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ABSTRACT

Technology and Education: Computers, Software, and the Internet*

A substantial amount of money is spent on technology by schools, families and policymakers with the hope of improving educational outcomes. This chapter explores the theoretical and empirical literature on the impacts of technology on educational outcomes. The literature focuses on two primary contexts in which technology may be used for educational purposes: i) classroom use in schools, and ii) home use by students. Theoretically, ICT investment and CAI use by schools and the use of computers at home have ambiguous implications for educational achievement: expenditures devoted to technology necessarily offset inputs that may be more or less efficient, and time allocated to using technology may displace traditional classroom instruction and educational activities at home. However, much of the evidence in the schooling literature is based on interventions that provide supplemental funding for technology or additional class time, and thus favor finding positive effects. Nonetheless, studies of ICT and CAI in schools produce mixed evidence with a pattern of null results. Notable exceptions to this pattern occur in studies of developing countries and CAI interventions that target math rather than language. In the context of home use, early studies based on multivariate and instrumental variables approaches tend to find large positive (and in a few cases negative) effects while recent studies based on randomized control experiments tend to find small or null effects. Early research focused on developed countries while more recently several experiments have been conducted in developing countries.

JEL Classification: I2

Keywords: technology, education, computers, internet, software

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1. Introduction

Schools and families around the world spend a substantial amount of money on computers, software, Internet connections, and other technology for educational purposes. The use of technology is ubiquitous in the educational system in most developed countries. For example, essentially all instructional classrooms in U.S. public schools have computers with Internet access (U.S. Department of Education 2012). Most countries in Europe also have high rates of computer access in schools (European Commission 2013). In addition to school level investment in technology, central governments frequently play an active role in providing or subsidizing investment in computer and Internet access. The U.S. federal government spends more than $2 billion and recently increased the spending cap to $3.9 billion per year on the E-rate program, which provides discounts to schools and libraries for the costs of telecommunications services and equipment (Puma, et al. 2000, Universal Services Administration Company 2013, Federal Communications Commission 2014). England provided free computers to nearly 300,000 low-income families at a total cost of £194 million through the Home Access Programme.[1] A growing number of schools are experimenting with one-to-one laptop or tablet programs that provide a computer to each student and often allow the student to take the computer home (Warschauer 2006; Maine Education Policy Research Institute 2007; Texas Center for Educational Research 2009).[2] These programs are potentially expensive -- for example, equipping each of the 50 million public school students in the United States with a laptop would cost tens of billions of dollars each year even if these laptops were replaced only every three years.

[1] The Euro 200 Program in Romania and the Yo Elijo Mi PC Program in Chile are additional examples of government programs providing computers to low-income children.
[2] Extensive efforts to provide laptops to schoolchildren also exist in many developing countries. For example, the One Laptop per Child program has provided more than 2 million computers to schools in Uruguay, Peru, Argentina, Mexico and Rwanda, and started new projects in Gaza, Afghanistan, Haiti, Ethiopia and Mongolia. See http://one.laptop.org/about/countries.

Families also spend a substantial amount of money on computers, software, and Internet connections each year. In the United States, for example, 86 percent of schoolchildren have access to a computer at home. Although current levels of access to home computers and Internet connections among schoolchildren are very high, access is not evenly distributed across countries or across the population within countries. Less than one quarter of schoolchildren in Indonesia, for example, have access to a computer at home that they can use for schoolwork. In the United States, 98 percent of the 12 million schoolchildren living in households with $100,000 or more in income have access to a computer at home, but only 67 percent of the 12 million schoolchildren living in households with less than $25,000 in income have access. These disparities in access to home computers and the Internet are known as the Digital Divide.

A better understanding of how computer technology affects educational outcomes is critical because it sheds light on whether such technology is an important input in the educational production process and whether disparities in access will translate into educational inequality. This chapter explores the theory and literature on the impacts of technology on educational outcomes. Although technology is a broad term, the chapter focuses on the effects of computers, the Internet, and software such as computer assisted instruction, which are currently the most relevant forms of new technology in education.[3] The discussion focuses primarily on the impacts of computers, the Internet and software on educational outcomes instead of impacts on other forms of human capital such as computer skills (although we discuss a few studies).[4] We consider studies that examine the

[3] The Census Bureau and Bureau of Labor Statistics define personal computers as "desktop, laptop, netbook, notebook or tablet computers" in the latest Current Population Survey (2012).
[4] Computer skills training (CST) or computer science, which are vocational or academic subjects with benefits in the labor market, have generally been of less interest in the area of the economics of education. Angrist and Lavy (2002) note that "CST skills seems undeniably useful, just as typing was a useful skill taught in American high schools earlier in the twentieth century, but most of the recent interest in the educational use of computers focuses on CAI and not CST." We also do not focus on the analysis of the relationship between technology and the labor market for which there has been an extensive literature.

impacts of technology on measurable educational outcomes, such as grades, test scores, retention, graduation, and attendance. Attention is also largely, but not entirely, restricted to studies from the economics literature.

The literature focuses on two primary contexts in which technology may be used for educational purposes: i) classroom use in schools, and ii) home use by students. These contexts differ fundamentally in terms of who makes the investment decision and who controls how the technology is used. Districts and schools determine the level of technology investment and control how it is used in the classroom to aid instruction. Parents and students make decisions over investment in computers, the Internet, software, and other technologies at home. One unifying theme of the discussion is that the use of technology is placed in the context of educational production functions commonly discussed in the economics literature.

Investment in computer hardware, software and connectivity may offset other inputs that affect student achievement in the context of the household and the school. Likewise, time spent using computers offsets other educational or recreational activities. We discuss the extent to which the estimates in the literature reflect these tradeoffs. Investment in computers for schools is divided into two broad areas: i) investment in information and communications technologies (ICT) generally, such as computer hardware and Internet connections, and ii) specific software used for computer aided instruction (CAI). Computer use at home poses a unique challenge for estimation as the context is less conducive to policy interventions and randomized trials. We examine the literature based on cross-sectional evaluations relative to more recent studies based on experimental and quasi-experimental designs.

See Autor (2001); Autor, Katz, and Krueger (1998); DiMaggio and Bonikowski (2008); DiNardo and Pischke (1997); Freeman (2002); Krueger (1993) for a few examples.

Section 2.1 discusses rates of computer use in schools. Section 2.2 highlights important theoretical considerations when interpreting estimates of the effects of technology in schools. Section 2.3 presents estimates from studies focusing on ICT and CAI investment in schools. Section 3.1 presents rates of access to computers at home, and Section 3.2 discusses theoretical considerations. Section 3.3 presents estimates of the effects of home computer use with an emphasis on differences in research design. Section 4 concludes and offers suggestions for future research.

2. Technology Use in Schools

2.1 Estimates of rates of technology use in schools

Access to computers in public schools has increased manifold in the last thirty years. In the United States, there were only 0.008 computers per student in 1984, or 1 computer per 125 students (Coley, Cadler, and Engel 1997). Figure 1 displays recent trends in the number of computers per student based on data from the National Center for Educational Statistics (NCES). As recently as 1998, there were 0.15 computers per student and only half of these computers had Internet access. The most recent data available from the NCES, which is from 2008, indicates that there are 0.32 computers per student and essentially all computers have Internet access.

Germany, the UK, Japan, and other OECD countries also have high levels of computer access. Table 1 reports the average number of computers available per student for the 50 most populous countries in the world with data reported in the 2012 Programme for International Student Assessment (PISA) conducted by the OECD. These data indicate that there are 0.95 computers per 15 year-old student in the U.S., 1.02 in the United Kingdom, 0.65 in Germany, and 0.56 in Japan. PISA data contain, to the best of our knowledge, the most uniform measure of computer access across all countries, but provide estimates of the number of computers per student that are much higher than most other sources. For example, the PISA estimates are nearly three times higher for the United States than those reported by the NCES, which is likely partly due to counting the number of "available" computers to students of a specific age, including those shared with students in other grades, but is also partly due to the most recent NCES data being from 2008.[5]

Table 2 presents the results of the European Commission's survey of school computer access and use. The survey reveals rates of computer access more similar to those in the U.S. for several countries, including Austria, Denmark and Spain. Across all EU countries represented in the study, there are 0.20 computers per student in the 8th grade and 0.33 computers per student in the 11th grade. More than 50 percent of middle school students in the EU reported using a computer during lessons at least once each week. It is clear that the computer has become a regular part of classroom instruction in developed countries.[6]

Interestingly, in the United States, schools serving students from the lowest income households have an almost identical number of computers per student as schools serving wealthier households (U.S. Department of Education 2012), though the quality of these computers may differ. However, there is a notable digital divide across countries. Many developing countries still have relatively low rates of computer and Internet access. PISA reports computer access rates in Brazil, Romania, Turkey, and Vietnam that are approximately one-fourth those in developed

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[5] To create their measure of computers per student, PISA uses responses to the following two questions: "At your school, what is the total number of students in the <national modal grade for 15-year-olds>?," and "Approximately, how many computers are available for these students for educational purposes?" This measure is different than those collected by other institutions such as the U.S. Department of Education, the European Commission, and UNESCO. These institutions consider the total number of school computers and the total number of school students.

[6] Simple counts of computers and Internet connections provide only a general sense of each country's level of technology adoption. Potentially important differences in the quality of technology and the intensity of technology use (e.g. hours per day) are rarely documented in a systematic way.

countries. UNESCO (2014) reports that the Philippines has more than 400 students per computer.[7] Due to a lack of uniform data over time, it is difficult to determine the rate at which computer access is changing in many countries and how persistent the digital divide is likely to be.

