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ICT and Educational Outcomes

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Abstract

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Abstract

As the global economy has transformed to a knowledge-based economy, ICT (Information and Communication Technology) is considered as a potential powerful educational resource to improve educational quality. Policy makers are enthusiastic about ICT use in education, and investing enormous amounts of money especially in developing countries. However, academic researchers have not reached a consensus on the presence of a causal impact of ICT on education. Furthermore, studies on the impact of ICT on education with macro-estimations, which is useful to policy design, are lacking.

The objective of this thesis is to build macroeconomic model based on theoretical framework of educational production function to find policy implications for the use of ICT in education. The main findings are as follows. First, ICT is significantly correlated with educational outcomes. I then present some evidence of a positive causal effect of ICT expenditure on secondary level students' academic achievement, and undesirable effect of home use of ICT on primary drop-out rate, though it is very difficult to obtain valid instruments in this context. Lastly, ICT is differently correlated with educational quality outcomes depending on national income.

Based on these results and a careful reading of relevant literature, national policies for ICT use in education has been suggested. First, governments should have a long-term budget and implementation plan for ICT use in education. In addition, government should encourage families to own computers and provide improved wireless environments through a national broadband plan. Finally, it is necessary to focus on ICT resource development.

Keywords ICT, ICT in education, educational outcome, educational quality, educational production function, macro estimation, ICT expenditure, home use of ICT, academic achievement, primary drop-out rate

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1 INTRODUCTION

1.1 Background and Motivation

Efforts to identify resources that improve education have been made by analysts based on general consensus as to the significant and positive impact of education on national economic performance. The assumption behind these studies is that government can invest in them for efficient schooling. (Heyneman & Loxley, 1983)

As the global economy has transformed to a knowledge-based economy, ICT (Information and Communication Technology) is also considered as a potential powerful educational resource to improve educational quality by policy makers as well as academic researchers. Students can have a real-time access to open resources by themselves, and thus participate in active learning process. ICT resources can be used in classrooms to increase students' interest, and further their academic performance. (Underwood, *et al.*, 2005)

Based on this belief, huge amounts of investment in ICT for education have been observed over the last 30 years. Investment comes from various entities. Policies that promote ICT use in education are adopted by many governments with the expectation that they will bring long-term economic growth. Countries in economic transition are especially concentrating on increasing their budget for educational use of ICT, pursuing long-term economic growth. For example, according to an announcement by the Indian government in 2009, they proposed a $189 million budget for ICT in education (Ng, 2009). Kenya also announced a budget for enhanced e-learning of about $60 millions (Itosno, 2013). Enlaces, a Chilean ICT in education program, has spent more than US$ 200 million in its 15 years of operation (Sánchez & Salinas, 2008).

International organizations such as UNESCO, the World Bank, the UNDP, and so on, as well as NGOs, are struggling to meet the Millennium Development Goals (MDGs) and Education for All (EFA) targets for encouraging students to use new technologies in their classroom. The World Bank and the UNESCO are cooperating to encourage ICT use in education, dealing with many issues related to ICT for educational use. Focusing on ICT in education projects by these organizations is mostly based on the belief that ICT can be used as an efficient tool to provide wider opportunities for students, overcoming the barriers of social, economic, and geographical isolation, and accordingly, to improve educational quality (Tinio, 2002).

Furthermore, national trends show a strong correlation between ICT and pupil achievement. Countries with high ICT indicators tend to have high pupil achievement. For example, East Asian countries many of which obtain the highest scores in student assessment usually have high ICT expenditure. In figures 1 to 3, it is easy to see that there is a correlation between educational achievement and several ICT indicators, which are key variables in this thesis.

Figure 1 ICT expenditure and educational performance: cross-country evidence

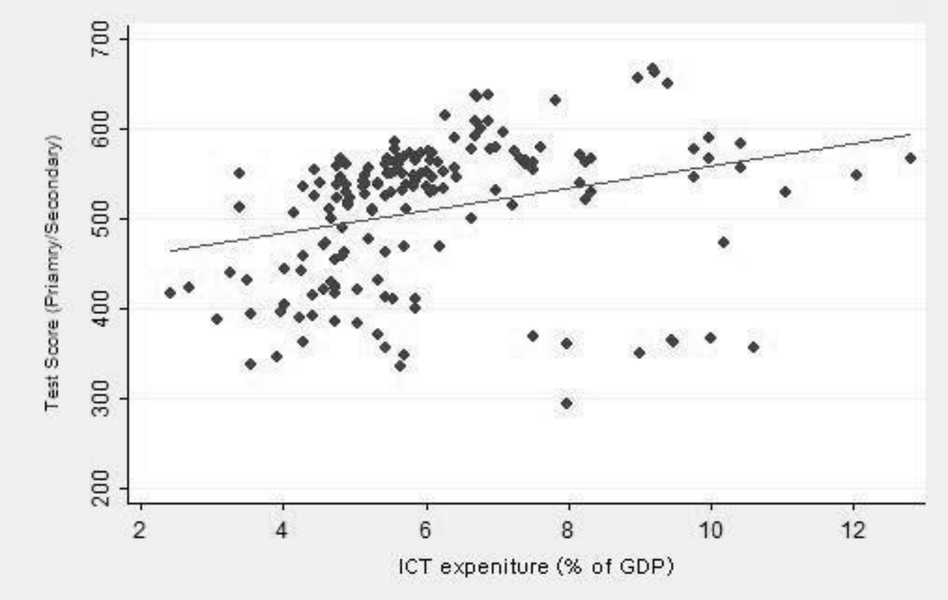


Figure 2 Households with pc and educational performance: cross-country evidence

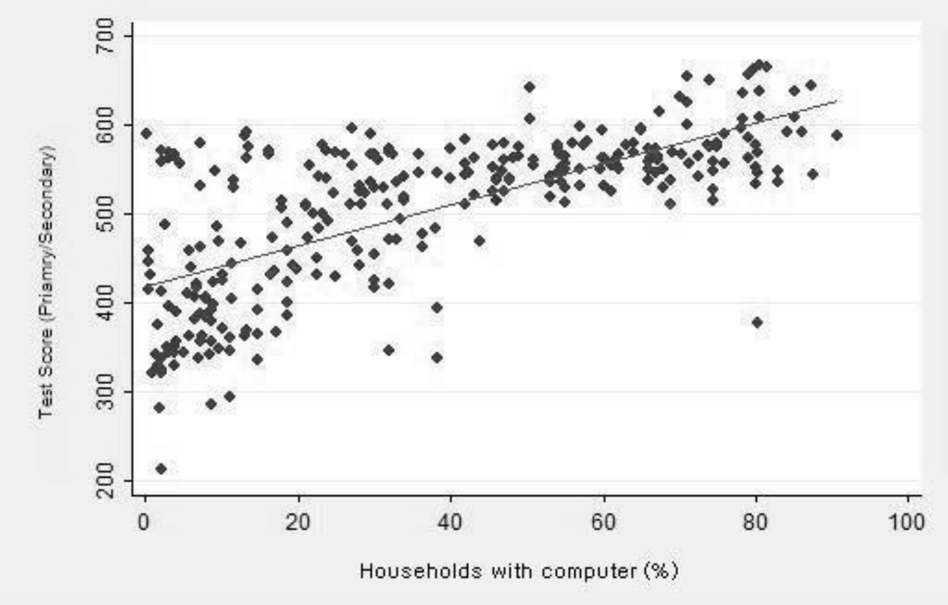
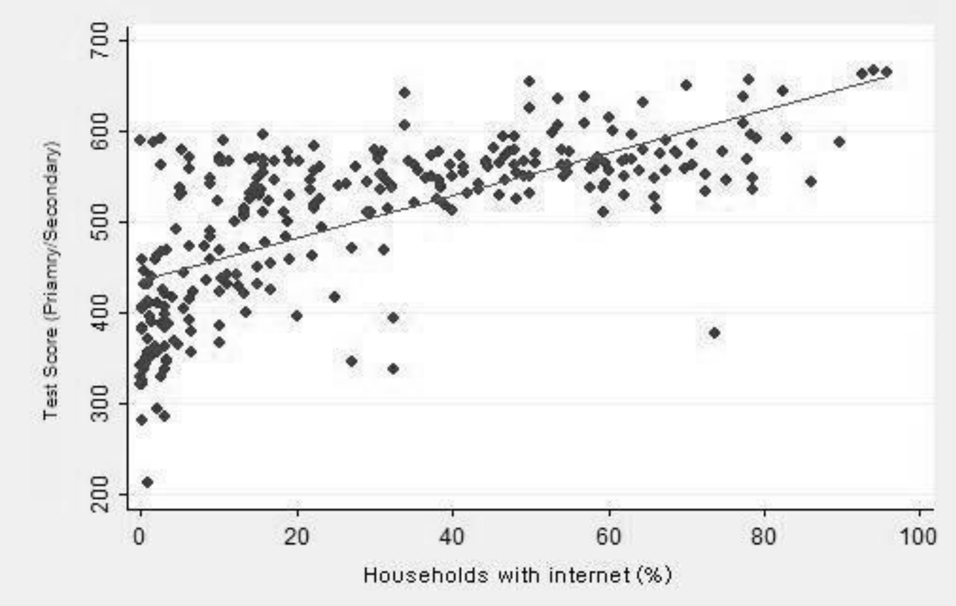


Figure 3 Households with internet and educational performance: cross-country evidence



However, academic researchers have become less enthusiastic raising a question of ICT's role in education based on studies that fail to find the empirical evidences that support the effectiveness of ICT use in education. Several studies show that ICT can aid students to access to information autonomously and to work as researchers from an early age, but even more studies say ICT has a neutral or negative impact on student engagement and academic performance. Furthermore, studies on the impact of ICT on educational equity are missing.

Even though many researchers found ICT does not matter as much as expected, educational policy makers are still carrying out investment in technologies (OECD, 2010). Clear evidence of the impact of ICT is urgent for policy planning to avoid waste of money. The introduction of ICT in education entails high fixed costs for physical facilities to start up. Variable costs to retain operations such as electricity fee and costs for places are also substantial.

An empirical macroeconomic model is especially required for policy design, because it is useful tool to evaluate the size of significance of the impact of different resources. (Serven & Solimano, 1991). However, studies on the impact of ICT on education are usually based on micro data and experimental design, which would lack external validity, mainly because of lacking cross-country data. Studies for developing countries are more depending on experimental design even though they are who actually need empirical evidences for policy design, because homogenous cross-country data are missing especially in developing countries.

1.2 Research Questions

This thesis answers the following three questions derived from this motivation:

1) Do countries with higher level of ICT investment and usage have better educational outcomes?
2) Do ICT investment and usage have a causal impact on educational outcomes?
3) Do ICT investment and usage have different impact on education according to national economic level?

Although many studies have attempted to assess the impact of ICT on education in various ways, they have often focused on partial aspects of input, output, and outcomes (Aristovnik, 2012). For example, the number of schools having a computer or the computer-student ratio, which is measured without relating them with its impact, is often used as an indicator for ICT in education. However, it is necessary to evaluate the efficiency of the huge investment being made by governments by investigating whether the expenditure on ICT brings wider opportunities and higher quality of education, which are the ultimate goals for ICT use in education.

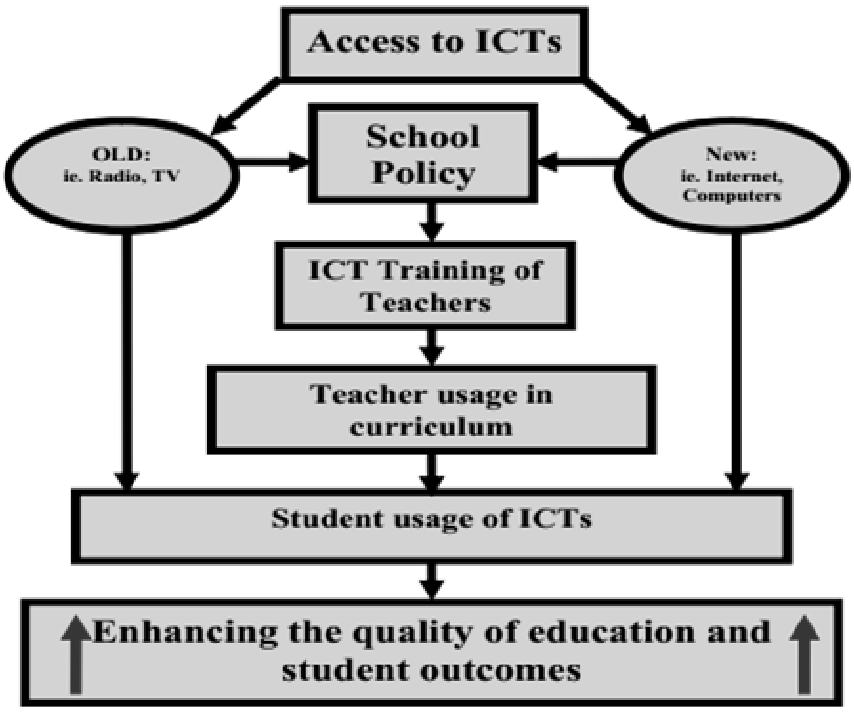
However, measuring the impact of ICT on educational outcomes is not easy because of the lack of data. There has been some discussion about how to measure indicators for the impact of ICT in education. Data are collected by the UNESCO Institute for Statistics (UIS), but the scope of the collected data is still narrow. Data are limited to a few countries in 2011 and 2012. Probably because of these, earlier studies that evaluate the impact of ICT on education are concentrated on using micro level of data within a country or experimental data collected by the authors. In addition, with data from randomized experiment, it is easier to estimate a causal relationship with less bias (Neyman, 1990). Especially for the question of education, a large number of development economics studies conduct randomized experiments (Imbens & Wooldridge, 2009).

The present paper will approach this in different ways to answer the question of the effectiveness of ICT on education. ICT factors at national level are the barometers for the degree of ICT development in the country. Children who have grown up in countries with high levels of ICT are more likely to be exposed to ICT environments and have more opportunities to experience new technologies. Therefore, data for ICT in general instead of

ICT in education can offer an alternative approach to explain children's familiarity with ICT and their ability to take advantage of it.

Figure 4, which shows the mechanism for ICT use in the field of education, supports the idea of using ICT at country level as alternative indicators for students' usage of ICT. This diagram shows that students can be affected by ICT either within the schools system or beyond it. Therefore, the national level of ICT can directly affect individual children's usage of ICT. I include two more indicators, which estimate the proportion of households with internet and personal computer (PC) to estimate the family influence of ICT use on children's usage beyond the school system. Based on this, the impact of ICT will be estimated by using cross-country data for ICT in general in this thesis.

Figure 4 Mechanism for ICT use by students



Source: UNESCO Institute for Statistics (2006)

The reason why the present study concentrates on a macroeconomic estimation, despite using alternative indicators, is that it is useful for policymakers in each country. Policy-based approach is especially considered as important to implement ICT-based education (Kozma,

2005) and policy makers are more enthusiastic about ICT use in education (OECD, 2010). Macroeconomic estimation is useful for policymakers in comparing policy choices and scenarios (Serven & Solimano, 1991; Pescatori & Zaman, 2011). Detailed issues about macro analysis will be discussed in following section.

Educational outcomes are measured in various ways, but we can classify theses into two: the quantity of and the quality of education. The ratios of enrolment, and attendance, and years of schooling are major indicators for the quantitative approach of educational outcomes. The quality of education, on the other hand, is measured by drop-out rates, completion rates, and standardized test in most economic studies. It can also be estimated with the influence of schooling on further education, performance in labour market, and job satisfaction.

Hanushek (1979) puts weigh more on the quality of education in measuring outcomes because each educated individual transforms fixed inputs to different quality attributes. Hanushek (2008) highlights again that quantitative estimates are biased because they presume that the same period of schooling results in the same amount of student achievement over time, regardless of countries. Glewwe and Kremer (2006) also agree to the importance of estimations of quality, finding that the quality of education in developing countries remains far lower than in developed countries despite the huge accomplishments in enhancing the educational quantity in the former. For these reasons, the present study is limited to measurement of educational quality.

Though there are several ways to measure the quality of education, it is common to relate ICT inputs and student achievement, and studies for the impact of ICT on other educational quality outcomes, such as drop-out rate, are missing. Thus, the present study will further this aspect by adding drop-out rate as an educational quality outcome.

However, estimations with data for ICT at the general level can have limitations in finding the causal impact of ICT on education because of the endogeneity problem caused by reverse causality. That is, higher educational quality in a country can also cause a higher level of ICT. Second research question is raised from this issue. How to manage this problem will be discussed later.

The third question is derived from the results of analysis for other types of educational resources. Earlier studies of educational production function have shown is that the impact of educational inputs appears to be different according to national economic level. For example, purchasable educational resources teacher experience, teacher education and class size do not have a significant impact in developed countries whereas they do have in developing countries. This difference is mainly originated from the different level of resources already possessed in countries. As developing countries usually have fewer teachers with high-quality, teacher variation brings more significant impact.

The results from the relevant literature for the impact of ICT in education are in the same vein. ICT use in education in developing countries turned out to be efficient, but not so in developed countries. The reason for the different impact of ICT is similar. Students in developed countries have more high-quality teachers, and thus, ICT can work as less efficient teaching tool than in developing countries.

However, there has been no non-experimental study for the impact of ICT on education in developing countries. Thus, this research will attempt to estimate with national level retrospective data assuming that ICT may also work in different ways as an educational input according to the economic level of the country. Comparing results in distinct estimations according to national income based on cross-country data would give us implications for policy.

Before providing the model that estimates the correlation between national level of ICT and educational outcomes, relevant literature is reviewed in the next section. The basic concept and methodologies to measure educational production function, and necessary variables to be included in the model will be discussed. A through literature review will also help derive policy advice in the concluding section.

2 LITERATURE REVIEW

This section introduces theoretical aspects of the education production function and its use for evaluating the impacts of various educational inputs, including ICT tools. First, this section will review the concept of the educational production function and several issues that are required to be considered when using the model—how to measure the impact of educational inputs for better decision making has been studied and discussed among economists since the mid-1990s. Next, literature on evaluating the impact of ICT based on the model of educational function will be reviewed. In particular, the controversy between optimists and pessimists about ICT in education will be investigated. Finally, given that the present study pursues macroeconomic analysis that is not attempted in earlier studies for evaluation of ICT as educational input yet, I analyse macro and micro estimations by presenting literature using each methodology.

