuine mistake. We have no way of testing for this eventuality, but if we assume that this is a random occurrence, its threat to the validity of our results is modest. Second, students can be swayed by comparing their ICT behaviour against their particular friendship group in class or school (self-referencing sample). The questions were formulated to induce a quantitative (e.g. two/three times a week) rather than a qualitative answer (often, rarely, etc.), so this should only be a minor problem.

All the other variables used in the analysis refer to controls for the student’s personal and family background, such as gender, immigrant background, family structure, pre-primary education (ISCED 0), month of birth, if he/she repeated a year in primary or secondary school, truancy at school, together with the PISA index of ESCS (as a proxy of family SES). At school level, we introduced the variables of type of school, location, classroom size, student truancy reported by the school head/principal, disciplinary climate at school and the ESCS index at school level (as a proxy of school mean SES). Finally, we used the test scores in reading, mathematics, and science to examine the students' achievement. We converted these scores into z-scores for our 12 countries, with the mean of the scores being 0 and the standard deviation being 1 (Brown, et al. 2007). The first plausible value for each score was used in the computation, and we obtained more or less identical results for the rest of the plausible values[5]. Table 1 sets out the definitions and labels of these variables and their categories.

[Table 1] around here

3.2 Summary statistics

The descriptive statistics of the variables used in our analysis are shown in Table 2, detailed country by country. There are differences in sample size country to country, with Italy and Spain being the countries with the highest number of sampled students[6]. Glancing at the results, the analyzed variables are heterogeneous between countries. Students from Belgium, Germany, Finland, Ireland and the Netherlands have higher average PISA scores in all the tests, while students from Greece and Sweden have the lowest PISA scores in our analytic sample.

Looking at the three ICT indices, clear differences between the countries are detected: Danish students show high average values for these indices, which indicates that they are top users of ICT both at school and at home, and slightly lower values for entertainment. The other countries show much lower values in these variables, and can even be negative in all of them, see, for example, Ireland. Apart from this, there is no clear pattern: students from some countries report a high ICT home use together with low use for entertainment (the Netherlands) or high use for entertainment and low home use (Italy). The availability of ICT devices at school is also different from country to country. Spain, Germany, Ireland and, above all, Belgium and Italy, show a negative value for this index. The Netherlands, Denmark, Finland and Sweden are the countries with the highest positive values.

When considering the individual variables, there are more first generation immigrants in some countries, such as Spain, Ireland and Belgium. At least one year's universal pre-primary education - ISCED 0 - is common practice in all countries except Ireland, where 14% of students have no ISCED 0. On the contrary, as a practice, grade retention (students repeating a year) is applied differently across countries. In Spain, Belgium and the Netherlands there are very high rates of year repetition (above 20%), while they are very low in Denmark, Finland, Greece, Ireland, Italy and Sweden (below 5%). The modal grade retention level shows negative values for most of the countries analyzed. Only in Ireland, Belgium and the Netherlands is there a positive average value for the grade retention variable. Truancy rates also vary across countries: in Spain, Greece, Portugal and Italy truancy shows the highest rates, the opposite is true for Austria, Belgium, Germany, the Netherlands and Ireland, which have the lowest

[5] Following the comment by the OECD (2009, p. 129): "On average, analyzing one plausible value instead of five plausible values provides unbiased population estimates as well as unbiased sampling variances on these estimates."

[6] The number of missing values varies across countries and among variables. As the number of missing values is not very high, we decided not to apply any sophisticated method to impute values to the missing values using therefore only the real information reported by students.

percentage of truancy rates. Similarly, the PISA ESCS index also differs across countries: the wealthier students are in the Nordic area, the opposite is true for the Mediterranean countries.

At school level, we also find that features of the schools attended by the majority of students vary from country to country: more students are in private schools in Ireland, Belgium, Spain and the Netherlands; more students are in rural areas in Austria, Denmark, Ireland, Portugal and Sweden. Finally, in all countries truancy is seen to be a worse problem for the head teachers/principals than for the students, but schools and students agree with regards to household socio-economic levels. Class size is around 25 students per class, lower only in Demark and Belgium.

[Table 2] around here

Focusing on the correlations among the ICT variables and student scores, Table 3 shows that here also the picture is one of heterogeneity across countries. There is a negative (and significant) relationship between availability of ICT at school and the students' scores in reading, mathematics and science, which is higher in Portugal, the Netherlands, Ireland and Germany, but with values lower than 0.20. On the contrary, ICT used at home for school-related tasks is correlated positively with the scores (Austria, the Netherlands) and negatively (Greece), but the most common case is almost no correlation (and therefore non-significant). In the case of ICT used for entertainment, there seems to be relatively little correlation with the scores, in terms of the value of the coefficient or significance, in all the countries except Finland, where the correlation is negative. Lastly, students using ICT for entertainment seem to use ICT for school-related tasks as well, as shown in the last column (correlation among *entuse* and *homsch*), with significantly high values for the coefficient of correlation (this relation is more pronounced for Greece and Portugal).

[Table 3] around here

3.3 Descriptive statistics: the determinants of being a top ICT user at home

To complete the description of the factors that can influence ICT use, such as academic achievement, it is interesting to analyze the determinants of being a top ICT home user for school tasks, in an attempt to disentangle some of the complexity surrounding ICT availability, use and test scores. Our questions are: What makes a student a top ICT home user? Are there any differences between the test scores of low and high users? Is the trend similar for all countries? To answer these questions, we ran a logistic model in which the dependent variable is whether or not the student is a top ICT home user for school-related tasks (first quartile of the *homsch* variable)[7]. The results show that the probability of being a top ICT home user

[7] We repeated the same process using low ICT users (25% of the lower users in the *homsch* variable) as the dependent variable in the logistic regression, obtaining the opposite results in terms of the sign for all the variables. Such findings corroborate the evidence reported in this section.

increases if students have greater access to ICT at school in all the countries, with this probability being much higher in some (Demark, Finland, Ireland and Sweden) – see Table 4. Belonging to a richer household (PISA ESCS index) is also positively related to being a top user, indicating that students from advantaged families tend to use ICT for operations that increases their academic capital. Being a girl is positively associated with the probability of being a top ICT user at home in Austria, Belgium, Germany, Ireland, the Netherlands and Portugal, while being a boy increases this probability in Denmark, Spain, Finland, Italy, Sweden and Greece. Being a first generation immigrant increases the probability of using ICT more intensely in all countries, except for Portugal and the Netherlands. There seems to be no difference between immigrant and native students in Spain and Greece. Students who have repeated a year have a higher probability of using ICT more at home in Spain, Italy, Portugal, Greece and Sweden, and of using it less in Austria, Denmark and the Netherlands. Students who skip classes are less likely to be a top at home-ICT-user, except in Greece, Austria, Finland and Italy.

Looking at the effect of school variables, most of the variables show a small effect in terms of the probability of using ICT at home. The variable with a highest effect is the school mean ESCS variable, with a positive and significant effect in most countries – meaning that students attending schools with relatively affluent classmates are more likely to use ICT at home for school-related purposes. Going to a private school increases the probability of a student being a top user in all countries, while the opposite is true in Austria, Belgium, Germany and Denmark, and it makes no difference in Portugal and the Netherlands. Interestingly, with the notable exception of the Netherlands, being a top ICT home user is negatively correlated with the test scores in mathematics – and similar results are available from the authors for negative correlations with the test scores in reading and science. The preliminary evidence is, therefore, that the students who perform better in the test scores are not those who use ICT more intensively at home for homework and school tasks. In the next section, we will look more closely at the nature of this apparently negative relationship between the two variables of interest.

[Table 4] around here

3.4 Descriptive statistics: the determinants of academic achievement and the role of ICT in school-related tasks

Taking the analysis a step further, we propose a multivariate approach to take jointly into account all ICT, personal, family and school background variables. We will, therefore, estimate the combined impact of the explanatory variables on the mathematics scores (without controlling for endogeneity or establishing causality), using an Ordinary Least Squares (OLS) linear regression, in which ICT variables, such as the individual and school variables, are introduced.

The results (robust with regards to heteroscedasticity and clustered by school) are presented in Tables 5A, 5B and 5C (Annex) for each subject. Focusing on our main variables under study and with reference to test scores in mathematics, the results show that using ICT at home for school tasks has a positive and significant correlation with the students' test scores in some countries (Belgium and the Netherlands), negative in others (Germany, Denmark, Spain, Greece, Ireland, Italy Portugal and Sweden) and non-significant in the rest (Austria and Finland). On the contrary, higher availability of ICT at school (*ictsch*) is significantly and negatively associated with mathematics scores in all countries, above all in Denmark, Ireland and the Netherlands. These results hold for the other two subjects (reading and science), although the Netherlands is the only country showing a positive and significant association of ICT use for school-related tasks with the students' test scores. Turning to the individuals' variables, the results are consistent with the previous findings in this literature: being from a wealthier household (ESCS) is significant and positively related to test scores, while being a girl, a first-generation immigrant, being born in the last part of the year (in general), repeating a year and skipping classes is found to be the opposite. Attending ISCED 0 has a positive link with scores in mathematics in Spain, Italy, Sweden, Portugal and Greece only. Lastly, belonging to a traditional family has a positive and significant correlation with test scores in Denmark, Finland, Ireland, Greece and the Netherlands. At school level, better disciplinary climate and higher mean SES within the school have statistically significant associations with higher test scores. Class size and the school being located in a rural area are not correlated with test scores, while in all countries there is a correlation between test scores and going to a private school and between test scores and school-level truancy rates.

[Tables 5A, 5B and 5C] around here

3.5 Descriptive statistics: the effect of socio-economic background on ICT use and test scores

We ran some additional models in an attempt to disentangle the role of a student's socio-economic background and how the interaction between family background and ICT variables affects academic achievement. As shown above and fully demonstrated in the findings of previous literature, the wealthier the students' household, the higher their academic achievement. Obviously, access to better resources, joined by an enquiring mindset and approach to study encouraged by the student's parental background, will have a powerful effect on results. This evident connection may not be overly clear when combined with the ICT-related variables. In order to provide evidence on this point, we have provided three additional models and empirical approaches to the mathematics scores that take these issues into account:

- first, we replicated our OLS baseline model, adding four possible interactions between our ICT variables (*homsch* and *ictsch*) and the SES variable (ESCS);
- second, we ran quantile regressions to control for the effect of these variables in different parts of the distribution of the test scores and the possible interactions;

- third, we replicated the models for the four quartiles of the ESCS in order to capture the possible diverse effects in the different parts of the socio-economic distribution, which is a proxy of the households' wealth.

Table 6 shows all the possible interactions between the *homsch* (ICT use for homework), *ictsch* (ICT availability at school) and ESCS variables and their effects on the scores in mathematics. The results show that the effect (in terms of sign and level of significance) of the variables relating to access to ICT at school and ICT used at home for school-related tasks is the same as in the baseline model. The interaction of *ictsch* and *homsch* is only significant for Spain, Italy and Portugal, and its sign is negative, meaning that the combination of higher values of ICT used at home and at school are associated with lower scores. The interaction of *ictsch* with the ESCS variable is negative for Greece and positive for Belgium and Ireland: wealthier households and higher use of ICT at school mean better scores, while the opposite is true for Greece. Finally, *homsch* and ESCS used jointly is only significant and negative for Austria, Denmark and Spain: the negative association between ICT used at home for school-related tasks and scores in mathematics is stronger for higher SES students than for lower SES students. This indicates that higher use of ICT at home for school-related tasks is negatively associated with mathematics test scores across the distribution of family SESs and that greater differences in the mathematics scores between the top ICT users and low ICT users are found at the higher end of family SES distribution. In other words, differences in test scores stemming from the different uses of ICT are more significant in the subgroup of more affluent students than in that of those who are disadvantaged.

[Table 6] around here

As shown in Tables 7A to 7D, we ran a quantile regression for the first, second and third tertile of the mathematics score distribution, that is, differentiating across type of students (top, average and low performers in mathematics), taking all the possible interactions into account. The main differences with respect to the previous models are found in Austria, where the effect of using ICT at home for school-related tasks becomes significant for most of the specifications, implying that the effect changes for different kinds of students. In the other countries, the previously detected effect of *homsch* (positive or negative) seems to be more pronounced for the top and middle tertiles of students, meaning that ICT at home is drastically more important (for good or for bad) for the top and average performers than for students with lower test scores.

[Tables 7A, 7B, 7C and 7D] around here

Lastly, Table 8 presents the replications of the OLS baseline model for the four quartiles of the ESCS variable, in order to check whether the results are different for wealthier and poorer households. To start with, the previous positive effect of *homsch* in Belgium, the Netherlands and Austria seems basically to be caused by a student belonging to certain kind of household (i.e. the effect is concentrated in a specific quartile of students), while the negative effect in the remaining countries remains significant for all kinds of household, with some exceptions (Ireland and Denmark). The *ictsch* variable retains, in general, its negative correlation with the test scores, whereas the ESCS variable loses its positive and significant effect on test scores in Austria, Belgium, Germany, the Netherlands, Italy and Portugal for most of the quartiles, suggesting substantially uniform performance within the inter-quartile distribution.

[Table 8] around here

4. Econometric analysis: methodological approach and results

4.1 An overview of the main econometric challenges for the analysis

Our aim in this paper is to determine to what extent using ICT at home for school tasks affects students' achievement, and whether this effect differs from country to country. As explained in the previous descriptive section, we acknowledge that there is substantial heterogeneity across countries, meaning that it is difficult to determine how decisions made by students and existing conditions at school (in terms of ICT) can affect their scores. In other words, we are attempting to shed some light into how the decision of using more or less ICT at home can have a positive or negative impact on performance. OECD-PISA and other large scale assessments (such as the Progress in International Reading Literacy Study (PIRLS) and TIMSS) seem to produce very interesting datasets with all the required information to test our research question. However, the nature of this assessment is intrinsically observational, that is, our results are not based on an experiment in which one group is exposed to a certain stimulus, treatment or policy, while a similar control group is not. This means that, as we are not working with randomly assigned students, we must use different econometric techniques to solve the different problems linked to the nature of these datasets, and so provide some suggestions about the causal relationship between the use of ICT and test scores. Furthermore, and as stated previously, the evaluation of the impact of ICT on learning outcomes is not at all simple, because of the many connections between our topic of interest (ICT use) and different aspects of the learning process (Biagi et al., 2013).

Based upon the features of the PISA dataset and the nature of ICT, we face no small econometric challenge when measuring the impact of ICT on test scores. The selection bias and problem of endogeneity implies that students who use ICT may be systematically different from those who do not, whether in terms of their generic or specific use of ICT, in all the various levels of intensity and in the place ICT is used. Using ICT, above all when at home, is a decision taken by the individual student which is closely linked to their families, teachers and schools. It follows that, by simply comparing the test scores of the students using ICT with the test scores of those who do not (which is the approach adopted in several studies in the past), the resulting estimations would be biased (see a discussion on this in Fariña et al., 2015).

Related to this topic, there are unobservable factors or omitted variables that we may not have taken into account. In this case, the relationship between ICT use and learning may be influenced by unobservable factors (e.g. attitude to ICT, ability, motivations and aspirations), resulting in unobservable variables or measurement errors in our estimates. Hence, if some omitted variables are strongly correlated with an explanatory variable, the error term will be correlated with the explanatory variable and an endogeneity problem arises (Wooldridge, 2009).

In this paper, we have done our best to overcome these issues using different econometric techniques. Specifically, we made use of Propensity Score Matching (PSM) and Instrumental Variables (IV), as detailed in the next sections; we read and interpreted the results from these techniques jointly, in order to achieve greater robustness of the results by combining the two methods.

4.2 Econometric analysis (a): Propensity Score Matching

Using a PSM approach involves creating a counterfactual, in the form of a control group and a treatment group, in order to isolate the contribution or impact of the variable we want to study. In our case, we would like to determine the differences in scores between the top users of ICT at home for school tasks and the rest of students. We want to compare the results of test scores in an experimental group with those of the rest of students (control group) who have very similar observable characteristics and so are as likely to belong to one group as the other (experimental vs. control).

We followed four steps when implementing the Propensity Scores Matching (PSM) methodology. Firstly, we split the sample of students into two groups. For other works in the educational field, this decision is more or less a "must" given the research question: going to a public school vs. a private school (Dronkers and Avram, 2010; Mancebón et al., 2015); nuclear families vs. non-nuclear families (Santín and Sicilia, 2015); level of openness towards inquiry-based instruction (Jiang and Comas, 2015); the influence of academic and vocational tracks on students' educational expectations (Lee, 2014); and perceived competition among schools (Agasisti and Murtinu, 2012). In our case, this choice was not straightforward, as we worked with a continuous variable of analysis (the index *homsch*) rather than two real groups. That is why we decided that our treated or experimental group (EG) would consist of the "top ICT home users" and, the control group (CG) would consist of the rest of the students, those not using ICT intensively at home. Secondly, we calculated the selection equation, which allowed us to then calculate the propensity score, i.e. a regression that expresses the probability that a student belongs to the experimental or the control group, given his/her observable features. The selection and estimation of the conditional probability of being treated can take different functional forms and be probit, logistic or discriminant (Guo and Fraser, 2011). We opted for a logit specification. In terms of selecting the variables, we included all those that can influence both the ICT variable and the test scores at the same time (Caliendo and Kopeinig, 2008), which are those we detected in the literature review and described in the previous section. Thirdly, we balanced both samples of students belonging to the treated and control groups using the propensity score indicator. This means that required observations with the same propensity score must have the same distribution as the observed covariates after being matched. We then carried out the matching process, which involved calculating the differences in test scores between the two groups of students (experimental and control) by matching each "treated" student with a "non-treated" counterpart having the most similar propensity scores. There are various kinds of matching - greedy matching, optimal matching and fine balance matching (Guo and Fraser, 2010) - and we selected "fine balance". We also choose our algorithm, opting for the Nearest Neighbour matching (NNM) with replacement 1 to 3.[8] Operationally, we then calculated the mean of the propensity score for all the variables in the model, as well as the differences of the means, the reduction in bias resulting from the matching, and the significance, for the unmatched sample and the matched sample in both the control group (CG) and the experimental group (EG) (Figure 1). As most of the variables are significantly different, if we look at the difference in the means between the two groups before and after matching them, without the matching the estimations would have been biased.

[Figure 1] around here

The results of the PSM estimation are given in Table 9. This contains the difference in the average z-scores (standardized scores) in reading, mathematics and science for the EG (top users) 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 low performers (third column), in order to test whether the effect of using ICT at home differs along the whole distribution, as well as for the best and worst students' scores.