2.2 Theory

Access to computers in schools may improve student outcomes in several ways. Computer software has the potential to provide self-paced instruction that is typically difficult to achieve in group instruction (Koedinger et al. 1997). Likewise, the content of instruction may be individualized to the strengths and weaknesses of the student. Because students can use instructional programs without the direct supervision of a teacher, ICTs and computer aided instruction hold the promise of increasing the overall amount of instruction that students receive (Cuban 1993 and Barrow, Markman, and Rouse 2009), while still allowing parents and teachers to monitor student progress. The Internet represents a potentially valuable resource for finding out information about a wide range of educational topics for reducing the coordination costs of group projects. Computers, the Internet, software and other technologies, because of their interactive nature, may engage schoolchildren in ways that traditional methods cannot (Cuban 2003). Further, enhanced computer skills may alter the economic returns to education, especially in fields in which computers are used extensively. These factors, in addition to the direct benefits of being computer literate in the workplace, society and higher education, are behind the decision to invest in ICT and CAI in schools.

[7] The United Nations Educational, Scientific and Cultural Organization (UNESCO) Institute for Statistics has recently been tasked with improving global data on ICT availability and use (UNESCO 2009). While UNESCO has produced reports for several regions since 2012 (Latin America, the Caribbean, and the Arab States), the coverage is still quite limited.

The most relevant policy question of interest is whether schools are choosing the optimal levels of technology relative to traditional inputs. That is, with limited financial resources and instructional time, can schools, district, states, or countries increase academic achievement by investing more in technology. The answer to this question necessarily involves a trade-off between inputs. Financial investment in computers, Internet connections, software and other ICTs is likely to offset investment in traditional resources such as teachers and textbooks. Likewise, time spent using computers in the classroom may offset traditional group instruction by the teacher or independent learning by the student. These tradeoffs imply that the theoretical predictions of the effect of ICT and CAI investment are ambiguous.

Computer resources can be added to a standard model of education production (for examples in the literature see Hanushek 1979, 1986; Rivkin, Hanushek, and Kain 2005; Figlio 1999; and Todd and Wolpin 2003). The binding constraints in such models are the budget for school resources and the amount of class time available for instruction. With these constraints, the comparison of interest is the effectiveness of a dollar invested in ICT relative to a dollar invested in traditional school resources and, analogously, the effectiveness of an hour of classroom time allocated to CAI relative to an hour of traditional instruction. In practice, however, the literature frequently estimates the effect of supplemental investment in ICT and supplemental class time using CAI.[8] These estimates of the effect of ICT and CAI reflect whether technology can have a positive effect on education in the absence of constraints.

[8] The distinction between estimates based on inputs that are supplements to, rather than substitutes for, traditional instruction is rarely made adequately in the literature. A notable exception is Linden (2008), which makes the distinction the focal point of parallel experiments – one that substitutes for traditional instruction with CAI and another that provides supplemental CAI outside of regular school hours.

We consider a model of value-added education that provides a framework in which to discuss the empirical studies discussed in the following section.[9]

(2.1) $A_{it}=f(X_{it},A_{it-1},S_{it},C_{it},T_{it}^{S},T_{it}^{C})$ $\quad s.t. \quad P_t^S S_{it} + P_t^C C_{it} \leq B_t \quad and \quad T_{it}^S + T_{it}^C \leq T$

A measure of academic achievement, A_{it}, is assumed to depend on the characteristics of a student and his or her family, X_{it}, prior year achievement, A_{it-1}, investment in traditional and computer resources, S_{it} and C_{it}, and time allocated to traditional and computer instruction, T_{it}^S and T_{it}^C. The investments S_{it} and C_{it} can be thought of as a per-student average allocation if they are not chosen at the student level, subject to prices P_t^S and P_t^C and a per-student budget B_{it}. Likewise, the amount of time spent on traditional and computer instruction is constrained by total available instructional time T. Note that this model could also be considered at the level of a specific subject of interest. Conversely, if schools or districts cannot choose individual specific input levels, academic outcomes and inputs could be in the aggregate (e.g. the median score on a math exam).

If schools choose the optimal levels of investment and time allocation, then an exogenous reallocation toward technology will result in a negative or zero effect on the educational outcome. If schools do not make optimal choices, then the resulting change is likely to depend on several factors. Shifting investment to technology may have a direct effect on the quality of instruction. Greater investment in technology could improve the effectiveness of time dedicated to computer-based instruction and the corresponding reduction in traditional resources may reduce the effectiveness of time dedicated to traditional instruction. Of course, complementarities between certain technologies and teacher skills could offset some of the negative effect on traditional

[9] See Hanushek (1979) for an early discussion of value-added models in the economics of education literature.

instruction. These effects, holding the respective time allocations fixed, will be positive if $\partial A/\partial C > \partial A/\partial S$. However, schools may change the allocation of instructional time in response to the change in resources. For example, a school with more computers may allocate more time to computer-based instruction and less to group instruction led by a teacher. Thus the total effect of changing the allocation of financial resources may also reflect a reallocation of instructional time, $[\partial A/\partial C + \partial A/\partial T^C * \partial T^C/\partial C] - [\partial A/\partial S + \partial A/\partial T^S * \partial T^S/\partial S]$.

This model can be extended to account for different assumptions about the allocation of classroom time. First, computers may increase the total amount of instruction a student receives if teachers must divide their time between group and individual instruction. In this scenario, some traditional class time, T^S, is wasted for students and CAI can fill in these down periods. This should cause increased investment in ICT, and CAI in particular, to be more likely to have a positive effect on educational outcomes. Alternatively, students may use computers for non-instructional activities that offset instructional time. Furthermore, mechanical problems with technology could create instructional downtime. That is, some computer-based instructional time, T^C, may be wasted and thus crowd out more productive instruction. This should cause ICT investment to be more likely to have a negative effect. We discuss each of these adjustments to the model and the implications for interpreting estimates in the literature.

Barrow, Markman, and Rouse (2009) propose a model to argue that CAI may increase total instructional time during a class period or school day. They assume that a teacher j divides class time between providing group instruction, T_j^G, and individualized instruction for each student i, T_{ij}. Each student receives group instruction and his or her share of individual instruction. Computer instruction, T_i^C, provides supplemental instruction during periods when the teacher is giving individual instruction to other students. This model differs from the baseline model presented above in that CAI replaces down time rather than traditional instruction. The revised constraints make these trade-offs clear.

(2.2) $T_{jt}^{G} + T_{ijt} + T_{it}^{C} \leq T$ and $T_{jt}^{G} + \sum T_{ijt} \leq T_j$

The return to computer-based instruction, $\partial A/\partial T^{C}$, is not offset by a reduction in traditional instruction, $\partial A/\partial T^{S}$. Modeled in this way, CAI will improve academic outcomes if it provides any academic benefit: $f(X_{it},A_{it-1},T_{it},T_t^{G},T_{it}^{C}) \geq f(X_{it},A_{it-1},T_{it},T_t^{G}, 0)$.[10]

Belo, Ferreira, and Telang (2014) model a case in which time spent using computers is not necessarily productive. For example, students may use computers to watch videos or engage in social networking activities that do not improve traditional academic outcomes. In this case, computer time T^{C} is divided between learning time T^{L} and distraction time T^{D}. Thus the new time constraint is $T_{it}^{S} + T_{it}^{L} + T_{it}^{D} \leq T$. This implies that the difference in the marginal returns, $\partial A/\partial T^{C} - \partial A/\partial T^{S}$, depends on both the effectiveness of T^{L} relative to T^{S} and the share of T^{C} that is spent on non-instructional activities. These two models highlight that the effects of CAI estimated in the literature may stem from differences in the quality of the two types of instruction or changes in productive instructional time.

In practice, many empirical studies identify the effects of ICT investment using policies that increase investment in technology at "treated" schools but not at "control" schools without an offsetting reduction in traditional resources. For example, policies exploited by Angrist and Lavy

[10] Note that time not allocated to active teacher or computer instruction is modeled to have no academic benefit for the student. In practice, time spent receiving individualized computer instruction is substituting for whatever the students would have been doing during this time, which may have been independent learning. Thus the estimated effect of CAI in this model may be the benefit of CAI relative to independent learning.

(2002) and Leuven et al. (2007) create some schools that are “winners” and receive larger shares of national ICT investment.[11] These designs seem to favor finding a positive effect relative to a design in which investment must satisfy the budget constraint. Specifically, there does not need to be an offsetting reduction in traditional resources. That is, these designs may estimate $[\partial A/\partial C + \partial A/\partial T^C * \partial T^C/\partial C] - [\partial A/\partial T^S * \partial T^S/\partial S]$ without the offsetting effect $\partial A/\partial S$. Further, there could be an income effect that increases investment in traditional resources (e.g. if funding normally used for computers is used to hire teachers’ aides). Thus a positive effect could be found even if the marginal dollar of investment in technology is not more effective than the marginal dollar invested in traditional resources, and (perhaps) even if technology has no benefit for educational production. Despite the fact that these designs favor finding positive effects, they could nonetheless produce negative estimates if time is reallocated to computer-based instruction and this has smaller returns than traditional instruction (e.g. if a high fraction of computer time is non-instructional). It is also possible that schools may reallocate funds away from traditional instruction to maintain or support investments in technology.

An analogous discussion is relevant for interpreting the results in the CAI literature. If CAI substitutes for traditional instruction, then the estimated effect is a comparison of the marginal effects of traditional instruction and CAI (i.e. $\partial A/\partial T^C - \partial A/\partial T^S$). This is the economic and policy question of interest. However, many policies and experiments used to evaluate CAI increase a student’s instructional time in a specific subject (e.g. Rouse and Krueger 2004) or total instructional time (e.g. Banerjee, Cole, Duflo, and Linden 2007). This occurs when non-academic classes or classes dedicated to other subjects are reallocated to the subject being considered, or when instruction is offered outside of regular school hours. That is, the estimated effects in the

[11] Goolsbee and Guryan (2006) exploit the E-Rate subsidy that results in varying prices of computing across schools and thus has both a price and an income effect.

literature frequently reflect an increase in T rather than just an increase in T^C and the corresponding reduction in T^S. Thus the results should be interpreted as some combination of the effect of substituting CAI for traditional instruction and increasing instructional time. It is worth noting that the benefits of CAI, like those of ICT more broadly, may be attenuated if students use computers for non-academic purposes instead of the intended instruction.