2.1. Education Production Function

Input–output analysis for educational policy became common after the *Coleman Report* (Coleman, *et al.*, 1966), which evaluates the efficiency of educational policy by relating school resources and pupil achievement. Economists contributed to this area by deriving production functions for estimating educational outcomes and their determinants. Production function, which was initially exploited in decision making for profit maximization with limited resources by firms, was applied to the education industry to maximize educational outcomes by choosing more efficient inputs with least cost. Inputs for manufacturing industry, capital and labour correspond, respectively, with material resources provided by government and households, and human resources including administrators, supervisors, managers as well as teachers in education (Hanushek, 1979).

However, the application of traditional production functions to the education sector is not that simple. The production function is based on assumptions that inputs are perfectly measurable and that input has a deterministic relationship with output.[1] However, in reality, this relationship is not clearly defined in education (Pritchett & Filmer, 1999). Moreover, educational processes are different from general production processes, as it is not possible to reproduce the same outputs from the same inputs consistently (Hanushek, 1979). For these

[1] A set of inputs should produce same amounts of output.

reasons, sociologists have criticised the econometric approach to education. Fuller and Clarke (1994), both of whom are educationalists, criticise the production function analysis for ignoring that teachers and students in different cultures accept or mobilize the same instructional materials in different ways. However, educational production function is still useful because it presents average coefficients for general groups.

It has been discussed over the last few decades how to properly apply the traditional production function model to education for addressing these problems. We have two options to estimate the educational production function: using retrospective data or randomized experiments. Retrospective studies are using non-experimental data from past records for students across schools and families.

Hanushek (1971) used retrospective data for Californian third grade students during the school year 1968–69. The conceptual model his research is based on is the position that educational achievement is the function of initial output, family influences, peer influences, individual innate ability, and school inputs. He focuses on examining the influence of teachers and constructs the model with several variables for teacher characteristics, such as years of educational experience, educational levels, and verbal test scores of teachers. His study finds that factors that are purchasable by schools, such as Master's degree of teachers and teaching experience, do not have a significant impact.

Rivkin, *et al*. (2005) assess the effects of various educational resources on academic performance of students using panel data from UTD Texas Schools Project, which combined data from several different sources to accumulate a dataset on schools, teachers, and students. The regression of student achievement on family, school, and teacher characteristics measures the direction and size of impact of each variable. They employ fixed effects for individual students and schools, to reduce the problems caused by omitted variables. Results of their fixed effects regression show that the impact of school and teacher characteristics is small, especially in high grades. By specifying the size of effects of each of those less efficient variables for public policy purposes, they focus on which specific factors have larger impacts than others. They find that improving teacher quality is more efficient than reducing class size. In addition, teaching experience for the first three years is important, though teachers having Master's degree does not appear to be significant.

However, studies for developing countries provide the opposite conclusion. Case and Deaton (1999), drawing retrospective data from various sources, present evidence that class size, which is considered as a school resource variable, plays an important role in determining educational quality in South Africa. They include regressands other than test scores. Educational quantity measurements, such as years of completed education and enrolment ratio, are added to measure educational attainment. Regressions of those two variables on pupil–teacher ratio and other regressors show that bigger class size negatively affects them especially in the group of black students. Test scores also have negative correlation with the pupil–teacher ratio. This is evident for black students, whereas the coefficient of class size for the white students is insignificant.

Urquiola (2006) examines a causal impact of class size on academic achievement in Bolivia attempting to isloate class size effect in two ways of using instrumental variables and variating the size of class in remote schools. First, teacher allocation pattern in Bolivia is quantified and it is used as an instrument. Second, variation of with a single class size was possible because there is usaully one class per grade in rural schools. Both estimations suggest the class size negatively affect test scores.

Dustmann, *et al*. (2002) measure educational outcomes (beyond exam scores of students) with students' decision to remain in full time education after minimum school leaving age and performance in the labour market. Each regression with longitudinal data for English students has a class size variable and family influence and school effect variables. All of them show that family has a significant influence, whereas class size has a small effect. On the other hand, another study with panel data for Egyptian students shows that students' decisions to remain in school are affected by school quality. Hanushek, *et al*. (2008) estimate dropout behaviour using maximum likelihood estimation (MLE) and a Probit model. From both estimations, they discover interesting results that are inconsistent with earlier studies. For Egyptian students, family factors do not significantly affect dropout rates, but schools with higher quality prevent dropouts more successfully.

Krueger (1999) and Krueger and Whitmore (2000) analyse the educational experiment Project STAR, which is designed to examine whether class size matters in improving student achievement. From 80 schools, 11,600 students were randomly assigned to three types of classes: small, regular, and regular with teacher's aide. The difference in student composition of each class was controlled by creating dummy variables. Experimental data for this project reveals the positive causal relationship between class size and test scores. Students in smaller classes scored higher by four percentile points, whereas the teacher aide effect is small.

Major findings from literature on educational production functions differ according to where data are obtained from and which methodological approach is used. In the U.S. and U.K., school resources do not significantly affect educational outcomes, whereas in South Africa, Bolivia and Egypt, which have lower economic level than the two former countries, the impact of school resources on educational outcomes is significantly large, and that of family influence is not significant. On the other hand, different results come from different methodological approaches even in same countries. The results from the experimental approach in the U.S. showing the strong effect of reducing class sizes are in contrast to the results from retrospective data, presenting evidence that school resources do not have significant power in improvement of educational quality.

The input of interest of in this paper is ICT, which is considered as a popular educational input in the contemporary educational world. As with other inputs, the effectiveness of ICT as an educational resource is also in dispute. We now turn to the discussion about this topic. In the next section, literature on ICT in education is reviewed.

2.2. ICT Use in Education and Student Achievement

The influence of ICT use as an educational input on pupil achievement has also been researched with a production function approach. However, it remained controversial as to whether ICT has positive impacts on student achievement outcomes. By analysing previous literature, I found that the conclusion of each study is different depending on its methodological approach and geographical source of the data.

Debate between advocates and opponents for use of computers to improve student educational achievement ignited in 1990s. According to Kulik (2003), in the 1980s, when computers were introduced, and thus, technology applications became numerous, the studies on the effectiveness of computer-based instruction tended to be positive. Many educational and psychological studies in the 1980s asserted a positive correlation of computer use and student achievement. A meta-analysis conducted by Kulik and Kulik (1991) with 254 previous studies on Computer-Based Instruction (CBI) found usually positive impacts on students.

Until recently, some educational researchers still insist that computers help students. Wenglinsky (1998) suggests the expansion of public investment to increase computer literacy teachers in his report by proving that computer use at school has an indirect but positive relationship with mathematic achievement. They measured the relationship between technology variables such as the frequency of computer use and outcomes, taking into account student and school background. According to their model, students who use computers at school often more likely use computers at home, and computer use at home is positively related to the outcomes.

Becta (2002) reports that there is a significant positive association between ICT and student achievement in some subjects. Their conclusion is resulted from comparison between predicted and actual test scores. Based on the initial test before the ICT programme started, the final test scores expected to be achieved through the programme were compared with actual results. A significant positive relationship between ICT and student achievement was proved by positive mean relative gains of the greater use of ICT.

On the other hand, the endogeneity problem in estimating the correlation between ICT and educational outcomes was raised by Kirkpatrick and Cuban (1998). Endogeneity occurs when the independent variable in the model has correlation with error terms. Major sources of endogeneity are omitted variables, measurement errors, and simultaneous causality bias. The authors are sceptical about the effectiveness of computer use on learning ability in the presence of endogeneity. They analyse earlier studies and question their methodological approaches, also pointing out that previous literature failed to disentangle influences other than computer use on test scores.

Their criticism of the simple correlation between computers and student performance inspired economics studies, and these tend to become more cynical about the effectiveness of ICT use in education. Fuchs and Woessmann (2004) include controls for school and individual characteristics, family background, and resource inputs to reflect multiple dimensions. Their multivariate analysis suggests that computer availability and use at school and at home does not have a significant relationship with the Programme for International Student Assessment

(PISA) results, whereas the OECD (2001) reported a significant positive correlation with a simple bivariate model.

This result supports the theory of *productivity paradox*, proposed by Brynjolfsson and Hitt, (2000).[2] It suggests that organizational change is a key factor for boosting the impact of ICT on education rather than introduction of new physical technologies (Spiezia, 2010). That is, as the schools with more computer use in their classrooms may provide students with other resources more as well, schools with higher willingness to improve their entire educational environment can enjoy higher efficiency in the impact of ICT on student achievement.

Mayston (2002) also points out the problems of endogeneity in a multivariate model when estimating the relationship between expenditure and pupil outcomes. Endogeneity bias occur in multivariate studies because, according to him, single equations do not consider the presence of reverse causality between independent and dependant variables (Mayston, 2002). This applies to the multivariate analysis by Fuchs and Woessmann (2004). Some input variables, such as parental support and number of books at home, in their model, may be affected by the test score in reverse because parents of academically excellent students would have high motivation to support their kids. They are already aware that their analysis is descriptive rather than causal, and suggest that experimental data are required to capture true causal effects of exogenous variables. Subsequently, experimental or quasi-experimental data have dominated in recent studies for estimating the causal impact of ICT use for educational purposes on student achievement.

Coates, *et al*. (2004) carry out an experiment that observes the difference in students' behaviour between online class and face-to-face class. The Internet is used in economic courses for those who enrolled in a distance learning class in three different college level institutions in the U.S. Ordinary least squares (OLS) estimation that regresses test scores estimated after the experiment period on the basis of a binary variable (1 if a student is in distance course and otherwise 0) and other control variables for individual student characteristics indicates that students who take online courses scored lower than those who take face-to-face classes. They detected that their experiment had self-selection bias, which indicated that students' choice between online and face-to-face courses may be determined by

[2] Productivity paradox is defined as a contradiction existed between the high development of ICT and the low growth rate of national outputs.

difference in their ability , and correct this problem with 2SLS and endogenous switching regressions. Results of both regressions indicate that there exists sample selection bias, and prove that students in online class receive fewer correct answers. That is, distance learning negatively affected students.

Rouse and Krueger (2004) present the result from a randomized experiment with *Fast ForWord* (FFW) programmes that are designed to improve language and reading skills. Students in an urban school district in which scores of students were below average for the state were randomly selected to participate in FFW. They regressed four indicators that measure different kinds of objective that is expected to achieve with the programme finding that the computerized instruction is helpful to improve some aspects of students' language skills. However, the programmes fail to develop these skills to broader types of ability such as language acquisition or actual reading skills.

Dynarski, *et al*. (2007) also used experimental design to evaluate the use of software products in the classroom. Products to be used in the experiment were selected based on volunatry participation. Participant schools and districts were concentrated on those with low pupil achievement and large proportion of poverty. According to their report, the effectiveness of educational software program in treatment group, which are randomly assingned, is partly observed in first and fourth grade; however, the effects are more likely to be corrletaed with school characteristics.

In contrast, the outcomes of a randomized experiment by Barrow, *et al*. (2007) support the positive role of the computerized instruction for mathematics. Students randomly assigned to computer-aided instruction scored higher than those in control groups. They employ an empirical model similar to that used by Rouse and Krueger (2004) Academic outcomes measured by test scores are regressed on a binary variable, a vector of student characteristics and dummy variables, and the binary variable is regressed with instrumental variables.

Similar experiments carried out in developing countries ensure the positive role of new technologies. Banerjee, *et al.* (2007) find that Indian students who regularly experienced instructional games and software for mathematics scored significantly higher in mathematics. They outline two groups that receive the programme ($\delta = 1$) or not ($\delta = 0$), and collect student test scores twice, before and after the programme. They regressed the difference in test score between before and after the experiment on the scores before the experiment and the dummy variable, which is binary specification of whether the school received programme or not. Thereby, they observed how much students in treatment school improved their maths score, relative to what would have been expected based on pre-test score, compared to the control group. As a result, Computer-Assisted Learning (CAL) has a strong effect, with standard deviation of 0.35 and 0.47 in the first and second year, respectively.

He, *et al.* (2008) report that an Indian educational programme with electronic machines (called a *PicTalk*) is effective to learn a second language. A PicTalk, whose purpose is to solve two problems of ineffectiveness of instruction for English as a second language and lack of access to new technology at an early age, was provided for each student in treatment schools for a year. They used the econometric model, which is similar to the one Banerjee, *et al.* (2007) used but additionally regressing on attendance rate. Implementation of the PicTalk programme increases about 0.25–0.35 standard deviation on average of students' English test scores, whereas it does not seem that the programme significantly affects student attendance rate.

Barrera-Osorio and Linden (2009) showed that computer use in the classroom has a positive but insignificant impact on pupil outcomes from an experiment in Columbia. Even though the 20-month programme succeeded in increasing the number of computers and students' computer use, this did not fully translate to the test scores. It is a small effect, compared to those for other educational programmes in developing countries, increasing 0.1 standard deviation of pupils' test scores. From surveys of teachers and students, they find that even after schools receive computers, the frequency of computer use for classroom activities does not increase. In other words, teachers do not incorporate the provided computers into classroom activities. Given this result, they emphasize the importance of teachers' practical use of computers in class to efficiently implement the programme.

Cristia, *et al*. (2012) evaluated the One Laptop per Child (OLPC) programme, which targets the poor to help their learning with government aid, in Peru. They add indices other than test score. Indices for student behaviour, such as attendance, enrolment, academic achievement, and cognitive skills, are compared between students in treatment schools and control schools, but it is found that there is no significant difference between student behaviour and achievement. Meanwhile, they succeeded in finding positive effects in general cognitive skills measured by Raven's Progressive Matrices. However, the lack of the impact on test score is rather because the programme is targeted to introduce technology and improve cognitive ability. This implies that the programme in Peru is effective in achieving its aim, and when it is designed with appropriate pedagogical models, it is likely to succeed.

To find better pedagogical implementations of computer use, Linden (2008) tested two different methods of implementation. He uses experimental data to assess CAL programme implemented both in-school and out-of-school in India. The in-school programme that replace classical teaching method has a negative effect of 0.57 standard deviation decrease in test scores, while the out-of-school programme that complements to in-class learning improves students' learning ability with a 0.28 standard deviation. Their study offers a basis to weigh more on using CAL as complementary tools rather than substitutes.

Table 1 Summary of researches for the correlation between ICT use and pupil achievement based on experimental data

Study	Subjects	Grade	Country group	Result
Coates, *et al*. (2004)	Economics	College	Developed	Negative
Rouse & Krueger (2004)	Language	Elementary, Middle, High	Developed	Negative
Dynarski (2007)	Language Mathematics	Elementary	Developed	Insignificant
Barrow, *et al*. (2007)	Mathematics	High	Developed	Positive
Banerjee, *et al*. (2007)	Language Mathematics	Elementary	Developing	Positive
He, *et al*. (2008)	Language	Elementary	Developing	Positive
Barrera-Osorio & Linden (2009)	Language Mathematics	Elementary, Middle	Developing	Positive (insignificant)
Cristia, *et al*. (2012)	Cognitive Skill	Elementary	Developing	Positive
Linden (2008)	Math Language	Elementary	Developing	Mixed

Experimental studies on the impact of ICT on education are summarised in Table 1. What appears to differentiate the findings of the studies is the different environment that participant students experience. Experimental studies that are conducted in the U.S., one of the most represented developed countries, tend to result in negative findings, whereas other experiments for students in developing countries are likely to report a positive impact of computer use in education. Other factors such as subject and grade do not seem to affect outcomes significantly. For example, two studies exploring the effectiveness of ICT in language and mathematics at elementary school level produce opposite conclusions. Whereas Dynarski, *et al*. (2007) find that little difference between classrooms using software products and not using them, results from experiments designed by Banerjee, *et al.* (2007) show that students benefit from educational software programs.

The opposite conclusion for developing countries and developed countries has been previously observed in school resources other than ICT. Whereas an extra school resource such as teachers or expenditure per student brings improved test scores in developing countries, it does not do so in developed nations (Hanushek, 2003). In other words, the significance of additional resources may be different depending on the level of resources already possessed.

The dominating explanation for the reason that computerized schooling is more productive in developing countries than in developed countries is they have poorer quality of teachers, who provide lower quality of education than computers do (Banerjee *et al.*, 2007; He *et al.*, 2008). Thus, it is possible to replace teachers with computers with less hesitation in developing countries.

This motivates my study to divide countries according to national income to see the different impacts of ICT in each group, as high-income countries tend to already have had a higher level of ICT in place as well as the higher quality of unobservable.

Hebenstreit (1985) gives us one more clue to understand the difference. In his report, it is stated that developing countries pursue different educational purposes in using computers in education. Prior concerns for education in developing countries are more fundamental—for example, increasing literacy rate. We can induce from this it might be easier to achieve the lower level of goals in developing countries.

On the other hand, many studies that estimate the correlation between public investment in ICT and student achievement have used various econometric methodologies to deal with the problem of endogeneity: Instrumental Variables (Machin, *et al*., 2006; Angrist & Lavy, 2002; Belo, *et al*., 2011), and Regression Discontinuity Design (Goolsbee & Guryan, 2006; Leuven, *et al*., 2007). These studies each revealed that the correlation between ICT funding and pupil outcomes is negative or, at best, mixed.

Machin, *et al*. (2006) estimates the impact of change in rules governing ICT expenditure for schools in England on student outcomes by exploiting Two-Stage Least Squares (2SLS) to estimate the effect of ICT investment on student outcomes. At the first stage, an Instrumental Variable (IV) strategy was devised to determine the amount of ICT expenditure student level by measuring the difference between the share in overall expenditure by the Local Education Authorities (LEA) before and after the policy change. Their findings show a positive role of ICT funding on pupil performance in English and Science at the primary school level.

Angrist and Lavy (2002) evaluate an Israeli educational programme, Tomorrow-98, which sponsored computerization of the education system in middle school. They use a non-linear instrumental variables as well as 2SLS. First, 2SLS specifies the endogenous variables, the intensity of computer use, at the first stage, and estimates test scores with endogenous variables. Second, non-linear IV is employed to correct bias because funding is determined based on ranking of town where each applicant school is located. Considering the non-linearity and non-monotonicity of function for funding, quadratic function is used for ranking controls. Both models report that increased numbers of computers by the programme led to an increase in computer use intensity, but failed to find evidence for a significant impact of increased of computer use in the classroom on test scores.

Belo, *et al.* (2011) assessed the impact of broadband use in school on student performance with school-level panel data. They also exploited 2SLS to solve the endogeneity between broadband usage and school performance. Broadband use was first specified with line-of-sight distance between each school and Central Office, chosen as an instrumental variable that is randomly distributed. The results show that the longer distance reduces students' broadband usage. At the second stage, school performance is estimated on the broadband use specified at the first stage, and findings showed a negative impact of broadband use regardless of gender, subject, and the quality of school.