For the sake of simplicity, we will start by commenting on the results for mathematics and then report on any differences in science and reading. The findings show that intense ICT use produces a positive effect on the students' scores in mathematics only in Belgium, while it has the opposite effect everywhere else. In Austria, Denmark, the Netherlands, Portugal and Sweden there are non-significant differences between both groups, if we consider all students, that is, using ICT at home has no effect on test scores. If we focus on the top and bottom performers, the results change slightly: only Denmark (followed very closely by Sweden) shows no effect of ICT on test scores in both the top- and low-performing groups, meaning that using ICT at home does not explain the different effect that ICT use has on test scores across the distribution of student performance. The average negative effect becomes more relevant for top and low performers in another group of countries composed of Spain, Finland, Greece, Ireland, Italy and Germany, the latter being the country with the highest negative value for the effect of ICT on test scores. It implies that, for the average student, using ICT for school-related tasks leads to lower scores (more or less pronounced, depending on the country), and this effect increases for the low-achieving students and, even more so, for the high-achievers. In Portugal, the effect of ICT use becomes significant for top and low performers, and is more detrimental for low-achieving students. In the Netherlands, the opposite holds true: ICT seems to help the more disadvantaged students. In Belgium, ICT helps these low-achieving students most, but also the top and average performers. In Austria, ICT benefits top performers and penalizes low

[8] We tried different algorithms to calculate the PSM, and the NMM approach turned out being the one achieving the highest reduction in bias.

performers. To summarize, for most of the analyzed countries, using ICT for school tasks is detrimental, and penalizes the top performers in mathematics above all. The positive effects of ICT are less common, and ICT can improve student achievement in only two countries (Belgium and the Netherlands[9]).

Most of our comments about the results in mathematics also hold for reading and science. In Sweden only, ICT effects become significant and negative for the top performers in reading and science. In Belgium the positive effect becomes significant, but only for low performers. In Denmark, the same is true, but this time for the top performers in reading and science.

To sum up, it is difficult to find common patterns across countries from the results obtained through PSM. Nevertheless, it seems that using ICT at home can have a negative effect on test scores in most countries, while there is no robust positive effect in any country. These findings were then tested by means of a different econometric strategy, as explained in the next section.

[Table 9] around here

4.3 Econometric analysis (b): Instrumental Variables

The IV method allows analysts to correct the omitted variables problem and, if the "instrument" is appropriate, to establish causality. To be used as an instrument, a variable must be highly correlated with the endogenous explanatory variable (ICT-use variable), but causally unrelated with the dependent variable (student performance). That is, the instrument should have no effect on the dependent variable, apart from its indirect effect through the endogenous explanatory variable, and it should not be endogenous to the dependent variable (Woessman and West, 2006). In our work, we want to estimate the impact of ICT used at home for school tasks on test scores. In order to establish the causality and the possible endogeneity of this variable with the test scores, we decided to employ the variable *entuse* (ICT use for entertainment) to the instrument or variable of analysis, *homsch*, that is, ICT use for school tasks[10]. From a purely technical point of view, Table 3 shows that the correlation with all the tests scores, although significant, is close to zero in all countries. On the other hand, the correlation between *homsch* and *entuse* is clearly positive and significant across countries, so we think that it is a good candidate for IV. As the non-correlation of the ICT variable with the

[9] In the Netherlands, Haelermans and Ghysels (2013) offer empirical evidence about the positive effects of using individual interactive digital tools to practice numeracy skills looking at 7th-grade students, in a randomized experiment.

[10] In the case of ICT, other variables that can be proposed as IVs are the use of computers at school, which may be correlated to ICT use at home and not with tests scores. Greater computer use at school could be more strictly related to the educational activities of the class, so that students can benefit from their teachers' support, while greater computer use at home could be an indication of the students' additional engagement and hence capture some variations in learning attitude that are not well represented by the other available variables (Biagi et al., 2013). Although not demonstrating causality, Fariña et al. (2015) use other ICT use indices developed in the PISA dataset, such as *usesch* and *homsch* referred to computer use for schoolwork. Given that schoolwork is set by the school and not decided by the individual, they consider these indices as exogenous variables (they are not correlated with the error term).

residuals of the education function cannot be proved, we need to provide arguments to support our choice of the instrument as good.

The rationale for this choice arises from the fact that students nowadays are "native users" of ICT; they can adopt and use ICT in a very natural way, above all for entertainment. But this does not mean that they are professional users of ICT (that is, that they can create real content, or good presentations, or solve a maths problem using a computer, etc.). Therefore, the variable *entuse* should not be related to scores (none of the items used to calculate this index are related directly to school tasks), because frequent use of ICT for entertainment does not mean that students can make the most of ICT to obtain good grades. On the contrary, the *entuse* variable is related to *homsch*, because being familiar with ICT (using ICT for fun/entertainment) may have a spill-over effect, since the student is more familiar with ICT devices and the ways of using them, although not necessarily for carrying out school tasks. Thus, using ICT intensively for entertainment may help to overcome the access barriers and can enhance the students' use for homework, as it is normal for them to use ICT out of school. That is, once an individual becomes a *natural* and *active* user, he/she can incorporate their knowledge into all aspects of life, although this does not imply being a "professional" user who can fully exploit the technology when completing more strictly school-related tasks.

From an econometric perspective, to apply the IV method, we have to estimate a two-stage regression model. The estimation strategy would be as follows: for every student *i* we want to estimate an educational attainment function (Y=scores), depending on a set of X explanatory variables, among which we include variable *homsch* (equation #2) – which remains our core variable of interest

$$Y_i = \beta X_i + \delta homsch_i + \varepsilon_i \qquad (2)$$

To proceed with IV, in a first step, we calculate the probability obtained by regressing $homsch_i$ against all the other covariates plus one, $entuse_i$, which is the instrument (equation #3) which acts as a proxy for *homsch*.

$$homsch_i = \gamma X_i + \theta entuse_i + u_i \qquad (3)$$

In the second stage, we use the predictions of this first regression to estimate the educational attainment, using our instrument to explain the educational attainment (equation #4):

$$Y_i = \beta X_i + \delta \widehat{homsch}_i + \varepsilon_i \qquad (4)$$

We, therefore, run this model using the explained estimation strategy, for every country, clustering by schools within each of them. Results are robust to heteroscedasticity. We test the robustness of our instrument, checking that the F-statistic on the instrument in the first stage of two-stage least squares exceeds 10 for all the cases (Stock, *et al.* 2002). The tests of joint significance of the endogenous covariates in the main equation are also validated for all countries. The instrument is also validated across countries using the Sargan-Hansen test.

The results of the IV estimation for the impact of ICT use at home on test scores are provided in Tables 10A, 10B and 10C. Consistent with other previous works using IV, the instrumental variable estimates are different to those obtained through OLS. The impact of using ICT at home for school tasks becomes negative and statistically significant for all countries, except for Spain, where the impact is positive for all subjects, above all in reading and science. The positive effect found for the Netherlands in OLS (see Tables 5A, 5B, and 5C) does not persist significantly with IV. Portugal, Ireland and Greece also show a non-significant (or very weak) effect. The value of the impact of ICT use at home on test scores with the IV estimation is typically more negative than suggested by the results obtained through OLS, indicating an upward bias of the OLS coefficients. According to the IV analysis, it can, therefore, be concluded that, for most countries, a high amount of the negative correlation between the ICT use at home and the test scores is due to the causal effect. In other words, using ICT at home for school tasks substantially diminishes the performance of students in most of the analyzed countries.

[Tables 10A, 10B and 10C] around here

With the aim of obtaining estimates that are conceptually more coherent with those derived through PSM, we also ran an alternative specification of the IV regression, by instrumenting not *homsch* per se, but instead *homsch*=1, if the student can be classified as an "intensive user" of ICT at home for school-related purposes. The instrument is again the variable *entuse*, to preserve comparability with the estimated reported in Tables 10a-c. In Table 10d, the results are reported considering scores in mathematics as the dependent variable – analogous tables for reading and science are available on request from the authors. The findings reveal some interesting patterns. First, the sign, coefficients and statistically significance of the control variables remain unchanged, providing an indirect test of the validity of our approach. Therefore, the explanatory power of the model itself is slightly lower (see R^2); in other words, the use of the whole distribution of *homsch*, instead of the newly built dummy for intense use, is better suited to capture the statistical relationship between the use of ICT at home and educational performance. When observing the coefficient of the variable of interest (*top_homsch*, instrumented through *entuse*) it should be noted that the estimated effect is negative and statistically significant for all countries, with the only exception of Spain and the Netherlands, as in Table 10a. The magnitude of the coefficient is much higher, thus, coherently with the idea of a higher negative effect associated to a more intense use of ICT. The interpretation is that the top users of ICT at home for school-related tasks are experiencing negative effects on their educational output, as measured by OECD PISA test scores on mathematics.

[Table 10d] around here

5. Discussion of main findings and concluding remarks

In this paper, we have used two complementary econometric techniques to shed light on the relationship between (i) ICT used at home for school-related tasks and (ii) the academic outcome of 15-year old students, as measured through their test scores in the OECD-PISA standardized tests for reading, mathematics and science. Our analyses were intended to deal with the group of EU-15 countries, although in the end only 12 of them could be included in the empirical study, because we had no comparable data for the United Kingdom, France or Luxembourg. This research is innovative in that it moves beyond the purely descriptive comparisons of ICT use and test scores in different countries, typical of OECD reports (as in OECD, 2015) and tries instead to establish a causal link between our variable of interest (*homsch*, ICT use at home for school-related tasks) and academic results. Additionally, by including several countries in our study, we can understand how much of the relationship between *homsch* and test scores is country-dependent (i.e. heterogeneity does exist because of structural reasons) or instead uniform across countries. In the spirit of a growing internationalization of policies about digital learning at European level, it is important to take the literature about single countries studies a step further, and to prefer meaningful comparisons across countries.

The findings from the analyses presented here reveal that simple OLS regressions seem to indicate the lack of correlation between *homsch* and test scores, for most countries, in almost all subjects. When modelling the educational production function with a more adequate set of econometric techniques, a different reality emerges, and a negative effect exerted by using ICT at home for schooling purposes on test scores can be detected. The two techniques employed (propensity score matching (PSM) and instrumental variables (IV)) are coherent in estimating such negative impact, for most countries in all subjects. The magnitude of the effect is not directly comparable between the two methods; indeed, while the PSM considers the effect of "highly-intensive" use of ICT (by "treatment", we mean having very high level of the index *homsch*), the IV approach estimates the effect of the whole distribution of *homsch* along the whole distribution of test scores. Nevertheless, the broad picture that emerges is substantially clear and points at demonstrating that a higher use of ICT at home, although explicitly connected with school-related tasks, is detrimental for the measured results in the subject-specific test scores.

While the exploration of the reasons that cause the negative correlation between *homsch* and test scores is well beyond the scope of this work, some potential hypotheses can be formulated here. First, it can be the case that the computers used and/or the software employed are not adequate for the purpose of schooling. If, for instance, computers are too old or slow for what is required, the amount of time spent using them is not a good proxy for the phenomenon of interest as we should not expect significant productivity gains from the use. In the same vein, if the software used are not developed enough to help the students for a substantial qualitative advancement in terms of competences, the observed test scores of high/low users cannot appear as statistically evident. A second potential explanation, even complementary, is that the instructions given for using computers at home are not good or detailed enough to make the use adequately productive to observe positive gains in competences. In this scenario, ICT use could be potentially a productive investment, but the students are not given the right guidelines from their teachers to extract the absolute most from their ICT use. In this sense, it can also be interpreted as a teachers' or class' fault. If teachers do not adapt their teaching methods to engender a more thorough use of ICT tools, simply using them more is not conducive to students performing better in comparison with their lower-use counterparts. As emphasized in the literature, the role of teachers is vital if digital learning is to have a truly positive effect (Jager and Lokman, 2000). This eventuality also raises the question about whether teachers are truly competent to facilitate the productive use of ICT, if the technology is to be integrated within formal learning processes. This is a crucial topic, as the positive gains in competences should stem from interaction between the students and the teachers' human capital, and ability on the one side, if not joined by that on the other, can in essence vanish. Thirdly, it can be that the students themselves make a wrong use of ICT at home for school purposes. Students can be distracted by the tools (for example, having access to internet, music and social media) and so they over-estimate the time they spend on their computers doing homework, which can then not be truly indicative. If students are not expert or mature enough in how they use computers for schoolwork, or are not given proper guidelines from their teachers (a hypothesis considered above), then parental involvement is certainly necessary. If this is also missing, students can struggle and waste time trying to use ICT for homework, without gaining any real benefit. It can even be the case that, all other things being equal, students lose their motivation or do not keep pace with their schoolmates who study in a more "traditional" (less-ICT) way. Fourth, another option is that high ICT use at home for school purposes does actually improve the students' educational results, but not such as to be reflected in test scores, such as for example teaching them various kinds of non-cognitive skills. In this perspective, further work to assess the student's skills more completely – instead of only looking at their subject-specific knowledge - may be required to gain a better understanding of the effects and impact of ICT.

Independently of which real channel(s) of influence are most relevant, we can derive some policy implications. The most important implication is that it may be dangerous to promote a policy of spreading ICT as a homework tool, if not backed by a clear idea about how the technology should be used. If students, who already use technology extensively in their daily life, are left to fend for themselves when using technology for homework, without being given support from their teachers and/or parents, the results may affect their academic achievement negatively. It follows that trialling ICT-assisted homework must be backed by a strong relationship between families and schools, and there must be suitable protocols concerning the "correct" use of technological resources. A further implication is that attention must be paid to the quality of tools and materials used for computer-supported homework. School heads/principals and teachers should not necessarily assume that this material is of the right quality; material must be reviewed to ensure that it can be used to generate positive learning benefits. Debating whether such ICT support material is suitable must become central to educational planning at school and classroom level. According to the evidence, schools are ever more likely to use ICT as part of teaching and clearly the process of constantly assessing whether the tools are effective should be incorporated into school culture. This last point opens up the discussion about the use of technology during school-time. It is possible that the positive use of computers at home depends on how students are taught at school. According to this view, school head/ principals and teachers should not only make decisions concerning the level of ICT use, but how it should be divided between school and home – in other terms, how the technology can be used most productively to improve education and learning in selected subjects and under specific circumstances.

We also turned our attention to the topic of equality, using evidence suggesting that availability and use of ICT in education varies according to the students' different socio-economic backgrounds. Although we have not found any causal evidence for the difference between better-off and disadvantaged students in our analyses concerning the effect of ICT home use on test scores, our descriptive analyses suggest that the (negative) impact of the former on the latter is more pronounced for the relatively affluent students. It appears that there is no specific equality matter at issue here, and the role of digital learning can even act contrary to expectations. It is probable that, given that socially advantaged students are more likely to have access to ICT technology at home, they use it more. In addition, to the extent that this use is negatively related to test scores, these students will feel the detrimental effects on their learning more severely than their disadvantaged counterparts. It does not, however, follow that their test scores are lower in absolute terms. The results from our empirical analyses continue to demonstrate that there is a positive correlation between test scores and the indicator for economic, social and cultural status (ESCS) – see Tables 10a, b and c – in all countries and for all subjects.

We also investigated another potential source of inequality, related to the composition effect at school level. For instance, it can be the case where ICT used at home for school purposes produces, on average, negative results, but the results are positive for students whose classmates(peers) are from more advantaged socio-economic backgrounds. There are several potential pointers for this. Socio-economically advantaged students can help each other to use ICT more productively, by doing homework together. Alternatively, schools with socio-economically affluent students may have more funds to train teachers and/or supply better hardware and software, which can combine with home use of ICT to achieve better academic results. Independently of the actual reasons for these heterogeneous results, we considered it interesting to test if the effects of *homsch* vary across schools with different SESs. In order to explore whether this is the case, it is not enough to control for school-average ESCS. Instead, we must use an alternative IV regression, segmenting the student population according to their school-average ESCS. More specifically, we created three school clusters on the basis of average ESCS tertiles, and we estimated our IV model (Equations 2-4) for the three groups separately. The results for mathematics are presented in Table 11, suggesting that there are no differences between the three groups. No patterns emerged, which only indicates that we are unable to demonstrate that ICT use at home for school-related purposes can benefit students in schools with a relatively more advantaged student population, or vice versa. There are, however, some exceptions. For example, in Italy, students at schools with socio-economically disadvantaged peers experience a positive effect from using ICT at home, whereas the contrary holds true for students at schools with relatively affluent peers. The opposite seems to be the case in Sweden, where students at socio-economically disadvantaged schools obtain lower test scores if they make greater use of ICT at home for school purposes, while this effect is not statistically significant for students at socio-economically-affluent schools. In interpreting these results about school-level determinants of the test scores, it should also be kept in mind that running the models separately for the ESCS tertiles partly masks the effect of private schools – for instance, in no country are there private schools with a low average ESCS. Overall, the findings tend to confirm that peer effects are not a major driver for the aspect under study, and that this effect is more likely to be driven more by individual behaviour and teacher-specific indications, as well as by the kind of support the students received at home when completing their homework using a computer.

[Table 11] around here

The results of our study call for future research to corroborate their external validity. Our findings deal with only a limited number of countries, and for the specific time frame captured by OECD PISA 2012. The analysis could be repeated to including a wider group of countries and, above all, by looking at other educational systems that differ substantially from those of Europe (such as those of Asian countries, the United States and Australia) and where there may be a very different relationship between students and technology. Heterogeneity across countries is a topic deserving of attention on its own merits. We have interpreted some of the results that deviate from the big picture in this key – for example, that, for Spanish students, home use of ICT have positive effects on test scores. Although this is the only case in which such a positive relationship emerges, it can well be the case that it depends on particular policies or initiatives promoted in that country. This vertical, country-specific empirical analysis is well beyond the scope of the present paper, while instead pointing out that this degree of heterogeneity is an important driver of knowledge. Future studies could investigate the reasons for the specific effects of ICT on test scores in single countries. Similar considerations hold for our specific cohort of students. ICT level of use – and type of use – varies very rapidly over time. It would be interesting to test whether the effects of ICT use at home on test scores are constant over time and/or are instead vary. A first move in this direction is to replicate the analyses for OECD PISA 2009 and 2015 (the cycles before and after our PISA 2012). Our expectations are that ICT used at home for school-related purposes has increased over time; however, the direction of change of its effect on subject-related test scores is difficult to predict in advance. In addition, our study covers OECD-PISA data only, i.e. students who are 15 years old. The negative effect of ICT use at home on test scores may be linked to this age group and moment in school life. When this is possible, an investigation into these ICT effects for cohorts in earlier years could certainly provide an extremely interesting extension. As noted by Cuhna and Heckman (2007), the technology to produce education can have cumulative effects, especially at early stages of life. In such a perspective, it can well be the case that ICT support for homework is more productive in lower years/ grades, and its effectiveness only emerges later in school and only for children who were exposed earlier to adequate investment. Unfortunately, the current versions of international programmes that test students in lower grades – such as TIMSS and PIRLS, international surveys prepared by the International Association for the Evaluation of Educational Assessment (IEA) – are not designed to answer this question. We trust that future developments to these projects will also cover consider this area of investigation.