Therefore, many empirical studies on ICT and CAI are structured in favor of finding positive effects on academic outcomes. Interpreting and comparing the estimates in the literature requires careful consideration of whether computer resources are supplementing or substituting for traditional investment. Estimates across studies are also likely to differ due to variation in treatment intensity (the amount of financial investment or the number of hours dedicated to computer use), the duration of the treatment, the quality of the investment, and the quality of the traditional investment or instruction that is offset.

2.3 Empirical Findings

2.3.1 Information and Communication Technologies Investment

Research on the effects of ICT investment in schools has closely mirrored the broader literature on the effects of school investment (see, for example, Betts 1996; Hanushek, Rivkin, and Taylor 1996; and Hanushek 2006). Early studies of ICT in the education literature focused on case studies and cross-sectional comparisons (see Kirkpatrick and Cuban 1998; Noll, et al. 2000 for reviews). Studies in the economics literature have often exploited natural policy experiments to generate variation over time in ICT investment (e.g. Angrist and Lavy 2002; Goolsbee and Guryan 2006; Leuven 2007; Machin, McNally, and Silva 2007). Recent studies of CAI have generally relied on randomized control trials (e.g. Rouse and Krueger 2004; Banerjee, Cole, Duflo, and

Linden 2007; Mathematica 2009; Carillo, Onofa and Ponce 2010; Mo et al. 2014). This section focuses on three important dimensions of variation in the literature: 1) the type of investment (ICT or CAI); 2) the research design (cross-sectional, natural experiment, or RCT); and 3) the interaction of the investment with traditional instruction (supplemental or substituting).

Fuchs and Woessmann (2004) examine international evidence on the correlation between computer access in schools (and homes) and performance on PISA, an internationally administered standardized exam. They show that simple cross-sectional estimates for 32 countries might be biased due to the strong correlation between school computers and other school resources. The authors note that evidence based on cross-sectional differences must be interpreted cautiously. Omitted variables are likely to generate positive bias in cross-country comparisons. However, cross-sectional estimates within countries may exhibit negative bias if governments target resources to schools that serve higher proportions of students from low income households. Once they control for an extensive set of family background and school characteristics, they find an insignificant relationship between academic achievement and the availability of school computers.

Most recent research on ICT investment has exploited policies that promote investment in computer hardware or Internet access. The majority of studies find that such policies result in increased computer use in schools, but few studies find positive effects on educational outcomes. This is in spite of the fact that many of these studies exploit policies that provide ICT investment that supplements traditional investment. The results suggest that ICT does not generate gains in academic outcomes or that schools allow computer-based instruction to crowd out traditional instruction. Regardless, a null result in this context is a stronger result than if there was a binding constraint that required substitution away from investment and time allocated to other inputs.

Angrist and Lavy (2002) find higher rates of computer availability in more disadvantaged schools in Israel, which may be due to the Israeli school system directing resources to schools on a remedial basis. Thus cross-sectional estimates of the effect of computer access are likely to be biased downward. To address this, the authors exploit a national program that provided computers and computer training for teachers in elementary and middle schools. The allocation of computers was based on which towns and regional authorities applied for the program, with the highest priority given to towns with a high fraction of stand-alone middle schools. They present reduced-form estimates of the effect of the program on student test scores and they use the program as an instrumental variable to estimate the effect of computer aided instruction (defined broadly) on test scores.[12] Survey results indicate that the computers were used for instruction, but the authors find negative and insignificant effects of the program on test scores. While the identification strategy estimates the effects of supplemental financial investment in ICT, it did not necessarily result in supplemental class time, so the estimates may reflect the tradeoff between computer aided and traditional instruction. The authors argue that computer use may have displaced other more productive educational activities or consumed school resources that might have prevented a decline in achievement.

The finding that ICT investment generates limited educational gains is common in the literature. Leuven et al. (2007) exploit a policy in the Netherlands that provided additional funding for computers and software to schools with more than seventy percent disadvantaged students. Using a regression discontinuity design, they find that while additional funding is not spent on more or newer computers, students do spend more time on a computer in school (presumably due to new software). But the estimates suggest a negative and insignificant effect on most test score

[12] An identifying assumption for the instrumental variables interpretation is that CAI is the sole channel by which computers would positively or negatively affect academic performance.

outcomes. The authors come to a similar to conclusion as Angrist and Lavy (2002) that computer instruction may be less effective than traditional instruction.

In the United States, Goolsbee and Guryan (2006) examine the federal E-Rate subsidy for Internet investment in California schools. The subsidy rate was tied to a school's fraction of students eligible for a free or reduced lunch, which generated variation in the rate of Internet investment, creating both an income and price effect.[13] Schools that received larger subsidies had an incentive to offset spending on traditional inputs with spending on Internet access. The authors find increased rates of Internet connectivity in schools, but do not find increases in test scores or other academic outcomes. The authors note that access to the Internet may not improve measurable student achievement and that promoting early adoption of technology may result in schools investing too soon in technologies and thus acquiring inferior or higher-cost products. In a more recent paper, Belo, Ferreira, and Telang (2014) examine if broadband use generates a distraction that reduces academic performance in Portugal. They find very large negative effects when using proximity to the internet provider as an instrument for the quality of the internet connection and time spend using broadband.

More recently, Cristia et al. (2014) examine the introduction of the Huascaran program in Peru between 2001 and 2006. The program provided hardware and non-educational software to a selected set of schools chosen on the basis of enrollment levels, physical access to the schools, and commitment to adopt computer use. Using various weighting and matching techniques, they find no effect of the program on whether students repeat a grade, drop out, or enroll in secondary school after primary school. These studies highlight the importance of considering the policy estimates in

[13] The authors attempt to exploit discrete cutoffs in prices to implement a regression discontinuity design. Unfortunately, this does not result in a strong enough first stage to generate reliable estimates, so they exploit time variation in a difference-in-differences design.

the context of an educational production function that considers classroom inputs and time allocation. Despite ICT funding being supplemental to traditional investment, computers may reduce the use of traditional inputs given time constraints.

There are, however, exceptions to the finding that ICT investment does not generate educational gains. Machin, McNally, and Silva (2007) exploit a change in how government ICT funds are allocated in England to generate variation in the timing of investment. This approach results in generally positive estimates for academic outcomes. The authors note that their results may be positive and significant in part because the schools that experienced the largest increases in ICT investment were already effective and thus may have used the investment efficiently. Barrera-Osorio and Linden (2009) find somewhat inconclusive results with statistically insignificant, but point estimates of effects, when they evaluate a randomized experiment at one hundred public schools as part of the "Computers for Education" program in Colombia. The program provided schools with computers and teacher training with an emphasis on language education, but they find that the increase in computer use was not primarily in the intended subject area, Spanish, but rather in computer science classes. Teacher and student surveys reveal that teachers did not incorporate the computers into their curriculum.

A recent trend in educational technology policy is to ensure that every student has his or her own laptop or tablet computer, which is likely to be a much more intensive treatment (in terms of per-student time spent using a computer) than those exploited in the policies discussed above. One of the first large scale one-to-one laptop programs was conducted in Maine in 2002, in which all 7th and 8th grade students and their teachers were provided with laptops to use in school. Comparing writing achievement before and after the introduction of laptops, it was found that writing performance improved by approximately one-third of a standard deviation (Maine

Education Policy Research Institute 2007). Grimes and Warschauer (2008) and Suhr et al. (2010) examine the performance of students at schools that implemented a one laptop program in Farrington School District in California relative to students at non-laptop schools. They find evidence that junior high school test scores declined in the first year of the program. Likewise, scores in reading declined for 4th grade students during the first year. At both grade levels, however, the scores increased in the second year, offsetting the initial decline. This pattern may reflect the fixed costs of adopting computer technology effectively. The changes in these cases are relatively modest in magnitude, but are statistically significant.

A study of the Texas laptop program by the Texas Center for Educational Research (2009) exploited trends at twenty-one schools that adopted the program relative to a matched control group. Schools were matched on factors including district and campus size, region, proportion of economically disadvantaged and minority students, and performance on the Texas Assessment of Knowledge and Skills (TAKS). The laptop program was found to have some positive effects on educational outcomes. Cristia et al. (2012) were able to exploit a government implemented randomized control trial (RCT) to estimate the effect of a laptop policy in Peru. After fifteen months, they find no significant effect on math or language test scores and small positive effects on cognitive skills.

Taken as a whole, the literature examining the effect of ICT investment is characterized by findings of little or no positive effect on most academic outcomes. The exception to this is mixed positive effects of one-laptop initiatives. The modest returns to computer investment is especially informative in light of the fact that nearly all of the estimates are based on policies and experiments that provided supplemental ICT investment. The lack of positive effects is consistent across studies that exploit policy variation and randomized control trials. Because these initiatives do not necessarily increase class time, the findings may suggest that technology aided instruction is not superior to traditional instruction. This finding may be highly dependent on specifically what technology is adopted and how it is integrated into a school's curriculum. The studies above generally do not specify the way in which ICT was used. In the next section, we examine studies that focus on the use of specific, well-defined software programs to promote mathematics and language learning.