Goolsbee and Guryan (2006) evaluate the program that supports schools in the U.S. with different amounts of subsidies that range from 20 to 90 percent depending on school characteristics for internet and communication investment. Regression Discontinuity Design (RDD) estimation, which estimates these cut-offs at different percentage of subsidy, was used to assess whether internet is well adopted with the subsidy in schools. However, its results are too weak to use, as the sample size is too small. Instead, they did regression of internet access per classrooms on the subsidy awarded for a school district with fixed effects estimation, and report that schools successfully increased internet with the use of subsidies. Furthermore, whether internet investment affects students' learning ability is examined by another regression with the same regressors. However, they do not find evidence that the investment had a significant effect on student test scores.

Leuven, *et al*. (2007) evaluate the effect of subsidies for disadvantaged students and also do not find positive impact of extra funding for computers. RDD is employed to specify the binary variable of whether a school is offered the subsidy. This is possible because the subsidy is provided to schools with at least 70 percent pupils from different disadvantaged groups. Coefficients that indicate the size of the effect of subsidies are rather negative for both arithmetic and language, with low significance. Outcomes of retrospective studies are summarized in Table 2.

Table 2 Summary of researches for the correlation between ICT use and pupil achievement based on retrospective data

Study	Input	Methodology	Country group	Result
Machin, *et al*. (2006)	ICT expenditure per student	2SLS	Developed	Positive
Angrist and Lavy (2002)	Computer use	2SLS	Developed	Negative
Belo *et al.* (2011)	Broadband use	2SLS	Developed	Negative
Goolsbee & Guryan (2006)	Subsidies for ICT	RDD	Developed	Negative
Leuven, *et al*. (2007)	Subsidies for computers	RDD	Developed	Negative

Reviewing literature on ICT investment evaluation, several aspects calling for further study emerge. First, previous studies have concentrated on student-level data rather than country-level data. Cross-country studies are limited, even in studies of the impact of general educational inputs, due to the lack of international data (Lee & Barro, 2001). However, this can be settled by readjusting data measured by different organizations. How to clean and recode heterogeneous data will be discussed in the next part, reviewing relevant literature concerning macroeconomic estimation.

It seems important to manage endogeneity problems caused by reverse causality in the general micro analysis literature on ICT in education. Microeconomic literature controls endogeneity by using experimental design or endogeneity techniques such as IV or RDD. It is important to utilise one of these techniques for macro-estimations.

Another tendency in the literature on the impact of ICT use in education is measuring the quality of education with test scores only. Test score can be considered one of the most important indicators that explain the quality of education, but it does not describe all aspects. Indicators for educational attainment, such as school primary drop-out rate, can be estimated as well. Adding estimation of variables other than test scores would be meaningful in evaluating ICT use for education because ICT expansion in education is partly based on the belief that ICT can contribute to equity in education, including all students at all levels (Robinson, 2008), and to reducing drop-out rates (Alvaro, 2010).

Finally, literature on estimating the impact of ICT on education in developing countries has concentrated on experimental data. To take the advantages of retrospective studies that are described above, in this paper, a macroeconomic model will be built with compiled cross-country data to find a correlation between ICT and educational outcomes. This approach will show whether ICT works in different ways as an educational input according to national economic level.

2.3 Macro Studies vs. Micro Studies

A macro question is interesting in its own right for policymakers and more readily internationally generalised. Serven and Solimano (1991) argue for the usefulness of macro modeling because comparison between the impacts of each macroeconomic policy is available. Macroeconomic model is also useful for forecasting policy scenario (Pescatori & Zaman, 2011)

Despite these advantages, the relationship between ICT and educational outcomes has not been estimated by macroeconomic model. Given this gap in the literature, I had to look at studies for the effects of other types of educational inputs, finding a few international comparative studies for education production functions.

Two issues are commonly discussed in cross-country studies. One is how to handle international data from heterogeneous sources. The other is the concerns about distinct characteristics of East Asia, in which students tend to score exceptionally high on international tests among developing countries. This section will now review following literature focusing on these two topics.

Heyneman and Loxley (1983) initiated country-level studies examining the influence of educational resources on academic achievement of students in both high- and low-income countries. Most of previous studies have focused on data within the United States, but they conclude that it is problematic to generalize these imbalanced results to other countries. Their attempt to collect data outside the United Sates through different channels and to recode them for unification is concretely described in their paper. With these readjusted data, they first measure the influence of educational inputs on the mean of test scores in each country, and then estimate the correlation between the measured influence and national per capita income. Their main purpose is to determine whether the impact of educational inputs varies with national economic development. According to their research results, in developing countries, family influence is smaller, but teacher influence is larger. This is the exact opposite result to those of earlier studies that focused on high-income countries. The discordance of result can be explained by the higher desire for education in developing countries regardless of their socioeconomic status. High demand for education by students in low-income countries is due to the scarcity of educational opportunity and the strong desire for upward social mobility. Their study provides enough motivation to use cross-country data to detect and explain the social and cultural difference between countries at different economic development levels.

However, Hanushek and Kimko (2000) maintain a sceptical opinion about school effect. They exploited test scores measured by International Association for the Evaluation of Education Achievement (IEA) and International Assessment of Educational Progress (IAEP). They handled these data in two ways: transformation of each test score set to a mean of 50 and normalization based on U.S. performance on the National Assessment of Educational

Progress (NAEP). The regression of these two different measurements of pupil achievement on indicators for educational inputs such as pupil–teacher ratio, current public expenditure per student, and total expenditure on education for each country proves that variation in school resources do not have strong impact on academic achievement. On the other hand, by regressing test scores excluding East Asian countries, the authors observe the sign of coefficients remains same but the size of impacts decreases.

Lee and Barro (1997; 2001), using the same sources for test scores, derive the opposite conclusion. They regress scores of each subject on family factors and school resources. The log of real per capita GDP and average primary schooling years of adults aged 25 and over are used as proxies for parents' income and education, respectively. Pupil–teacher ratio, real public educational spending per student in primary school, real salary per primary school teacher, and the length of the primary school year are indicators for school resources. The family influence on test scores is significantly positive, as confirmed in previous studies. However, the correlation of school resources with test scores is mixed. Whereas coefficients for pupil–teacher ratio and teacher salary indicate a significant and positive impact of school resources, expenditure on education and the length of schooling year both turns out to be insignificant. In the same study, the authors measure the existence of 'Asian Value' by using a regional dummy for East Asian countries. High coefficients for the dummy variable imply that there are unmeasured factors in estimated models other than family and school inputs for East Asian countries.

Altinok (2007) carries on this study after Lee and Barro (2001). Data and method used for his study are based on studies of Hanushek and Kimko (2000) and Lee and Barro (1997; 2001). Data after their studies are collected from UNESCO and World Bank. To readjust compiled data from different sources, Altinok distinguishes two groups: tests that United States participated in and those that it did not. The first group of test allows an anchoring on an American test NAEP, and the second group is anchored on the results of countries that took part in at least two different assessments. Educational and economic variables are the same as in the model of Lee and Barro (1997; 2001). Family factors consistently turn out to have significant positive impacts on proficiency test scores. On the other hand, empirical result shows school resources have mixed impact again, though the signs of impact of each factor are different. Teacher salaries and educational expenditure have significant positive impacts, whereas pupil–teacher ratio has insignificant negative correlation with test scores. He furthers his study by classifying groups of data based on economic level of countries to analyse the inconsistencies. Presenting significant different result from general estimation, this emphasized economic level of countries as an important factor. For example, the impact of pupil–ratio is positive and significant in high-income countries, but negative in low- and intermediate-income countries.

There have been several cross-country studies measuring the output of education with indicators other than test scores. Lee and Barro (1997; 2001) established repetition and drop-out rates data and regress them on variables for family and school inputs. The result of regression shows that children in richer and better-educated families are less likely to repeat or drop-out from school. A lower pupil–teacher ratio, on the other hand, has significant positive relationship with repetition and drop-out rates, whereas educational expenditure and teacher salaries do not have significant impacts.

Al Samarrai (2006) chose indicators for qualitative educational outcome such as survival rate to primary grade five, and primary school completion rate. The result of his regression of these two indicators on educational inputs and socioeconomic factors using OLS illustrates a weak correlation between resources and these outcomes. Only primary expenditure per pupil turns out to have significant positive impact on primary survival rate. The impact of socioeconomic factors on educational attainment also appears to be weak. Only the Muslim proportion of the population has a positive and significant impact.

In contrast, Gupta, *et al*. (2002) present a positive relationship of educational resources with educational attainment in developing and transition countries. They regress persistence through Grade 4 and primary drop-out rates on educational inputs and socioeconomic factors using OLS and 2SLS. Instruments used for 2SLS estimation are aid per capita, aid in percent of government expenditures, military spending in percent of government expenditures, and total government spending. Total educational spending has a significantly positive correlation with primary drop-out rates and primary and secondary education spending has significantly positive correlation with persistence through grade 4 for OLS specification.

To compare with the macroeconomic estimation, two pieces of literature on micro education production function with cross-country data will be reviewed here. Wößmann (2000) used Third International Mathematics and Science Study (TIMSS) data based on individual student information. TIMSS is well-designed for micro estimation. When students were tested, they were required to answer questions regarding their family background, and their teachers provided information about school characteristics. On the other hand, TIMSS data do not provide balanced information, because developing countries outside East Asia are not included. The estimated impacts of family influence and school influence are consistent with most of the literature, in that family influence is strong and school resources are not closely related or negatively related with student performance.

Hanushek and Luque (2003) also did a student-level study using TIMSS data. They did regressions on as many as the number of countries that have datasets on educational inputs both from family and school, then count the number of positive and negative coefficients of each educational input variable. The international evidence that Hanushek and Luque find shows us that school influence is weaker than family influence, which turns out to be significant and strong. On the other hand, the degree of school influence results in international data is slightly stronger than solely in the U.S. Its result is, again, imbalanced with data weighted on high-income countries.

Both studies, which present consistent results with macro studies, indicate their objectives to pursue micro estimation by pointing out the limitation of macro estimation in education production function. According Hanushek and Luque (2003), aggregated production functions at national level fail to capture the different school systems in each country. Wößmann (2003) explains that macro education production functions do not consider students' individual different influence on academic performance. Furthermore, it restricts analysis to the system-level institutional determinants.

Despite weaknesses of using aggregate data, Hanushek (1979) argues that the aggregation of data brings about a less innocuous consequence either when the deterministic relationship of educational production is linear or when more complicated, as long as the variables are not correlated. This is because an econometric model at the individual student level does not consider that different production functions can be existed where the differences are not simply parameterized, whereas aggregated estimation presents average coefficients for each group.

Finally, the macro estimation is better in measurement. In practice, the level of measured data is usually different. Even though school influences to each student in a different way, data regarding school resources are typically measured at school level, whereas test scores and family background are estimated at the individual student level.

2.4. Methodological Issues

Several methodological issues are discussed by economic researchers. When estimating with OLS regression, it is not necessary to have all data for unobserved elements that are unlikely to correlated with the vectors for which one has data, but if the omitted variable is part of an error term, the estimation would be biased (Glewwe & Kremer, 2006). This is where the problems for regression analysis of educational production function frequently come from. Intangible elements, which are common in educational production function, are not easily observed and specified. In this case, researchers choose proper proxy indicators for such omitted variables (Todd & Wolpin, 2003). Innate ability and parental willingness are measured by IQ test and parental education level, respectively. However, cross-country panel data on IQ test results are often not available.

Hanushek (1986) highlights an empirical problem regarding measurement error in using retrospective data. Since the educational process is cumulative—previously added inputs have lasting effects—it is unclear whether the additional input is exogenous or endogenous. Todd and Wolpin (2003) introduce several options to address this problem. When assuming we have series of data on current and past inputs, we can estimate cumulative effects of each input; however, this requires a full dataset, which is almost impossible to obtain. We need alternatives, such as contemporaneous specification, and value-added specification. The contemporaneous specification relates test score solely to contemporaneous measures on school and family inputs. The value-added specification relates an outcome to a lagged achievement measure as well as contemporaneous school and family input measures.

Value-added estimation is the most common way to alleviate this problem, because other methodologies require huge amounts of data. This estimation is specified by academic achievement measured at different points of time, supposedly twice: one before and one after the experiment. It will help us to focus only on the change between two points (Hanushek, 1986). As first test scores signify the outcomes that reflect the influence of inputs previously applied or innate ability, we no longer need to attempt to measure endowment.

Rothstein (2010) employs value-added modelling to disentangle individual student ability from teacher effect. He presents three different types of value-added models: the gain score model, lagged score model and fixed effects in gains model. The gain score model is a regression of gain scores on grade and contemporaneous classroom indicators. The lagged score model is a regression of score levels on classroom indicators and the lagged score. The fixed effects in gains model is a regression that stacks gain scores from several grades and adds student fixed effects. All three models are common, but the lagged score model is more widely used by recent economists. A dummy variable is added in regression analysis to describe fixed effects. Many educational production function studies employ this to evaluate the effectiveness of inputs while avoiding the requirement of providing a detailed specification of the separate characteristics of inputs that are important. Rothstein's (2010) results based on gain score model and lagged score model imply that teacher quality in the 4th grade has a large impact on students' score gains in the 5th grade.

Randomized and natural experiments are alternatively employed to evaluate the impact of ICT on education. In experimental studies based on random assignment of students with different resources, it is not necessary to specify cumulated impacts of previously added resources (Krueger, 1999). Experimental design requires randomized samples that help to avoid biased outcome and identify exogeneous variables (Kirk, 2009). Researchers who study the impact of ICT on education through experiments usually randomize samples by randomly assigning schools in a specific area to either treatment or control groups. The random assignment of participants can address the possible problems caused by correlation between either observable or unobservable variables for educational resources and individual factors (Linden, 2008).

Nevertheless, randomized experiments that target humans generate other kinds of problems. Glewwe and Kremer (2006) comment on the several potential problems raised by experimental studies. First, sample selection bias can occur in experimental research. In fact, it is difficult to randomly assign subjects to treatment groups in reality. This may be because of ethical reasons and participants' preference. It would be unethical to provide students with different quality of education for experimental purposes, and parents of students who are assigned to a control group may want their kids to be in treatment groups.

Second, people who participate in the experiment may behave unnaturally, being conscious of the evaluation. Kirk (2009) defines three factors that cause this phenomenon: demand characteristics, participant-predisposition effects, and experimenter-expectancy effects. In other words, participants can perform as they perceive that they are expected to in the experiment, based on their perception or past experience, and researcher who carry out the experiment can unobtrusively require participants to show certain of behaviour to obtain the data they intend. All these factors would affect the internal validity of an experiment. Such generic problems can happen during experiments in educational settings as well when data are highly depending on answers from teachers and students.

In addition, the external validity lacks in experimental studies. Whether a result of an experimental study based on a specific situation and population would be generalized to other situation and population is not guaranteed. It would be useless if the experiment results in different behaviour or responses when it becomes generalized. That is, it would not be simple to generalize the effectiveness of a certain resource that is known as a key factor in a school that has unique characteristics.

Finally, even capturing a causal impact can be threatened in experiments. When there are spill over effects from the treatment group to untreated students, it would be complicated to identify the impact of treatment.

In conclusion, there are trade-offs between capturing a causal relationship and generalizability of results in answering to the question of the impact of ICT on education. Macroeconomic approach is limited to find a causal impact, but it would offer new insights to find generalizable results for policy design, and further, for analysis of progress toward MDGs. By employing endogeneity techniques, it is even possible to attempt to detect a causal impact of ICT on education. Therefore, the present study will use macroeconomic estimation to find the impact of ICT on education.

3 EMPIRICAL SPECIFICATION AND DATA

An educational production function is estimated based on panel datasets of educational outputs and inputs that are compiled from various sources. The econometric method employed in this thesis is based on OLS. Each dependent variable for educational outcomes is regressed on the set of variables that include ICT resources and educational inputs from households and schools. Each variable is specified in the next few paragraphs. The model can be expressed as;

$$Q_{it} = \alpha_0 + ICT_{it} * \beta_1 + F_{it} * \beta_2 + R_{it} * \beta_3 + C_{it} * \beta_4 + \varepsilon_{it,}$$

where Q_{it} denotes educational outcomes in individual country *i* in year *t* (2003 to 2008); ICT_{it}, F_{it} and R_{it}, respectively, denote ICT factors, family influence and school resources for country *i* in year *t*; C_{it} denotes control variables, that can be related to educational outcomes for country i in year t; ε_{it} denotes the unmeasured factors; and β_1, β_2, β_3, and β_4 are the parameters to be estimated.

As suggested in the previous section, two indicators are chosen as dependent variables that indicate educational quality outcomes in this study. First is academic achievement, which is the most common measurement for educational achievement in previous studies on the impact of educational resources. Cross-country level data for test scores are scarce, even though pupil achievement across the countries is assessed in several types of standardized tests. Aggregating data from different types of examinations is not easy because not every country participates in each type of examination. Comparable data are lacking, particularly in developing countries.