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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: Tradicional (dummy)
	month_birth	Month of birth
	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)
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)
Country level	AUT	Austria
	BEL	Belgium
	DEU	Germany
	DNK	Denmark
	ESP	Spain
	FIN	Finland
	GRC	Greece
	IRL	Ireland
	ITA	Italy
	NLD	Netherlands
	PRT	Portugal
	SWE	Sweden

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
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
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
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

Table 4. Logistic model of being a top user student of ICT at home for school tasks (variable: homsch), by country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
VARIABLES	AUT	BEL	DEU	DNK	ESP	FIN	GRC	IRL	ITA	NLD	PRT	SWE
z_pv1math	-0.0764***	0.0579***	-0.479***	-0.262***	-0.318***	-0.241***	-0.477***	-0.352***	-0.269***	0.108***	-0.209***	-0.336***
	(0.0127)	(0.0125)	(0.00583)	(0.0155)	(0.00722)	(0.0138)	(0.0114)	(0.0175)	(0.00540)	(0.00978)	(0.0149)	(0.0116)
gender	0.0475**	0.0594***	-0.110***	-0.107***	-0.161***	-0.139***	-0.610***	0.0785***	-0.342***	0.394***	0.0347	-0.315***
	(0.0202)	(0.0177)	(0.00847)	(0.0229)	(0.0103)	(0.0214)	(0.0175)	(0.0266)	(0.00858)	(0.0130)	(0.0212)	(0.0190)
immigrant	0.221***	0.0991**	0.728***	0.403***	-0.0383*	1.134***	0.0399	0.738***	0.142***	-0.404***	-0.388***	0.457***
	(0.0461)	(0.0397)	(0.0237)	(0.0732)	(0.0203)	(0.0793)	(0.0400)	(0.0422)	(0.0209)	(0.0501)	(0.0757)	(0.0440)
preprimary_no	-0.197**	-0.238***	-0.537***	-0.520***	-0.00194	-0.0476	-0.352***	0.0754*	-0.0168	-0.477***	0.0595*	-0.112***
	(0.0800)	(0.0680)	(0.0225)	(0.113)	(0.0237)	(0.0723)	(0.0426)	(0.0403)	(0.0231)	(0.0448)	(0.0320)	(0.0374)
famst	0.0356	0.288***	0.0745***	0.176***	0.0646***	0.189***	0.0739**	0.0830*	0.118***	0.0600***	0.0901***	-0.0500
	(0.0288)	(0.0282)	(0.0124)	(0.0336)	(0.0173)	(0.0309)	(0.0298)	(0.0440)	(0.0147)	(0.0209)	(0.0325)	(0.0321)
month_birth	0.00861**	-0.00791***	-0.0301***	-0.00959***	-0.0116***	0.00175	0.00706***	-0.00686	-0.0220***	-0.0301***	0.0226***	-0.00922***
	(0.00371)	(0.00257)	(0.00169)	(0.00363)	(0.00147)	(0.00337)	(0.00256)	(0.00492)	(0.00123)	(0.00232)	(0.00306)	(0.00285)
repeat_once	-0.167***	0.0277	-0.128***	-0.322***	0.0228	-0.0772	0.247***	-0.267***	0.269***	-0.0874***	0.129***	0.614***
	(0.0495)	(0.0343)	(0.0188)	(0.0907)	(0.0271)	(0.0794)	(0.0735)	(0.0800)	(0.0263)	(0.0210)	(0.0477)	(0.0796)
truan_someclass	0.212***	-0.181***	-0.106***	-0.155***	-0.0708***	-0.0109	0.152***	-0.134***	0.0443***	-0.164***	-0.172***	-0.127***
	(0.0274)	(0.0402)	(0.0150)	(0.0317)	(0.0111)	(0.0298)	(0.0173)	(0.0395)	(0.00872)	(0.0213)	(0.0251)	(0.0245)
ictsch	0.477***	0.401***	0.249***	0.154***	0.508***	0.400***	0.308***	0.527***	0.251***	0.354***	0.479***	0.337***
	(0.0131)	(0.00925)	(0.00501)	(0.0167)	(0.00595)	(0.0156)	(0.00829)	(0.0173)	(0.00375)	(0.0101)	(0.0139)	(0.0130)
escs	0.147***	0.164***	0.148***	0.197***	0.0657***	0.161***	0.170***	0.286***	0.133***	0.101***	0.151***	0.168***
	(0.0142)	(0.0118)	(0.00543)	(0.0166)	(0.00616)	(0.0159)	(0.0107)	(0.0189)	(0.00502)	(0.00963)	(0.0108)	(0.0137)
grade	0.178***	-0.210***	0.147***	0.254***	0.251***	-0.0661*	0.478***	0.125***	0.124***	-0.0268	0.0382	1.068***
	(0.0251)	(0.0235)	(0.0109)	(0.0370)	(0.0189)	(0.0361)	(0.0484)	(0.0229)	(0.0124)	(0.0179)	(0.0263)	(0.0507)
private	-0.439***	-0.271***	-0.509***	0.591***	0.0670***	0.318***	0.379***	0.00969	-0.0372*	0.00101	-0.0126	0.926***
	(0.0365)	(0.0214)	(0.0169)	(0.0294)	(0.0126)	(0.0565)	(0.0371)	(0.0295)	(0.0198)	(0.0137)	(0.0377)	(0.0262)
rural	-0.149***	-0.0896***	-0.0993***	-0.0901***	0.251***	-0.0338	0.0433**	-0.299***	-0.122***	-0.214***	0.213***	-0.303***
	(0.0209)	(0.0206)	(0.00939)	(0.0240)	(0.0122)	(0.0259)	(0.0203)	(0.0286)	(0.0115)	(0.0187)	(0.0253)	(0.0212)
disclima_m	0.214***	-0.0669***	0.269***	0.00354	-0.117***	0.0795**	-0.0287	-0.137***	0.0100	0.0199	0.0910***	-0.0639**
	(0.0241)	(0.0235)	(0.0117)	(0.0323)	(0.0116)	(0.0356)	(0.0261)	(0.0337)	(0.0103)	(0.0197)	(0.0302)	(0.0279)
clsize_m	0.0184***	-0.0533***	-0.0111***	0.0309***	0.00509***	0.00469	0.00335***	-0.0139***	-0.00277***	0.0137***	-0.00600***	-0.00781***
	(0.00109)	(0.00272)	(0.00112)	(0.00358)	(0.000961)	(0.00372)	(0.00107)	(0.00397)	(0.000453)	(0.00234)	(0.00197)	(0.00269)
truan	-0.105***	-0.110***	0.130***	0.0850***	0.0501***	-0.0326	0.0526***	0.0630**	0.0303***	-0.197***	0.117***	0.224***
	(0.0200)	(0.0241)	(0.0121)	(0.0253)	(0.0143)	(0.0228)	(0.0188)	(0.0301)	(0.00969)	(0.0165)	(0.0234)	(0.0231)
escs_m	0.444***	0.227***	0.859***	0.460***	0.207***	0.534***	0.131***	0.104**	0.260***	0.531***	0.0262	0.803***
	(0.0304)	(0.0288)	(0.0126)	(0.0374)	(0.0133)	(0.0482)	(0.0240)	(0.0425)	(0.0115)	(0.0264)	(0.0231)	(0.0348)
Constant	-1.696***	-0.0164	-0.543***	-1.840***	-1.331***	-1.618***	-1.179***	-1.274***	-0.915***	-1.371***	-1.552***	-1.409***
	(0.0928)	(0.0931)	(0.0414)	(0.144)	(0.0401)	(0.114)	(0.0607)	(0.124)	(0.0309)	(0.0807)	(0.0721)	(0.0844)
Observations	4,056	6,087	2,675	4,999	16,910	7,316	4,477	3,739	21,539	3,327	3,507	3,730

Robust standard errors (clustered at school level) below coefficients
***p<0.01,**p<0.05,*p<0.1

Table 5A. OLS regression about the determinants of Z-PV1MATH (test scores in mathematics), by country

Variables	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
homsch	0.0283	0.0256*	-0.103***	-0.0495***	-0.0761***	-0.0247	-0.106***	-0.0387**	-0.0432***	0.0774***	-0.0259*	-0.0745***
	(0.0211)	(0.0136)	(0.0236)	(0.0181)	(0.0107)	(0.0155)	(0.0110)	(0.0177)	(0.00929)	(0.0211)	(0.0155)	(0.0180)
gender	-0.358***	-0.273***	-0.314***	-0.167***	-0.264***	-0.0591**	-0.224***	-0.160***	-0.361***	-0.221***	-0.283***	-0.0431
	(0.0457)	(0.0200)	(0.0273)	(0.0230)	(0.0175)	(0.0253)	(0.0255)	(0.0313)	(0.0211)	(0.0236)	(0.0254)	(0.0294)
immigrant	-0.127*	-0.217***	-0.0465	-0.277***	-0.110**	-0.322***	0.000651	0.0437	-0.0522	-0.0695	0.133*	-0.175**
	(0.0676)	(0.0529)	(0.108)	(0.0630)	(0.0430)	(0.0642)	(0.0626)	(0.0486)	(0.0389)	(0.0927)	(0.0700)	(0.0841)
preprimary_no	0.0790	-0.0525	0.0699	0.194	0.219***	0.110	0.172***	-0.0266	0.234***	0.0509	0.0874*	0.149**
	(0.0834)	(0.101)	(0.0823)	(0.144)	(0.0427)	(0.0772)	(0.0549)	(0.0363)	(0.0430)	(0.0903)	(0.0473)	(0.0607)
famst	-0.0415	0.0350	-0.0437	0.0535*	-0.0152	0.0584*	0.0771*	0.0940**	-0.00706	0.115**	-0.0675*	0.0223
	(0.0392)	(0.0278)	(0.0410)	(0.0317)	(0.0302)	(0.0340)	(0.0416)	(0.0408)	(0.0244)	(0.0451)	(0.0375)	(0.0584)
month_birth	0.0122**	-0.00546**	0.0152**	0.00485	-0.00121	-0.0114***	-0.00912***	-0.0118**	-0.00909***	0.0262***	-0.00457	-0.00433
	(0.00475)	(0.00264)	(0.00615)	(0.00366)	(0.00239)	(0.00350)	(0.00342)	(0.00546)	(0.00191)	(0.00466)	(0.00435)	(0.00434)
repeat_once	-0.311***	-0.378***	-0.110	-0.262***	-0.197***	-0.558***	-0.470***	-0.367***	-0.278***	-0.138***	-0.464***	-0.241*
	(0.0658)	(0.0381)	(0.0736)	(0.0889)	(0.0454)	(0.0773)	(0.114)	(0.0693)	(0.0625)	(0.0378)	(0.0589)	(0.134)
truan_someclass	-0.144***	-0.209***	-0.134**	-0.314***	-0.139***	-0.295***	-0.0735***	-0.131***	-0.118***	-0.129**	-0.116***	-0.391***
	(0.0446)	(0.0397)	(0.0545)	(0.0332)	(0.0189)	(0.0316)	(0.0271)	(0.0377)	(0.0172)	(0.0637)	(0.0332)	(0.0360)
ictsch	-0.0474**	-0.0335***	-0.0525**	-0.143***	-0.0359***	-0.0705***	-0.0897***	-0.118***	0.0181*	-0.149***	-0.0735***	-0.0922***
	(0.0193)	(0.0116)	(0.0218)	(0.0192)	(0.0130)	(0.0187)	(0.0129)	(0.0174)	(0.00925)	(0.0283)	(0.0177)	(0.0230)
escs	0.126***	0.0962***	0.0780***	0.285***	0.138***	0.258***	0.196***	0.261***	0.0427***	0.0637***	0.162***	0.252***
	(0.0176)	(0.0134)	(0.0200)	(0.0192)	(0.0107)	(0.0163)	(0.0150)	(0.0189)	(0.00799)	(0.0157)	(0.0132)	(0.0223)
grade	0.313***	0.429***	0.467***	0.277***	0.526***	0.417***	0.225**	0.115***	0.171***	0.461***	0.347***	0.632***
	(0.0451)	(0.0265)	(0.0401)	(0.0342)	(0.0348)	(0.0378)	(0.105)	(0.0238)	(0.0321)	(0.0347)	(0.0330)	(0.106)
private	-0.202	0.109**	-0.270**	-0.0384	-0.00617	0.0430	-0.147	0.0339	-0.454***	0.0717	-0.0733	-0.0464
	(0.127)	(0.0461)	(0.106)	(0.0426)	(0.0395)	(0.0709)	(0.126)	(0.0374)	(0.0894)	(0.0698)	(0.0586)	(0.0501)
rural	0.111	-0.00217	0.0187	0.00372	-0.00834	0.0606*	0.0471	0.0644*	0.0114	0.0980	0.101**	-0.0753*
	(0.0678)	(0.0423)	(0.0644)	(0.0344)	(0.0373)	(0.0345)	(0.0545)	(0.0364)	(0.0589)	(0.0796)	(0.0485)	(0.0401)
disclima_m	0.320***	0.304***	0.253***	0.176***	0.0630*	0.0398	0.323***	0.127***	0.223***	0.311**	0.134**	0.117**
	(0.0775)	(0.0518)	(0.0726)	(0.0421)	(0.0375)	(0.0489)	(0.0658)	(0.0416)	(0.0451)	(0.144)	(0.0609)	(0.0557)
clsize_m	0.00833*	0.00955	0.0104	0.00774	-0.00353	0.0115**	0.000729	0.00571	0.00148	0.0478***	0.000391	0.00125
	(0.00480)	(0.00609)	(0.00639)	(0.00588)	(0.00286)	(0.00476)	(0.00289)	(0.00496)	(0.00188)	(0.0145)	(0.00377)	(0.00574)
truan	0.0280	-0.0620	-0.0774	-0.0444	-0.0842**	-0.0707**	-0.0532	-0.0785**	-0.313***	-0.101	-0.0929**	-0.000988
	(0.0673)	(0.0484)	(0.0775)	(0.0418)	(0.0413)	(0.0329)	(0.0541)	(0.0357)	(0.0434)	(0.0791)	(0.0425)	(0.0453)
escs_m	0.816***	0.602***	0.946***	0.274***	0.154***	0.165***	0.442***	0.414***	0.673***	1.004***	0.126***	0.286***
	(0.0662)	(0.0571)	(0.0644)	(0.0512)	(0.0394)	(0.0597)	(0.0568)	(0.0487)	(0.0462)	(0.142)	(0.0391)	(0.0736)
Constant	0.0143	0.433**	-0.242	-0.212	0.376***	0.0185	-0.300***	-0.119	0.196***	-1.518***	0.681***	-0.206
	(0.159)	(0.177)	(0.199)	(0.191)	(0.0978)	(0.128)	(0.108)	(0.144)	(0.0752)	(0.354)	(0.123)	(0.158)
Observations	4,056	6,087	2,675	4,999	16,910	7,316	4,477	3,747	21,539	3,327	3,507	3,730
R-squared	0.377	0.514	0.457	0.239	0.378	0.164	0.303	0.229	0.332	0.512	0.337	0.180

Robust standard errors (clustered by school) in parentheses

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

Table 5B. OLS regression about the determinants of Z-PV1READ (test scores in reading), by country

Variables	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
homsch	0.0141	-0.0133	-0.0830***	-0.0395*	-0.0750***	-0.0396**	-0.132***	-0.0571***	-0.0553***	0.0883***	-0.0476***	-0.0313
	(0.0201)	(0.0138)	(0.0227)	(0.0225)	(0.0124)	(0.0166)	(0.0118)	(0.0170)	(0.00971)	(0.0214)	(0.0144)	(0.0217)
gender	0.264***	0.182***	0.321***	0.297***	0.223***	0.570***	0.370***	0.304***	0.245***	0.176***	0.261***	0.438***
	(0.0456)	(0.0219)	(0.0258)	(0.0255)	(0.0173)	(0.0276)	(0.0289)	(0.0325)	(0.0217)	(0.0233)	(0.0260)	(0.0310)
immigrant	-0.145*	-0.171***	-0.185*	-0.209***	-0.0743*	-0.593***	-0.0672	-0.0601	-0.214***	-0.0774	0.0740	-0.309***
	(0.0846)	(0.0501)	(0.100)	(0.0675)	(0.0451)	(0.0706)	(0.0605)	(0.0474)	(0.0441)	(0.100)	(0.0753)	(0.0997)
preprimary_no	0.0896	0.0628	0.0682	0.355***	0.132***	0.118	0.180***	0.0107	0.160***	-0.000354	0.0481	0.180**
	(0.0829)	(0.106)	(0.0857)	(0.113)	(0.0465)	(0.0751)	(0.0625)	(0.0368)	(0.0452)	(0.0941)	(0.0395)	(0.0706)
famst	-0.0286	0.0195	-0.0629	0.0300	-0.0382	-0.0242	0.179***	0.0934**	-0.0809***	-0.0189	-0.0679*	-0.0130
	(0.0354)	(0.0294)	(0.0382)	(0.0345)	(0.0367)	(0.0320)	(0.0402)	(0.0393)	(0.0256)	(0.0448)	(0.0347)	(0.0611)
month_birth	0.00753	-0.00520*	0.0125**	0.00518	-0.00158	-0.0118***	-0.00742*	-0.0140***	-0.00975***	0.0195***	0.000155	-0.00429
	(0.00481)	(0.00275)	(0.00539)	(0.00383)	(0.00256)	(0.00362)	(0.00380)	(0.00531)	(0.00184)	(0.00494)	(0.00388)	(0.00481)
repeat_once	-0.308***	-0.312***	-0.133**	-0.359***	-0.200***	-0.637***	-0.499***	-0.361***	-0.363***	-0.124***	-0.354***	-0.433***
	(0.0688)	(0.0406)	(0.0583)	(0.0953)	(0.0545)	(0.0700)	(0.139)	(0.0675)	(0.0618)	(0.0411)	(0.0612)	(0.162)
truan_someclass	-0.0689	-0.157***	-0.107**	-0.256***	-0.111***	-0.349***	-0.129***	-0.220***	-0.0874***	-0.266***	-0.163***	-0.352***
	(0.0460)	(0.0462)	(0.0488)	(0.0308)	(0.0212)	(0.0336)	(0.0276)	(0.0416)	(0.0166)	(0.0654)	(0.0293)	(0.0431)
ictsch	-0.0496**	-0.0742***	-0.0413**	-0.166***	-0.0356**	-0.0391*	-0.107***	-0.138***	-0.0116	-0.195***	-0.0861***	-0.0836***
	(0.0213)	(0.0123)	(0.0191)	(0.0187)	(0.0157)	(0.0205)	(0.0133)	(0.0177)	(0.00854)	(0.0291)	(0.0202)	(0.0272)
escs	0.112***	0.0812***	0.0672***	0.280***	0.130***	0.238***	0.146***	0.271***	0.0322***	0.0744***	0.135***	0.269***
	(0.0184)	(0.0134)	(0.0178)	(0.0168)	(0.0125)	(0.0165)	(0.0161)	(0.0175)	(0.00763)	(0.0151)	(0.0127)	(0.0237)
grade	0.188***	0.353***	0.343***	0.201***	0.500***	0.317***	0.248**	0.0893***	0.169***	0.352***	0.343***	0.445***
	(0.0474)	(0.0313)	(0.0347)	(0.0389)	(0.0392)	(0.0407)	(0.116)	(0.0238)	(0.0358)	(0.0372)	(0.0344)	(0.137)
private	-0.248***	0.100**	-0.218**	-0.0225	0.00207	0.133	-0.175*	0.0787*	-0.376***	0.0668	-0.0514	0.0642
	(0.0822)	(0.0494)	(0.103)	(0.0488)	(0.0511)	(0.0918)	(0.104)	(0.0409)	(0.0755)	(0.0625)	(0.0690)	(0.0761)
rural	0.0497	0.0110	-0.0421	-0.0263	-0.0904**	0.0229	0.00555	0.0875**	-0.0405	0.0926	0.0811	-0.103
	(0.0679)	(0.0439)	(0.0680)	(0.0393)	(0.0449)	(0.0462)	(0.0652)	(0.0399)	(0.0594)	(0.0787)	(0.0499)	(0.0629)
disclima_m	0.324***	0.266***	0.173**	0.160***	0.0351	-0.0318	0.379***	0.119**	0.197***	0.377**	0.208***	0.161**
	(0.0728)	(0.0535)	(0.0772)	(0.0441)	(0.0480)	(0.0592)	(0.0876)	(0.0487)	(0.0431)	(0.151)	(0.0775)	(0.0762)
clsize_m	0.00878**	0.0208***	0.00791	0.0113*	-0.00206	0.0172***	0.00204	0.00661	0.00340*	0.0458***	0.00549	0.0110
	(0.00351)	(0.00646)	(0.00702)	(0.00595)	(0.00319)	(0.00629)	(0.00344)	(0.00644)	(0.00200)	(0.0141)	(0.00370)	(0.00775)
truan	-0.0165	-0.0624	-0.137*	0.0443	-0.0584	-0.0246	-0.0337	-0.0804*	-0.264***	-0.0270	-0.0789	0.0253
	(0.0688)	(0.0520)	(0.0760)	(0.0517)	(0.0508)	(0.0411)	(0.0625)	(0.0418)	(0.0476)	(0.0786)	(0.0483)	(0.0715)
escs_m	0.865***	0.578***	0.805***	0.296***	0.136***	0.123	0.521***	0.392***	0.716***	0.963***	0.118**	0.270***
	(0.0699)	(0.0574)	(0.0605)	(0.0702)	(0.0460)	(0.0823)	(0.0620)	(0.0552)	(0.0443)	(0.140)	(0.0459)	(0.0978)
Constant	-0.502***	-0.244	-0.400*	-0.718***	0.238**	-0.307*	-0.421***	-0.170	0.0345	-1.467***	0.262**	-0.586***
	(0.145)	(0.195)	(0.228)	(0.174)	(0.101)	(0.159)	(0.117)	(0.174)	(0.0753)	(0.358)	(0.108)	(0.207)
Observations	4,056	6,087	2,675	4,999	16,910	7,316	4,477	3,747	21,539	3,327	3,507	3,730
R-squared	0.398	0.483	0.444	0.252	0.332	0.229	0.353	0.271	0.356	0.477	0.330	0.206