2.3.2 Computer Assisted Instruction

Computer aided instruction is the use of specific software programs on computers in the classroom.[14] Frequently these programs are individualized or self-paced in order to accommodate differences in student ability or speed. CAI lends itself to evaluation using randomized control trials because access to software can be offered at the student or classroom level. CAI frequently targets a specific subject area that is tested before and after the software is introduced. Kulik and Kulik (1991) and Liao (1992) summarize the early education literature, which generally suggests positive effects. The evidence from economic studies is mixed and suggests that the characteristics of the intervention are important. Studies in this area differ significantly in the extent to which CAI is a substitute or a supplement to traditional instruction. Interestingly, evidence of positive effects appears to be the strongest in developing countries. This could be due to the fact that the instruction that is being substituted for is not as of high quality in these countries.[15]

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[14] Computer aided instruction (CAI), computer aided learning (CAL), and E-learning are used synonymously in the economics and education literatures.

[15] There are well documented deficiencies in teacher quality and attendance and other education factors in developing countries. For example, Chaudhury et al. (2006) examine the rate of teacher absenteeism, which is 19 percent, and teacher effort in Bangladesh, Ecuador, India, Indonesia, Peru and Uganda.

Rouse and Krueger's (2004) evaluation of "Fast ForWord", a language and reading program, is one of the earliest examples of evaluating a specific CAI using an RCT. They conducted a randomized study that exploited within-school, within-grade variation at four schools that serve a high fraction of non-native English speakers in the northeastern United States. The intervention pulled students out of their otherwise scheduled classes to receive 90-100 minutes of individualized computer aided instruction. The instruction these students missed was not necessarily in reading and language, so treated students received supplemental instruction in this subject area as a result. Despite the construction of the experiment, which favors gains in reading and language skills, they find little to no positive effects across a range of standardized tests that should be correlated with reading and language skills. The authors argue that computers may not be as effective as traditional classroom instruction.

In a large randomized study, the U.S. Department of Education and Mathematica Policy Research (2007, 2009) evaluated six reading and four math software products for students in elementary, middle, and high school. Randomization was across teachers within the same schools. Nine of the ten products were found to have no statistically significant effect, while the tenth product (used for 4th grade reading) had a positive effect. The study also examined how usage and effects changed between the first and the second years of implementation, allowing the researchers to test if teacher experience with the products was an important determinant of outcomes. They found that usage actually decreased on average in the second year and there were no positive effects.

Some studies, however, find positive effects of CAI initiatives. Barrow, Markman and Rouse (2009) exploit a within-school randomization at the classroom level in three large urban districts in the U.S. They find statistically significant positive effects of computer aided instruction when treated classes are taught in the computer lab using pre-algebra and algebra software. They also find some evidence that the effects are larger for classrooms with greater enrollment, which is consistent with the predictions of their model of time allocation (discussed in Section 2.2). The authors note that such effects may not translate to different software or different schools, but conclude that the positive findings suggest that CAI deserves additional evaluation and policy attention especially because it is relatively easy to implement compared with other interventions.

Banerjee, Cole, Duflo, and Linden (2007) note that the generally insignificant effects of computer interventions in developed countries may not hold in developing countries where computers may replace teachers with less motivation and training. They test an intervention in India in which trained instructors guided students through two hours of computer instruction per week, one hour of which was outside of the regular school day. Thus the intervention was a combination of guided computer instruction by a supplemental instructor and additional class time. They find that the intervention has large and statistically significant effects on math scores, but also find significant fade-out in subsequent years. However, Linden (2008) finds very different results when attempting to separate the effects of in-class “substitution” for standard instruction from out-of-school “complements”. Using two randomized experiments, test score effects for 2nd and 3rd graders in India were large and negative for the in-school intervention and insignificant and positive for the out-of-school intervention. The negative in-school results could stem from the fact that the program was implemented in “well-functioning network of NGO-run schools” or that the specific software being used was ineffective. That is, both the nature of the technology and what is being substituted for are important considerations when evaluating effect sizes.

Carrillo, Onofa and Ponce (2010) find positive effects of the Personalized Complementary and Interconnected Learning software in Ecuador. The program was randomized at the school level and provided three hours of individualized math and language instruction to treated students each week. The initiative produced positive gains on math scores and no effect on language scores. Mo et al. (2014) conduct a randomized experiment at 72 rural schools in China. The intervention provided 80 minutes of supplemental math instruction (math based computer games) per week during what would otherwise be a computer skills class. The intervention was estimated to generate an increase in math scores of 0.17 standard deviations for both 3rd and 5th grade students. It is important to note that the instruction was supplemental both in terms of providing additional mathematics instruction and not offsetting another academic subject.[16]

In an analysis of randomized interventions (both technological and non-technological) in developing countries, Kremer, Brannen, and Glennerster (2013) hypothesize that CAI tailored to each student may be the most effective. McEwan (2014) concludes that computer based interventions in primary schools have higher average effects (0.15 standard deviations) than teacher training, smaller classes, and performance incentives. However, he makes the important point that it is "misleading" to compare effect sizes without considering cost.

2.3.3 Computer Skills

Computer use in schools may benefit students in two ways: through the acquisition of computer skills that are useful in the labor market; and through the acquisition of basic skills such as math, reading, and writing. The economics literature has provided different justifications for focusing on the effectiveness of computers as a pedagogical tool for acquiring basic skills. Angrist and Lavy (2002) argue that computer skills training (CST) "seems undeniably useful" whereas the

[16] The authors note that their results may differ from Linden (2008) due to the fact "that by integrating the CAL program during a relatively unproductive period of time…the substitution effect may have been minimized."

evidence for CAI "is both limited and mixed". Fuchs and Woessmann (2004) provide the antithetical justification for focusing on CAI, arguing that the literature finds little evidence that computer skills have "direct returns on the labor market" whereas the returns to basic academic skills are undeniable. There is clearly a need for more research on the effect of computer skills on labor market outcomes.

Most of the studies discussed in this paper do not estimate the effect of ICT on computer skills. A primary challenge is that academic exams do not provide a direct measure of computer skills, so these benefits may go unmeasured. For example, Goolsbee and Guryan (2006) note that ICT may "build skills that are unmeasured by standard tests". Several studies find evidence that enhance education in computer skills may be the primary result of many initiatives. For example, Barrera-Osorio and Linden (2009) find a significant increase in computer use in computer science and not in any other subject. Likewise, Bet, Ibarrarán and Cristia (2014) find that increased availability of technology affected time spent teaching digital skills, but computers were not used in math and language. Recent one-to-one laptop program policies have highlighted the need for "21st century skills", which go beyond basic computer skills and are likely even more difficult to measure.

2.3.4 Online College Courses

A new and rapidly growing area of research related to CAI is estimating the effectiveness of online instruction for college courses. In this context, online education is frequently a method for delivering traditional instruction (e.g. streaming videos of college lectures). The primary question of interest is how student performance in online courses compares to performance in the equivalent traditional course. Evidence from the first wave of studies appears to show that, at this time, Internet courses are less effective than in-person instruction. However, because online courses are lower cost per student, performance differences do not necessarily mean that online courses are not cost effective. Further, online courses may expand the number of students able to take courses due to financial, enrollment, or geographic constraints.

Several recent studies exploit randomized assignment of students to online and in-person education at the college level. Figlio et al. (2013) conduct a randomized experiment at a U.S. university and find evidence that in-person instruction results in higher performance in introductory microeconomics, especially for males, Hispanics, and lower-achieving students. Alpert, Couch and Harmon (2015) use a random experiment to evaluate instruction in an introductory economics course by traditional face-to-face classroom instruction, blended face-to-face and online instruction, and exclusive online instruction. They find evidence of negative effects on learning outcomes from online instruction relative to traditional instruction, but no evidence of negative effects from blended instruction relative to traditional instruction. Bowen et al. (2014) conduct an experiment at six college campuses to compare traditional instruction to "hybrid" in-person and online instruction for a statistics course. They find no significant performance difference in performance between the two groups. Bettinger et al. (2014), using variation in access to in-person courses as an instrument, find lower performance and higher variation for students enrolled in online courses. Patterson (2014) proposes internet distractions as a possible reason for reduced performance in online courses. He conducts an experiment which finds that student performance improves when they use a commitment device to limit access to certain webpages. In related work, Joyce et al. (2014) find experimental evidence that the frequency of class meetings remains important even when course materials are available online.

Summary

Several patterns emerge when evaluating the effects of computer use in schools. Divisions in the literature emerge in terms of the nature of the intervention being studied, the research design, the parameter being estimated, and the school context. We provide an overview of each study and its key characteristics and findings in Table 4. The most prominent distinction is the division between ICT and CAI focused studies, which tend to coincide with methodological differences. The high cost of ICT hardware and connections, and the fact that it does not target specific students has meant that the majority of rigorous empirical research has exploited natural experiments generated by government policies. In contrast, several studies evaluating CAI software, which can target specific classrooms or students, have used randomized control trial designs. It is important to note that despite the division between these two types of studies, ICT investment is likely to be a necessary condition for making CAI available.[17]

Both ICT and CAI produce somewhat mixed evidence of the effect of computers on student outcomes, though there appears to be more evidence of positive effects in studies of CAI. There are several reasons why CAI studies may be more likely to find positive effects. One explanation is methodological. Beyond differences in research design, it may be the case that targeted CAI is more likely to generate positive effects than broader ICT initiatives. Specifically, CAI studies are more likely to result in supplemental instructional time. That is, while ICT studies may reflect a tradeoff between time allocated to computer-based instruction and traditional instruction, CAI estimates may reflect the net increase in instruction and therefore be biased in favor of positive findings. Further, ICT investment may not result in an increase in educational software and may

[17] This has a direct analogue in the economics of education literature more broadly. Many studies examine how funding affects student outcomes (with little regard for the specific inputs the funding makes possible) while other studies examine the effects of specific inputs.

increase computer use that detracts from traditional instruction (e.g. non-educational computer games, social networking, or internet use). By contrast, CAI studies focus narrowly on specific software and the educational outcomes that these are likely to affect.