A recent study has aggregated results of various international and regional examinations. Altinok, *et al.* (2013) provide a panel dataset created by combining pupils' achievement in regional learning assessments as well as international learning assessments. International assessments include five tests: The TIMSS and Progress in International Reading Literacy (PIRLS), organized by the *International Association for the Evaluation of Educational Achievement* (IEA); the PISA, launched by the OECD; and the *National Assessment of Educational progress* (NAEP), *International Assessment of Educational Progress* (IAEP), and *Monitoring Learning Achievement* (MLA), undertaken by UNESCO and UNICEF. In addition, three major regional assessments conducted in Africa and Latin America are the

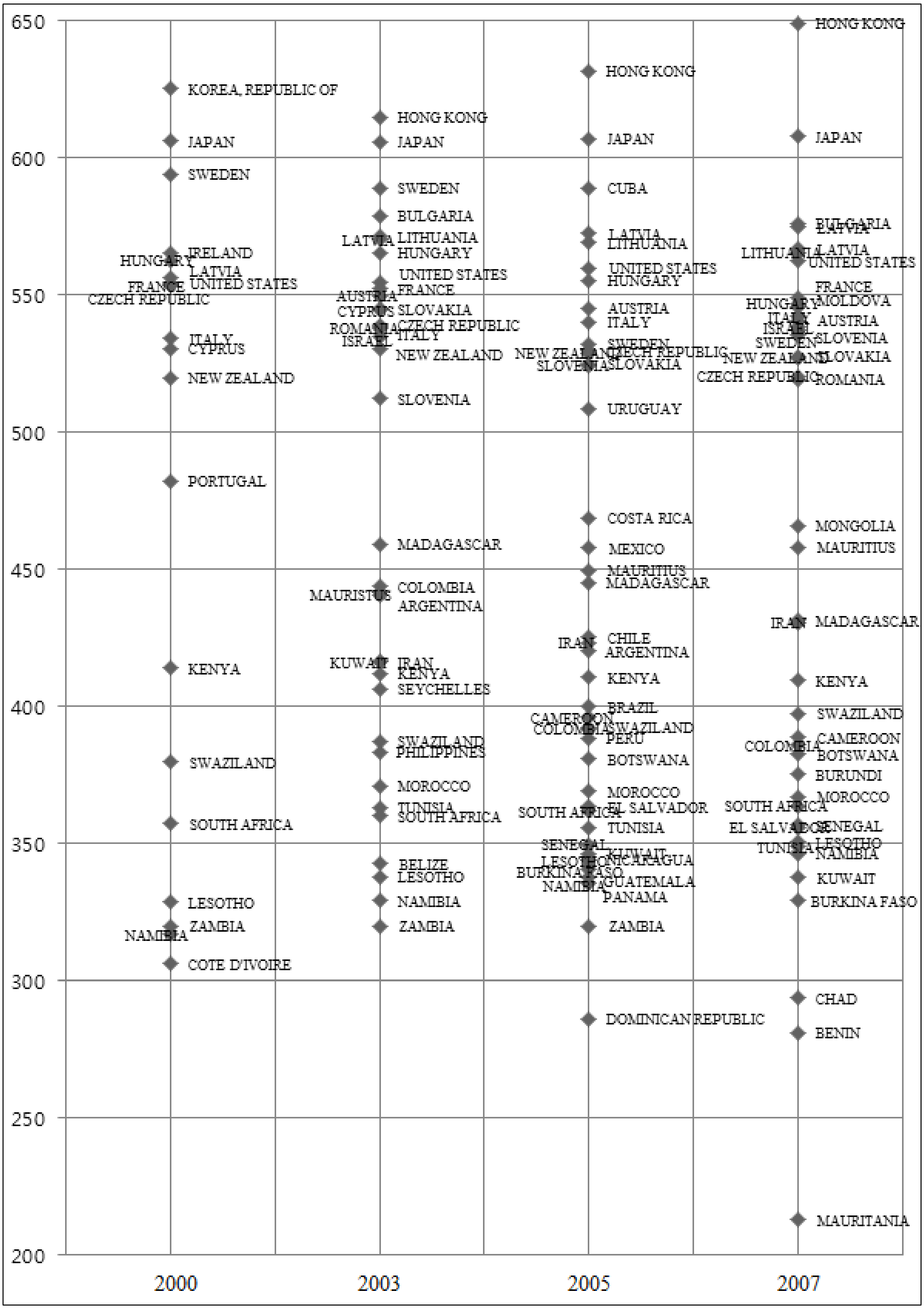
Africa Consortium for Monitoring Educational Quality (SACMEQ), *Programme d'Analyse des Systems Educatifs* (PASEC), and *Latin American Laboratory for Assessment of the Quality of Education* (LLECE).

International test results that are from different sources—and thus, are not directly comparable without adjustment because of the different level of difficulty of tests and the different score units—are aggregated by anchoring other assessments on a specific assessment. Tests that occurred prior to 1995 are adjusted by anchoring other assessment on NAEP assessment that measures pupil achievement in the U.S., which has participated in all kinds of international assessment. On the other hand, for recent assessment, which is designed to allow analysis of country across time by giving pupils the same level of difficulty of test pieces over time, assessment results are anchored on its first assessment. In other words, TIMSS 2003 results are anchored on TIMSS 1995 results. Adjusting regional assessments with the NAEP test needs one more step before anchoring, because the U.S. does not participate in all regional tests. They compare international and regional assessment results of a country that takes part in both, and anchor these data on IEA assessments. Adjusted test scores are averaged by country.

Aggregated test scores by Altinok, *et al.* (2013) are available from 1965 to 2010 at irregular intervals. As most of data for ICT factors and educational inputs, which will be described soon, are measured from the beginning of the 2000, pupil achievement data are taken after 2000. Data for students at primary level are available in 2000, 2003, 2005, and 2007. For secondary level students, data are available in 2000, and biannually from 2003 to 2009. As not all of these countries have test results every time, overall samples for test scores tend to be imbalanced. Sample size of primary school students is 139 for 63 countries, and for secondary level the sample size is 170 for 53 countries. In estimating the regression described above, test scores are separated into primary and secondary level.

An overview of student performance on these tests is presented in Figure 5, for primary level from 2003 to 2007. This shows a tendency for East Asian countries to outperform countries in other regions, and developing countries in Latin America and Caribbean and Sub-Saharan Africa are located in low-level results. This pattern is consistent with what was observed in another dataset previously aggregated with international tests by Hanushek and Luque (2003).

Figure 5 Aggregate pupil achievement at primary level



Another dependent variable for schooling quality is drop-out rate of students at primary school age. Drop-out rate of primary students is the proportion of pupils in any grade of primary in a given school year who no longer attend school the following school year (except the final year). Choosing this indicator as a dependent variable is derived from the second Millennium Development Goals (MDGs) of completing primary schooling for everyone.[3] Data are obtained from the UNESCO Institute for Statistics (UIS). Drop-out rate dataset has 319 observations for 101 countries from 2000 to 2011.

Compared to test scores, drop-out rate data are more abundant for low-income countries. When countries are classified into four different levels of national income based on the World Bank definition, this dataset has 31 high-income countries, 26 upper middle-income countries, 26 lower middle-income countries, and 21 low-income countries. However, there are many lower-income countries that do not have series of data, meaning that the dataset is imbalanced. On the other hand, the dataset for the test score variable has 30 high-income countries, 27 upper middle-income countries, 18 lower middle-income countries, and 7 low-income countries. Fewer countries with low national income participate in international and regional tests.

OLS estimations in the present dissertation are based on robust estimation to manage heteroskedasticity, which means that the variance of each variable is not constant. This can be caused by data imputation and compilation from different sources. Heteroskedasticity can also occur because I am using data on the different economic units such as households, schools and countries. Since the classic linear regression model is based on the assumption that a model is homoskedastic, the existence of heteroskedasticity can lead to skewed results. Robust standard errors estimated by using the variance of least squares estimator would help to allow the model not to include heteroskedasticity without changing coefficients for variables.

These dependent variables are regressed on a set of indicators for educational resources including ICT factors as well as resources from school and family. These regressions illustrate how much of the cross-country variation in educational outcomes can be explained by differences in ICT factors.

[3] The second MDG states that 'ensure that, by 2015, children everywhere, boys and girls alike, will be able to complete a full course of primary schooling'.

ICT factors

ICT indicators, the primary variables of interest in this paper, include the ICT expenditure as percentage of GDP, the proportion of household with computers, and the proportion of households with internet. ICT expenditure includes computer hardware and computer and communication services. The data on ICT expenditure are from surveys by the World Information Technology and Services Alliance (WITSA).

Indicators for the proportion of households with computer and internet are chosen because they illustrate students' use ICT at home. The proportion of households with computer is calculated by dividing the number of households with a computer by the total number of households surveyed. A computer includes a desktop, portable or handheld computer.[4] The proportion of households with internet is similarly calculated as the proportion of households with computer, by counting the number of households with and without internet access. Access is not assumed to be only via a computer—it may also be by mobile phone, digital TV etc. The data on the proportion of households with computers and internet are from surveys by the International Telecommunication Union (ITU).

The ideas of using data for household computer ownership and internet access as proxies for and the level of children's ICT use at home are derived from Clotfelter, *et al*. (2010) and Schmitt and Wadsworth (2004). According to the former, parental background and behaviour determine the ownership of computer and habits of using them. The latter use data for household PC ownership based on the assumption that it is a good proxy for actual use at home.

The present study focuses on data for ICT use in general instead of data for ICT use in education because cross-country data for ICT in education are limited. Furthermore, using national level ICT data is based on the assumption that ICT investment at national level will contribute to education in the end by building ICT capacity of students as depicted in Figure 4. Figures 1 to 3 also suggest that there is a link between ICT factors and educational performance. ICT expenditure data are obtained from the World Bank, and the other two data sets are from the ITU.

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[4] It does not include equipment with some embedded computing abilities such as mobile phones.

ICT data at the country level have been recently measured especially for developing countries, which usually have a short history of ICT development. Hardly any data were measured before 2000, and available data are weighted to high-income countries. ICT expenditure data are available from 2003, and most of the other two data types have been tracked since 2000.

The amount of expenditure on ICT varies with each country's level of development. Figure 6 shows that higher-income countries spend the larger amount of dollars in ICT. In Figure 7, it seems that countries in North America and Western Europe and East Asia and Pacific region, on average, invest more than in other regions.

Figure 6 Average ICT expenditure by national income

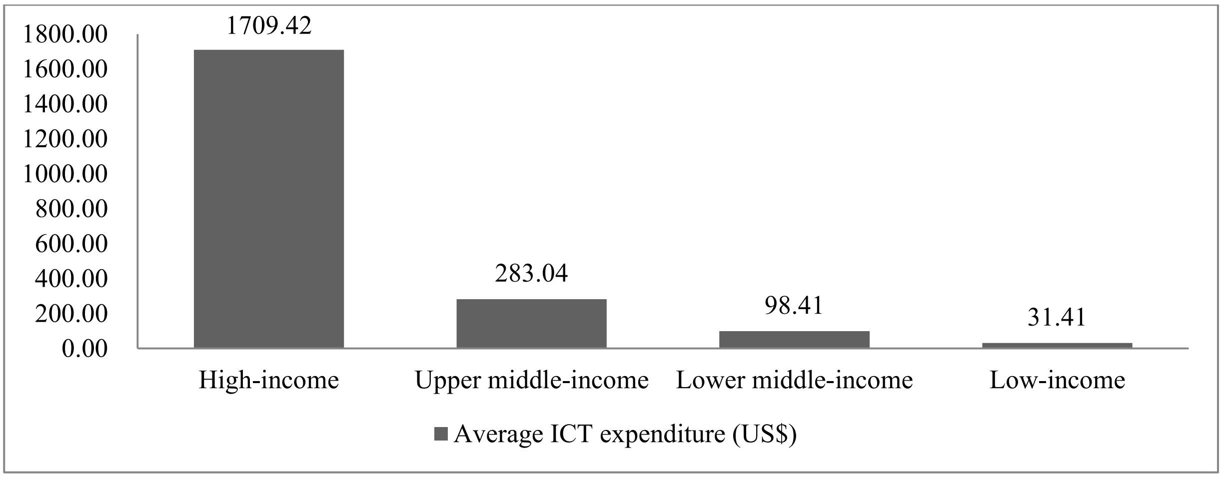


Figure 7 Average ICT expenditure by region

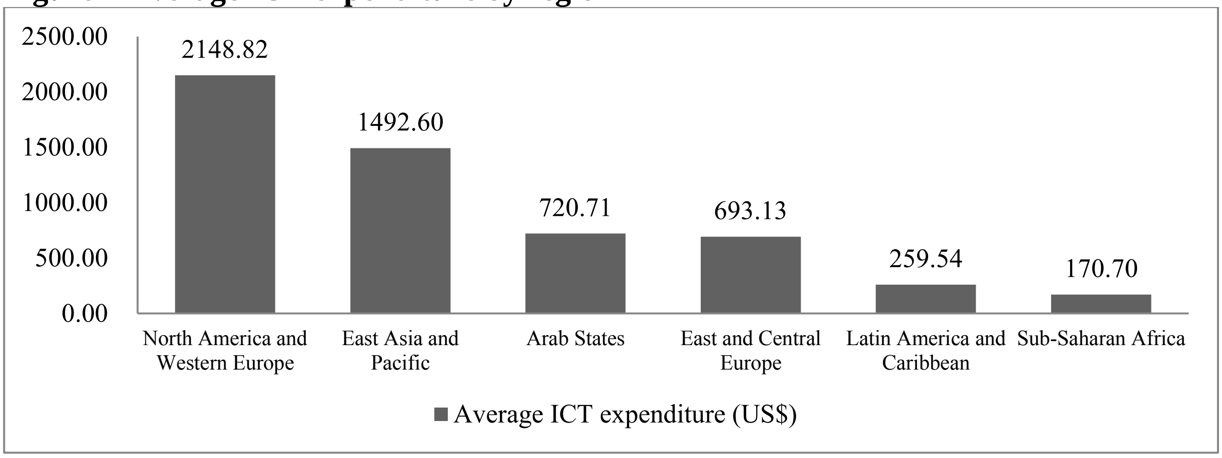


Figure 8 shows that there tend to be a higher proportion of households with computer and internet in countries at higher economic levels. This may also imply a high correlation between the two variables and indicators for national income. We can see the similar trend of ICT expenditure by region in both measures in Figure 9; there are more households with computer in North American and West Europe than in any other regions, and East Asia has the biggest number of those who use new internet. Sub-Saharan Africa and Latin America and Caribbean are the most deprived regions in terms of home computers and internet.

Figure 8 Average households with computer and internet users by national income

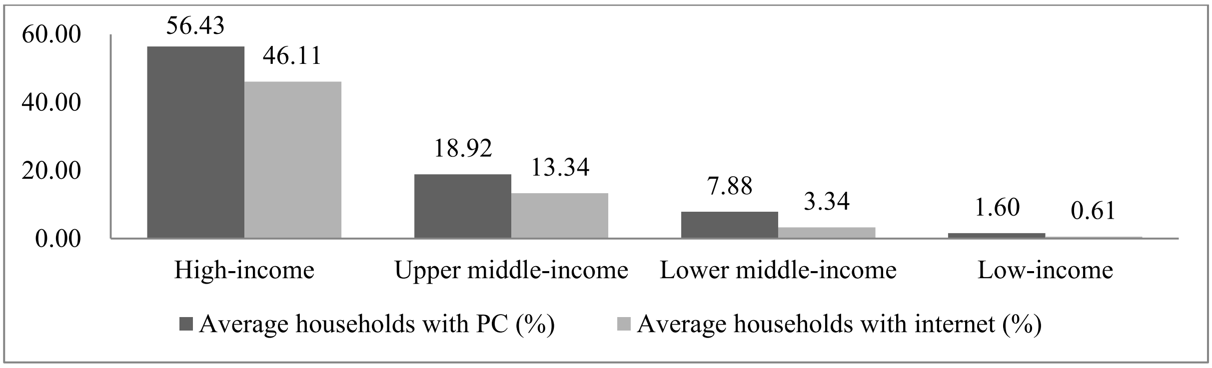
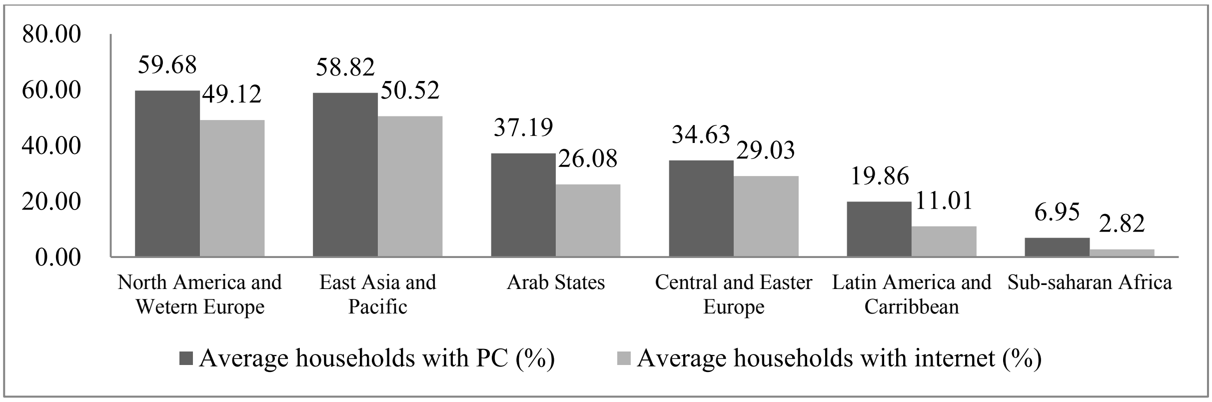


Figure 9 Average households with computer and internet by region



Sample sizes vary because each ICT variable has the different size of dataset in which data are missing, particularly for developing countries. Data for expenditure on ICT are more limited than the other two datasets, the proportions of households with computers and internet. The number of observation for the estimation with ICT expenditure is relatively smaller than the other two.

Family factors

For family influence variables, GDP per capita and schooling years for adults are employed. These are general proxies, respectively, for parents' income and parents' education in researches for educational production function with macroeconomic analysis (Lee & Barro, 1997; 2001; Al Samarrai, 2006; Hanushek & Kimko, 2000). In most previous studies, parents appeared to have more significant influence than school resources. Parents with higher education level tend to put more weight on education when their children are at school age. A high-income family can afford to provide their children with more and better educational materials, and can take care of children’s health more carefully to let them continue their education. The data on GDP per capita are available from the World Bank and the data on schooling year over age 25 are from the Barro-Lee dataset[5].

School factors

Indicators for school resources are expenditure per student as percentage of GDP per capita and pupil–teacher ratio. Teacher salaries are usually included for school resource variables in other educational production function studies; however, this thesis does not consider this variable because data for teachers’ wage in developing countries are frequently lacking. Low number of samples decreases the p-value in the econometric analysis. Data on school resources are collected from panel datasets from UNESCO.

Other factors

The population growth rate is used for an additional variable to measure the allocation of limited resources. High population growth rate usually stems from rapid growth of young people who need to be educated (Bloom, *et al.*, 2003). Thus, children in a country with a high population growth rate can have a smaller share of school resources and public expenditure than in a country with a low rate. Population growth rate can control the different amount of allocated resources to individual students across countries. Hanushek and Kimko (2000) add the population growth rate as an control variable.

A dummy variable for East Asia is included to capture cultural differnce that leads to outstanding academic performance of studetns. Parents in this region tend to provide stronger support for their kids’ education. For this reason, many studies on macroestimations fo educational production function use East Asia dummy and find it is a significant predictor in their work. (Lee & Barro, 1997; 2001)

[5] The data are available from https://data.undp.org/dataset/Mean-years-of-schooling-of-adults-years-/m67k-vi5c.

One limitation in estimating this model with the datasets explained above is that data for educational resources are sporadically missing particularly for developing economies. As stated above, data are more weighted to high-income countries. Countries with higher-income have more data for ICT as well. This imbalance of data is corrected by estimating the model splitting samples according to the level of national income, and its results will be shown separately.

Furthermore, due to missing data for educational resources, the whole sample is spread within the period between 2000 and 2011. Most data for expenditure per student are measured only after 2000. Annual data for schooling years over age 25 are collected from 2005. Since it was measured by 5 years or 10 years before 2005, I averaged data in 2000 and 2005 to match data for test scores in 2003. Test scores that are available between 2000 and 2005 are only in 2003 both for primary and secondary students. However, for the estimation of primary drop-out rate, which is annually surveyed, I dropped samples 2001 to 2004 because the results could mislead if each year of data for four years is based on predicted values using any methods.