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

Table 5C. OLS regression about the determinants of Z-PV1SCIE (test scores in science), by country

Variables	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
homsch	0.0170	-0.0171	-0.107***	-0.0266	-0.0676***	-0.0542***	-0.108***	-0.0392**	-0.0558***	0.0991***	-0.0317**	-0.0778***
	(0.0200)	(0.0139)	(0.0234)	(0.0250)	(0.0133)	(0.0172)	(0.0119)	(0.0186)	(0.0103)	(0.0228)	(0.0145)	(0.0198)
gender	-0.210***	-0.192***	-0.134***	-0.148***	-0.160***	0.0977***	-0.00603	-0.0646*	-0.184***	-0.133***	-0.120***	-0.00561
	(0.0436)	(0.0215)	(0.0272)	(0.0277)	(0.0176)	(0.0275)	(0.0249)	(0.0361)	(0.0234)	(0.0253)	(0.0248)	(0.0295)
immigrant	-0.266***	-0.187***	-0.163	-0.301***	-0.133***	-0.617***	0.00439	0.0408	-0.127***	-0.0264	0.0611	-0.362***
	(0.0841)	(0.0524)	(0.113)	(0.0688)	(0.0404)	(0.0723)	(0.0652)	(0.0523)	(0.0414)	(0.0934)	(0.0798)	(0.0901)
preprimary_no	0.266***	0.243**	0.0734	0.301*	0.172***	0.171*	0.189***	-0.00662	0.236***	-0.111	0.0557	0.0991
	(0.0866)	(0.102)	(0.101)	(0.156)	(0.0407)	(0.0897)	(0.0604)	(0.0414)	(0.0535)	(0.0905)	(0.0415)	(0.0667)
famst	-0.0364	0.0421	-0.0512	0.0428	-0.0496	0.0487	0.0965**	0.133***	-0.0176	0.0722	0.0258	0.0378
	(0.0356)	(0.0290)	(0.0410)	(0.0378)	(0.0338)	(0.0345)	(0.0423)	(0.0421)	(0.0252)	(0.0490)	(0.0351)	(0.0610)
month_birth	0.00359	-0.00581**	0.0193***	-0.000736	-0.00214	-0.0151***	-0.00775**	-0.0161***	-0.0103***	0.0221***	-0.00541	-0.00130
	(0.00475)	(0.00277)	(0.00614)	(0.00408)	(0.00257)	(0.00371)	(0.00368)	(0.00599)	(0.00208)	(0.00504)	(0.00411)	(0.00463)
repeat_once	-0.323***	-0.401***	-0.0913	-0.302***	-0.162***	-0.626***	-0.728***	-0.344***	-0.378***	-0.0899**	-0.307***	-0.445***
	(0.0655)	(0.0398)	(0.0741)	(0.114)	(0.0590)	(0.0772)	(0.114)	(0.0816)	(0.0616)	(0.0410)	(0.0595)	(0.151)
truan_someclass	-0.158***	-0.228***	-0.129**	-0.293***	-0.124***	-0.383***	-0.137***	-0.203***	-0.109***	-0.170**	-0.143***	-0.343***
	(0.0428)	(0.0395)	(0.0503)	(0.0374)	(0.0228)	(0.0325)	(0.0284)	(0.0459)	(0.0176)	(0.0711)	(0.0306)	(0.0392)
ictsch	-0.0374**	-0.0307**	-0.0519**	-0.131***	-0.0522***	-0.0582***	-0.102***	-0.127***	0.00715	-0.139***	-0.0661***	-0.112***
	(0.0188)	(0.0119)	(0.0207)	(0.0221)	(0.0141)	(0.0201)	(0.0143)	(0.0191)	(0.00952)	(0.0326)	(0.0185)	(0.0275)
escs	0.167***	0.120***	0.102***	0.299***	0.140***	0.255***	0.174***	0.285***	0.0378***	0.100***	0.148***	0.263***
	(0.0178)	(0.0130)	(0.0187)	(0.0219)	(0.0114)	(0.0196)	(0.0163)	(0.0204)	(0.00825)	(0.0154)	(0.0125)	(0.0232)
grade	0.176***	0.330***	0.403***	0.228***	0.437***	0.344***	0.144	0.0766***	0.136***	0.387***	0.349***	0.434***
	(0.0459)	(0.0288)	(0.0424)	(0.0388)	(0.0435)	(0.0374)	(0.108)	(0.0262)	(0.0397)	(0.0358)	(0.0346)	(0.142)
private	-0.198**	0.0839*	-0.195*	-0.0399	-0.00290	0.0357	-0.141	0.0480	-0.396***	0.0587	-0.103	-0.00836
	(0.0886)	(0.0477)	(0.118)	(0.0499)	(0.0446)	(0.102)	(0.162)	(0.0442)	(0.0791)	(0.0679)	(0.0679)	(0.0669)
rural	0.0664	0.0761*	0.0210	0.0467	-0.0931**	0.0696*	0.0221	0.0822*	-0.0325	0.133*	0.00683	-0.0386
	(0.0641)	(0.0427)	(0.0686)	(0.0411)	(0.0382)	(0.0386)	(0.0630)	(0.0434)	(0.0622)	(0.0736)	(0.0467)	(0.0564)
disclima_m	0.344***	0.210***	0.263***	0.0824	0.0553	0.0361	0.337***	0.126**	0.139***	0.338**	0.163**	0.148**
	(0.0726)	(0.0505)	(0.0719)	(0.0514)	(0.0417)	(0.0585)	(0.0836)	(0.0506)	(0.0461)	(0.151)	(0.0699)	(0.0692)
clsize_m	0.00832**	0.0139**	0.0110	0.00911	-0.00379	0.0151***	0.00226	0.00186	0.00202	0.0427***	0.00433	0.00729
	(0.00402)	(0.00554)	(0.00708)	(0.00629)	(0.00313)	(0.00571)	(0.00330)	(0.00636)	(0.00196)	(0.0139)	(0.00362)	(0.00724)
truan	0.0217	-0.0692	-0.104	-0.0516	-0.0751	-0.0472	-0.0195	-0.0245	-0.285***	-0.0785	-0.115***	-0.0104
	(0.0642)	(0.0515)	(0.0778)	(0.0546)	(0.0469)	(0.0351)	(0.0579)	(0.0461)	(0.0476)	(0.0766)	(0.0393)	(0.0630)
escs_m	0.791***	0.493***	0.791***	0.353***	0.0982**	0.0436	0.425***	0.449***	0.685***	0.961***	0.123***	0.370***
	(0.0700)	(0.0541)	(0.0633)	(0.0699)	(0.0430)	(0.0699)	(0.0675)	(0.0574)	(0.0481)	(0.143)	(0.0410)	(0.0941)
Constant	-0.318**	-0.181	-0.297	-0.489**	0.424***	0.0637	-0.408***	0.0134	0.0919	-1.265***	0.373***	-0.391**
	(0.147)	(0.172)	(0.230)	(0.209)	(0.0966)	(0.157)	(0.117)	(0.180)	(0.0777)	(0.355)	(0.106)	(0.194)
Observations	4,056	6,087	2,675	4,999	16,910	7,316	4,477	3,747	21,539	3,327	3,507	3,730
R-squared	0.380	0.450	0.397	0.209	0.300	0.151	0.291	0.214	0.299	0.433	0.308	0.179

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

Table 6. OLS regression about the determinants of Z-PV1MATH (test scores in mathematics), homsch, ictsch and escs interactions, by country

Variables	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
homsch /escs												
homsch	0.0267	0.0246*	-0.103***	-0.0381**	-0.0819***	-0.0173	-0.108***	-0.0377**	-0.0432***	0.0756***	-0.0290*	-0.0712***
	(0.0208)	(0.0135)	(0.0231)	(0.0179)	(0.0114)	(0.0162)	(0.0112)	(0.0177)	(0.00930)	(0.0209)	(0.0155)	(0.0179)
escs	0.127***	0.0959***	0.0775***	0.304***	0.139***	0.239***	0.194***	0.246***	0.0427***	0.0537***	0.166***	0.249***
	(0.0175)	(0.0134)	(0.0205)	(0.0193)	(0.0107)	(0.0225)	(0.0152)	(0.0210)	(0.00801)	(0.0189)	(0.0137)	(0.0224)
c.homsch#c.escs	-0.0463**	0.00966	-0.00276	-0.0453**	-0.0209**	-0.0241	-0.0172	-0.0240	-0.000293	0.0212	-0.00945	-0.0181
	(0.0187)	(0.0162)	(0.0248)	(0.0176)	(0.0105)	(0.0169)	(0.0116)	(0.0185)	(0.00765)	(0.0198)	(0.0115)	(0.0160)
ictsch	-0.0461**	-0.0332***	-0.0525**	-0.143***	-0.0363***	-0.0705***	-0.0896***	-0.117***	0.0181*	-0.150***	-0.0737***	-0.0921***
	(0.0191)	(0.0116)	(0.0218)	(0.0190)	(0.0129)	(0.0187)	(0.0129)	(0.0176)	(0.00925)	(0.0285)	(0.0177)	(0.0230)
ictsch /escs												
ictsch	-0.0491**	-0.0380***	-0.0587***	-0.144***	-0.0368***	-0.0691***	-0.0912***	-0.124***	0.0178*	-0.146***	-0.0777***	-0.0759***
	(0.0189)	(0.0113)	(0.0213)	(0.0201)	(0.0130)	(0.0179)	(0.0125)	(0.0173)	(0.00922)	(0.0270)	(0.0183)	(0.0229)
escs	0.125***	0.104***	0.0801***	0.282***	0.137***	0.260***	0.200***	0.265***	0.0459***	0.0684***	0.164***	0.270***
	(0.0175)	(0.0137)	(0.0205)	(0.0238)	(0.0109)	(0.0172)	(0.0150)	(0.0191)	(0.00860)	(0.0184)	(0.0130)	(0.0240)
c.ictsch#c.escs	0.0146	0.0263**	0.0215	0.00298	-0.00484	-0.00370	-0.0343***	0.0374**	0.00663	-0.0117	-0.0205	-0.0551**
	(0.0203)	(0.0104)	(0.0220)	(0.0214)	(0.0102)	(0.0218)	(0.0115)	(0.0182)	(0.00831)	(0.0237)	(0.0146)	(0.0258)
homsch	0.0281	0.0266*	-0.103***	-0.0495***	-0.0763***	-0.0247	-0.107***	-0.0395**	-0.0431***	0.0777***	-0.0267*	-0.0746***
	(0.0211)	(0.0136)	(0.0236)	(0.0181)	(0.0107)	(0.0155)	(0.0110)	(0.0177)	(0.00930)	(0.0211)	(0.0155)	(0.0177)
ictsch/homsch												
ictsch	-0.0475**	-0.0327***	-0.0536**	-0.151***	-0.0335**	-0.0724***	-0.0917***	-0.118***	0.0179*	-0.148***	-0.0573***	-0.0943***
	(0.0197)	(0.0116)	(0.0224)	(0.0242)	(0.0132)	(0.0215)	(0.0133)	(0.0192)	(0.00925)	(0.0291)	(0.0194)	(0.0231)
homsch	0.0283	0.0306**	-0.103***	-0.0652**	-0.0788***	-0.0239	-0.108***	-0.0387**	-0.0471***	0.0787***	-0.0216	-0.0646***
	(0.0211)	(0.0141)	(0.0237)	(0.0316)	(0.0113)	(0.0163)	(0.0107)	(0.0177)	(0.00979)	(0.0236)	(0.0156)	(0.0202)
c.ictsch#c.homsch	-0.00112	0.0159	-0.00567	0.0187	-0.0233*	-0.00241	0.00894	0.000304	-0.00959*	-0.00242	-0.0388**	-0.0236
	(0.0194)	(0.0103)	(0.0200)	(0.0281)	(0.0124)	(0.0183)	(0.00841)	(0.0161)	(0.00543)	(0.0186)	(0.0168)	(0.0171)
escs	0.126***	0.0971***	0.0780***	0.285***	0.137***	0.258***	0.196***	0.261***	0.0427***	0.0637***	0.161***	0.252***
	(0.0176)	(0.0133)	(0.0200)	(0.0191)	(0.0107)	(0.0163)	(0.0150)	(0.0189)	(0.00799)	(0.0157)	(0.0132)	(0.0224)
ictsch/homsch/escs												
ictsch	-0.0495**	-0.0369***	-0.0605***	-0.149***	-0.0335**	-0.0733***	-0.0934***	-0.125***	0.0175*	-0.147***	-0.0612***	-0.0792***
	(0.0192)	(0.0114)	(0.0221)	(0.0227)	(0.0133)	(0.0224)	(0.0130)	(0.0196)	(0.00920)	(0.0285)	(0.0201)	(0.0229)
homsch	0.0266	0.0307**	-0.103***	-0.0511	-0.0845***	-0.0162	-0.109***	-0.0385**	-0.0474***	0.0773***	-0.0243	-0.0643***
	(0.0208)	(0.0142)	(0.0231)	(0.0319)	(0.0119)	(0.0171)	(0.0109)	(0.0177)	(0.00980)	(0.0239)	(0.0157)	(0.0193)
c.ictsch#c.homsch	-0.00495	0.0145	-0.00797	0.0151	-0.0234*	-0.00292	0.0104	-0.00268	-0.0102*	-0.00256	-0.0385**	-0.0195
	(0.0198)	(0.0102)	(0.0197)	(0.0271)	(0.0121)	(0.0186)	(0.00839)	(0.0159)	(0.00550)	(0.0191)	(0.0162)	(0.0168)
escs	0.126***	0.104***	0.0794***	0.303***	0.139***	0.239***	0.199***	0.247***	0.0463***	0.0580***	0.166***	0.267***
	(0.0173)	(0.0139)	(0.0209)	(0.0253)	(0.0109)	(0.0250)	(0.0152)	(0.0211)	(0.00863)	(0.0211)	(0.0137)	(0.0242)
c.homsch#c.escs	-0.0499**	0.00367	-0.00577	-0.0442**	-0.0211**	-0.0244	-0.00977	-0.0292	-0.00196	0.0202	-0.00601	-0.0116
	(0.0195)	(0.0166)	(0.0246)	(0.0181)	(0.0102)	(0.0178)	(0.0116)	(0.0185)	(0.00769)	(0.0196)	(0.0121)	(0.0170)
c.ictsch#c.escs	0.0248	0.0244**	0.0226	6.47e-05	0.00194	0.00133	-0.0328***	0.0422**	0.00795	-0.00937	-0.0182	-0.0496*
	(0.0212)	(0.0108)	(0.0221)	(0.0212)	(0.00992)	(0.0230)	(0.0113)	(0.0183)	(0.00846)	(0.0234)	(0.0151)	(0.0264)

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

Table 7A. Quantile regression for the determinants of Z-PV1MATHS (test scores in mathematics), homsch and escs interaction, by country