Some of the notable exceptions to the pattern of null effects occur in studies set in the context of developing, rather than developed countries. This may indicate that the quality of the education or other activities being substituted for is lower. There also appears to be some evidence that interventions which target math are more likely to generate positive effects than interventions that target language. This could be due to the relative ease of making effective software for math relative to language or the relative ease of generating gains in math.

The finding that the results do not adhere to clear patterns should not be surprising. Policies and experiments differ in cost, the type of treatment (the specific hardware or software provided), the length of the intervention (number of years), the intensity of the treatment (hours per day), whether they supplement or substitute for other inputs, the grade levels treated, and the academic subject targeted. We highlight these differences in Table 4. Also, relatively little attention is given in the literature to heterogeneity in treatment effects by student characteristics, which is likely due in part to the finding of no effect overall in many studies. Nonetheless, some studies do differentiate the effects by gender and by baseline academic performance. While no patterns by gender emerge, some studies find evidence that computer resources benefit lower performing students more than the highest performing students (e.g. Banerjee, Cole, Duflo, and Linden 2007 and Barrow, Markman, and Rouse 2009).

3. Technology Use at Home by Students

3.1 Estimates of rates of technology use at home by students

Computer and Internet use at home has grown rapidly over the past two decades. It is astonishing that only 20 years ago less than one-fourth of the U.S. population had access to a computer at home (see Figure 2). Only 17 years ago, less than one-fifth of the U.S. population had an Internet connection at home. The most recent data available for the United States, which are for 2012, indicate that roughly 80 percent of the population has access to a home computer and 75 percent of the population has access to an Internet connection at home.

Schoolchildren have even higher rates of access to computers and the Internet at home. Eighty-six percent have access to computers and 83 percent have access to the Internet. These rates are considerably higher than when the CPS first collected information on home computer access. In 1984, roughly 15 percent of children had access to a computer at home (U.S. Census Bureau 1988) Access to home computers and the Internet also rises with the age of the student (see Figure 3). Home Internet use rises especially sharply with the age of the student.

Surveys from the 2012 Programme for International Student Assessment (PISA) conducted by the OECD provide information on computer and Internet access at home among schoolchildren across a large number of countries. Table 2 reports estimates for the 50 largest countries in the world with available data. In most developed countries a very large percentage of schoolchildren have access to a computer at home that they can use for schoolwork. In contrast, schoolchildren in developing countries often have very low levels of access. For example, only 26 percent of schoolchildren in Indonesia and 40 percent of schoolchildren in Vietnam have access to a home computer. In most developed countries a very large percent of schoolchildren also report having an Internet connection. Although data availability is more limited for Internet connection rates, the

PISA data provide some evidence that children in developing countries have lower levels of access than developed countries. Only 52 percent of schoolchildren in Mexico, for example, report having an Internet connection at home. These patterns of access to home computers and Internet among schoolchildren generally follow those for broader household-based measures of access to home computers and the Internet published by the OECD (2104) and International Telecommunications Union (2014a).[18] ITU data indicate that 78 percent of households in developed countries have Internet access compared with 31 percent of households in developing countries (ITU 2014b).

Over the past decade the percentage of students with home computers has increased. Figure 4 displays trends in home computer access from 2003 to 2012 for selected large countries with available data. Home computer rates for schoolchildren have been very high in high-income countries such as the United States and Germany over the past decade. Other large countries have experienced rapid improvements in access to computers among schoolchildren over the past decade. Russia has caught up with high-income countries, and access to computers in Brazil grew from 36 percent as recently as 2006 to 72 percent in 2012. Schoolchildren in Mexico and Turkey have also seen rapid improvements in access to home computers over the past decade. Access to home computers has grown over the past decade for Indonesian schoolchildren, but remains relatively low.

Even with very high rates of access to home computers and the Internet in developed countries, large disparities remain within countries.[19] In the United States, for example, 9 million schoolchildren do not have access to the Internet at home with the lack of access being

[18] See Caselli and Coleman (2001); Wallsten (2005); Dewan, Ganley and Kraemer (2010); Andrés et al. (2010); Chinn and Fairlie (2007, 2010) for a few examples of previous studies of disparities in computer and Internet penetration across countries.

[19] See Hoffman and Novak 1998; Mossberger, Tolbert, and Stansbury 2003; Warschauer (2003); Ono and Zavodny 2007; Fairlie 2004; Mossberger, Tolbert, and Gilbert 2006; Goldfarb and Prince 2008 for examples of previous studies of disparities in computer and Internet use within countries.

disproportionately concentrated among low-income and disadvantaged minority schoolchildren.[20] Among schoolchildren living in households with $25,000 or less of income 67 percent have access to a home computer and 59 percent have access to the Internet at home, whereas 98 percent of schoolchildren living in households with $100,000 or more in income have access to a home computer and 97 percent have access to the Internet at home. Large disparities also exist across race and ethnicity. Among African-American schoolchildren 78 percent have home computers and 73 percent have home Internet access, and among Latino schoolchildren 78 percent have home computers and 71 percent have home Internet access. In contrast, 92 percent of white, non-Latino schoolchildren have home computers and 89 percent have home Internet access.

Disparities in access to home computers within countries and across countries may contribute to educational inequality. However, the rapidly expanding use of computers and the Internet at home in developing countries might have implications for relative trends in educational outcomes.

3.2 Theoretical Issues

In addition to teacher and school inputs, student and family inputs are important for the educational production function. The personal computer is an example of one of these inputs in the educational production process, and there are several reasons to suspect that it is important. First, personal computers make it easier to complete course assignments through the use of word processors, the Internet, spreadsheets, and other software (Lenhart, et al. 2001, Lenhart, et al. 2008). Although many students could use computers at school and libraries, home access represents the highest quality access in terms of availability, flexibility and autonomy, which may

[20] These estimates are calculated from October 2012 Current Population Survey, Internet Use Supplement microdata.

provide the most benefits to the user (DiMaggio and Hargittai 2001). Children report spending an average of 16 minutes per day using computers for schoolwork (Kaiser Family Foundation 2010). Access to a home computer may also improve familiarity with software increasing the effectiveness of computer use for completing school assignments and the returns to computer use at school (Underwood, et al. 1994, Mitchell Institute 2004, and Warschauer and Matuchniak 2009). As with computers used in school, owning a personal computer may improve computer specific skills that increase wages in some fields. Finally, the social distractions of using a computer in a crowded computer lab may be avoided by using a computer at home.

On the other hand, home computers are often used for games, social networking, downloading music and videos, communicating with friends, and other forms of entertainment potentially displacing time for schoolwork (Jones 2002; U.S. Department of Commerce 2004; Kaiser Family Foundation 2010).[21] Children report spending an average of 17 minutes per day using computers for playing games and an average of 21 minutes per day using computers for watching videos and other entertainment (Kaiser Family Foundation 2010). A large percentage of computer users report playing games at least a few times a week (Lenhart, Jones and Rankin 2008). Time spent using social networking sites such as Facebook and Myspace and other entertainment sites such as YouTube and iTunes has grown rapidly over time (Lenhart 2009). Children report spending an average of 22 minutes per day using computers for social networking (Kaiser Family Foundation 2010). Computers are often criticized for displacing more active and effective forms of learning and for emphasizing presentation (e.g. graphics) over content (Giacquinta, et al. 1993, Stoll 1995 and Fuchs and Woessmann 2004). Computers and the Internet also facilitate cheating and plagiarism and make it easier to find information from non-credible sources (Rainie and Hitlin

[21] Similar concerns were expressed earlier over television crowding out schoolwork time (see Zavodny 2006 for example).

2005). In the end, it is ambiguous as to whether the educational benefits of home computers outweigh their distraction and displacement costs.

Beltran, Das and Fairlie (2010) present a simple theoretical model that illustrates these points in the context of a utility maximization problem for a high school student. A linear random utility model of the decision to graduate from high school is used. Define U_{i0} and U_{i1} as the *i*th person's indirect utilities associated with not graduating and graduating from high school, respectively. These indirect utilities can be expressed as:

(3.1) $U_{i0} = \alpha_0 + \beta_0'X_i + \gamma_0 C_i + \lambda_0 t(W_i, C_i) + \theta Y_0(Z_i, C_i) + \varepsilon_{i0}$, and

(3.2) $U_{i1} = \alpha_1 + \beta_1'X_i + \gamma_1 C_i + \lambda_1 t(W_i, C_i) + \theta Y_1(Z_i, C_i) + \varepsilon_{i1}$,

where X_i, Z_i and W_i may include individual, parental, family, geographical, and school characteristics; C_i is the presence of a home computer; Y_0 and Y_1 are expected future earnings; and t is the child's achievement (e.g. test score), and ε_i is an additive error term. X_i, Z_i *and* W_i do not necessarily include the same characteristics because the individual, family and other characteristics affecting utility, test scores and expected future earnings may or may not differ. Achievement is determined by the characteristics, W_i, and the presence of computers is allowed to have different effects on the utility from the two educational choices. Expected earnings differ between graduating from high school and not graduating from high school, and are functions of the characteristics, Z_i, and home computers.

In the model, there are three major ways in which home computers affect educational outcomes. First, there is a direct effect of having a home computer on the utility of graduating from high school, γ_1. Personal computers make it easier to complete homework assignments through the use of word processors, spreadsheets, Internet browsers and other software, thus increasing the utility from completing schoolwork. Home access to computers offers more availability and autonomy than school access and may familiarize students with computers increasing the returns to computer use in the classroom. Second, access to home computers may have an additional effect on the utility of staying in school beyond making it easier to finish homework and complete assignments. In particular, the use of home computers may "open doors to learning" and doing well in school (Cuban 2001 and Peck, et al. 2002), and thus encourage some teenagers to graduate from school. Third, personal computers also provide utility from games, email, chat rooms, downloading music, and other non-education uses creating an opportunity cost from doing homework. The higher opportunity cost increases the utility of not graduating from high school. On the other hand, the use of computers at home, even for these non-educational uses, keeps children off the street, potentially reducing delinquency and criminal activities. These activities increase the utility from dropping out of school. The two opposing factors make it difficult to sign the effect of computers on the utility from not graduating from high school, γ_0.