Table 3 presents summary statistics of all these variables used in the present study. There are three separate datasets respectively for primary students' test scores, secondary students' test scores and primary drop-out rate. Academic performance of primary level ranges 212.64 to 648.97 with a mean around 459.54 and a standar deviation around 99.62, and that of secondary level ranges 293.62 to 665.53 with a mean around 530.77 and a standard devation around 68.94. Primary drop-out rate ranges 0.02 to 72.19 with a mean around 16.55 and a standard deviation around 18.08.

Indicators for ICT investment and usage, which are the main regressors of interest, are summarized in the table. Descriptive statistics for control variables and instrumental variables are also presented from next lines. GDP per capita and schooling years that are proxies for parental infuluence have high mean values in datasets for test scores than in the drop-out rate dataset. This is a little evidence that samples for test score are more weighted to developed countries. It is perhaps because not so many developing countries did not participate in international or regional tests yet.

Table 3 Summary statistics of variables for selected countries

Variables	Source	Pupil achievement regression (primary: 2003, 2005, 2007; Secondary: 2003, 2005, 2007, 2009)				Drop-out rate regression (2000-2010)			
		Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Pupil achievement, primary	Altinok, *et al*. (2013)	459.54	99.62	212.64	648.97				
Pupil achievement, secondary	Altinok, *et al*. (2013)	530.77	68.94	293.62	665.53				
Drop-out rates, primary	UNESCO					16.55	18.08	0.02	72.19
ICT expenditure (% of GDP)	WITSA	6.11	1.86	2.41	12.83	6.44	2.05	2.91	12.45
Households with computer (%)	ITU	37.41	26.49	0.16	90.75	34.17	27.93	0.16	89.50
Households with internet (%)	ITU	29.85	25.42	0.00	95.91	27.42	27.42	0.00	95.91
GDP per capita	World Bank	15864.58	15825.17	162.83	106919.5	10454.70	13125.80	130.42	52730.78
Schooling years (over age 25)	Barro & Lee (2013)	9.10	2.50	1.3	13.3	8.05	3.24	1.1	13.3
Expenditure per student, primary (% of GDP per capita)	UNESCO	17.16	6.63	5.36	40.24	17.54	9.25	4.43	61.64
Expenditure per student, secondary (% of GDP per capita)	UNESCO	22.44	7.14	6.46	42.52				
Pupil–teacher ratio, primary	UNESCO	24.84	12.96	9.59	65.86	24.91	14.40	8.68	84.32
Pupil–teacher ratio, secondary	UNESCO	13.76	5.25	7.14	37.09				
Annual population growth rate (%)		.94	1.29	-1.08	14.05	1.20	1.19	-1.59	5.32
Corruption Perception Index	Transparency International	5.36	2.06	1.80	10.00	4.43	1.99	1.60	10.00
Trade openness	UNCTAD	87.03	42.95	20.89	280.62	94.39	56.84	20.45	445.62

4 RESULT AND ANALYSIS

4.1 Basic Result

Estimations of the educational production function for primary level students' academic achievement are presented in Table 4. Coefficients for the key interest variable for ICT factors will be heavily analysed. Comparing between the coefficients for the influence of ICT inputs resources will be also useful to determine which is more correlated with students' academic achievement, and thus to suggest efficient policies.

In the first three columns, key parameters of interest, two of which are positive and significant, are presented. They show that ICT spending has insignificant and negative correlations with test results, while ICT use at home has significant and positive correlations. Both estimated coefficients for households with computer and internet (coefficient 0.003; standard error 0.001) indicate that a one per cent increase in the proportion of households either with computer or internet increases test score by 0.3 percentages. Wenglinsky (1998) explain this significnat correlation between computer use at home and educaitonal outomces for studetns who use computer at school more likely to use computer at home, and their use at home is correlated with academic performance.

Looking at other control variables, parental influence such as parents' income and educational attainment seems more strongly correlated with test scores than school resources such as pupil–teacher ratio and expenditure per student. Schooling years over age 25 as a proxy for parents' educational attainment has a significant and positive correlation in each estimation. The coefficients for GDP per capita as a proxy for parents' income are mixed. Regression on ICT expenditure shows the expected results imply that when using more money, test score is also high, but, when estimating with households having computer and internet in columns (2) and (3), coefficients have negative signs even though one of them (in Column (3)) is insignificant. On the other hand, the estimated coefficients for expenditure per student show that their correlations are not significant. Coefficients for pupil–teacher ratio, which is expected to have negative signs, have negative coefficients except in Column (1).

Higher population growth rate is negatively and significantly associated with test scores as expected, implying that students in countries with rapid population growth rate are more

Table 4 OLS and Fixed Effects estimation results for education achievement (primary)

	Dependent variable: natural log of test scores (primary)										
	OLS				Regional dummy variable				Fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ICT expenditure (% GDP)	-.002			-.0002	-.003			-.0009	.02*		
	(.007)			(.006)	(.006)			(.005)	(.008)		
Household with PC		.003***		.003		.002**		.002		-.00005	
(% overall households)		(.001)		(.002)		(.001)		(.002)		(.0004)	
Household with internet			.003***	.001			.002**	.0009			-.00001
(% overall households)			(.001)	(.002)			(.001)	(.002)			(.0004)
Natural log of GDP per capita	.05***	-.05**	-.03	-.02	.03*	-.04*	-.03	-.01	-.09***	-.05	-.05
($)	(.02)	(.02)	(.02)	(.03)	(.01)	(.02)	(.02)	(.03)	(.03)	(.03)	(.03)
Schooling years (over age 25)	.03***	.04***	.04***	.02***	.03***	.04***	.04***	.03***	.02	.03	.03
	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.006)	(.02)	(.02)	(.02)
Expenditure per student	.004	.002	.002	-.0006	.005**	.003	.003*	.0005	.006**	.002	.002
(% GDP per capita)	(.002)	(.002)	(.001)	(.003)	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)	(.002)
Pupil–teacher ratio	.003	-.004**	-.003*	-.001	.0009	-.004***	-.004**	-.001	.002	.0001	.0005
	(.002)	(.002)	(.001)	(.003)	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)	(.002)
Population growth rate (%)	-.06***	-.03***	-.03**	-.05***	-.06***	-.03**	-.03**	-.05***	-.03*	-.03	-.03
	(.01)	(.01)	(.01)	(.01)	(.01)	(.10)	(.01)	(.01)	(.01)	(.02)	(.02)
East Asia					.10**	.08**	.09**	.05			
					(.04)	(.04)	(.04)	(.04)			
Constant	5.36***	6.17***	6.03***	6.09***	5.55***	6.16***	6.04***	6.03***	6.54***	6.30***	6.27***
	(.19)	(.22)	(.23)	(.31)	(.20)	(.22)	(.22)	(.30)	(.18)	(.16)	(.21)
R^2	0.7604	0.7350	0.7392	0.8088	0.7863	0.7449	0.7507	0.8146	0.2448	0.1426	0.1322
Number of Observation	77	128	124	75	77	128	124	75	77	128	124

Note:

1. Robust standard errors are reported in parenthesis.

2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

likely to compete with other students, and thus, less likely to have benefits compared to their peers than in countries with lower population growth rates.

When regressing on all three key variables together, it is possible to see which factor is more closely correlated with a dependent variable. However, in Column (4), coefficients for these variables are all not significant. Variables for households that turned out to be significantly correlated in columns (2) and (3) are not significantly correlated here. This can be because these three variables are highly collinear, meaning they are correlated with each other, and they move together. Therefore, it is hard to include all three variables, especially in a small sample.

The model has a regional dummy variable to identify abnormality that is observed in East Asian countries. Significant coefficients for this variable would imply that there is an *Asian value*, which depicts cultural features of emphasizing education in the East Asian countries. In addition, in this study, an East Asia dummy variable may capture the factors that determine the huge allocation of their budget to ICT and wider use of computers and internet by households in this region, as described in figures 7 and 9.

Column (5) to (8) in Table 4 present the results of regressions with a regional dummy variable. A regional dummy variable that specifies East Asian countries appears to play a significant role. Large coefficients for a dummy variable imply that countries in this region have unmeasured factors that explain their high test scores. The significance of an East Asian dummy variable is also observed in studies of Lee and Barro (1997; 2001).

Signs and significance of coefficients for ICT variables are parallel with simple OLS results. ICT expenditure does not play a significant role in determining the educational quality at primary level, but students' home use of computer and internet is significantly and positively correlated with educational achievement. These simple results of OLS suggest that more ICT infrastructure encouraged by adding expenditure do not have a significant association with primary test results, while home use computers and internet seems significantly positive. Both estimated coefficients for households having computer and internet (coefficient: 0.002; standard error: 0.001) shows that one per cent increase in the proportion of household using either new technologies causes test scores at primary level increase by 0.2 per cent. As ICT expenditure include what is not relevant to education sector, it is not so surprising that it does not matter for educational outcomes whereas the other two do.

However, the fixed effect estimation for primary test scores suggests different aspects of expenditure and having ICT in households, indicating switched signs and significance for ICT coefficients in column (9) to (11). The fixed effects model is a statistical model that each entity in the model as not random to control heterogeneity possibly presented by individual entities. That is, in this case, individual countries have their own dummy variables that explain unmeasured factors for each country considering each country's own characteristics.

Fixed estimation suggests show that students do not necessarily improve their test scores when individual countries encourage each household to have electronic devices and use new technology. This is inconsistent with OLS results that show the high level of using ICT at home may have a strong association with educational outcomes. This can be interpreted in a way that the correlation between ICT factors and educational outcomes might be endogenous or a coincidence. On the other hand, the positive and significant coefficient for ICT expenditure, which had the negative and insignificant coefficient in the OLS estimations, implies that increased spending on ICT by an individual country can have an important role in improving pupil achievement.

The inconsistent (with fixed effect estimation) results may be caused by the small number of observations in the panel. The dataset includes primary students' test scores measured, at most, four times. However, not all countries have four observations. Data are missing, especially for developing countries.

Fixed effect estimation could be asymptotically biased as it does not satisfy asymptotic properties, where the number of time periods, T, is small and fixed and the number of countries, N, goes to infinity. However, the number of countries with the fixed number of time periods is very small here. Hence, in this case with the small number of countries, OLS results with a regional dummy variable are the preferred specification to fixed effects estimation results.

Furthermore, fixed effects estimation does not identify the effects of variables that change little over time. This can justify my results because the change in ICT variables tends to be small within a 10 year timeframe.

Table 5 OLS and Fixed Effects estimation results for education achievement (secondary)

	Dependent variable: natural log of test scores (secondary)										
	OLS				Dummy variable				Fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ICT expenditure (% GDP)	.02***			.02***	.01**			.01**	.02***		
	(.005)			(.006)	(.005)			(.006)	(.007)		
Household with PC		.001**		.003***		.0005		.002**		-.0007**	
(% overall households)		(.0006)		(.001)		(.0005)		(.001)		(.0003)	
Household with internet			.001**	.00003			.0003	-.0004			-.0006**
(% overall households)			(.0005)	(.001)			(.0004)	(.000)			(.0003)
Natural log of GDP per capita	.05***	.03**	.04***	-.008	.05***	.04***	.05***	.01	-.01	.02	.01
($)	(.01)	(.01)	(.01)	(.02)	(.009)	(.01)	(.01)	(.02)	(.01)	(.02)	(.01)
Schooling years (over age 25)	.008*	.01**	.01***	.001	.007**	.01**	.01**	.003	.002	.001	.008
	(.004)	(.004)	(.004)	(.004)	(.003)	(.004)	(.004)	(.003)	(.01)	(.009)	(.009)
Expenditure per student	-.001	-.002*	.002*	-.002*	.00008	-.001	-.001	-.0007	.0003	.0006	.0003
(% GDP per capita)	(.001)	(.001)	(.001)	(.001)	(.0008)	(.001)	(.001)	(.001)	(.001)	(.001)	(.001)
Pupil–teacher ratio	-.006	-.007***	-.007***	-.008**	-.008**	-.008***	-.008**	-.008**	-.003	-.003	-.004
	(.004)	(.002)	(.002)	(.004)	(.004)	(.002)	(.002)	(.004)	(.003)	(.004)	(.002)
Population growth rate (%)	-.05***	-.04***	-.04***	-.05***	-.06***	-.04***	-.04***	-.05***	-.01*	-.01	-.02
	(.009)	(.005)	(.006)	(.009)	(.008)	(.007)	(.007)	(.007)	(.01)	(.01)	(.01)
East Asia					.11***	.11***	.11**	.08***			
					(.03)	(.03)	(.02)	(.02)			
Constant	5.73***	6.01***	5.92***	6.30***	5.82***	5.90***	5.82***	6.13***	6.31***	6.21***	6.18***
	(.12)	(.13)	(.12)	(.26)	(.12)	(.13)	(.11)	(.23)	(.18)	(.18)	(.18)
R^2	0.7168	0.6897	0.7119	0.7707	0.7882	0.7537	0.7707	0.8028	0.1824	0.0712	0.1635
Number of Observation	91	160	158	90	91	160	158	90	91	160	158

Note:

1. Robust standard errors are reported in parenthesis.

2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

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Table 5 presents regression results for secondary school students' educational outcomes. Its results are partly parallel with students at primary level, but slightly different in several respects. The first difference is found in the coefficients for ICT expenditure in OLS estimation. Coefficients are positive and significant in estimation either with or without a regional dummy variable. Coefficient for ICT expenditure in OLS estimation without a regional dummy variable in Column (1) (coefficients: 0.02; standard error: 0.005) shows that a one per cent increase in ICT expenditure can cause a two per cent increase in test scores for secondary level students. Coefficient for ICT expenditure in OLS estimation with a regional dummy variable in Column (5) (coefficients: 0.01; standard error: 0.005) shows that one per cent increase in ICT expenditure can cause a one per cent increase in test scores for secondary level students. The size of correlation is bigger than that of correlation between household variables and test scores.

Second, it was found that differences in significance of coefficients for household having ICT, which had significant and positive coefficients when regressed without the dummy variable, are insignificant and positive when adding a regional dummy variable shown in column (6) to (7). This implies that the distinctness of East Asian countries is more pronounced in secondary schools.

Third, when regressing all three ICT variables, two of them seem to be significantly correlated with test scores as presented in columns (4) and (8). ICT expenditure and households with computer are significant, whereas the variable of households with internet access is not significant. It shows that two variables are more highly correlated with academic achievement at the secondary level.

Fourth, coefficients for parents' income are positive in columns (1) and (2) whereas some of them were negative in estimations for primary level students. This difference is may be because the dataset for secondary level students has larger observations, and thus, it produces more accurate results.

Table 6 OLS results for primary drop-out rate

	Dependent variable: primary drop-out rate										
	OLS				Dummy Variable				Fixed effects		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ICT expenditure (% GDP)	-.25			-.46	-.14			-.39	-.45		
	(.21)			(.29)	(.23)			(.27)	(.39)		
Household with PC (% overall households)		.07**		.07		.10***		.04		.06	
		(.03)		(.06)		(.03)		(.05)		(.07)	
Household with internet (% overall households)			.07**	-.01			.10***	.07			.04
			(.03)	(.06)			(.03)	(.05)			(.05)
Natural log of GDP per capita ($)	-3.44***	-4.45***	-4.69***	-4.38***	-3.39***	-4.95***	-5.31***	-5.36***	-1.53***	-2.94	-2.88
	(.76)	(.86)	(.88)	(1.23)	(.75)	(.87)	(.90)	(1.13)	(.45)	(1.86)	(1.91)
Schooling years (over age 25)	-.84***	-.60	-.45	-.99***	-.81***	-.57	-.44	-.98***	-4.70	-.41	.22
	(.32)	(.40)	(.40)	(.31)	(.31)	(.40)	(.40)	(.31)	(3.81)	(1.35)	(1.33)
Expenditure per student (% GDP per capita)	.39***	-.13**	-.15***	.35***	.36***	-.17*	-.20*	.26**	.15	-.07	-.04
	(.10)	(.06)	(.06)	(.11)	(.10)	(.06)	(.06)	(.11)	(.11)	(.15)	(.15)
Pupil–teacher ratio	.59***	.58***	.55***	.59***	.60***	.56***	.51***	.55***	-.30	.70**	.73**
	(.11)	(.09)	(.10)	(.13)	(.11)	(.09)	(.10)	(.12)	(.64)	(.28)	(.39)
Population growth rate (%)	1.56**	.74	.83	1.40*	1.73**	.89	.97	1.58**	.11	1.30	.68
	(.73)	(.60)	(.62)	(.79)	(.73)	(.57)	(.59)	(.70)	(1.46)	(1.89)	(1.90)
East Asia					-1.69	-4.89***	-4.99***	-4.25**			
					(1.45)	(1.32)	(1.33)	(1.82)			
Constant	30.44***	42.63***	45.15***	39.77	29.62***	47.31***	51.67***	49.90***	73.30	23.86	18.91
	(7.28)	(8.74)	(9.35)	(12.26)	(7.01)	(9.01)	(9.85)	(11.89)	(48.02)	(18.93)	(21.56)
R^2	0.8219	0.7778	0.7845	0.8258	0.8250	0.7855	0.7918	0.8380	0.1469	0.0852	0.0738
Number of Observation	95	260	252	94	95	260	252	94	95	260	252

Note:

1. Robust standard errors are reported in parenthesis.

2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Lastly, in fixed effect estimations, the negative association between test scores and the proportion of households with computer and internet is more apparent among secondary level students. This may imply that students at secondary level become more adept in using computers, and, thus, that they can be more likely to be distracted by new technologies from studying.

The limitation of fixed effects estimation with the dataset with the small number of countries is presented here again. Though, the coefficients for key variables in column (7) to (9) are all significant. The reason why academic performance of secondary level students is more correlated with ICT variables may be they are more adept in using ICT based on their higher cognitive skills for using ICT than primary level students or because of cumulative training. However, it may be still incorrect because the number of countries is small and explanatory variables are time invariant in the panel.

Primary drop-out rate is regressed on variables for ICT and educational resource, and the results are shown in Table 6. Reviewing family inputs first, the signs of coefficients appear consistent with expectation. Family factors such as parental income and parental education tend to play a significant role in decreasing drop-out rate. However, parents' educational attainment seems insignificant when estimating with the proportion of households with computer and internet. However, among school resources, expenditure per student is associated with drop-out rates in unexpected ways. Coefficients for this variable in columns (1) and (4) show that the more spent per student, the more students drop-out.