Variables	(25%) AUT	(50%) AUT	(75%) AUT	(25%) BEL	(50%) BEL	(75%) BEL	(25%) DEU	(50%) DEU	(75%) DEU	(25%) DNK	(50%) DNK	(75%) DNK
homsch	0.0479***	0.0284***	0.0328	0.0337***	0.0410**	0.0357***	-0.107***	-0.125***	-0.114***	-0.0523***	-0.0729***	-0.0840***
	(0.0172)	(0.0104)	(0.0212)	(0.00789)	(0.0200)	(0.0133)	(0.0186)	(0.0251)	(0.0279)	(0.0177)	(0.0205)	(0.0263)
escs	0.130***	0.125***	0.120***	0.0812***	0.0876***	0.117***	0.0835***	0.0716***	0.0775**	0.265***	0.284***	0.320***
	(0.0195)	(0.0239)	(0.0271)	(0.0149)	(0.0156)	(0.0200)	(0.0234)	(0.0239)	(0.0311)	(0.0188)	(0.0171)	(0.0220)
c.homsch#c.escs	-0.0284	-0.0264	-0.0399	0.00271	0.0162	0.0346***	-0.0226	0.00848	-0.0158	-0.0321*	-0.0408**	-0.0504*
	(0.0202)	(0.0233)	(0.0330)	(0.0200)	(0.0145)	(0.0133)	(0.0386)	(0.0279)	(0.0236)	(0.0182)	(0.0193)	(0.0285)
ictsch	-0.0364	-0.0210	-0.0390	-0.0428***	-0.0480**	-0.0358**	-0.0500**	-0.0642***	-0.0489**	-0.138***	-0.148***	-0.155***
	(0.0245)	(0.0243)	(0.0239)	(0.0157)	(0.0196)	(0.0157)	(0.0205)	(0.0233)	(0.0228)	(0.0173)	(0.0203)	(0.0286)

Variables	(25%) ESP	(50%) ESP	(75%) ESP	(25%) FIN	(50%) FIN	(75%) FIN	(25%) GRC	(50%) GRC	(75%) GRC	(25%) IRL	(50%) IRL	(75%) IRL
homsch	-0.0674***	-0.0721***	-0.0675***	-0.0799***	-0.0619***	-0.0470***	-0.0900***	-0.118***	-0.130***	-0.0313	-0.0277*	-0.0425*
	(0.0101)	(0.00967)	(0.0134)	(0.0124)	(0.0129)	(0.0160)	(0.0147)	(0.0151)	(0.0145)	(0.0214)	(0.0151)	(0.0222)
escs	0.101***	0.117***	0.124***	0.266***	0.277***	0.272***	0.169***	0.202***	0.224***	0.215***	0.274***	0.273***
	(0.00727)	(0.00760)	(0.0109)	(0.0161)	(0.0177)	(0.0198)	(0.0185)	(0.0178)	(0.0184)	(0.0362)	(0.0233)	(0.0345)
c.homsch#c.escs	-0.0171*	0.00151	-0.00565	0.0108	-0.0174	-0.0388**	-0.0217	-0.0220**	-0.0232	-0.0420*	-0.0362	-0.0516**
	(0.00929)	(0.00876)	(0.00779)	(0.0176)	(0.0146)	(0.0154)	(0.0160)	(0.0107)	(0.0173)	(0.0253)	(0.0226)	(0.0252)
ictsch	-0.0568***	-0.0386***	-0.0315***	-0.0522***	-0.0613***	-0.0855***	-0.0960***	-0.0849***	-0.108***	-0.102***	-0.103***	-0.107***
	(0.00787)	(0.00955)	(0.0118)	(0.0168)	(0.0133)	(0.0274)	(0.0124)	(0.0175)	(0.0163)	(0.0204)	(0.0210)	(0.0185)

Variables	(25%) ITA	(50%) ITA	(75%) ITA	(25%) NLD	(50%) NLD	(75%) NLD	(25%) PRT	(50%) PRT	(75%) PRT	(25%) SWE	(50%) SWE	(75%) SWE
homsch	-0.0346***	-0.0342***	-0.0422***	0.0694***	0.0670***	0.0674**	-0.0315	-0.0515*	-0.0649**	-0.0469**	-0.0862***	-0.113***
	(0.00714)	(0.00673)	(0.00991)	(0.0134)	(0.0227)	(0.0308)	(0.0258)	(0.0285)	(0.0285)	(0.0228)	(0.0168)	(0.0253)
escs	0.0356***	0.0388***	0.0422***	0.0258	0.0438**	0.0197	0.149***	0.177***	0.170***	0.223***	0.230***	0.269***
	(0.00577)	(0.00738)	(0.00739)	(0.0244)	(0.0206)	(0.0302)	(0.0239)	(0.0190)	(0.0241)	(0.0248)	(0.0224)	(0.0227)
c.homsch#c.escs	-0.00925	-0.0118	-0.00760	0.0358*	0.00485	0.0377	-0.0471**	-0.00627	0.00805	-0.0401*	-0.0492***	-0.0117
	(0.00742)	(0.00737)	(0.00969)	(0.0195)	(0.0184)	(0.0287)	(0.0190)	(0.0206)	(0.0187)	(0.0228)	(0.0159)	(0.0190)
ictsch	0.0170***	0.0190***	0.0309***	-0.116***	-0.144***	-0.118***	-0.0637***	-0.104***	-0.108***	-0.0884***	-0.101***	-0.115***
	(0.00545)	(0.00554)	(0.00843)	(0.0318)	(0.0168)	(0.0256)	(0.0244)	(0.0199)	(0.0258)	(0.0291)	(0.0265)	(0.0214)

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

Table 7B. Quantile regression for the determinants of Z-PV1MATHS (test scores in mathematics), ictsch and escs interaction, by country

	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)
Variables	AUT	AUT	AUT	BEL	BEL	BEL	DEU	DEU	DEU	DNK	DNK	DNK
ictsch	-0.0381*	-0.0295	-0.0490*	-0.0542***	-0.0516***	-0.0328***	-0.0524	-0.0694**	-0.0583**	-0.113***	-0.136***	-0.141***
	(0.0201)	(0.0246)	(0.0262)	(0.0106)	(0.0126)	(0.0110)	(0.0351)	(0.0293)	(0.0239)	(0.0146)	(0.0179)	(0.0270)
escs	0.132***	0.130***	0.131***	0.0864***	0.0975***	0.132***	0.0767**	0.0708**	0.0830**	0.289***	0.297***	0.311***
	(0.0208)	(0.0191)	(0.0212)	(0.0139)	(0.0217)	(0.0191)	(0.0301)	(0.0305)	(0.0355)	(0.0212)	(0.0275)	(0.0250)
c.ictsch#c.escs	0.0210	0.0442**	0.0733**	0.0294***	0.0363**	0.0272*	0.00527	0.0109	0.0299	-0.0520***	-0.0365*	-0.0227
	(0.0225)	(0.0223)	(0.0287)	(0.01000)	(0.0173)	(0.0142)	(0.0227)	(0.0265)	(0.0361)	(0.0185)	(0.0205)	(0.0242)
homsch	0.0422**	0.0288*	0.0371*	0.0313***	0.0409***	0.0370***	-0.113***	-0.123***	-0.116***	-0.0642***	-0.0707***	-0.0923***
	(0.0180)	(0.0154)	(0.0201)	(0.00835)	(0.0111)	(0.0135)	(0.0240)	(0.0279)	(0.0229)	(0.0216)	(0.0200)	(0.0220)
	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)
Variables	ESP	ESP	ESP	FIN	FIN	FIN	GRC	GRC	GRC	IRL	IRL	IRL
ictsch	-0.0572***	-0.0387***	-0.0291**	-0.0551***	-0.0634***	-0.0736***	-0.0977***	-0.0915***	-0.110***	-0.105***	-0.103***	-0.125***
	(0.00861)	(0.00811)	(0.0123)	(0.0133)	(0.0152)	(0.0278)	(0.0119)	(0.0145)	(0.0140)	(0.0282)	(0.0176)	(0.0310)
escs	0.100***	0.118***	0.126***	0.260***	0.284***	0.305***	0.177***	0.212***	0.231***	0.259***	0.294***	0.304***
	(0.00722)	(0.00779)	(0.00911)	(0.0169)	(0.0176)	(0.0205)	(0.0145)	(0.0171)	(0.0198)	(0.0327)	(0.0226)	(0.0236)
c.ictsch#c.escs	-0.00166	0.00558	0.0162	-0.00706	0.00104	-0.00669	-0.0253**	-0.0411***	-0.0290**	0.0169	0.0363*	0.0573**
	(0.00946)	(0.0103)	(0.0101)	(0.0190)	(0.0206)	(0.0275)	(0.0125)	(0.0148)	(0.0146)	(0.0252)	(0.0193)	(0.0289)
homsch	-0.0612***	-0.0718***	-0.0652***	-0.0778***	-0.0704***	-0.0579***	-0.0827***	-0.118***	-0.133***	-0.0329*	-0.0367**	-0.0540**
	(0.0114)	(0.00722)	(0.00865)	(0.0142)	(0.0169)	(0.0215)	(0.0175)	(0.0146)	(0.0180)	(0.0193)	(0.0164)	(0.0222)
	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)	(25%)	(50%)	(75%)
Variables	ITA	ITA	ITA	NLD	NLD	NLD	PRT	PRT	PRT	SWE	SWE	SWE
ictsch	0.0174***	0.0177**	0.0303***	-0.112***	-0.141***	-0.123***	-0.0773***	-0.114***	-0.110***	-0.0883***	-0.0871***	-0.103***
	(0.00626)	(0.00766)	(0.00922)	(0.0295)	(0.0176)	(0.0249)	(0.0208)	(0.0191)	(0.0275)	(0.0323)	(0.0290)	(0.0317)
escs	0.0398***	0.0419***	0.0443***	0.0523**	0.0539**	0.0329	0.137***	0.179***	0.177***	0.243***	0.236***	0.299***
	(0.0103)	(0.00792)	(0.0103)	(0.0230)	(0.0223)	(0.0223)	(0.0140)	(0.0141)	(0.0191)	(0.0293)	(0.0291)	(0.0306)
c.ictsch#c.escs	0.00855	-0.00406	0.00319	-0.0114	-0.0154	0.00474	-0.0174	-0.0415**	-0.00195	-0.0409	-0.0330	-0.0527*
	(0.00633)	(0.00607)	(0.00732)	(0.0288)	(0.0249)	(0.0326)	(0.0220)	(0.0191)	(0.0175)	(0.0340)	(0.0299)	(0.0317)
homsch	-0.0376***	-0.0338***	-0.0431***	0.0662***	0.0693***	0.0763***	-0.00909	-0.0440**	-0.0729***	-0.0388**	-0.0906***	-0.117***
	(0.00951)	(0.00919)	(0.0109)	(0.0220)	(0.0205)	(0.0249)	(0.0190)	(0.0207)	(0.0201)	(0.0197)	(0.0260)	(0.0230)

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

Table 7C. Quantile regression for the determinants of Z-PV1MATHS (test scores in mathematics), ictsch and homsch interaction, by country

Variables	(25%) AUT	(50%) AUT	(75%) AUT	(25%) BEL	(50%) BEL	(75%) BEL	(25%) DEU	(50%) DEU	(75%) DEU	(25%) DNK	(50%) DNK	(75%) DNK
ictsch	-0.0399*	-0.0244	-0.0350	-0.0449***	-0.0488***	-0.0344**	-0.0476**	-0.0775***	-0.0527**	-0.148***	-0.145***	-0.147***
	(0.0231)	(0.0279)	(0.0234)	(0.0114)	(0.0152)	(0.0162)	(0.0241)	(0.0248)	(0.0258)	(0.0158)	(0.0228)	(0.0329)
homsch	0.0444**	0.0274*	0.0325*	0.0387**	0.0439**	0.0425**	-0.106***	-0.139***	-0.109***	-0.0770***	-0.0734**	-0.0865*
	(0.0185)	(0.0154)	(0.0175)	(0.0162)	(0.0188)	(0.0167)	(0.0294)	(0.0299)	(0.0227)	(0.0220)	(0.0304)	(0.0448)
c.ictsch#c.homsch	-0.0128	0.00329	0.00438	0.0173	0.0274*	0.00521	0.0246	-0.0320	-0.0221	0.0162	-0.00219	-0.00165
	(0.0190)	(0.0209)	(0.0248)	(0.0109)	(0.0144)	(0.0106)	(0.0225)	(0.0215)	(0.0202)	(0.0205)	(0.0253)	(0.0297)
escs	0.125***	0.134***	0.136***	0.0800***	0.0902***	0.118***	0.0852***	0.0707***	0.0803***	0.245***	0.274***	0.292***
	(0.0294)	(0.0264)	(0.0278)	(0.0111)	(0.0160)	(0.0246)	(0.0243)	(0.0234)	(0.0282)	(0.0172)	(0.0156)	(0.0191)

Variables	(25%) ESP	(50%) ESP	(75%) ESP	(25%) FIN	(50%) FIN	(75%) FIN	(25%) GRC	(50%) GRC	(75%) GRC	(25%) IRL	(50%) IRL	(75%) IRL
ictsch	-0.0545***	-0.0401***	-0.0313***	-0.0631***	-0.0791***	-0.119***	-0.0999***	-0.0875***	-0.110***	-0.103***	-0.109***	-0.110***
	(0.00963)	(0.0103)	(0.00877)	(0.0168)	(0.0135)	(0.0238)	(0.0139)	(0.0138)	(0.0188)	(0.0296)	(0.0249)	(0.0281)
homsch	-0.0654***	-0.0729***	-0.0648***	-0.0752***	-0.0599***	-0.0389*	-0.0867***	-0.116***	-0.137***	-0.0309	-0.0349*	-0.0450**
	(0.00989)	(0.0109)	(0.0110)	(0.0143)	(0.0143)	(0.0209)	(0.0174)	(0.0104)	(0.0126)	(0.0250)	(0.0193)	(0.0213)
c.ictsch#c.homsch	-0.0141**	-0.0150**	-0.0115	-0.0122	-0.0274***	-0.0478***	0.00525	0.00768	0.0110	-0.00374	-0.00336	0.00776
	(0.00650)	(0.00662)	(0.0118)	(0.0140)	(0.00709)	(0.0174)	(0.00926)	(0.0106)	(0.0134)	(0.0271)	(0.0128)	(0.0281)
escs	0.0997***	0.116***	0.123***	0.262***	0.288***	0.296***	0.169***	0.207***	0.229***	0.254***	0.293***	0.303***
	(0.00784)	(0.00621)	(0.0102)	(0.0216)	(0.0238)	(0.0246)	(0.0245)	(0.0226)	(0.0178)	(0.0333)	(0.0180)	(0.0184)

Variables	(25%) ITA	(50%) ITA	(75%) ITA	(25%) NLD	(50%) NLD	(75%) NLD	(25%) PRT	(50%) PRT	(75%) PRT	(25%) SWE	(50%) SWE	(75%) SWE
ictsch	0.0168**	0.0210**	0.0288***	-0.116***	-0.144***	-0.120***	-0.0560*	-0.0863***	-0.0977***	-0.0931***	-0.0891***	-0.119***
	(0.00810)	(0.00851)	(0.00592)	(0.0193)	(0.0195)	(0.0251)	(0.0295)	(0.0300)	(0.0229)	(0.0292)	(0.0311)	(0.0199)
homsch	-0.0384***	-0.0397***	-0.0510***	0.0729***	0.0651***	0.0925***	0.00253	-0.0435***	-0.0673***	-0.0377**	-0.0746***	-0.0912***
	(0.00850)	(0.00612)	(0.00782)	(0.0209)	(0.0233)	(0.0262)	(0.0145)	(0.0144)	(0.0244)	(0.0183)	(0.0222)	(0.0178)
c.ictsch#c.homsch	-0.0154***	-0.0192***	-0.0265***	-0.00739	0.00345	-0.0138	-0.0438**	-0.0393	-0.0193	-0.0264*	-0.0573**	-0.0388
	(0.00552)	(0.00512)	(0.00480)	(0.0233)	(0.0257)	(0.0212)	(0.0208)	(0.0259)	(0.0236)	(0.0155)	(0.0229)	(0.0269)
escs	0.0362***	0.0424***	0.0421***	0.0474**	0.0487**	0.0346	0.134***	0.176***	0.175***	0.234***	0.228***	0.268***
	(0.00815)	(0.00874)	(0.0105)	(0.0239)	(0.0200)	(0.0222)	(0.0173)	(0.0181)	(0.0182)	(0.0274)	(0.0252)	(0.0185)

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

Table 7D. Quantile regression for the determinants of Z-PV1MATHS (test scores in mathematics), ictsch, homsch and escs interaction, by country

Variables	(25%) AUT	(50%) AUT	(75%) AUT	(25%) BEL	(50%) BEL	(75%) BEL	(25%) DEU	(50%) DEU	(75%) DEU	(25%) DNK	(50%) DNK	(75%) DNK
ictsch	-0.0353*	-0.0383	-0.0559**	-0.0575***	-0.0529***	-0.0375**	-0.0483**	-0.0815***	-0.0622*	-0.124***	-0.145***	-0.141***
	(0.0196)	(0.0234)	(0.0238)	(0.0129)	(0.0119)	(0.0151)	(0.0205)	(0.0269)	(0.0319)	(0.0254)	(0.0204)	(0.0338)
homsch	0.0453***	0.0243	0.0296	0.0349**	0.0449***	0.0382**	-0.104***	-0.137***	-0.114***	-0.0685	-0.0882***	-0.0698
	(0.0151)	(0.0167)	(0.0187)	(0.0144)	(0.0163)	(0.0183)	(0.0255)	(0.0328)	(0.0354)	(0.0435)	(0.0312)	(0.0450)
c.ictsch#c.homsch	-0.0142	-0.00301	-0.00131	0.0139	0.0208	-0.000344	0.0233	-0.0316	-0.0154	0.0183	0.0100	-0.0113
	(0.0194)	(0.0193)	(0.0163)	(0.0114)	(0.0166)	(0.0126)	(0.0230)	(0.0315)	(0.0239)	(0.0273)	(0.0197)	(0.0274)
escs	0.137***	0.124***	0.129***	0.0909***	0.0988***	0.123***	0.0847**	0.0714***	0.0821***	0.307***	0.301***	0.334***
	(0.0193)	(0.0267)	(0.0280)	(0.0151)	(0.0216)	(0.0190)	(0.0336)	(0.0260)	(0.0262)	(0.0227)	(0.0232)	(0.0325)
c.homsch#c.escs	-0.0395	-0.0303*	-0.0624***	-0.00348	0.00246	0.0216	-0.0184	0.0129	-0.00974	-0.0275	-0.0372**	-0.0470*
	(0.0247)	(0.0168)	(0.0209)	(0.0181)	(0.0187)	(0.0160)	(0.0305)	(0.0212)	(0.0340)	(0.0233)	(0.0185)	(0.0284)
c.ictsch#c.escs	0.0328	0.0486	0.0815***	0.0339***	0.0312*	0.0202	-1.95e-06	0.0161	0.0306	-0.0501***	-0.0244	-0.0143
	(0.0219)	(0.0306)	(0.0296)	(0.0124)	(0.0161)	(0.0141)	(0.0317)	(0.0285)	(0.0253)	(0.0190)	(0.0244)	(0.0340)