Another way in which personal computers affect the high school graduation decision is through their effects on academic achievement. Computers could improve academic performance directly through the use of educational software and focusing time use on content. Computers and the Internet, however, may displace other more active forms of learning, emphasize presentation over content, and increase plagiarism. Therefore, the theoretical effects of computers on academic achievement, dt/dC, and thus on the utility from graduating from high school, $\lambda_1 dt/dC$, is ambiguous. Finally, computer skills may improve employment opportunities and wages, but mainly in combination with a minimal educational credential such as a high school diploma, implying that $dY_1/dC > dY_0/dC$.

Focusing on the high school graduation decision, we assume that the individual graduates from high school if $U_{i1} > U_{i0}$. The probability of graduating from high school, $y_i=1$, is:

$$(3.3)\ P(y_i=1) = P(U_{i1} > U_{i0})=$$

$$F[(\alpha_1-\alpha_0) + (\beta_1-\beta_0)'X_i +(\gamma_1 - \gamma_0)C_i + \theta(Y_1(Z_i, C_i) - Y_0(Z_i, C_i)) + (\lambda_1 - \lambda_0)t(W_i, C_i)]$$

where F is the cumulative distribution function of $\varepsilon_{i1}-\varepsilon_{i0}$. In (3.3), the separate effects of computers on the probability of graduating from high school are expressed in relative terms. Home computers have a direct effect on the graduation probability through relative utility, and indirect effects through improving achievement and altering relative earnings. The net effect of home computers on high school graduation, however, is theoretically ambiguous.

Vigdor, Ladd and Martinez (2014) model the adolescent's maximization problem as one of allocating time and money across competing uses. Adolescents devote time t_i and pay a monetary cost p_i to engage in different activities within the set of all potential activities. Each activity contributes directly to the adolescent's utility, and some activities also contribute indirectly to utility through building human capital and increasing future living standards. Utility can be written as $U = U(A, S(A))$, where A is the vector of activity choices and $S(A)$ is the future living standard given these activity choices. Not all activities increase future living standards, and adolescents place at least some weight on future living standards in the their computation of utility. Adolescents also face a time constraint and a budget constraint. The solution to the resulting utility maximization problem equates the ratio of prices of any two activities to the ratio of marginal utilities of the two activities.

Using this framework, the introduction of home computers and broadband Internet can be viewed as a shock to the prices and time costs of various activities. Vigdor, Ladd and Martinez (2014) provide several examples in which computer technology reduces the prices and time costs of activities, and thus potentially increases their use. They note that access to word processing software reduces the cost of revising a term paper, and access to broadband reduces the cost of conducting research for an essay. Computer and broadband access also reduce the marginal cost of playing games or engaging in multiparty conversations with friends. The first two examples of activities presumably have a positive impact on expected future living standards, whereas the impact on expected future living standards of games and social networking is less clear. Even if these two activities have positive returns, they might have smaller returns to future living standards than the activities that they displace.

Vigdor, Ladd, and Martinez (2014) also note that the simple model could be expanded to incorporate the cost of technology. Although the adolescent is unlikely to purchase computers with his/her own money, the family's purchase of computers and Internet service could crowd out other "educational" expenditures. Another issue is that the maximization problem requires adolescents to make decisions with long-run consequences, and they may not be "neurologically" developed enough to make such decisions. This is less of a problem, however, if adolescents have at least weak preferences for building human capital and improving future living standards. Another point that Vigdor, Ladd and Martinez raise is that in many cases the realized time allocations of adolescents will be determined not only by their own preferences, but by constraints placed on them by parents, teachers and other adults. The model could be revised to incorporate these restrictions on activities, but one important implication is that the impact of computer technology on educational outcomes could vary with parental supervision.

These theoretical models provide some insights into how home computers might exert both positive and negative influences on educational outcomes, and demonstrate that the net total effect is difficult to determine. Families and students are likely to make decisions about computer purchases and Internet subscriptions in part based on these comparisons. If households are rational and face no other frictions, those households without computers have decided not to buy a computer because the returns are relatively low. However, it is also possible that various constraints prevent households from investing in home computers even if the returns are high. Parents may face credit constraints, be unaware of the returns to computer use, not be technically comfortable with computers, and have concerns about privacy. There is reason to suspect that these constraints might be important, given that households without computers tend to be substantially poorer and less educated than other households. Thus, the effect of computers for such families is an open and important question.

3.3 Empirical Findings

3.3.1 Effects of home computers and the Internet on educational outcomes

Although the theoretical models provide some insights into how home computers might exert positive and negative effects on the educational outcomes, they do not provide a prediction of the sign and magnitude of the net effect. A small, but growing empirical literature estimates the net effects of home computers on a wide range of educational outcomes. The literature on the topic has evolved over time primarily through methodological improvements. Earlier studies generally regress educational outcomes on the presence of a home computer while controlling for student, family and parental characteristics. More recent studies focus on quasi-experimental approaches and randomized control experiments.

One of the first studies to explore whether home computers have positive educational effects on children was Attewell and Battle (1999). Using the 1988 National Educational Longitudinal Survey (NELS), they provide evidence that test scores and grades are positively related to access to home computers among eighth graders even after controlling for differences in several demographic and individual characteristics including typically unobservable characteristics of the educational environment in the household.[22]

Using data from the 2001 Current Population Survey (CPS), Fairlie (2005) estimates the relationship between school enrollment and having a home computer among teenagers. Controlling for family income, parental education, parental occupation and other observable characteristics in probit regressions for the probability of school enrollment, he finds a difference of 1.4 percentage points (base rate of 85 percent). In a subsequent paper, Beltran, Das and Fairlie (2010) use panel data from the matched CPS (2000-2004) and the National Longitudinal Survey of Youth (1997- 2002) to estimate the relationship between home computers and subsequent high school graduation. They find that teenagers who have access to home computers are 6–8 percentage points more likely to graduate from high school than teenagers who do not after controlling for individual, parental, and family characteristics. Using detailed data available in the NLSY97, they also find that the estimates are not sensitive to the inclusion of difficult-to-find characteristics of the educational environment in the household and extracurricular activities of the student.[23] Estimates indicate a strong positive relationship between home computers and

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[22] They include measures of the frequency of child-parent discussions of school-related matters, parents' familiarity with the parents of their child's friends, attendance in "cultural" classes outside of school, whether the child visits science or history museums with the parent, and an index of the educational atmosphere of the home (e.g. presence of books, encyclopedias, newspapers, and place to study).

[23] The controls include religion, private school attendance, whether a language other than English is spoken at home, whether there is a quiet place to study at home, and whether the child takes extra classes or lessons, such as music, dance, or foreign language lessons.

grades, a strong negative relationship with school suspension, and suggestive evidence of a negative relationship with criminal activities.

Schmitt and Wadsworth (2006), using the British Household Panel Survey (1991-2001), find a significant positive association between home computers and performance on the British school examinations. The results are robust to the inclusion of individual, household and geographical controls, including proxies for household wealth and prior educational attainment. Fiorini (2010) provides evidence on the impacts of home computers among young Australian children ages 4 to 7. She shifts the focus from access to home computers to computer use among children (although some results include computer access as an instrumental variable for computer use). Using data from the Longitudinal Study of Australian Children (2004-06), she finds evidence of a positive relationship between computer use and cognitive skills among young children.

In contrast to these findings of positive effects of home computers on educational outcomes, Fuchs and Woessmann (2004) find a negative relationship between home computers and student achievement using data from 31 developed and emerging countries among teenagers. Using the PISA database, they find that students with home computers have significantly lower math and reading test scores after controlling for student, family and school characteristics and country fixed effects. They find a large positive association between home computers and test scores in bivariate comparisons without controls.

Although regressions of educational outcomes on home computers frequently control for numerous individual, family and school characteristics, they may nonetheless produce biased estimates of causal effects due to omitted variables. In particular, if the most educationally motivated families (after controlling for child and family characteristics) are more likely to purchase computers, then a positive relationship between academic performance and home computers may capture the effect of unmeasurable motivation on academic performance. Conversely, if the least educationally motivated families are more likely to purchase computers, perhaps motivated by their entertainment value, then estimates will be downward biased.

To address these concerns, a few recent studies (including some discussed above) estimate the impacts of home computers on educational outcomes using instrumental variable techniques, individual-student fixed effects, and falsification tests. Fairlie (2005) addresses the endogeneity issue by estimating instrumental variable models. Bivariate probit models of the joint probability of school enrollment and owning a home computer result in large positive coefficient estimates (7.7 percentage points). Use of computers and the Internet by the child's mother and father, and MSA-level home computer and Internet rates are used as exclusion restrictions. Some supporting evidence is provided that these variables should affect the probability of the family purchasing a home computer but should not affect academic performance after controlling for family income, parental education and occupation, and other factors. Beltran, Das and Fairlie (2010) also estimate bivariate probits for the joint probability of high school graduation and owning a home computer and find point estimates similar to those from a multivariate regression. Similar exclusion restrictions are used with the addition of the presence of another teenager in the household. Fiorini (2010) uses instrumental variables for computer use in her study of young Australian children and generally finds larger positive estimates of computer use on test scores than in OLS regressions. The number of older siblings and Internet use at work by men and women at the postcode level are used as exclusion restrictions.