Some ICT factors also appear to unexpectedly have a positive association with drop-out rates. The estimated results indicate that when there are more new technologies students can access, more students drop-out of primary education. A one per cent change in the proportion of households with computer and internet would increase drop-out rate respectively by 0.07 per cent. When regressing with a regional dummy variable, the size of correlation is even bigger. One per cent change in the proportion of households with computer and internet would increase drop-out rate respectively by 0.10 percent. As coefficients for ICT expenditure, which has negative signs, are insignificant, I cannot say that additional expenditure on ICT would encourage students to remain in schools.

Fixed effects estimation seems unhelpful for primary drop-out rate, which has a severely unbalanced dataset. This is confirmed by the results with insignificant coefficients in Columns (9) to (11).

The odd results for drop-out rate may be caused by poor data measurement. Primary drop-out rate is estimated by using enrolment and repeaters rate, which rely on population data. When estimating population data, it is based on measurement in the last census, and basically assumed that population has grown since the census. For this reason, Al Samarrai (2006) indicates that regressions on the predicted estimation can have an error.

However, a negative correlation between educational resources and outcomes that are not based on population data is usually observed in similar cross-country studies that use different types of data. As already reviewed in the previous section, Hanushek and Kimko (2000) and Wößmann (2003) respectively discovered the negative association between educational inputs from household and school and pupil outcomes from cross-country data.

Another possible factor that leads to unexpected results is the omission of relevant variables. As explained above, the present study uses data for ICT in general instead of data for ICT in the education sector as consistent indicators at the country level data are lacking. In addition, it hinders finding a causal relationship between ICT factors and educational outcomes, as the causal relationship between the two variables may go either way. For example, people with higher educational outcomes may encourage more expenditure on ICT and expansion of technologies. In addition, some omitted variables can cause both ICT expenditure and educational achievement at the same time. To control this endogeneity problem, I employ IVs estimation in the next section.

4.2 Endogeneity Regression Techniques

Instrumental variable (IV) estimation moderates a possible bias caused by reverse causality between independent and dependent variables. Good instruments should be required to affect the endogenous explanatory variables, which are suspected to cause reverse causality (i.e., they should not influence the dependent variable outside of explanatory variables), but not to be correlated with error term in the model. In the first stage, an endogenous variable is regressed on instrumental variables that are correlated with the endogenous variable and other exogenous variables. The estimated value for the endogenous variable is replaced in the regression of interest in the next stage.

ICT variables are instrumented by indices for corruption and trade openness. These are based on a study that reports the significant role of the degree of corruption in increasing ICT factors. Mauro (1998) finds that corruption determines the composition of public expenditure, especially reducing education expenditure. From these results, it is possible that the allocation of public spending to technology is also affected by corruption. The Corruption Perception Index (CPI), compiled by Transparency International, is used.

On the other hand, several regional studies report the significant role of trade in ICT expansion. Shirazi, *et al*. (2010) show a positive impact of trade liberalization on ICT diffusion. Baliamoune-Lutz (2003) examines the a significant association between trade policies and ICT expansion in developing countries. Trade openness, which is taken from the United Nations Conference of Trade and Development (UNCTAD), is measured by dividing the sum of imports and exports by GDP. This indicator is correlated with educational outcome variables, and they are supposed to be uncorrelated with error terms of the model.

However, the 2SLS results with these instruments may have limitations because chosen IVs can be wrong (i.e., not satisfying requirements for IV). When instruments have a direct impact on dependent variables not through endogenous variables, they can be ruled out according to exclusion restriction. That is, CPI and trade openness are valid as IVs only when they have no effect on educational outcomes other than via correlation with ICT variables. As a result of using instruments that are correlated with error terms or omitted variables, 2SLS results can be biased. Bias caused by instruments correlated with an omitted variable or error terms is much bigger than the bias in OLS estimates.

Respective IVs will be used for each ICT variable first for comparison between them. After that, I use both IVs for each ICT variable. When using both IVs, since more variables are used as IVs than the number of instrumented variables, it is possible to check whether instruments are exogenous or not by using the overidentifying restriction test proposed by Sargan (1958). It is also possible to check whether the excluded instrument violates exclusion restriction with this test to some degree.

The system of equations allowing for reverse causality is as follows:

$$Q_{it} = \alpha_0 + ICT_{it} * \beta_1 + F_{it} * \beta_2 + R_{it} * \beta_3 + \varepsilon_{it}^{d}$$
$$ICT_{it} = \gamma_0 + IV_{it} * \delta_1 + F_{it} * \delta_2 + R_{it} * \delta_3 + \varepsilon_{it}^{s}$$

IV refers to instruments, CPI and trade openness.

2SLS results for primary students' test scores using CPI as IV are shown in Table 7. No causal relationship is observed in all estimations for primary test scores. Overall coefficients of key variables are insignificant.

Table 7 2SLS results for test scores (primary), instrumented by CPI

	Dependent variable: natural log of test scores (primary)					
	(1)		(2)		(3)	
	1^{st} stage	2^{nd} stage	1^{st} stage	2^{nd} stage	1^{st} stage	2^{nd} stage
ICT expenditure (% GDP)		-.05 (.07)				
Household with PC (% overall households)				.003 (.004)		
Household with internet (% overall households)						.001 (.003)
Corruption Perception Index (CPI)	.16 (.22)		2.52*** (.93)		3.01*** (.92)	
GDP per capita ($)	-.07 (.48)	.04 (.03)	12.24*** (1.95)	-.06 (.06)	9.34*** (1.99)	-.02 (.05)
Schooling years (over age 25)	.06 (.13)	.03*** (.01)	1.84*** (.61)	.04*** (.008)	1.81*** (.61)	.04*** (.007)
Expenditure per student (%GDP per capita)	.04 (.04)	.007 (.005)	.64*** (.16)	.003 (.003)	.51*** (.16)	.004 (.003)
Pupil–teacher ratio	.05 (.05)	.003 (.005)	.48*** (.17)	-.004 (.003)	.39** (.17)	-.003 (.002)
Population growth rate (%)	-.38 (.26)	-.07** (.03)	1.94 (1.20)	-.04*** (.01)	1.56 (1.20)	-.03*** (.01)
East Asia	.02 (.77)	.11** (.05)	12.93*** (3.44)	.07 (.06)	11.14*** (3.37)	.10* (.05)
Constant	-.50 (4.23)	5.66*** (.26)	-130.75*** (17.39)	6.29*** (.57)	-110.74*** (17.53)	5.93*** (.47)
F-statistic	1.21		88.14		68.24	
R^2	0.3115	0.6193	0.8417	0.7498	0.8101	0.7457
Number of Observation	76		124		124	
Hausman	0.14		4.48		6.65	

Note:
1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Staiger and Stock (1997) suggest that instruments are weakly correlated with endogenous variables if the F-statistic of first-stage is less than 10. Weak instruments cause problems by producing similar results of corresponding OLS estimates. F-tests in the first-round regressions exceed 10 in estimation with household ICT variables, suggesting that the instrument of corruption are sufficiently correlated with ICT factors to serve as good instruments. However, in Column (1) in Table 7, for ICT expenditure, the F-statistic is lower than 10. Hence, the chosen instruments for ICT expenditure are not strong enough.

Even though the household variables are well instrumented by the CPI when we consider the F-statistic of first-stage regressions, they turn out to be insignificant in second-stage regressions. This implies the absence of an impact of the number of households using computers and internet on primary educational achievement.

In Table 8, it seems that there is no impact on test scores for secondary level students, either. The coefficients for CPI in first stage in each regression are insignificant, and though the F-statistic is less than 10 in Column (1). Furthermore, in second-stage regressions, coefficient for each key variable is insignificant, suggesting the absence of an impact of ICT on education.

Table 9 shows the 2SLS results for primary drop-out rate. The causal relationship between ICT expenditure and primary drop-out rate is presented in Column (1), but the F-statistic of first stage regression is less than 10. Therefore, this relationship does not seem robust. On the other hand, it seems that there are robust relationships between households having ICT and drop-out rate. CPI has significant coefficients, and the F-statistic in first-stage regressions is much higher than 10. However, the relation is unexpectedly positive, implying that the more families use ICT, the more students drop-out from their primary education. Distinct estimation by national income will explain this unexpected result in following section.

However, results of 2SLS that use CPI as an instrument could be biased because the instrument may be correlated with the error term. Corruption may have an impact on educational achievement by misallocating resources and abusing expenditure allocated to educational sectors. Mauro (1998) shows how corruption affects education expenditure, and many studies prove that reduced expenditure on education either positively or negatively affect educational outcomes. This means that corruption can have a direct impact on educational outcomes through spending on education as well as through ICT expenditure. Thus, CPI may not be a valid instrument.

Table 8 2SLS results for test scores (secondary), instrumented by CPI

	Dependent variable: natural log of test scores (secondary)					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		-.005 (.12)				
Household with PC (% overall households)				-.003 (.006)		
Household with internet (% overall households)						-.008 (.02)
Corruption Perception Index (CPI)	.05 (.13)		1.00 (.80)		.55 (.93)	
GDP per capita ($)	-1.10*** (.37)	.13 (.12)	15.65*** (1.84)	.11 (.11)	15.76*** (1.66)	.18 (.28)
Schooling years (over age 25)	.50*** (.12)	.02 (.06)	3.29*** (.67)	.02 (.02)	3.91*** (.88)	.04 (.07)
Expenditure per student (%GDP per capita)	.14*** (.03)	.002 (.02)	.34** (.16)	.0005 (.003)	.52** (.20)	.003 (.01)
Pupil–teacher ratio	-.03 (.04)	-.008** (.003)	.27 (.25)	-.007* (.004)	.47** (.23)	-.005 (.008)
Population growth rate (%)	.36 (.24)	-.05 (.04)	1.30 (.80)	-.04*** (.01)	.77 (1.31)	-.03 (.02)
East Asia	1.72*** (.48)	.14 (.20)	12.51*** (2.98)	.16* (.08)	15.13*** (4.46)	.24 (.28)
Constant	8.24*** (2.89)	5.95*** (.86)	-155.64*** (15.71)	5.29*** (1.07)	-173.72*** (13.77)	4.43 (3.08)
F-statistic	6.60		79.19		54.99	
R^2	0.3603	0.7483	0.7859	0.6535	0.7223	0.0794
Number of Observation	90		159		156	
Hausman	0.04		0.49		0.32	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Table 9 2SLS results for primary drop-out rate, instrumented by CPI

	Dependent variable: primary drop-out rate					
	(1)		(2)		(3)	
	1^{st} stage	2^{nd} stage	1^{st} stage	2^{nd} stage	1^{st} stage	2^{nd} stage
ICT expenditure (% GDP)		3.47** (1.43)				.
Household with PC (% overall households)				.26*** (.10)		
Household with internet (% overall households)						.24*** (.08)
Corruption Perception Index (CPI)	.32* (.18)		3.41*** (.60)		4.24*** (.69)	
GDP per capita ($)	-.70 (.45)	-2.78** (1.34)	11.68*** (1.32)	-7.53*** (1.94)	11.28*** (1.49)	-7.51*** (1.74)
Schooling years (over age 25)	.08 (.14)	-1.05 (.67)	1.96*** (.49)	-.82** (.41)	1.75*** (.55)	-.60 (.41)
Expenditure per student (%GDP per capita)	.10* (.05)	.01 (.26)	.42*** (.08)	-.23*** (.08)	.61*** (.10)	-.27*** (.08)
Pupil–teacher ratio	.02 (.04)	.53** (.25)	.23** (.10)	.53*** (.10)	.55*** (.12)	.46*** (.11)
Population growth rate (%)	-.20 (.29)	2.19* (1.31)	2.17** (.99)	.35 (.68)	1.10 (1.12)	.64 (.65)
East Asia	1.16* (.58)	-6.41* (3.85)	8.82*** (2.54)	-6.11*** (1.76)	16.83*** (2.84)	-7.99*** (2.21)
Constant	8.61** (3.76)	10.20 (16.65)	-113.64*** (11.16)	68.07*** (17.01)	-129.90*** (12.58)	71.17** (17.02
F-statistic	1.57		187.97		134.97	
R^2	0.1121	0.3081	0.8425	0.7727	0.7974	0.7843
Number of Observation	95		254		248	
Hausman	2.41		3.85		5.78	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Now, key ICT variables are instrumented by another IV, trade openness. Results for primary pupil achievement are summarized in Table 10. The chosen IV seems weak in these regressions. Trade openness has a significant coefficient in the first-stage regression in Column (1), but its F-statistic in the first round is less than 10. On the other hand, in columns (2) and (3), even though the F-statistic is larger than 10, coefficients for trade openness are not significant.

In Column (2), estimations have negative R-squared values. R-squared is a measure of the proportion of variation in dependent variable explained by independent variable within the regression model.[6] The negative R-squared values are possible in IV estimation because the sum of squares of regression (SSR) can exceed the sum of squares total (SST). SSR is the variation in dependent variable explained by the model, and SST is the total variation in dependent variable from its mean.

Table 10 2SLS results for test scores (primary), instrumented by trade openness

	Dependent variable: natural log of test scores (primary)					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		.007 (.02)				
Household with PC (% overall households)				-.12 (.97)		
Household with internet (% overall households)						-.01 (.02)
Trade Openness	.01** (.006)		.003 (.02)		.02 (.02)	
GDP per capita ($)	.34 (.35)	.03* (.02)	15.75*** (1.70)	1.81 (15.17)	13.89*** (1.65)	.15 (.25)
Schooling years (over age 25)	.003 (.13)	.03*** (.006)	1.92*** (.52)	.27 (1.88)	1.82*** (.54)	.07* (.04)
Expenditure per student (%GDP per capita)	.06 (.04)	.004* (.002)	.77*** (.17)	.09 (.75)	.67*** (.14)	.01 (.01)
Pupil–teacher ratio	.08* (.05)	.0003 (.003)	.63*** (.16)	.07 (.61)	.59*** (.14)	.004 (.01)
Population growth rate (%)	-.38 (.25)	-.05*** (.01)	2.01 (1.31)	.21 (1.91)	1.54 (1.14)	-.009 (.03)
East Asia	.30 (.67)	.10** (.03)	15.14*** (3.65)	1.87 (14.66)	13.87*** (4.24)	.27 (.23)
Constant	-.51 (3.69)	5.52*** (.19)	-156.36 *** (16.54)	-12.25 (150.50)	-145.29*** (15.49)	4.19 (2.61)
F-statistic	1.98		88.14		62.21	
R^2	0.1672	0.7774	0.8417	-31.0366	0.7897	0.3628
Number of Observation	77		124		124	
Hausman	0.21		0.01		0.35	

Note:
1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

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[6] $R^2 = \frac{SSR}{SST} = \frac{\sum_{i=1}^{N}(\hat{y}_i-\bar{y})^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2} = 1 - \frac{SSE}{SST} = 1 - \frac{\sum_{i=1}^{N}\hat{e}_i^2}{\sum_{i=1}^{N}(y_i-\bar{y})^2}$. The closer R-squared is to 1, the closer the sample values are to the fitted regression equality.

Negative R-squared values reported in IV estimation do not matter except when computing the F-statistic. In OLS estimations, higher R-squared values are pursued, but it is not of interest in IV estimates. IV estimation is intended to estimate the *ceteris paribus effect* of an endogenous variable on dependent variable. However, F-test, which is based on SSR, can be restricted. (Wooldridge, 2009). Since the F-statistic for joint hypothesis testing are not used in this paper, negative R-squared values are fine.

Table 11 2SLS results for test scores (secondary), instrumented by trade openness

	Dependent variable: natural log of test scores (secondary)					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		.01*** (.006)				
Household with PC (% overall households)				-.11 (.68)		
Household with internet (% overall households)						.02 (.03)
Trade Openness	.02*** (.004)		-.003 (.02)		.02 (.03)	
GDP per capita ($)	-.45* (.77)	.05*** (.009)	17.39*** (1.36)	2.03 (11.84)	15.76*** (1.66)	-.22 (.43)
Schooling years (over age 25)	.29** (.11)	.005 (.004)	3.26*** (.69)	.38 (2.22)	3.91*** (.88)	-.06 (.11)
Expenditure per student (%GDP per capita)	.12*** (.03)	-.0006 (.002)	.40*** (.15)	.04 (.27)	.52** (.20)	-.01 (.01)
Pupil–teacher ratio	.02 (.04)	-.007** (.003)	.40 (.25)	.04 (.28)	.47** (.23)	-.02 (.01)
Population growth rate (%)	.19 (.21)	-.06*** (.007)	1.22 (.81)	.10 (.83)	.77 (1.31)	-.06** (.01)
East Asia	1.65*** (.42)	.10 (.02)	12.75*** (3.02)	1.57 (8.73)	15.13*** (4.46)	-.15 (.41)
Constant	2.57 (2.21)	5.79*** (.09)	-168.85*** (13.04)	-13.39 (115.16)	-173.72*** (13.77)	8.81* (4.69)
F-statistic	12.48		77.32		54.99	
R^2	0.5127	0.7845	0.7819	-97.4971	0.7223	-2.1949
Number of Observation	91		159		159	
Hausman	0.45		0.02		0.40	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Table 11 shows the 2SLS results using trade openness as an IV for secondary level students' test scores. The IV seems be strong in Column (1), which presents the F-statistic in first stage regression indicating that the IV is significant. ICT expenditure turned out to be significant in Column (1), implying that there is a causal impact of ICT expenditure on secondary students' achievement. On the other hand, coefficients for the percentage of households having computers and internet access are insignificant, even though the F-statistic is higher than 10.

Table 12 2SLS results for primary drop-out rate, instrumented by trade openness

	Dependent variable: primary drop-out rate					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		-.02 (.38)				.
Household with PC (% overall households)				.27 (.24)		
Household with internet (% overall households)						.35 (.29)
Trade Openness	.02*** (.003)		.03** (.01)		.03** (.01)	
GDP per capita ($)	-.34 (.29)	-3.24*** (.77)	15.86*** (1.35)	-7.57** (3.85)	16.75*** (1.44)	-9.56* (4.97)
Schooling years (over age 25)	.08 (.12)	-.82*** (.31)	1.70*** (.65)	-.88 (.60)	1.56** (.68)	-.84 (.67)
Expenditure per student (%GDP per capita)	.15*** (.05)	.35*** (.10)	.54*** (.11)	-.25* (.14)	.76*** (.13)	-.38* (.23)
Pupil–teacher ratio	.05* (.04)	.62*** (.11)	.36*** (.10)	.52*** (.11)	.70*** (.11)	.36* (.21)
Population growth rate (%)	-.38 (.26)	1.65*** (.64)	1.57 (1.19)	.46 (.79)	1.27 (1.17)	.51 (.83)
East Asia	.09 (.60)	-2.49 (1.55)	7.62*** (2.62)	-6.38** (2.95)	15.77*** (3.80)	-10.22* (5.91)
Constant	3.52*** (2.83)	27.48*** (7.39)	-139.64*** (10.25)	69.36** (33.64)	-164.98*** (11.96)	92.26* (48.60)
F-statistic	5.34		156.56		111.66	
R^2	0.3006	0.8264	0.8136	0.7674	0.7628	0.7534
Number of Observation	95		259		251	
Hausman	0.15		3.85		10.90*	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Any causal relationship between ICT factors and primary drop-out rate is not observed in Table 12, even though ICT variables are well instrumented in columns (2) and (3). These are different results from the result using CPI as IV in Table 9, which show the presence of the causal impact of the proportion of household with ICT on primary drop-out rate.