Variables	(25%) ESP	(50%) ESP	(75%) ESP	(25%) FIN	(50%) FIN	(75%) FIN	(25%) GRC	(50%) GRC	(75%) GRC	(25%) IRL	(50%) IRL	(75%) IRL
ictsch	-0.0543***	-0.0397***	-0.0271**	-0.0614***	-0.0821***	-0.126***	-0.101***	-0.0940***	-0.117***	-0.109***	-0.106***	-0.138***
	(0.00836)	(0.00946)	(0.0121)	(0.0212)	(0.0228)	(0.0318)	(0.0139)	(0.0120)	(0.0155)	(0.0205)	(0.0185)	(0.0200)
homsch	-0.0683***	-0.0727***	-0.0681***	-0.0783***	-0.0511***	-0.0214	-0.0895***	-0.117***	-0.133***	-0.0381*	-0.0277*	-0.0389
	(0.00834)	(0.00873)	(0.00869)	(0.0164)	(0.0164)	(0.0219)	(0.0121)	(0.00961)	(0.0118)	(0.0203)	(0.0162)	(0.0265)
c.ictsch#c.homsch	-0.0134	-0.0141	-0.00882	-0.0147	-0.0230	-0.0510**	0.00814	0.00724	0.00939	-0.00360	0.000775	-0.0132
	(0.0104)	(0.00938)	(0.00936)	(0.0144)	(0.0144)	(0.0226)	(0.00919)	(0.00954)	(0.0122)	(0.0160)	(0.0198)	(0.0229)
escs	0.100***	0.117***	0.126***	0.269***	0.274***	0.266***	0.177***	0.209***	0.231***	0.224***	0.271***	0.279***
	(0.00912)	(0.00800)	(0.00819)	(0.0165)	(0.0196)	(0.0305)	(0.0160)	(0.0162)	(0.0222)	(0.0306)	(0.0156)	(0.0260)
c.homsch#c.escs	-0.0140*	-0.00188	-0.0101	0.0181	-0.0155	-0.0404*	-0.0170	-0.0133	-0.00999	-0.0413*	-0.0394**	-0.0562**
	(0.00777)	(0.00782)	(0.00770)	(0.0211)	(0.0205)	(0.0211)	(0.0110)	(0.0123)	(0.0132)	(0.0229)	(0.0161)	(0.0261)
c.ictsch#c.escs	-0.000534	0.00601	0.0180*	-0.00901	0.00390	0.00349	-0.0260*	-0.0367***	-0.0285*	0.0232	0.0269	0.0686**
	(0.0106)	(0.0114)	(0.0104)	(0.0160)	(0.0150)	(0.0227)	(0.0145)	(0.0129)	(0.0168)	(0.0309)	(0.0221)	(0.0323)

Variables	(25%) ITA	(50%) ITA	(75%) ITA	(25%) NLD	(50%) NLD	(75%) NLD	(25%) PRT	(50%) PRT	(75%) PRT	(25%) SWE	(50%) SWE	(75%) SWE
ictsch	0.0182**	0.0199***	0.0273***	-0.114***	-0.139***	-0.113***	-0.0655**	-0.0993***	-0.0990***	-0.0886***	-0.0856**	-0.116***
	(0.00737)	(0.00629)	(0.00667)	(0.0245)	(0.0170)	(0.0340)	(0.0281)	(0.0242)	(0.0306)	(0.0314)	(0.0348)	(0.0333)
homsch	-0.0408***	-0.0390***	-0.0504***	0.0657***	0.0723***	0.0852***	-0.0276	-0.0399*	-0.0621**	-0.0288	-0.0678**	-0.0759***
	(0.00919)	(0.00720)	(0.00866)	(0.0240)	(0.0215)	(0.0217)	(0.0176)	(0.0210)	(0.0296)	(0.0247)	(0.0274)	(0.0290)
c.ictsch#c.homsch	-0.0166***	-0.0193***	-0.0266***	0.00135	-0.00515	-0.0283	-0.0313*	-0.0317	-0.0205	-0.0218	-0.0576*	-0.0539*
	(0.00509)	(0.00538)	(0.00533)	(0.0232)	(0.0232)	(0.0256)	(0.0186)	(0.0215)	(0.0250)	(0.0196)	(0.0307)	(0.0295)
escs	0.0406***	0.0398***	0.0439***	0.0377	0.0523*	0.0193	0.150***	0.182***	0.170***	0.243***	0.225***	0.290***
	(0.0113)	(0.00787)	(0.00783)	(0.0332)	(0.0299)	(0.0287)	(0.0213)	(0.0140)	(0.0155)	(0.0229)	(0.0246)	(0.0289)
c.homsch#c.escs	-0.0135	-0.0140**	-0.00883	0.0342*	-0.00185	0.0409	-0.0433**	-0.00238	0.00815	-0.0392**	-0.0392*	-0.00971
	(0.00897)	(0.00577)	(0.00896)	(0.0177)	(0.0215)	(0.0297)	(0.0186)	(0.0128)	(0.0129)	(0.0195)	(0.0229)	(0.0269)
c.ictsch#c.escs	0.00928	0.00259	0.00650	-0.0124	-0.0119	-0.00279	-0.00535	-0.0452***	-0.00775	-0.0258	-0.0153	-0.0519
	(0.00759)	(0.00801)	(0.00715)	(0.0303)	(0.0114)	(0.0249)	(0.0234)	(0.0166)	(0.0128)	(0.0262)	(0.0331)	(0.0367)

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

Table 8. OLS regressions for the determinants of Z-PV1MATHS (test scores in mathematics) by quartiles of ESCS (from 1, low to 4, top) without interactions, by country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	AUT_Q1	AUT_Q2	AUT_Q3	AUT_Q4	BEL_Q1	BEL_Q2	BEL_Q3	BEL_Q4	DEU_Q1	DEU_Q2	DEU_Q3	DEU_Q4
homsch	0.0698**	0.0257	0.0177	-0.0279	0.0338	0.00433	0.0516**	0.00948	-0.0751**	-0.130***	-0.0721*	-0.105*
	(0.0302)	(0.0347)	(0.0332)	(0.0389)	(0.0279)	(0.0230)	(0.0229)	(0.0302)	(0.0352)	(0.0401)	(0.0418)	(0.0573)
ictsch	-0.0628**	-0.0568*	-0.0384	-0.0254	-0.0580***	-0.0499**	-0.000160	-0.0128	-0.0832**	-0.0612*	-0.0316	-0.0379
	(0.0304)	(0.0316)	(0.0345)	(0.0368)	(0.0190)	(0.0198)	(0.0202)	(0.0212)	(0.0405)	(0.0336)	(0.0378)	(0.0382)
escs	0.256***	0.285	0.133	0.0354	0.000376	0.0789	0.103	0.0181	0.134	0.166	-0.105	-0.152*
	(0.0754)	(0.176)	(0.135)	(0.0498)	(0.0552)	(0.0944)	(0.0906)	(0.0758)	(0.0988)	(0.151)	(0.128)	(0.0831)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	DNK_Q1	DNK_Q2	DNK_Q3	DNK_Q4	ESP_Q1	ESP_Q2	ESP_Q3	ESP_Q4	FIN_Q1	FIN_Q2	FIN_Q3	FIN_Q4
homsch	-0.0206	-0.0186	-0.0353	-0.151***	-0.0200	-0.0739***	-0.135***	-0.0775***	0.0275	-0.0421	-0.0468*	-0.0530
	(0.0313)	(0.0280)	(0.0388)	(0.0390)	(0.0216)	(0.0182)	(0.0242)	(0.0198)	(0.0287)	(0.0280)	(0.0250)	(0.0359)
ictsch	-0.163***	-0.172***	-0.136***	-0.112***	-0.0385*	-0.0246	-0.0628***	-0.0194	-0.0956***	-0.0476	-0.0389	-0.0997**
	(0.0396)	(0.0345)	(0.0457)	(0.0333)	(0.0205)	(0.0245)	(0.0202)	(0.0229)	(0.0305)	(0.0298)	(0.0347)	(0.0419)
escs	0.246***	0.408***	0.398**	0.250***	0.116**	0.204**	0.110	0.0983*	0.157**	0.120	0.321**	0.182**
	(0.0556)	(0.108)	(0.181)	(0.0857)	(0.0558)	(0.0878)	(0.0715)	(0.0562)	(0.0627)	(0.130)	(0.131)	(0.0841)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	GRC_Q1	GRC_Q2	GRC_Q3	GRC_Q4	IRL_Q1	IRL_Q2	IRL_Q3	IRL_Q4	ITA_Q1	ITA_Q2	ITA_Q3	ITA_Q4
homsch	-0.0779***	-0.0931***	-0.130***	-0.124***	-0.0133	-0.0496	0.00858	-0.117***	-0.0514***	-0.0246	-0.0601***	-0.0351**
	(0.0196)	(0.0189)	(0.0196)	(0.0222)	(0.0304)	(0.0303)	(0.0399)	(0.0318)	(0.0151)	(0.0159)	(0.0173)	(0.0152)
ictsch	-0.0387*	-0.101***	-0.107***	-0.129***	-0.143***	-0.179***	-0.0835**	-0.0514	0.00264	0.0283**	0.0254**	0.0100
	(0.0217)	(0.0242)	(0.0200)	(0.0255)	(0.0340)	(0.0382)	(0.0369)	(0.0319)	(0.0169)	(0.0138)	(0.0127)	(0.0151)
escs	0.266***	0.0565	0.208**	0.172*	0.191**	0.357**	0.125	0.292***	0.149***	-0.0735	-0.0276	0.0475
	(0.0577)	(0.124)	(0.0814)	(0.0922)	(0.0904)	(0.142)	(0.139)	(0.0833)	(0.0411)	(0.0757)	(0.0706)	(0.0380)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	NLD_Q1	NLD_Q2	NLD_Q3	NLD_Q4	PRT_Q1	PRT_Q2	PRT_Q3	PRT_Q4	SWE_Q1	SWE_Q2	SWE_Q3	SWE_Q4
homsch	0.0720**	0.0535	0.110***	0.0706	0.0191	0.00387	-0.111***	-0.00773	-0.0597**	-0.0406	-0.0889***	-0.112***
	(0.0301)	(0.0364)	(0.0390)	(0.0500)	(0.0328)	(0.0291)	(0.0362)	(0.0253)	(0.0289)	(0.0331)	(0.0317)	(0.0349)
ictsch	-0.149***	-0.125***	-0.125***	-0.184***	-0.0543	-0.0513	-0.0802**	-0.0979***	-0.0265	-0.127***	-0.0607	-0.141***
	(0.0372)	(0.0389)	(0.0414)	(0.0443)	(0.0351)	(0.0327)	(0.0308)	(0.0349)	(0.0391)	(0.0459)	(0.0428)	(0.0437)
escs	0.0653	-0.0149	0.00490	-0.0470	-0.0294	0.105	-0.0629	0.283***	0.185***	0.371**	0.0865	0.286***
	(0.0648)	(0.122)	(0.162)	(0.0763)	(0.0923)	(0.123)	(0.0899)	(0.0484)	(0.0626)	(0.148)	(0.155)	(0.103)

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

Table 9. 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 10A. IV Regression for determinants of Z-PV1MATH (test scores in math) instrumenting *homsch* with *entuse*, by country

Variables	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
homsch	-0.193***	-0.152***	-0.363***	-0.207***	0.0771*	-0.511***	-0.0444*	-0.0513	-0.0880***	-0.0776	-0.0755*	-0.226***
	(0.0585)	(0.0430)	(0.0648)	(0.0543)	(0.0401)	(0.0822)	(0.0227)	(0.0449)	(0.0265)	(0.0517)	(0.0392)	(0.0574)
gender	-0.326***	-0.264***	-0.273***	-0.162***	-0.271***	-0.0161	-0.214***	-0.159***	-0.362***	-0.204***	-0.282***	-0.0475
	(0.0489)	(0.0208)	(0.0316)	(0.0237)	(0.0175)	(0.0291)	(0.0257)	(0.0316)	(0.0210)	(0.0245)	(0.0251)	(0.0295)
immigrant	-0.0962	-0.205***	0.00494	-0.227***	-0.117***	-0.0351	-0.0136	0.0459	-0.0477	-0.0963	0.133*	-0.127
	(0.0667)	(0.0584)	(0.119)	(0.0661)	(0.0426)	(0.0771)	(0.0629)	(0.0491)	(0.0388)	(0.0990)	(0.0703)	(0.0860)
preprimary_no	0.0619	-0.0903	0.0691	0.154	0.218***	0.0833	0.174***	-0.0322	0.239***	0.0466	0.0877*	0.149**
	(0.0857)	(0.106)	(0.0896)	(0.135)	(0.0414)	(0.0767)	(0.0542)	(0.0352)	(0.0431)	(0.0939)	(0.0468)	(0.0619)
famst	-0.0285	0.0629**	-0.0203	0.0701**	-0.0329	0.0883**	0.0710*	0.0940**	-0.00540	0.114**	-0.0642*	0.0213
	(0.0432)	(0.0297)	(0.0424)	(0.0341)	(0.0318)	(0.0403)	(0.0418)	(0.0406)	(0.0243)	(0.0455)	(0.0376)	(0.0593)
month_birth	0.0115**	-0.00583**	0.0133**	0.00401	-0.000795	-0.0120***	-0.00919***	-0.0124**	-0.00939***	0.0255***	-0.00419	-0.00451
	(0.00478)	(0.00262)	(0.00626)	(0.00379)	(0.00242)	(0.00355)	(0.00349)	(0.00540)	(0.00196)	(0.00465)	(0.00438)	(0.00437)
repeat_once	-0.336***	-0.384***	-0.153**	-0.305***	-0.193***	-0.531***	-0.492***	-0.371***	-0.282***	-0.147***	-0.461***	-0.202
	(0.0707)	(0.0402)	(0.0725)	(0.0976)	(0.0463)	(0.0852)	(0.113)	(0.0697)	(0.0623)	(0.0377)	(0.0596)	(0.133)
truan_someclass	-0.123***	-0.246***	-0.140**	-0.336***	-0.128***	-0.318***	-0.0776***	-0.133***	-0.117***	-0.148**	-0.119***	-0.403***
	(0.0455)	(0.0404)	(0.0575)	(0.0338)	(0.0188)	(0.0369)	(0.0269)	(0.0384)	(0.0173)	(0.0643)	(0.0332)	(0.0373)
ictsch	0.000441	-0.00527	-0.0213	-0.128***	-0.0681***	0.0280	-0.102***	-0.117***	0.0247**	-0.135***	-0.0598***	-0.0649**
	(0.0263)	(0.0131)	(0.0228)	(0.0214)	(0.0159)	(0.0252)	(0.0136)	(0.0187)	(0.0106)	(0.0291)	(0.0221)	(0.0264)
escs	0.147***	0.112***	0.0923***	0.298***	0.132***	0.293***	0.191***	0.264***	0.0457***	0.0706***	0.165***	0.266***
	(0.0181)	(0.0140)	(0.0197)	(0.0195)	(0.0105)	(0.0202)	(0.0153)	(0.0194)	(0.00827)	(0.0163)	(0.0131)	(0.0230)
grade	0.312***	0.437***	0.457***	0.278***	0.513***	0.421***	0.212**	0.112***	0.173***	0.459***	0.352***	0.672***
	(0.0507)	(0.0281)	(0.0390)	(0.0366)	(0.0344)	(0.0408)	(0.106)	(0.0234)	(0.0321)	(0.0347)	(0.0330)	(0.111)
private	-0.238*	0.0926*	-0.300***	-0.00453	-0.0111	0.126*	-0.162	0.0327	-0.456***	0.0773	-0.0744	0.0218
	(0.134)	(0.0495)	(0.108)	(0.0452)	(0.0400)	(0.0722)	(0.122)	(0.0370)	(0.0890)	(0.0718)	(0.0581)	(0.0543)
rural	0.101	-0.0163	0.00547	-0.00528	-0.0152	0.0416	0.0496	0.0630*	0.00783	0.0782	0.104**	-0.102**
	(0.0754)	(0.0459)	(0.0656)	(0.0347)	(0.0377)	(0.0423)	(0.0544)	(0.0369)	(0.0587)	(0.0827)	(0.0481)	(0.0439)
disclima_m	0.322***	0.306***	0.283***	0.166***	0.0730*	0.0536	0.332***	0.126***	0.225***	0.325**	0.138**	0.102*
	(0.0892)	(0.0549)	(0.0740)	(0.0446)	(0.0390)	(0.0577)	(0.0668)	(0.0413)	(0.0447)	(0.146)	(0.0599)	(0.0562)
clsize_m	0.0109**	0.00659	0.0128*	0.00838	-0.00395	0.0124**	0.000452	0.00548	0.00151	0.0501***	0.000350	0.000717
	(0.00536)	(0.00639)	(0.00678)	(0.00584)	(0.00292)	(0.00541)	(0.00294)	(0.00493)	(0.00186)	(0.0150)	(0.00376)	(0.00582)
truan	0.0290	-0.0756	-0.0700	-0.0372	-0.0773*	-0.103***	-0.0530	-0.0773**	-0.312***	-0.117	-0.0909**	0.0136
	(0.0739)	(0.0525)	(0.0784)	(0.0411)	(0.0431)	(0.0390)	(0.0535)	(0.0355)	(0.0433)	(0.0822)	(0.0420)	(0.0463)
escs_m	0.903***	0.623***	0.989***	0.301***	0.148***	0.242***	0.443***	0.414***	0.679***	1.041***	0.125***	0.346***
	(0.0739)	(0.0606)	(0.0671)	(0.0530)	(0.0404)	(0.0713)	(0.0564)	(0.0477)	(0.0457)	(0.146)	(0.0388)	(0.0795)
Constant	-0.0669	0.527***	-0.368*	-0.160	0.380***	-0.421**	-0.287***	-0.110	0.191**	-1.511***	0.692***	-0.242
	(0.173)	(0.186)	(0.213)	(0.186)	(0.0972)	(0.166)	(0.109)	(0.145)	(0.0747)	(0.363)	(0.122)	(0.161)
Clusters (schools)	177	256	187	292	764	292	183	166	1,003	154	185	199
Observations	4,049	6,079	2,662	4,995	16,884	7,302	4,475	3,741	21,504	3,324	3,506	3,722
Instr. F-statistic	247.45	195.11	191.72	216.40	322.41	188.59	411.73	336.36	714.09	155.86	247.41	183.39
R-squared	0.337	0.491	0.415	0.221	0.356	-0.048	0.297	0.229	0.329	0.500	0.335	0.157

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

Table 10B. IV Regression for the determinants of Z-PV1READ (test scores in reading), instrumenting *homsch* with *entuse*, by country