Another approach, first taken by Schmidt and Wadsworth (2006), is to include future computer ownership in the educational outcome regression. A positive estimate of future computer ownership on educational attainment would raise concerns that current ownership proxies for an unobserved factor, such as educational motivation. Future computer ownership, however, is not found to have a positive relationship with educational outcomes similar to the positive relationship found for contemporaneous computer ownership (Schmidt and Wadsworth 2006 and Beltran, Das and Fairlie 2010). Along these lines of falsification tests or "pencil tests" (DiNardo and Pischke 1997), Schmidt and Wadsworth (2006) do not find evidence that other household assets which proxy for wealth such as dishwashers, driers and cars have similar effects on educational attainment. Similarly, Beltran, Das and Fairlie (2008) do not find evidence of a positive relationship between educational attainment and having a dictionary or cable television at home, which also might be correlated with unobserved educational motivation or wealth.

A couple of studies address selection concerns by estimating fixed effect models. The inclusion of student fixed effects controls for differences in unobservable characteristics that are time-invariant. Vigdor, Ladd and Martinez (2014), using panel data from North Carolina public schools, find modestly-sized negative effects of home computer access and local-area access to high-speed Internet connections on math and reading test scores when including fixed effects. In contrast, they find positive estimates when student fixed effects are excluded. Beltran, Das and Fairlie (2010) find that adding student fixed effects results in smaller positive point estimates that lose significance.

Malamud and Pop-Eleches (2010) address the endogeneity problem with a regression discontinuity design (RDD) based on the effects of a government program in Romania that allocated a fixed number of vouchers for computers to low-income children in public schools. The basic idea of the RDD is that schoolchildren just below the income threshold for eligibility for a computer voucher are compared to schoolchildren just above the income threshold. The two groups of schoolchildren close to the threshold have nearly identical characteristics and differ only in their eligibility for the computer voucher. Estimates from the discontinuity indicate that Romanian children winning vouchers have lower grades, but higher cognitive ability as measured by Raven's Progressive Matrices.

A few randomized control experiments have been conducted to evaluate the effects of home computers on educational outcomes. The first random experiment involving the provision of free computers to students for home use was Fairlie and London (2012). The random-assignment evaluation was conducted with 286 entering students receiving financial aid at a large community college in Northern California.[24] Half of the participating students were randomly selected to receive free computers. After two years, the treatment group of students who received free computers had modestly better educational outcomes than the control group along a few measures. Estimates for a summary index of educational outcomes indicate that the treatment group is 0.14 standard deviations higher than the control group mean. Students living farther from campus and students who have jobs appear to have benefitted more from the flexibility afforded by home computers. The results from the experiment also provide the only evidence in the literature on the effects of home computers for post-secondary students.

Fairlie and Robinson (2013) also conduct a random experiment, but shift the focus from college students to schoolchildren. The experiment includes 1,123 students in grades 6-10 attending 15 schools across California. All of the schoolchildren participating in the study did not have computers prior to the experiment and half were randomly selected to receive free computers. The results indicate that even though there was a large effect on computer ownership and total hours of computer use, there is no evidence of an effect on a host of educational outcomes,

[24] The focus on the impacts of computers on community college students is important, unlike four-year colleges where many students live on campus and have access to large computer labs, community college students often have limited access to on-campus technology.

including grades, standardized test scores, credits earned, attendance, and disciplinary actions. No test score effects are found at the mean, at important cutoffs in the distribution (e.g. passing and proficiency), or at quantiles in the distribution. The estimates are precise enough to rule out even moderately-sized positive or negative effects. Consistent with these results, they find no evidence that treatment students spent more time on homework and that the computers had an effect on turning homework in on time, software use, computer knowledge, or other intermediate inputs in education. Treatment students report spending more time on computers for schoolwork, but they also report spending more time on computers playing games, social networking and for other entertainment.

Most of the evidence in the literature focuses on the effects of home computers on the educational outcomes of schoolchildren in developed or transition economies. A couple of previous studies use random experiments to examine the impacts of one laptop per child (OLPC) laptops on educational outcomes in developing countries.[25] Beuermann et al. (2012) examine the impacts of randomly providing approximately 1,000 laptops for home use to schoolchildren in grades 1 through 6 in Peru.[26] They find that the laptops have a positive, but small and insignificant effect on cognitive skills as measured by the Raven's Progressive Matrices test (though the effect is significant among children who did not already have a home computer before the experiment).

[25] Although the One Laptop per Child program in Peru (Cristia et al. 2012) and the Texas laptop program (evaluated with a quasi-experiment in Texas Center for Educational Research 2009) were initially intended to allow students to take computers home when needed in addition to using them in school, this did not happen in most cases. In Peru, some principals, and even parents, did not allow the computers to come home because of concerns that the laptops would not be replaced through the program if they were damaged or stolen. The result is that only 40 percent of students took the laptops home, and home use was substantially lower than in-school use. In Texas, there were similar concerns resulting in many schools not allowing computers to be taken home or restricting their home use. The main effect from these laptop programs is therefore to provide one computer for every student in the classroom, rather than to increase home access.

[26] Recipients of the laptops were also provided with an instruction manual and seven weekly training sessions.

Teachers reported that the effort exerted in school was significantly lower for treatment students than control students and that treated children reported reading books, stories or magazines less than control children. Mo et al. (2012) randomly distribute OLPC laptops to roughly half of a sample of 300 young schoolchildren (grade 3) in China.[27] They find some evidence that the laptops improved math test scores, but no evidence of effects on Chinese tests. They also find that the laptops increased learning activity use of computers and decreased time spent watching television.

3.3.2 Heterogeneity in Home Computer Effects

The effects of home computers on educational outcomes might differ across subgroups of the student population. For example, minority students might benefit more or less from having a home computer because of more limited opportunities for alternative places of access, social interactions with other computer users, and learning about use from parents, siblings and friends. Girls and boys may differ in how they use computers possibly resulting in differential effects. Several studies estimate separate home computer effects by demographic group and other student characteristics. For example, in Attewell and Battle's (1999) study of home computer effects on the test scores and grades of eighth graders they find evidence of stronger positive relationships between home computers and educational outcomes for higher SES children, boys, and whites. Fiorini's (2010) study of the impacts of home computer use on cognitive and non-cognitive skills among Australian children ages 4 to 7 finds evidence of larger effects for girls and children with less educated parents. Fairlie (2012) finds larger effects of home computers on educational outcomes for minority college students than non-minority college students.

[27] The laptops included some tutoring software and one training session was provided.

As with school-based interventions, the evidence is mixed with several studies not finding evidence of heterogeneity in the effects of home computers. For example, Beltran, Das and Fairlie (2010) estimate regressions that include interactions between home computers and race, income or gender and, in almost all cases, do not find statistically significant interaction effects. Fairlie and Robinson (2013) and Fairlie (2015) find no evidence of heterogeneous treatment effects by pre-treatment academic achievement, parental supervision, propensity for non-game use, grade, race, or gender. Beuermann et al. (2012) find some evidence of a larger reduction in school effort for younger Peruvian children, but essentially no difference in effects on cognitive skills for younger children and no difference in effects on school effort and cognitive skills by gender. In their study of Romanian schoolchildren, Malumud and Pop-Eleches (2010) do not find evidence of differential effects by gender, but do find that younger children experience larger gains in cognitive skills. Given the lack of consistency in findings across studies for any subgroup, it is difficult to draw strong conclusions on this question.

3.3.3 Effects on Computer Skills and Other Outcomes

Several previous studies examine the impacts of home computers on computer skills. There is some evidence of positive impacts, but surprisingly the overall evidence is not universally strong. For example, Fairlie (2012) finds evidence of positive effects of home computers on computer skills among college students, whereas Fairlie and Robinson (2013) find no evidence of home computers on computer knowledge or skills among schoolchildren. Among young children in Peru, Beuermann et al. (2012) find strong evidence that the OLPC laptops improved scores on a proficiency test in using the laptop, but find no effects on skills for using a Windows based computer or using the Internet. Mo et al. (2013) finds large positive effects on computer skills from OLPC laptops for young children in China. Finally, Malamud and Pop-Eleches (2010) find that winning a computer vouchers increased computer knowledge, fluency and applications, but not web and email fluency among Romanian children.

Research has also focused on the impacts of specific types of computer use or impacts on other educational or social outcomes. For example, a few studies have explored the effects of Facebook use among college students on academic outcomes and find mixed results (see Pasek and Hargittai 2009, Kirschner and Karpinski 2010, and Junco 2012 for example). Bauernschuster, Falck and Woessmann (2014) use German data to examine the effects of broadband Internet access on children's extra-curricular school activities such as sports, music, arts, and drama and do not find evidence of crowd out. Finally, Beuermann et al. (2012), using data from Peru's randomization across and within schools, do not find evidence of spillovers to classmates and friends (though close friends appear to become more proficient at using a laptop).

Summary

A few patterns emerge from the review of the empirical literature on home effects. First, studies using multivariate regressions and instrumental variable models tend to show large positive (and in some cases negative) effects, but studies using randomized control experiments tend to show zero or small positive effects. As noted above, the contrast in findings may be due to selection bias. Fairlie and London (2012) find evidence that non-experimental estimates for community college students are nearly an order of magnitude larger than the experimental estimates. Second, most studies estimate impacts on grades and test scores, but many studies examine additional outcomes such as homework time, enrollment and graduation. Although there are some differences in results across outcomes they are generally consistent within the same study. The lack of consistent variation in findings for different outcome measures is at least a little surprising because we might expect intermediate inputs such as homework time and grades that are related to effort to be affected more by potential crowd-out or efficiency gains than test scores which capture the amount of information children learned during the school year. Although not the focus of the chapter, we also review a few papers examining impacts on computer skills and find some evidence of positive effects. But perhaps these findings are not surprising as there is no reason to suspect a negative influence.