Trade openness, again, could produce biased results because it likely correlates with omitted variables, as explained above. Trade openness could directly affect education not only through ICT expansion but also through foreign direct investment (FDI), which is omitted in the model. Especially in many developing countries, trade openness is found to have an impact on FDI inflows and, accordingly, output growth. Cross-country studies by Liargovas and Skandalis (2012) find the emprical evidence of the causal impact of trade openness on FDI from panel regression analysis. Goldar and Banga (2007) also find industiries with a higher degree of trade openness attract more FDI in India. FDI has been considered as an important factor to affect educational outcomes by raising the amount of educational spendings (Zhuang, 2012). Nevertheless, FDI is not included in my model because of possible endogeneity of it.

Keeping the problems with each instrument in mind, key ICT variables are instrumented by two chosen IVs, CPI and trade openness, together. The correlation between instruments and error term can be assessed by overidentifying restriction test since I use two instruments for one variable in estimation with ICT expenditure.

Results for primary students' achievement are presented in table 13. J-test results in the last row detect the exogeneity of two chosen IVs failing to reject null hypothesis (that over-identifying restrictions are valid). However, whereas CPI one of the instruments has significant coefficients, coefficients for another instrument, trade openness, are insignificant. A causal relationship is not found here.

In Table 14, a causal relationship is shown between ICT expenditure and test scores of students in secondary level in column (1). The Sargan test result in the last row shows that overidentifying IVs are valid. The F-statistic is marginally above 10, and trade openness is significant, whereas CPI is not. ICT expenditure has a significant causal impact on academic achievement of students in secondary level. The coefficient for ICT expenditure (coefficient 0.02; standard error 0.006) implies that a one per cent increase in ICT expenditure can increase secondary students' test scores by two per cent. However, parameters for home use of ICT turned out to be insignificant in columns (2) and (3), and Sargan test result in Column (2) implies invalidity of overidentifying instruments even though the F-statistic values in both columns (2) and (3) are satisfactory.

Table 13 2SLS results for test scores (primary), instrumented by CPI and trade openness

	Dependent variable: natural log of test scores (primary)					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		.003 (.02)				
Household with PC (% overall households)				.003 (.004)		
Household with internet (% overall households)						.0009 (.003)
Corruption Perception Index (CPI)	.16 (.20)		2.52*** (.94)		3.01*** (.92)	
Trade Openness	.01** (.006)		.008 (.03)		.02 (.03)	
GDP per capita ($)	.09 (.47)	.03* (.02)	12.32*** (1.97)	-.05 (.06)	9.62*** (2.01)	-.01 (.05)
Schooling years (over age 25)	.006 (.13)	.03*** (.006)	1.82*** (.62)	.04*** (.008)	1.75*** (.61)	.04*** (.008)
Expenditure per student (%GDP per capita)	.05 (.04)	.004* (.002)	.64*** (.17)	.003 (.003)	.52*** (.16)	.004* (.003)
Pupil-teacher ratio	.07 (.05)	.0005 (.003)	.49*** (.18)	-.004 (.003)	.42** (.17)	-.003 (.002)
Population growth rate (%)	-.35 (.25)	-.05** (.01)	2.00 (1.23)	-.04*** (.01)	1.75 (1.22)	-.03*** (.01)
East Asia	.07 (.73)	.10** (.04)	13.02*** (3.47)	.08 (.06)	11.37*** (3.38)	.10** (.05)
Constant	1.19 (4.26)	5.53*** (.19)	-132.34*** (18.16)	6.23*** (.57)	-115.70*** (18.31)	5.87*** (.45)
F-statistic	1.80		76.54		59.76	
R^2	0.1751	0.7831	0.8419	0.7512	0.8116	0.7552
Number of Observation	77		124		120	
Hausman	0.09		6.20		0.35	
Sargan	0.51		0.87		0.27	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Table 14 2SLS results for test scores (secondary), instrumented by CPI and trade openness

	Dependent variable: natural log of test scores (secondary)					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		.02***				
		(.006)				
Household with PC (% overall households)				-.004		
				(.007)		
Household with internet (% overall households)						.007
						(.008)
Corruption Perception Index (CPI)	-.02		1.01		.51	
	(.004)		(.80)		(.94)	
Trade Openness	.02***		-.003		.02	
	(.004)		(.02)		(.03)	
GDP per capita ($)	-.41	.05***	15.68***	.13	14.87***	-.05
	(.35)	(.009)	(1.86)	(.12)	(2.17)	(.13)
Schooling years (over age 25)	.29***	.005	3.31***	.03	3.91***	-.01
	(.11)	(.004)	(.69)	(.02)	(.81)	(.03)
Expenditure per student (%GDP per capita)	.12***	-.0007	.36**	.0007	.51***	-.005
	(.03)	(.002)	(.16)	(.003)	(.19)	(.004)
Pupil-teacher ratio	.03	-.007**	.29	-.006	.41**	-.01***
	(.04)	(.003)	(.26)	(.004)	(.30)	(.004)
Population growth rate (%)	.19	-.06***	1.36*	-.04***	.99	-.05***
	(.21)	(.007)	(.81)	(.01)	(.94)	(.009)
East Asia	1.65***	.10***	12.55***	.18*	14.92***	.02
	(.42)	(.02)	(3.00)	(.09)	(3.48)	(.12)
Constant	2.33***	5.78***	-156.75***	5.05***	-167.71***	6.93***
	(2.78)	(.09)	(16.35)	(1.18)	(19.15)	(1.42)
F-statistic	10.79		79.19		48.00	
R^2	0.5129	0.7844	0.7859	0.6535	0.7245	0.3740
Number of Observation	91		159		155	
Hausman	0.46		0.71		0.67	
Sargan	0.10		10.24***		2.13	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

Table 15 shows a causal relationship between drop-out rate and households having ICT. First -stage regression in column (1) shows the significance of IVs, but its F-statistic is less than 10. On the other hand, first-stage regressions in columns (2) and (3) show that CPI win over trade openness as an IV for household variables for drop-out regressions. Coefficients of CPI are significant, but those of trade openness are insignificant. ICT variables in columns (2) and (3) are significantly correlated with primary drop-out rate, implying the causal impact of home use of computer and internet. Coefficients imply that one per cent increases of households having computers and internet access cause 2.6 and 2.4 per cents increases, respectively. Distinct estimation by national income will explain this unexpected result in following section.

Table 15 2SLS results for drop-out rate, instrumented by CPI and trade openness

	Dependent variable: primary drop-out rate					
	(1)		(2)		(3)	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
ICT expenditure (% GDP)		.27				.
		(.38)				
Household with PC				.26***		
(% overall households)				(.10)		
Household with internet						.24***
(% overall households)						(.08)
Corruption Perception	.19***		3.22***		4.08***	
Index (CPI)	(.16)		(.61)		(.70)	
Trade Openness	.02***		.02		.01	
	(.003)		(.01)		(.02)	
GDP per capita ($)	-.67*	-3.21***	11.79***	-7.54***	11.42***	-7.62***
	(.40)	(.78)	(1.32)	(1.89)	(1.49)	(1.76)
Schooling years	.09	-.84***	1.95***	-.82*	1.74***	-.62
(over age 25)	(.12)	(.31)	(.49)	(.42)	(.55)	(.42)
Expenditure per student	.15***	.32***	.45***	-.23***	.65***	-.28***
(%GDP per capita)	(.05)	(.09)	(.09)	(.08)	(.10)	(.09)
Pupil-teacher ratio	.07*	.61***	.25**	.53***	.57***	.45***
	(.04)	(.11)	(.11)	(.10)	(.12)	(.11)
Population growth rate	-.40	1.70**	2.15**	.35	1.08	.63
(%)	(.26)	(.67)	(.99)	(.70)	(1.12)	(.66)
East Asia	.15	-2.81*	7.81***	-6.12***	16.29***	-8.12***
	(.60)	(1.67)	(2.62)	(1.81)	(2.93)	(2.29)
Constant	5.71***	26.02***	-116.83***	68.23***	-132.62***	72.41***
	(.19)	(7.66)	(11.26)	(16.75)	(12.74)	(17.33
F-statistic	4.87		165.80		118.49	
R^2	0.3118	0.8195	0.8446	0.7721	0.7993	0.7826
Number of Observation	95		253		247	
Hausman	1.26		3.68		5.90	
Sargan	11.46***		0.002		0.13	

Note:

1. Robust standard errors are reported in parenthesis.
2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

From these 2SLS results, it is found that the resulted coefficients for ICT variables are not significantly different from zero except in regressions of secondary students' test scores on

ICT expenditure and those of primary drop-out rate on households using computers and internet. The significant correlation that is presented in OLS estimation is not causal if these IVs are to be believed.

The lack of the causality might be caused by the weak spill over effect of ICT investment toward the education field. As I explained, because an indicator for overall ICT expenditure is chosen due to the lack of cross-country data for ICT investment in the educational field, the model used in this paper estimates the expected spill over effects. Insignificant coefficients for ICT expenditure imply that general level of ICT infrastructures does not have a direct impact on education.

The second possible reason for insignificant impact of ICT expenditure on educational quality is the superior impact of traditional educational inputs over ICT resources. Parental influence, subcategorized by parental education and parental income, has been considered as an important factor that determines pupil achievement. The present regression analysis also shows a significant role of family influence in improving test scores and reducing drop-out rate, whereas estimated impact of ICT expenditure on educational quality is indistinguishable from zero.

Thirdly, we may need a longer time to observe the impact. Many studies say that it takes time to pedagogically implement a technology into curriculums as well as to detect its impact. Even if ICT infrastructure is ready with high level of investment, teachers and students need time to become literate in computer and internet use. Sandholtz, *et al.* (1992) emphasizes the importance of longitudinal investigation for the impact of ICT on education because educational change through ICT is slow. Hence, ten years, the length of the panel dataset used in this study, might be not long enough to gauge the real impact of implemented ICT in education. As it is explained for the reason why fixed effects estimation with my data, there is little variation in ICT factors during about ten years.

Alternatively, the IVs that are used here are invalid, and they might fail to detect the causal relationship. Explanations for why chosen IVs can be bad and how they might produce biased results are given above. These instruments are possibly correlated with omitted variables or error terms. Furthermore, some estimations show that they are weakly correlated with endogenous variables. Therefore, OLS, and fixed estimation results, only seem more reliable if we have a larger sample, since significant relationships are found from those estimations.

However, 2SLS results show secondary level students are affected by spending on ICT, but not primary level students are not. There is no study that finds the difference of impact of ICT between primary and secondary schools. Instead, the reason for this difference can be supposed from few examples that show the implementation of ICT in education is more focused on secondary schools across countries. McCartney (2009) reports that in Norway, priamry schools fall far behind secondary schools in ICT use in education. Nigerian government also planned to diffuse computer education first to all secondary schools and then primary schools (Adomi & Kpangban, 2010). It is possible to assume that the amount of expenditure assigned to secondary schools among overall ICT expenditure is bigger.

Drop-out rate also has a causal relationship with ICT factors, but its relationship is unexpectedly positive. 2SLS results show that home use of ICT increases drop-out rate. According to our expectation, families that have willingness and ability to have computer and internet access would send their kids to school more. However, the present results indicate the opposite. The next section will help to explain this.

4.3 Distinction based on Economic Level of the Countries

As many of earlier studies show that educational inputs affect educational outcomes in different ways according to economic level of country (Heyneman & Loxley, 1983; Altinok, 2007), ICT also can be assumed not to have same impact in countries at different economic levels.

According to level of national income, countries have different behaviour of ICT use and different levels of access to technologies. Differences originate from different societal, cultural and economic environments between high- and non-high-income countries. The purpose of application of ICT in education would be different and thus, its impact would be different. High-income countries have plenty of teachers at all levels, whereas there is lack of good teachers in non-high-income countries. In non-high-income countries, because the number of high quality teachers are less than necessary, ICT can be used to alternate with the teachers' role. However, in high-income countries, ICT is useful to assist teachers in classroom. Furthermore, primary concerns of education in developing countries are quite different from those in developed countries. For example, developing countries place weight on basic education such as increasing literacy rate or still prioritizing the educational quantity, as expressed enrolment ratio. Thus, what they want to achieve by employing ICT in education would be different from the aims of developed countries.

In addition, the degree of ICT familiarity is different between children in high- and non-high-income countries. Technologies are more developed in high-income countries. In addition, children who are more likely to have been exposed to new technologies such as electronic machines from an early age become more familiar with computer or internet more easily. Hebenstreit (1985) explains this difference by showing an example of children mastering keyboards without any problem in developed countries because they have simlar experience pushing buttons of machines in daily life.

Developed countries have more educational resources based on ICT. As technology develops, countries have invested to create and design good programmes and software that help children to study. Even though students in developing countries can use educational resources designed by developed countries, they may have barriers caused by cultural and language difference. Therefore, even if students use the same hardware, how they are affected would differ depending on whether they have easy access to educational resources.

Experimental studies confirm the positive and significant impact of ICT in developing countries, whereas they are sceptical of the positive role of ICT in developed countries as reviewed in a previous section. In this section, by separating countries based on economic level, whether results with cross-country data are consistent with results with experimental data will be examined.

Economic levels of countries are defined with gross national income (GNI) per capita by the World Bank. Countries are sorted based on the GNI data in 2012. Based on this definition, the dataset for test scores is weighted toward high-income countries. Therefore, countries are divided into two groups, high-income countries and non-high-income countries (which middle- and low-income countries belong to) in estimation of pupil achievement. There are 29 high-income countries and 50 non-high-income countries for regression of test scores. On the other hand, the dataset for primary drop-out rate has 31 high-income countries and 71 non-high-income countries. Small size of samples due to country split can lead biased results.

Table 16 OLS results for test scores with distinction based on economic level (primary)

	Dependent variable: natural log of test scores (primary)							
	High-income countries				Non high-income countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT expenditure (% GDP)	.02***			.02***	-.01			-.007
	(.006)			(.007)	(.008)			(.006)
Household with PC		.00009		.001		.004*		-.003
(% overall households)		(.0007)		(.002)		(.002)		(.004)
Household with internet			.0002	-.00008			.008***	.01**
(% overall households)			(.0007)	(.001)			(.002)	(.005)
Natural log of GDP per capita ($)	.06***	.03	.03	.03	-.08**	-.14***	-.13***	-.12**
	(.01)	(.02)	(.02)	(.04)	(.03)	(.03)	(.03)	(.05)
Schooling years (over age 25)	.001	.007	.006	-.001	.05***	.06***	.06***	.04***
	(.006)	(.005)	(.005)	(.006)	(.01)	(.01)	(.009)	(.008)
Expenditure per student	.003	.002	.002	.002	.004	.001	.002	.0001
(% GDP per capita)	(.002)	(.002)	(.002)	(.002)	(.003)	(.002)	(.002)	(.003)
Pupil-teacher ratio	.006**	.007***	.007***	.006**	.002	-.007***	-.007***	.0007
	(.003)	(.002)	(.002)	(.003)	(.004)	(.002)	(.002)	(.004)
Population growth rate (%)	-.07***	-.07***	-.07***	-.07***	-.11**	-.03	-.003	-.07**
	(.01)	(.01)	(.01)	(.02)	(.05)	(.03)	(.02)	(.04)
East Asia	.06***	.05*	.05*	.04	-.14***	-.03	-.06	-.16***
	(.02)	(.03)	(.03)	(.03)	(.04)	(.08)	(.09)	(.03)
Constant	5.50***	5.84***	5.86***	5.75***	6.44***	6.80***	6.72***	6.73***
	(.14)	(.20)	(.19)	(.31)	(.33)	(.29)	(.27)	(.39)
R^2	0.8787	0.7972	0.7972	0.8838	0.6694	0.6137	0.6833	0.7880
Number of Observation	41	56	55	41	36	72	69	34

Note:

1. Robust standard errors are reported in parenthesis.

2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

It is evident that the association of ICT expenditure on primary educational achievement is different between high-income countries and non-high-income countries, as observed in table 16. The higher percentage of investment in ICT appears to improve the educational quality in developed countries at significant level, whereas in developing countries, the correlation appears to be insignificant and negative. In high-income countries, a one per cent increase in ICT expenditure leads to increase primary students' test scores by two per cent.

The proportion of households that own computers and use internet has significant and positive correlation with pupil achievement in non-high-income countries, whereas its correlation is insignificant in high-income countries. This implies that household ownership of ICT may have stronger power for primary level students in non-high-income countries than high-income countries. In non-high-income countries, a one per cent increase in the proportion of households with computer and internet leads to increase students' test scores by 0.4 and 0.8 per cent, respectively. In non-high-income countries that have a smaller proportion of households that use computer and internet, having ICT at home matters for students in primary level more than in high-income countries where ICT is already prevalent.

The significant association between family influence and primary students test scores is also observed in non-high-income countries, even though coefficients for parents' incomes appear to be negative. Coefficients for parents' educational attainment are significant in non-high-income countries, whereas they are insignificant in high-income countries. Meanwhile, pupil–teacher ratio seems to have a statistically significant correlation with primary educational achievement in both high- and non-high-income countries, even though the correlations in high-income countries appeared as unexpectedly positive.

On the other hand, in Table 17, it seems ICT factors are significantly and positively correlated with test scores for secondary level students in high-income countries. A one per cent increase in ICT expenditure improves test scores by one per cent. One per cent in household with computer and internet increases test scores by 0.09 and 0.05 per cent, respectively. However, in non-high-income countries, ICT variables are not correlated with secondary pupil achievement. Comparing key ICT variables each other, all three are significantly correlated in high-income countries, but none of them is significant in non-high-income countries. Significant correlation can be partly resulted from bigger sample size of high-income countries.