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	AUT	BEL	DEU	DNK	ESP	FIN	GRC	IRL	ITA	NLD	PRT	SWE
homsch	-0.150***	-0.0232	-0.261***	-0.164***	0.133***	-0.341***	0.0505*	-0.0308	-0.0689**	0.0681	-0.0132	-0.159***
	(0.0555)	(0.0442)	(0.0559)	(0.0570)	(0.0477)	(0.0797)	(0.0297)	(0.0439)	(0.0277)	(0.0520)	(0.0430)	(0.0594)
gender	0.288***	0.182***	0.349***	0.301***	0.213***	0.597***	0.401***	0.298***	0.244***	0.177***	0.260***	0.434***
	(0.0481)	(0.0221)	(0.0289)	(0.0261)	(0.0175)	(0.0292)	(0.0292)	(0.0328)	(0.0217)	(0.0230)	(0.0260)	(0.0309)
immigrant	-0.123	-0.174***	-0.150	-0.170**	-0.0833*	-0.414***	-0.109*	-0.0700	-0.213***	-0.0796	0.0741	-0.269***
	(0.0838)	(0.0502)	(0.107)	(0.0806)	(0.0447)	(0.0870)	(0.0607)	(0.0481)	(0.0436)	(0.103)	(0.0750)	(0.101)
preprimary_no	0.0769	0.0598	0.0709	0.323***	0.130***	0.101	0.188***	0.00579	0.162***	0.00454	0.0479	0.181**
	(0.0840)	(0.106)	(0.0887)	(0.113)	(0.0465)	(0.0729)	(0.0648)	(0.0359)	(0.0453)	(0.0959)	(0.0394)	(0.0710)
famst	-0.0196	0.0217	-0.0482	0.0432	-0.0621	-0.00615	0.162***	0.0868**	-0.0797***	-0.0186	-0.0703**	-0.0145
	(0.0380)	(0.0307)	(0.0396)	(0.0361)	(0.0393)	(0.0348)	(0.0418)	(0.0397)	(0.0255)	(0.0447)	(0.0342)	(0.0614)
month_birth	0.00687	-0.00520*	0.0108*	0.00448	-0.00110	-0.0122***	-0.00766*	-0.0144***	-0.00985***	0.0193***	-0.000104	-0.00433
	(0.00475)	(0.00274)	(0.00552)	(0.00390)	(0.00263)	(0.00367)	(0.00404)	(0.00532)	(0.00188)	(0.00491)	(0.00387)	(0.00477)
repeat_once	-0.325***	-0.313***	-0.166***	-0.394***	-0.199***	-0.620***	-0.564***	-0.359***	-0.365***	-0.126***	-0.355***	-0.401**
	(0.0721)	(0.0406)	(0.0573)	(0.108)	(0.0567)	(0.0732)	(0.138)	(0.0679)	(0.0619)	(0.0409)	(0.0611)	(0.160)
truan_someclass	-0.0538	-0.157***	-0.112**	-0.273***	-0.0969***	-0.365***	-0.142***	-0.218***	-0.0869***	-0.268***	-0.161***	-0.364***
	(0.0463)	(0.0456)	(0.0506)	(0.0316)	(0.0205)	(0.0361)	(0.0277)	(0.0418)	(0.0165)	(0.0637)	(0.0289)	(0.0442)
ictsch	-0.0140	-0.0726***	-0.0201	-0.154***	-0.0794***	0.0220	-0.143***	-0.145***	-0.00929	-0.193***	-0.0956***	-0.0610**
	(0.0252)	(0.0143)	(0.0196)	(0.0196)	(0.0193)	(0.0275)	(0.0153)	(0.0188)	(0.00946)	(0.0298)	(0.0240)	(0.0296)
escs	0.128***	0.0821***	0.0761***	0.291***	0.122***	0.260***	0.133***	0.268***	0.0338***	0.0760***	0.133***	0.281***
	(0.0186)	(0.0139)	(0.0172)	(0.0182)	(0.0124)	(0.0191)	(0.0175)	(0.0179)	(0.00786)	(0.0153)	(0.0127)	(0.0243)
grade	0.187***	0.353***	0.336***	0.201***	0.480***	0.319***	0.210*	0.0873***	0.170***	0.351***	0.340***	0.477***
	(0.0511)	(0.0316)	(0.0344)	(0.0407)	(0.0397)	(0.0422)	(0.109)	(0.0237)	(0.0357)	(0.0370)	(0.0343)	(0.141)
private	-0.274***	0.0993**	-0.235**	0.00396	-0.00417	0.184**	-0.221**	0.0767*	-0.375***	0.0671	-0.0505	0.121
	(0.0891)	(0.0499)	(0.104)	(0.0487)	(0.0520)	(0.0867)	(0.0945)	(0.0401)	(0.0754)	(0.0624)	(0.0686)	(0.0816)
rural	0.0424	0.00986	-0.0518	-0.0334	-0.0989**	0.0114	0.0122	0.0903**	-0.0414	0.0888	0.0786	-0.126*
	(0.0733)	(0.0441)	(0.0680)	(0.0402)	(0.0462)	(0.0468)	(0.0655)	(0.0396)	(0.0591)	(0.0788)	(0.0497)	(0.0657)
disclima_m	0.325***	0.266***	0.193**	0.152***	0.0485	-0.0229	0.407***	0.119**	0.198***	0.379**	0.205***	0.149*
	(0.0812)	(0.0535)	(0.0785)	(0.0435)	(0.0508)	(0.0589)	(0.0907)	(0.0480)	(0.0429)	(0.149)	(0.0776)	(0.0766)
clsize_m	0.0107***	0.0207***	0.00969	0.0118*	-0.00264	0.0177***	0.00122	0.00648	0.00347*	0.0461***	0.00552	0.0105
	(0.00393)	(0.00646)	(0.00706)	(0.00606)	(0.00331)	(0.00646)	(0.00365)	(0.00632)	(0.00197)	(0.0141)	(0.00365)	(0.00775)
truan	-0.0161	-0.0615	-0.134*	0.0499	-0.0487	-0.0445	-0.0333	-0.0799*	-0.263***	-0.0284	-0.0803*	0.0395
	(0.0732)	(0.0520)	(0.0770)	(0.0527)	(0.0527)	(0.0424)	(0.0618)	(0.0413)	(0.0475)	(0.0795)	(0.0480)	(0.0721)
escs_m	0.930***	0.582***	0.833***	0.317***	0.129***	0.174**	0.522***	0.390***	0.716***	0.968***	0.119***	0.321***
	(0.0718)	(0.0577)	(0.0611)	(0.0696)	(0.0474)	(0.0846)	(0.0622)	(0.0538)	(0.0437)	(0.141)	(0.0456)	(0.103)
Constant	-0.560***	-0.239	-0.489**	-0.677***	0.245**	-0.579***	-0.382***	-0.133	0.0307	-1.471***	0.255**	-0.616***
	(0.152)	(0.196)	(0.230)	(0.188)	(0.103)	(0.180)	(0.120)	(0.174)	(0.0746)	(0.357)	(0.107)	(0.209)
Clusters (schools)	177	256	187	292	764	292	183	166	1,003	154	185	199
Observations	4,049	6,079	2,662	4,995	16,884	7,302	4,475	3,741	21,504	3,324	3,506	3,722
Instr. F-statistic	247.45	195.11	191.72	216.40	322.41	188.59	411.73	336.36	714.09	155.86	247.41	183.39
Observations	4,049	6,079	2,662	4,995	16,884	7,302	4,475	3,741	21,504	3,324	3,506	3,722
R-squared	0.375	0.484	0.420	0.241	0.294	0.160	0.310	0.271	0.355	0.477	0.328	0.194

Robust standard errors (clustered by school) in parentheses

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

Table 10C. IV Regression for the determinants of Z-PV1SCIE (test scores in science), instrumenting *homsch* with *entuse*, by country

Variables	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
homsch	-0.134**	-0.133***	-0.257***	-0.133**	0.147***	-0.459***	0.0197	-0.0259	-0.0515*	0.0376	-0.0296	-0.0972*
	(0.0571)	(0.0452)	(0.0614)	(0.0655)	(0.0430)	(0.0865)	(0.0271)	(0.0475)	(0.0284)	(0.0531)	(0.0398)	(0.0584)
gender	-0.188***	-0.187***	-0.111***	-0.145***	-0.170***	0.133***	0.0154	-0.0687*	-0.186***	-0.127***	-0.120***	-0.00504
	(0.0452)	(0.0216)	(0.0306)	(0.0282)	(0.0177)	(0.0300)	(0.0254)	(0.0368)	(0.0232)	(0.0259)	(0.0247)	(0.0294)
immigrant	-0.245***	-0.178***	-0.126	-0.268***	-0.142***	-0.378***	-0.0251	0.0347	-0.128***	-0.0357	0.0611	-0.358***
	(0.0814)	(0.0552)	(0.117)	(0.0739)	(0.0404)	(0.0837)	(0.0667)	(0.0534)	(0.0411)	(0.0983)	(0.0794)	(0.0902)
preprimary_no	0.254***	0.219**	0.0855	0.274*	0.170***	0.148*	0.194***	-0.0118	0.239***	-0.108	0.0557	0.101
	(0.0878)	(0.105)	(0.105)	(0.147)	(0.0419)	(0.0890)	(0.0590)	(0.0403)	(0.0535)	(0.0939)	(0.0413)	(0.0664)
famst	-0.0275	0.0597*	-0.0383	0.0540	-0.0743**	0.0724*	0.0842**	0.128***	-0.0181	0.0725	0.0257	0.0370
	(0.0383)	(0.0305)	(0.0422)	(0.0389)	(0.0367)	(0.0391)	(0.0429)	(0.0422)	(0.0254)	(0.0489)	(0.0349)	(0.0608)
month_birth	0.00307	-0.00617**	0.0182***	-0.00133	-0.00155	-0.0156***	-0.00792**	-0.0165***	-0.0103***	0.0219***	-0.00542	-0.00120
	(0.00473)	(0.00278)	(0.00624)	(0.00413)	(0.00262)	(0.00381)	(0.00377)	(0.00596)	(0.00207)	(0.00501)	(0.00409)	(0.00457)
repeat_once	-0.338***	-0.404***	-0.119*	-0.333***	-0.158***	-0.604***	-0.773***	-0.344***	-0.380***	-0.0941**	-0.308***	-0.442***
	(0.0674)	(0.0409)	(0.0725)	(0.121)	(0.0595)	(0.0782)	(0.119)	(0.0817)	(0.0618)	(0.0400)	(0.0593)	(0.150)
truan_someclass	-0.144***	-0.255***	-0.132**	-0.308***	-0.110***	-0.403***	-0.146***	-0.203***	-0.109***	-0.175**	-0.143***	-0.344***
	(0.0432)	(0.0395)	(0.0522)	(0.0371)	(0.0224)	(0.0356)	(0.0284)	(0.0459)	(0.0176)	(0.0698)	(0.0305)	(0.0389)
ictsch	-0.00465	-0.0132	-0.0343	-0.121***	-0.0970***	0.0238	-0.127***	-0.131***	0.00727	-0.134***	-0.0666***	-0.109***
	(0.0247)	(0.0138)	(0.0209)	(0.0230)	(0.0176)	(0.0269)	(0.0151)	(0.0200)	(0.0105)	(0.0336)	(0.0223)	(0.0304)
escs	0.181***	0.131***	0.109***	0.308***	0.132***	0.283***	0.165***	0.284***	0.0389***	0.104***	0.148***	0.267***
	(0.0179)	(0.0136)	(0.0182)	(0.0229)	(0.0115)	(0.0223)	(0.0171)	(0.0209)	(0.00854)	(0.0157)	(0.0125)	(0.0233)
grade	0.176***	0.335***	0.397***	0.228***	0.418***	0.347***	0.117	0.0750***	0.137***	0.387***	0.349***	0.436***
	(0.0494)	(0.0298)	(0.0412)	(0.0391)	(0.0422)	(0.0394)	(0.107)	(0.0260)	(0.0396)	(0.0353)	(0.0346)	(0.141)
private	-0.222**	0.0744	-0.208*	-0.0173	-0.00989	0.104	-0.173	0.0462	-0.394***	0.0610	-0.103	-0.00142
	(0.0938)	(0.0498)	(0.118)	(0.0514)	(0.0456)	(0.102)	(0.156)	(0.0437)	(0.0787)	(0.0686)	(0.0675)	(0.0710)
rural	0.0595	0.0667	0.0136	0.0405	-0.102**	0.0537	0.0268	0.0833*	-0.0298	0.124	0.00668	-0.0442
	(0.0694)	(0.0440)	(0.0688)	(0.0412)	(0.0407)	(0.0420)	(0.0630)	(0.0437)	(0.0618)	(0.0761)	(0.0463)	(0.0581)
disclima_m	0.345***	0.211***	0.277***	0.0757	0.0692	0.0481	0.357***	0.126**	0.141***	0.344**	0.163**	0.147**
	(0.0790)	(0.0521)	(0.0733)	(0.0484)	(0.0443)	(0.0610)	(0.0844)	(0.0500)	(0.0458)	(0.151)	(0.0695)	(0.0693)
clsize_m	0.0100**	0.0120**	0.0125*	0.00954	-0.00438	0.0157**	0.00168	0.00172	0.00206	0.0436***	0.00433	0.00729
	(0.00446)	(0.00574)	(0.00719)	(0.00631)	(0.00323)	(0.00613)	(0.00349)	(0.00628)	(0.00194)	(0.0142)	(0.00360)	(0.00714)
truan	0.0220	-0.0783	-0.102	-0.0469	-0.0651	-0.0737**	-0.0193	-0.0243	-0.284***	-0.0844	-0.116***	-0.00245
	(0.0684)	(0.0535)	(0.0787)	(0.0548)	(0.0483)	(0.0375)	(0.0572)	(0.0458)	(0.0474)	(0.0783)	(0.0392)	(0.0625)
escs_m	0.851***	0.506***	0.816***	0.371***	0.0905**	0.111	0.426***	0.446***	0.680***	0.975***	0.123***	0.378***
	(0.0762)	(0.0550)	(0.0648)	(0.0705)	(0.0449)	(0.0761)	(0.0672)	(0.0560)	(0.0472)	(0.144)	(0.0408)	(0.0976)
Constant	-0.372**	-0.121	-0.385	-0.454**	0.431***	-0.299	-0.380***	0.0410	0.0905	-1.269***	0.373***	-0.399**
	(0.156)	(0.179)	(0.236)	(0.208)	(0.0995)	(0.188)	(0.119)	(0.180)	(0.0768)	(0.356)	(0.105)	(0.193)
Clusters (schools)	177	256	187	292	764	292	183	166	1,003	154	185	199
Observations	4,049	6,079	2,662	4,995	16,884	7,302	4,475	3,741	21,504	3,324	3,506	3,722
Instr. F-statistic	247.45	195.11	191.72	216.40	322.41	188.59	411.73	336.36	714.09	155.86	247.41	183.39
R-squared	0.360	0.439	0.381	0.202	0.255	0.024	0.266	0.214	0.298	0.432	0.308	0.179

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

Table 10D. IV Regression for determinants of Z-PV1MATH (test scores in math) instrumenting dummy *homsch* (1=top quartile) with *entuse,* by country

VARIABLES	(1) AUT	(2) BEL	(3) DEU	(4) DNK	(5) ESP	(6) FIN	(7) GRC	(8) IRL	(9) ITA	(10) NLD	(11) PRT	(12) SWE
top_homsch	*-0.521****	*-0.487****	*-0.947****	*-0.480****	*0.187*	*-1.158****	*-0.241****	*-0.213**	*-0.266****	*-0.214*	*-0.275****	*-0.783****
	(0.155)	(0.135)	(0.160)	(0.131)	(0.116)	(0.171)	(0.0874)	(0.126)	(0.0803)	(0.133)	(0.0998)	(0.184)
gender	-0.336***	-0.260***	-0.287***	-0.144***	-0.251***	-0.0803***	-0.217***	-0.161***	-0.374***	-0.181***	-0.264***	-0.0662**
	(0.0466)	(0.0204)	(0.0318)	(0.0248)	(0.0188)	(0.0268)	(0.0272)	(0.0304)	(0.0216)	(0.0272)	(0.0256)	(0.0312)
immigrant	-0.182**	-0.326***	-0.0620	-0.322***	-0.168***	-0.180**	-0.0851	0.0449	-0.115***	-0.198**	-0.0963	-0.200**
	(0.0729)	(0.0656)	(0.122)	(0.0760)	(0.0432)	(0.0786)	(0.0646)	(0.0498)	(0.0369)	(0.0970)	(0.0705)	(0.0874)
preprimary_no	0.0408	0.0170	0.000292	0.149	0.250***	0.112	0.176***	-0.0300	0.241***	0.0759	0.0740	0.122*
	(0.0937)	(0.111)	(0.0883)	(0.142)	(0.0444)	(0.0793)	(0.0557)	(0.0353)	(0.0476)	(0.128)	(0.0491)	(0.0698)
famst	-0.0225	0.0723**	-0.0395	0.0602*	-0.0324	0.0859**	0.0715*	0.0626	0.00372	0.0957*	-0.0443	0.0208
	(0.0425)	(0.0308)	(0.0453)	(0.0325)	(0.0329)	(0.0384)	(0.0409)	(0.0405)	(0.0246)	(0.0491)	(0.0405)	(0.0590)
month_birth	-0.0201***	-0.0114***	-0.0411***	-0.00734**	-0.00366	0.00232	-0.00911***	-0.0228***	-0.0119***	-0.0125***	0.00722	-0.00887*
	(0.00500)	(0.00265)	(0.00522)	(0.00373)	(0.00250)	(0.00330)	(0.00347)	(0.00423)	(0.00196)	(0.00420)	(0.00449)	(0.00480)
repeat_once	-0.506***	-0.808***	-0.514***	-0.395***	-0.865***	-0.874***	-0.697***	-0.436***	-0.428***	-0.473***	-0.998***	-0.476***
	(0.0688)	(0.0334)	(0.0698)	(0.0880)	(0.0281)	(0.0846)	(0.122)	(0.0716)	(0.0567)	(0.0372)	(0.0470)	(0.136)
truan_someclass	-0.131***	-0.261***	-0.120**	-0.307***	-0.135***	-0.265***	-0.0752***	-0.125***	-0.114***	-0.148**	-0.122***	-0.374***
	(0.0460)	(0.0431)	(0.0567)	(0.0344)	(0.0190)	(0.0365)	(0.0277)	(0.0380)	(0.0171)	(0.0690)	(0.0326)	(0.0374)
escs	0.153***	0.130***	0.110***	0.303***	0.144***	0.285***	0.183***	0.262***	0.0513***	0.0805***	0.172***	0.258***
	(0.0193)	(0.0141)	(0.0194)	(0.0185)	(0.0103)	(0.0187)	(0.0156)	(0.0197)	(0.00850)	(0.0172)	(0.0139)	(0.0233)
private	-0.256*	0.0936*	-0.322***	0.0510	0.00358	0.114	-0.192	0.0430	-0.439***	0.0879	-0.0907	0.0644
	(0.131)	(0.0531)	(0.103)	(0.0496)	(0.0408)	(0.0781)	(0.137)	(0.0357)	(0.0895)	(0.0731)	(0.0581)	(0.0676)
rural	0.0870	-0.00563	-0.0154	0.00359	-0.0313	0.0580	0.0627	0.0520	0.0102	0.0736	0.0902*	-0.0883*
	(0.0726)	(0.0487)	(0.0660)	(0.0342)	(0.0398)	(0.0424)	(0.0543)	(0.0363)	(0.0582)	(0.0864)	(0.0489)	(0.0463)
disclima_m	0.348***	0.319***	0.279***	0.157***	0.0817**	0.0595	0.329***	0.112***	0.220***	0.356**	0.156***	0.136**
	(0.0845)	(0.0581)	(0.0701)	(0.0556)	(0.0398)	(0.0570)	(0.0669)	(0.0403)	(0.0448)	(0.154)	(0.0556)	(0.0648)
clsize_m	0.0108**	0.00321	0.00932	0.0111*	-0.00371	0.0123**	0.000565	0.00706	0.00142	0.0549***	0.000704	0.00478
	(0.00512)	(0.00702)	(0.00667)	(0.00573)	(0.00295)	(0.00546)	(0.00289)	(0.00462)	(0.00187)	(0.0147)	(0.00353)	(0.00718)
truan	0.0227	-0.0894	-0.0543	-0.0394	-0.0654	-0.0681*	-0.0406	-0.0615*	-0.302***	-0.107	-0.0817*	0.0734
	(0.0688)	(0.0549)	(0.0742)	(0.0401)	(0.0450)	(0.0374)	(0.0540)	(0.0348)	(0.0429)	(0.0869)	(0.0421)	(0.0540)
escs_m	0.881***	0.656***	1.024***	0.317***	0.150***	0.275***	0.466***	0.416***	0.674***	1.104***	0.163***	0.413***
	(0.0667)	(0.0642)	(0.0658)	(0.0514)	(0.0404)	(0.0733)	(0.0556)	(0.0468)	(0.0459)	(0.149)	(0.0388)	(0.0886)
Constant	0.144	0.570***	0.628***	-0.284	0.322***	0.0768	-0.261**	0.0844	0.248***	-1.162***	0.583***	-0.141
	(0.167)	(0.217)	(0.208)	(0.187)	(0.103)	(0.147)	(0.105)	(0.137)	(0.0801)	(0.352)	(0.117)	(0.177)
Observations	4,054	6,137	2,672	5,007	16,916	7,344	4,487	3,737	21,577	3,330	3,644	3,730
R-squared	0.319	0.448	0.341	0.190	0.322	-0.093	0.287	0.222	0.328	0.455	0.355	0.106