Table 17 OLS results for test scores with distinction based on economic level (secondary)

	Dependent variable: natural log of test scores (secondary)							
	High-income countries				Non high-income countries			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ICT expenditure (% GDP)	.01***			.01***	.0009			.001
	(.006)			(.003)	(.02)			(.02)
Household with PC		.0009**		.003***		.0009		-.002
(% overall households)		(.0004)		(.0007)		(.0006)		(.004)
Household with internet			.0005*	-.001***			.001	.006
(% overall households)			(.0003)	(.0005)			(.001)	(.006)
Natural log of GDP per capita ($)	.01	-.01	.001	-.01	.04	.07***	.06***	.005
	(.009)	(.01)	(.01)	(.01)	(.03)	(.02)	(.02)	(.04)
Schooling years (over age 25)	-.003	-.002	.002	-.006*	.02	.004	.008	.01
	(.004)	(.004)	(.005)	(.003)	(.01)	(.01)	(.01)	(.01)
Expenditure per student	.002	.0003	.0009	.002	.0007	-.002	-.003	.0003
(% GDP per capita)	(.001)	(.001)	(.001)	(.001)	(.002)	(.002)	(.002)	(.002)
Pupil-teacher ratio	.009***	.007***	.006***	.008***	-.01*	-.009***	-.009***	-.01
	(.002)	(.002)	(.002)	(.002)	(.006)	(.003)	(.003)	(.007)
Population growth rate (%)	-.05***	-.04***	-.04***	-.05***	-.02	-.04**	-.03**	-.003
	(.009)	(.005)	(.007)	(.007)	(.04)	(.02)	(.02)	(.05)
East Asia	.06***	.05**	.06**	.04***	.10	.13**	.11**	.08
	(.02)	(.02)	(.02)	(.02)	(.08)	(.06)	(.05)	(.07)
Constant	6.07***	6.34***	6.19***	6.25***	5.91***	5.74***	6.72***	6.18***
	(.07)	(.10)	(.12)	(.10)	(.25)	(.23)	(.27)	(.41)
R^2	0.8402	0.7651	0.7576	0.8748	0.6549	0.6650	0.6833	0.6665
Number of Observation	57	100	100	57	34	60	58	33

Note:

1. Robust standard errors are reported in parenthesis.

2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

It seems ICT use at home helps secondary students to improve their test scores in high-income countries, whereas it was not useful for primary students. First, it suggests students show slow reaction a few years after using ICT, as the educational process is cumulative. Second, secondary students become more adept in using computers and internet and motivated to use ICT for educational purpose, and thus, they can use them efficiently and effectively. It is revealed that the way of using computer and internet by secondary level students is more independent (Balanskat, 2007).

However, in non-high-income countries, perhaps because there is a lack of high quality educational software or web sources students can access to find educational help, home use of ICT cannot make significant differences at the secondary level, even though having computers and internet access at home significantly mattered when they were at primary schools.

Results in Table 17 differ from relevant studies. What previous studies have suggested was that additional educational resources do not have strong and positive impacts on educational outcomes in developed countries, whereas they work efficiently in developing countries. However, regression estimated in Table 17 shows a significant correlation between ICT and educational outcomes in high-income countries and insignificant correlation in non-high-income countries.

The difference of results is possibly caused by data used in the present study. Whereas previous studies use data that measure ICT inputs specifically in schools and classes, I use data for ICT expenditure and prevalence of ICT in households in general. Therefore, regressions with overall national ICT expenditure more likely show whether expenditure on ICT spilled over into educational fields or not. From results in table 16 and 17, in non-high-income countries, it is induced that ICT expenditure has not had an impact on students yet. It seems that students in high-income countries benefits from national ICT expenditure.

However, results for regressions with variables of households with computer and internet, which are assumed to depict the use of ICT by children better, computer and internet use at home is significantly and strongly correlated with academic achievement for secondary level students in high-income countries.

Table 18 OLS results for primary drop-out rate with distinction based on economic level

	Dependent variable: primary drop-out rate							
	High-income				Non high-income			
	(1)	(2)	(3)	(4)	(9)	(10)	(11)	(12)
ICT expenditure (% GDP)	-.40			-.45	-.13			-3.72*
	(.40)			(.51)	(.27)			(1.48)
Household with PC		.06*		.05		-.33*		-2.14*
(% overall households)		(.03)		(.10)		(.19)		(.69)
Household with internet			.05*	.05			-.40*	4.68*
(% overall households)			(.03)	(.07)			(.24)	(1.67)
Natural log of	-1.18	-2.10**	-1.93**	-2.76	-27.72	-5.25**	-7.38***	-25.30**
GDP per capita ($)	(1.73)	(.99)	(.96)	(1.77)	(14.84)	(2.43)	(2.26)	(6.64)
Schooling years	-.31	-.78***	-.72**	-.58	11.97	-.21	.27	4.96
(over age 25)	(.38)	(.29)	(.30)	(.38)	(7.40)	(.84)	(.86)	(5.42)
Expenditure per student	.0002	-.07	-.07	-.15	-.13	-.46***	-.45**	2.28*
(% GDP per capita)	(.09)	(.05)	(.06)	(.09)	(.55)	(.17)	(.18)	(.91)
Pupil-teacher ratio	.09	-.02	-.02	.02	-2.34	.44***	.41**	-1.01
	(.13)	(.11)	(.12)	(.17)	(1.75)	(.16)	(.16)	(1.08)
Population growth rate	.08	.22	.27	.04	8.75***	-.57	-.60	5.83**
(%)	(.43)	(.31)	(.32)	(.34)	(1.71)	(1.94)	(1.95)	(1.69)
East Asia	-1.61	-3.31***	-3.61***	-4.12*	-57.07	-6.22**	-7.11***	-37.21
	(1.46)	(.99)	(.99)	(2.12)	(33.06)	(2.46)	(2.62)	(23.34)
Constant	19.31	30.22***	29.45***	36.77**	249.52	63.47***	76.40***	222.22**
	(12.09)	(10.57)	(10.82)	(17.82)	(139.85)	(24.02)	(24.24)	(61.96)
R^2	0.1936	0.1756	0.1747	0.2845	0.9437	0.5761	0.5905	0.9891
Number of Observation	52	104	101	52	43	156	151	43

Note:

1. Robust standard errors are reported in parenthesis.

2. *, ** and *** indicate significance at the 10, 5 and 1 per cent levels, respectively.

On the other hand, distinct estimations of primary drop-out rate according to national income show similar results with previous studies. The difference of educational production function between high-income countries and non-high income countries is apparent in table 18. In high-income countries, variables of household with ICT have positive and significant association with drop-out rate, whereas they have negative and significant correlation in non-high-income countries.

Children's ICT use at home is significantly and positively associated with drop-out in the primary level education in high-income countries. A one per cent increase in the proportion of households with computer and internet increases primary drop-out rate 0.06 and 0.05 per cent, respectively. It seems parents' computer and internet use does not help, but rather hinders their kids to go to schools in high-income countries.

However, the correlation between primary drop-out rate and the proportion of households with computer and internet is negative and significant in non-high-income countries. A one per cent increase in the proportion of households with computer and internet decreases primary drop-out rate 0.33 and 0.40 per cent, respectively.

In summary, in lower-income countries, it appears that ICT inputs are strongly correlated with primary drop-out rate in positive ways, whereas this is not so in higher-income countries. Unexpected positive correlations between primary drop-out rate and ICT use at home found in OLS and 2SLS estimates possibly caused by observations in high-income countries.

ICT expenditure seems to have the positive power to reduce drop-out rate, but it is insignificant in two groups of countries. However, when regressing all three ICT variables, ICT expenditure turns out to be significant along with the proportion of households with computer in non-high-income countries.

When empirical findings suggest the negative role of ICT in high-income countries in previous studies, it is usually explained by wider options available for students in developed countries than those in less-developed countries. For example, since well-trained teachers can produce higher quality of education in high-income countries than computers can, students may not have or have less benefit from using computers as an educational tool. However, in non-high-income countries where students lack alternative educational tools, computers can be an efficient tool.

This can explain the present results. High-income countries with the higher proportion of households with ICT may have many more choices than schools alone to be educated. Home schooling with ICT resources and distance-learning can be examples. On the other hand, it seems that in non-high-income countries that provide main education nowhere but in school system, families with the capability and willingness to own ICT at home send their children to school.

OLS results sorted by national income suggest that countries at different levels may have different educational production function. These results would give us implications for policy design. The next section will discuss this in detail.

5 IMPLICATIONS FOR POLICY

The main findings are as follows. First, ICT is significantly correlated with educational outcomes. I then present some evidence of a positive causal effect of ICT expenditure on secondary level students' academic achievement, and undesirable effect of home use of ICT on primary drop-out rate, though it is very difficult to obtain valid instruments in this context. Lastly, ICT is differently correlated with educational quality outcomes depending on national income.

This section will focus on implications of these findings for policy and practice. The first finding implies students in countries with higher level of ICT tend to show better academic performance and, though more students tend to leave primary education. Home use of ICT matters to improve test scores, but increases drop-out rate at the primary level, and spending on ICT is important for higher test scores at the secondary level.

With countries sorted by national income, it is found that these correlations are different according to how rich countries are. ICT use at home helps primary students in non-high-income countries and secondary students in high-income countries to increase their academic performance. Countries with higher proportion of families with ICT are more likely to have higher primary drop-out rates in high income countries, but in non-high-income countries, students who have ICT at home are less likely to leave primary education.

Interpretation of why the same factor matters differently for different level students and different group of counties provides implications for policy and practice. Since ICT is more prevalent in high-income countries, having ICT at home or not is not important for primary students in terms of academic achievement. However, it becomes significant in the secondary level. Students in high-income countries show a slow reaction a few years after beginning ICT use.

In contrast, in non-high-income countries, home use of ICT becomes insignificant at the secondary level whereas it is important at primary level. As ICT is not common in non-high-income countries, children with parents who can decide to have ICT at home may be outstanding in academic achievement within primary education. The correlation disappears as students go on to higher education possibly because of students' and parents' inefficient use of ICT due to either lack of instruction for good use of ICT or lack of educational resources based on ICT. This implies that the physical tool itself does not bring changes without good educational programs and software.

On the other hand, non-high-income countries enjoy the benefits of intensive home use of ICT in reducing drop-out rate; however, primary students in high-income countries with the higher proportion of households with ICT are more likely to leave their schools. However, this result alone does not guarantee that encouraging governments in non-high-income countries (where reducing drop-out rate is still one of the main concerns) to support families to use ICT at home for their children would reduce drop-out rate before a causal relationship between two is found. Parents who can afford to equip ICT at home may have high willingness to send their children. That is, home use of ICT itself does not necessarily have a causal impact on drop-out rate.

ICT expenditure does not have a significant correlation with educational outcomes in primary level but does in secondary level. Countries with higher proportions of spending on ICT tend to have academically excellent secondary students. A causal relationship is also found between ICT expenditure and secondary pupils' test scores. The different impact of ICT expenditure between primary and secondary schools might be attributed to larger share of spending to secondary schools as shown in several countries. (McCartney, 2009; Adomi & Kpangban, 2010)

Whether ICT expenditure matters for academic performance depends on national income. Among high-income countries, those with a high proportion of ICT expenditure tends to have academically excellent students. However, in non-high-income countries spending on ICT is not playing a significant role. High-income countries have a larger spillover effect of investment of ICT on the education sector. This difference implies that the steady investment to establish ICT infrastructure is required to have a real impact of ICT on students. As high-income countries introduced ICT quite earlier, students as end users in these countries have an easier access to ICT; thus it is possible that their results in examination are significantly correlated with ICT investment.

Nevertheless, policy makers should keep in mind that there was a failure to find a causal relationship between ICT and educational outcomes except between home use of ICT and primary drop-out rate and between ICT expenditure and secondary students' academic performance. Failure to find a causal relationship is either due to the absence of causal relationship as estimated or weak instruments having been chosen. In the former case, ICT may be reversely affected by educational outcomes, or it is possible there is a common factor that causes both at the same time. Alternatively, it may be because the panel data is not long enough so that it is early to find the causal impact of ICT on education. Thus, the simple policy implementation without specification considering the multifaceted relationships among different factors may not bring the expected results.

Reviewing all suggestions from results, governments' role in improving educational outcomes through using ICT needs to be discussed. First, governments should have a long-term budget and implementation strategy for ICT use in education with policy-based approach. One of reasons for success of ICT-based education reform in Singapore and Finland is a long-term national policy which describes detailed plans (Kozma, 2005). It takes time to establish ICT infrastructure in the education sector, to create and manage educational programs and software, and to train students, teachers and parents how to make good use of ICT for educational purposes. Therefore, policy should describe technical support and maintenance in schools, financial aid for schools and families to purchase physical ICT tools, development of ICT resources for education, and end-user education.

Evaluating budget performance should also be long-term oriented. Policy makers should carefully change expenditure plan, even if there is no remarkable improvement of educational quality in the primary level because the investment would become, in effect, in secondary level, cumulative in its impacts. Instead, they need to keep track of students to see whether they are positively affected by investment in ICT a few years later like Krueger and Whitmore (2000) did for class size. They evaluated the long-term effect of students' past experience of participation in small classes on college-taking and middle school test, and they found a significant impact of early intervention.

At the same time, it is also important for governments to provide financial aid for the home use of ICT and train parents and children how to use ICT for educational purposes. They can carry out promotion campaigns that emphasize the importance of using ICT at home. It is possible to encourage parents to equip computers and internet at their home by issuing vouchers to parents through local authorities and schools having partnerships with relevant companies. We have an example of English government that provided low-income families with computers and 12 month broadband subscription aiming higher academic performance in 2010 (The Telegraph, 2010).

Furthermore, governments need to focus on setting up and improving wireless environments through which students can have access to open resources, and find knowledge on their own. High-speed connection, which tends to be more developed in high-income countries, would help students to make efficient use of ICT at home. With a national broadband plan, governments of developing countries can achieve affordability of broadband infrastructure, and thus, can advance students' use of internet. Infrastructure is a prerequisite to implement plan for ICT in education. The Broadband Commission Working Group on Education (2013) emphasizes its importance by analysing that Republic of Korea succeeded in the implementation of ICT use in education mainly because most of students can access to high-speed broadband.

ICT resources based on their own language and cultural background should be developed to facilitate teaching of and learning by students. The simple introduction of physical technologies in education does not necessarily bring educational improvement. Appropriate pedagogical models and resources based on ICT should be accompanied (Barrera-Osorio & Linden, 2009; Cristia, et al., 2012). Developing indigenous resources based on local needs not importing foreign materials is important in education (Hebenstreit, 1985).

Government can be involved in the development of ICT resources by experts training, financial aid to develop educational programs and surveys of teachers and schools for needs analysis. As pedagogical skills and methods should be considered in software design, an effort to cultivate educational experts who can develop ICT resources for education should be made by governments. They can encourage private companies to develop educational software as well by supporting development cost. In addition, governments can help to improve the quality of ICT resources by carrying out national surveys to analyse teachers' needs.

Governments, especially in developing countries which have not sufficient resources, cannot solely work for improved educational quality through ICT. Kozma (2008) suggests partnership with private sector, especially the technology industry, for sustainable development of ICT use in education. Private-public partnership is required for digital content development for teachers and students, and financial aid to home use of ICT. Governments can also cooperate with international organizations that carry out projects to provide families with physical ICT tools, educational software, and ICT trainings.

6 SUMMARY AND CONCLUDING REMARKS

In this study, I have attempted to take the first steps toward a new way of evaluating the role of ICT in education. By building up a macroeconomic model using cross-country data, I aimed at examining the relationship between national development of ICT and educational outcomes. This was mainly motivated by the requirement to provide ideas to policy makers who need to decide on the introduction and expansion of ICT for educational purpose.

My model is based on the theoretical framework of educational production function. As the literature review outlined, dependent variables that measure educational outcomes and other control variables are included. As dependent variables, test score of students in primary and secondary level and primary drop-out rate are regressed. It is common to use test score as an indicator for educational outcome when evaluating ICT in education; however, the approach used in the present paper, estimating a correlation between drop-out rate and ICT, is the first such attempt. I included primary drop-out rate because educational equity is also one of the main concerns for deployment of ICT for educational purpose.

In addition, I choose ICT variables, ICT expenditure, and the proportion of households with computers and internet, which are of interest in this paper. I used comprehensive ICT sector variables because of lack of cross-country homogenous data for ICT in the education sector. This is based on the assumption that students can have access to ICT outside schools as well.

My simple results prove that there is a significant correlation between ICT in general and educational outcomes. Home use of ICT is significantly correlated with both test scores and drop-out rates in primary schools, and ICT expenditure has a significant and positive correlation with secondary students' academic performance.

I further attempted estimating a causal impact of ICT on education based on 2SLS estimates because it is possible that educational outcomes can reversely affect ICT factors or that there is a common factor that cause both at the same time. Instrument variables are chosen according to theoretical principles, and their validity is evaluated by statistical tests. As a result, causal relationships are presented only between ICT expenditure and test scores of secondary students, and between home use of ICT and primary drop-out rate. However, reasons to doubt instruments are given in the previous section, simple OLS associations are interests, nonetheless.

My thesis is also useful because it triggers attempts to use retrospective data for estimating the correlation between ICT and education in developing countries. The literature review showed few studies that examine the impact of ICT on education in developing countries, and most of them concentrate on experimental data rather than retrospective data. Estimation with retrospective data is more useful for national policy design because it is hard to generalize or compare results of experimental studies based on a certain group of students.

Countries are grouped by national income, and correlation between ICT and education is estimated for each group of countries. This distinction was motivated by relevant literature that shows the different effect of ICT in developed and developing countries. Why the significance of ICT input in education is different depending on national income is perhaps because the level of resources possessed by students in each group of countries possess is different. Overall, research on developed countries finds a negative impact of ICT on education, whereas findings from studies on developing countries confirm that ICT has a positive impact.

Comparing estimates between high- and non-high-income countries gives us several policy relevant findings. First, in high-income countries, ICT expenditure is significantly and positively correlated with academic performance. Second, ICT use at home has a significant correlation with primary level students’ performance in non-high-income countries and secondary level students’ performance in high-income countries. Third, home use of ICT is, unexpectedly, positively correlated with primary drop-out rate in high-income countries, but it is negatively correlated in non-high-income countries.

Based on environmental and cultural difference of ICT usage in two groups of countries, relevant policies are suggested. First, governments should have a long-term budget and implementation plan for ICT use in education since it would take time to reach and train students, teachers, and parents as end-users. In addition, government should encourage families to own computers and provide improved wireless environments through a national broadband plan. Finally, it is necessary to focus on ICT resource development with pedagogical consideration.

Overall assessment of a causal impact of ICT on education is difficult based on 2SLS estimates with weak instruments that are chosen in this paper. It is difficult to think of satisfactory IVs even in principle. In order to give clear answers, more researches are required. Further efforts to cumulate cross-country data for more direct indictors that can measure ICT in education sector and students' use of ICT at school and home have to be made for more accurate evaluation. With the long panel data, longitudinal studies on the impact of ICT education should be done.

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