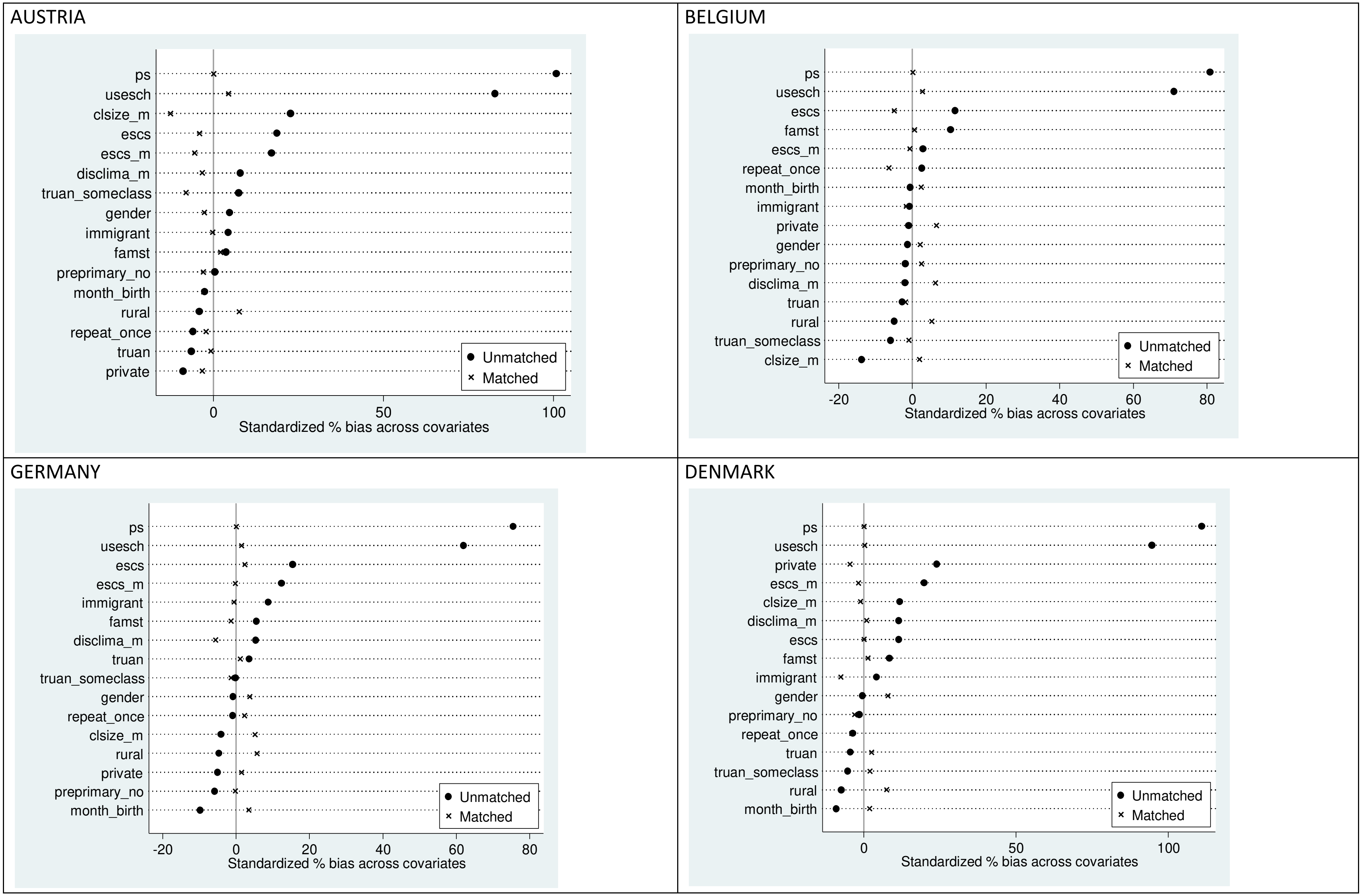
Robust standard errors (clustered by school) in parentheses
***p<0.01, **p<0.05, *p<0.1

Table 11. Instrumental Variable (IV) Regression for determinants of Z-PV1MATH (test scores in math) instrumenting *homsch* with *entuse,* differentiating by SES level at school, by country

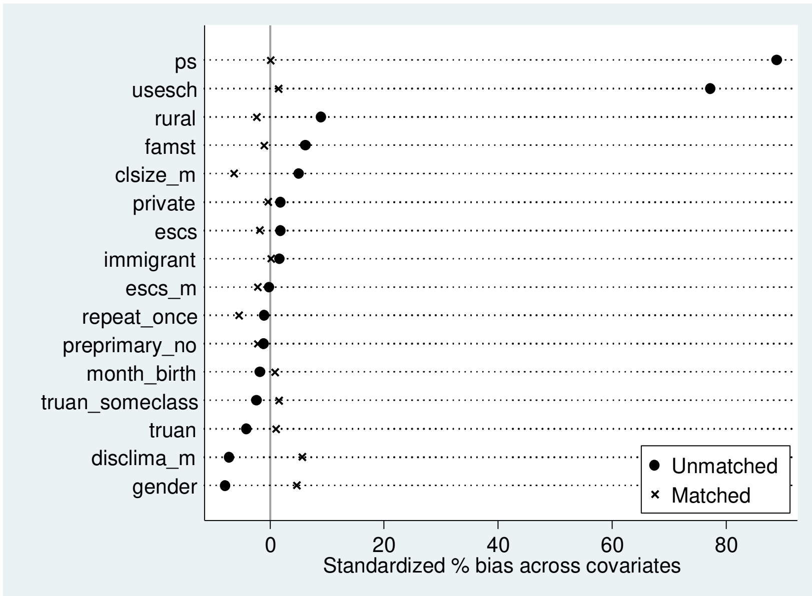
	Low	Medium	High	Low	Medium	High	Low	Medium	High	Low	Medium	High
VARIABLES	AUT	AUT	AUT	BEL	BEL	BEL	DEU	DEU	DEU	DNK	DNK	DNK
homsch	0.00846	-0.327***	-0.329***	-0.188**	-0.194***	-0.0766	-0.336***	-0.373***	-0.469***	-0.0406	-0.286**	-0.291***
	(0.0869)	(0.0964)	(0.0731)	(0.0824)	(0.0653)	(0.0786)	(0.105)	(0.113)	(0.111)	(0.0562)	(0.127)	(0.0908)
Observations	1,217	1,406	1,431	1,417	2,197	2,523	697	919	1,056	1,998	1,612	1,397
R-squared	0.131	0.174	0.197	0.315	0.269	0.277	0.125	0.169	0.080	0.222	0.090	0.168
VARIABLES	ESP	ESP	ESP	FIN	FIN	FIN	GRC	GRC	GRC	IRL	IRL	IRL
homsch	0.103	0.0584	0.0400	-0.530***	-0.415***	-0.494***	0.00439	-0.0704	-0.135***	-0.0316	-0.100	-0.0995
	(0.0641)	(0.0558)	(0.0931)	(0.141)	(0.122)	(0.110)	(0.0334)	(0.0481)	(0.0382)	(0.0747)	(0.0717)	(0.0829)
Observations	4,450	6,144	6,322	2,400	2,144	2,800	1,363	1,562	1,562	1,186	1,250	1,309
R-squared	0.304	0.298	0.213	-0.136	-0.007	0.007	0.187	0.144	0.191	0.199	0.142	0.093
VARIABLES	ITA	ITA	ITA	NLD	NLD	NLD	PRT	PRT	PRT	SWE	SWE	SWE
homsch	0.0835**	-0.126***	-0.222***	0.00836	-0.230*	-0.132	-0.0448	-0.0645	-0.155***	-0.243***	-0.336***	-0.136
	(0.0418)	(0.0404)	(0.0487)	(0.0527)	(0.128)	(0.149)	(0.0606)	(0.0612)	(0.0562)	(0.0892)	(0.0858)	(0.111)
Observations	5,572	7,985	8,020	1,228	1,008	1,094	831	1,198	1,615	1,118	1,263	1,349
R-squared	0.134	0.144	0.100	0.299	0.225	0.136	0.406	0.290	0.202	0.095	0.087	0.130

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

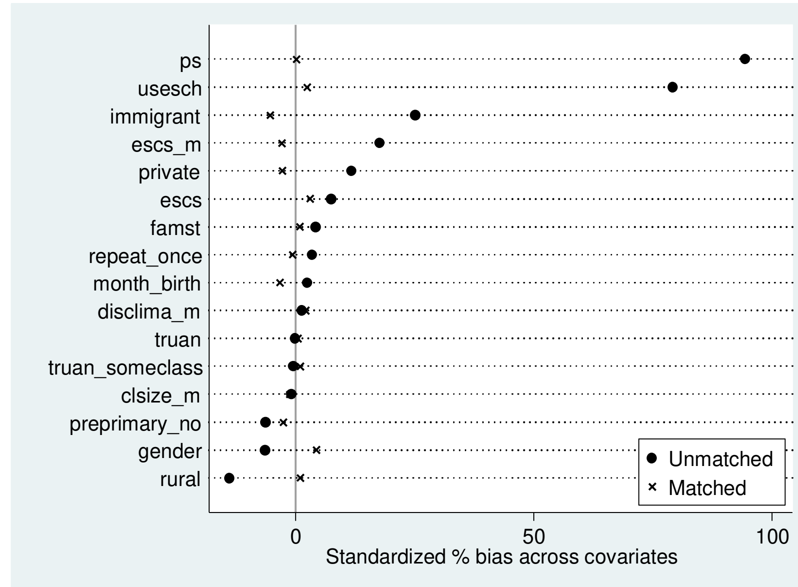
Figure 1. Bias reduction pre and post matching, by country



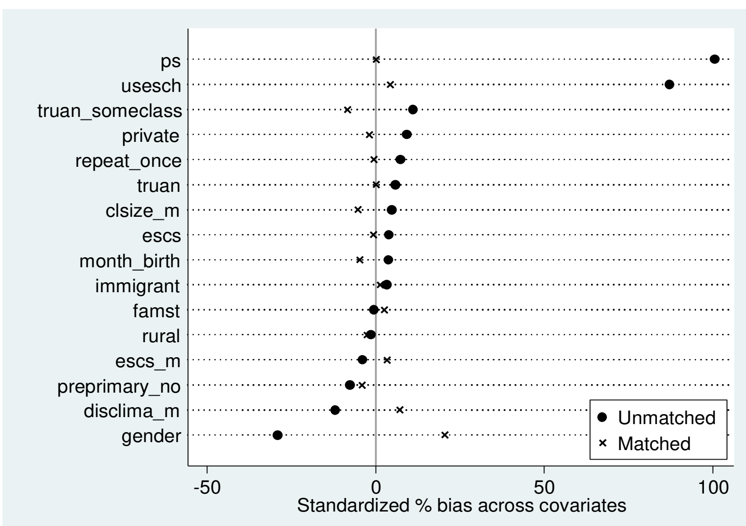
SPAIN



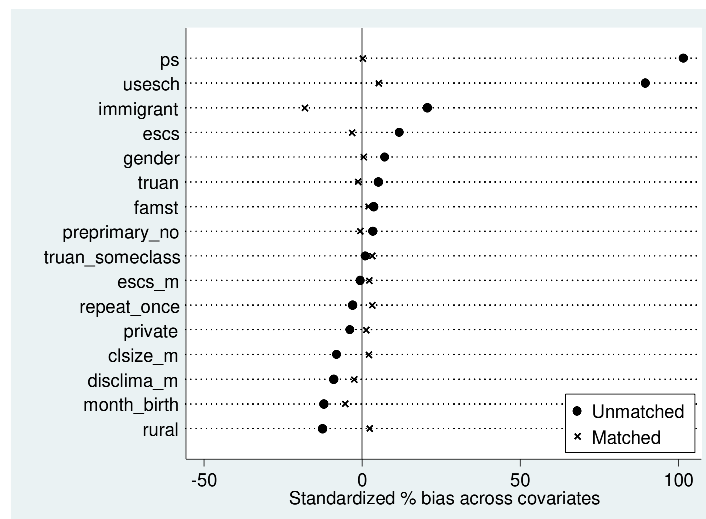
FINLAND



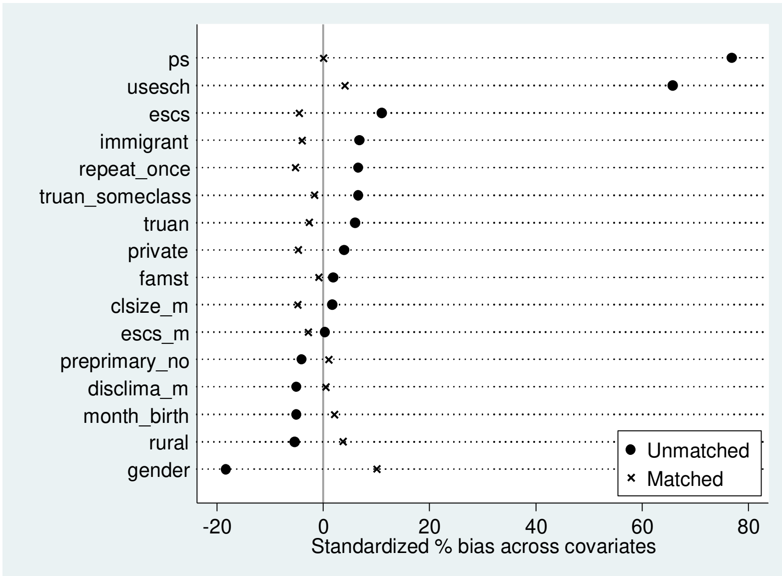
GREECE



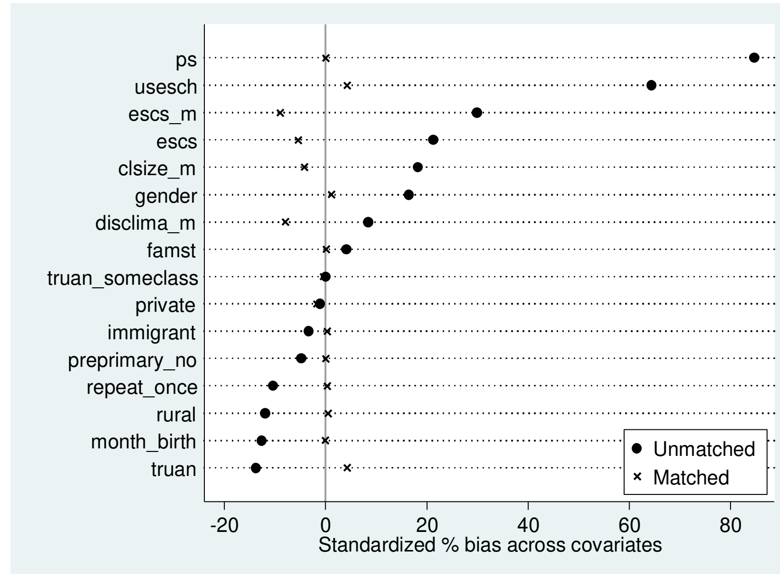
IRELAND



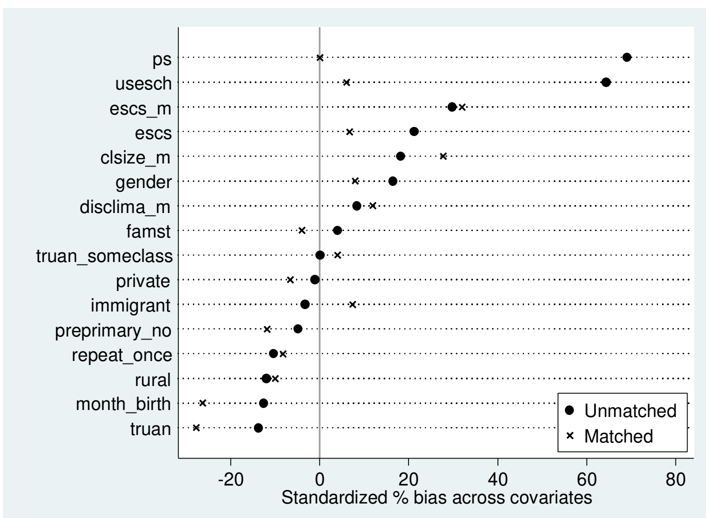
ITALY



NETHERLANDS



PORTUGAL



SWEDEN