Most of the earlier research was on the United States and other developed countries, but several recent studies examine home computer impacts in developing countries. The research focusing on developing countries tends to find smaller impacts, but it is difficult to disentangle this from their methodological focus on random experiments. Theoretically, the effects might be very different in the United States and other countries with a greater reliance on technology throughout the educational system. Finally, several studies explore heterogeneity in the effects of home computers on educational outcomes. Most of the studies examining heterogeneity focus on main demographic groups such as race and gender, but studies also examine heterogeneity by pre-treatment academic performance, parental supervision, and propensity for entertainment use of computers. The evidence on heterogeneity is decidedly mixed with no clear evidence even for the same group across studies.

Overall, these results suggest that increasing access to home computers among students who do not already have access is unlikely to greatly improve educational outcomes, but is also unlikely to negatively affect outcomes.

4. Conclusions

Theoretically, the net effects of ICT investments in schools, the use of CAI in schools, and the use of computers at home on educational outcomes are ambiguous. Expenditures and time devoted to using computers, software, the Internet and other technologies may be more efficient than expenditures on other educational inputs or may be less efficient. New technologies may displace other more effective instructional and learning methods and distract schoolchildren, or they may represent an effective learning tool and engage schoolchildren in learning. Thus, it is perhaps not surprising that the findings from the rapidly growing empirical literature on the effects of computers, the Internet and computer assisted instruction are mixed.

The implications from these findings suggest that we should not expect large positive (or negative) impacts from ICT investments in schools or computers at home. Schools should not expect major improvements in grades, test scores and other measures of academic outcomes from investments in ICT or adopting CAI in classrooms, though there might be exceptions such as some CAI interventions in developing countries. Existing and proposed interventions to bridge the digital divide in the United States and other countries, such as large-scale voucher programs, tax breaks for educational purchases of computers, and one-to-one laptop programs with check-out privileges are unlikely to substantially reduce the achievement gap on their own.

An important caveat to this tempered conclusion, however, is that there might be other educational effects of having a computer that are not captured in measurable academic outcomes. For example, computers may be useful for finding information about colleges and financial aid. They might be useful for communicating with teachers and schools and parental supervision of student performance, attendance and disciplinary actions through the spreading use of student information system software (e.g. School Loop, Zangle, ParentConnect, and Aspen). Similar to other aspects of society, schools, professors and financial aid sources are rapidly expanding their use of technology to provide information and course content to students. A better understanding of these potential benefits is important for future research.

More research is clearly needed in additional areas. First, more research is needed on benefit-cost analyses of computers, Internet connections, software, and other technologies with attention devoted to whether expenditures on these interventions are substituting for other inputs or represent new expenditures. The cost of various interventions is rarely documented or considered. Though purchase costs are declining, maintenance costs may be high and devices may become obsolete or need to be replaced frequently. Second, more research is needed on the shape of the educational returns to technology. For example, are the marginal benefits from a few hours of computer use in the classroom high, but then decline rapidly when computers are used more extensively in the classroom? Third, more research is needed on the related question of online education. There is considerable momentum towards offering online courses by colleges, massive open online courses (MOOCs), creation of online colleges, and "flipped" classrooms, but we know relatively little about their effectiveness relative to costs. Fourth, more research is needed on the impacts of specific uses of computers. For example, computer use for researching topics might be beneficial, whereas computer use for practicing skills may displace other more productive forms of learning (Falck, Mang and Woessmann 2015). Each new use of computer technology poses new possible benefits in terms of customization and flexibility, but also creates potential pitfalls that may interfere with education.[28] One of the fundamental challenges of studying the effects of computer technology on educational outcomes is that research consensus often lags the

[28] See Los Angeles Unified School District's one-to-one iPad program for a high profile example of the challenges of adopting new and relatively untested technology. Several schools attempted to abandon the program after students by-passed security filters in order to access the Internet, which was not intended. The program was suspended in light of possible flaws in the bidding process for technology provision.

implementation of new initiatives. Computer technology is expanding rapidly from desktop computers to laptops iPads and phones, and from educational software to Internet learning applications and social media.

References

Alpert, William T. , Kenneth A. Couch, and Oskar R. Harmon. 2015. “Online, Blended, and Classroom Teaching of Economics Principles: A Randomized Experiment,” University of Connecticut, Department of Economics Working Paper.

Andrés, Luis, David Cuberes, Mame Diouf, and Tomás Serebrisky. 2010. "The diffusion of the Internet: A cross-country analysis." *Telecommunications Policy,* 34(5): 323-340.

Angrist, Joshua, and Victor Lavy. 2002. "New Evidence on Classroom Computers and Pupil Learning," *Economic Journal* 112(482): 735–765.

Attewell, Paul, and Juan Battle. 1999. "Home Computers and School Performance," *The Information Society* 15: 1-10.

Autor, David H. 2001. "Wiring the Labor Market." *Journal of Economic Perspectives*. 15: 1, 25-40.

Autor, David, Lawrence Katz, and Alan Krueger. 1998. "Computing Inequality: Have Computers Changed the Labor Market?" *Quarterly Journal of Economics*. 113:4, 1169-214.

Banerjee, A., Cole, S., Duflo, E. and Linden, L. 2007. "Remedying Education: Evidence from Two Randomized Experiments in India," *Quarterly Journal of Economics* 122(3): 1235-1264.

Barrow, Lisa, Lisa Markman, and Cecelia E. Rouse. 2009. "Technology's Edge: The Educational Benefits of Computer-Aided Instruction," *American Economic Journal: Economic Policy* 1(1): 52-74.

Barrera-Osorio, Felipe, and Leigh L. Linden. 2009. “The Use and Misuse of Computers in Education: Evidence from a Randomized Experiment in Colombia,” Policy Research Working Paper 4836, Impact Evaluation Series No. 29, The World Bank.

Beltran, Daniel O., Kuntal K. Das, and Robert W. Fairlie. 2010. "Home Computers and Educational Outcomes: Evidence from the NLSY97 and CPS," *Economic Inquiry* 48(3): 771-792.

Beuermann, D. W., Cristia, J. P., Cruz-Aguayo, Y., Cueto, S., and Malamud, O. 2012. "Home Computers and Child Outcomes: Short-Term Impacts from a Randomized Experiment in Peru," Inter-American Development Bank Working Paper No. IDB-WP-382.

Bauernschuster, Stefan, Oliver Falck, and Ludger Woessmann. 2014. "Surfing Alone? The Internet and Social Capital: Evidence from an Unforeseeable Technological Mistake," *Journal of Public Economics*, 117: 73–89.

Belo, Rodrigo, Pedro Ferreira, Rahul Telang. 2014. “Broadband in School: Impact on Student Performance,” *Management Science* 60 (2): 265-282.

Bet, G., P. Ibarrarán and J. Cristia. 2014. “The Effects of Shared School Technology Access on Students’ Digital Skills in Peru.” Washington, DC, United States: Inter-American Development Bank, Research Department. Mimeographed document.

Bettinger, Eric, Lindsay Fox, Susanna Loeb and Eric Taylor. 2014. “Changing Distributions: How online college classes alter student and professor performance”. Working paper.

Betts, Julian. 1996. “Is There a Link between School Inputs and Earnings? Fresh Scrutiny of an Old Literature”, In Gary Burtless (Ed.) *Does Money Matter? The Effect of School Resources on Student Achievement and Adult Success*, Washington, D.C.: Brookings Institution: 141-191.

Bowen, William G., Matthew M. Chingos, Kelly A. Lack, Thomas I. Nygren. 2014."Interactive Learning Online at Public Universities: Evidence from a Six-Campus Randomized Trial," *Journal of Public Policy Analysis and Management* 33(1): 94-111.

Carrillo, Paul, Mercedes Onofa, and Juan Ponce. 2010. "Information Technology and Student Achievement: Evidence from a Randomized Experiment in Ecuador," Inter-American Development Bank Working Paper.

Caselli, F. and Coleman, W.J., II. 2001. "Cross-country technology diffusion: the case of computers," *American Economic Review*, 91: 328–35.

Chaudhury, N., Hammer, J., Kremer, M., Muralidharan, K., and Rogers, F. H. 2006. "Missing in Action: Teacher and Health Worker Absence in Developing Countries." *Journal of Economic Perspectives*, 20(1): 91-116.

Chinn, Menzie D. and Robert W. Fairlie. 2007 "The Determinants of the Global Digital Divide: A Cross-Country Analysis of Computer and Internet Penetration," *Oxford Economic Papers*, 59:16–44.

Chinn, Menzie D. and Robert W. Fairlie, 2010. "ICT Use in the Developing World: An Analysis of Differences in Computer and Internet Penetration," *Review of International Economics*, 18(1): 153-167.

Coley, Richard J., John Cradler, and Penelope K. Engel. 1997. “Computers and Classrooms: The Status of Technology in U.S. Schools,” ETS Policy Information Report: 1-69.

Cristia, J. P., Ibarraran, P., Cueto, S., Santiago, A., and Severin, E. 2012. "Technology and Child Development: Evidence from the One Laptop per Child Program," Inter-American Development Bank Working Paper No. IDB-WP-304.

Cristia, Julia P., Alejo Czerwonko, and Pablo Garofalo. 2014. “Does Technology in Schools Affect Repetition, Dropout and Enrollment?” Inter-American Development Bank Working Paper No. IDB-WP-477.

Cuban, Larry. 1993. “Computers Meet Classroom: Classroom Wins,” *Teachers College Record* 95(2): 185-210.

Cuban, Larry. 2001. *Oversold and underused: computers in the classroom*. Cambridge: Harvard University Press.

Dewan, Sanjeev, Dale Ganley, and Kenneth L. Kraemer. 2010. "Complementarities in the diffusion of personal computers and the Internet: Implications for the global digital divide." *Information Systems Research*, 21(4): 925-940.

DiMaggio, Paul J. and Eszter Hargittai. 2001. “From digital divide to digital inequality: studying internet use as penetration increases”, Working Paper No. 15, Princeton University.

DiMaggio, P., & Bonikowski, B. 2008. “Make money surfing the web? The impact of Internet use on the earnings of US workers.” *American Sociological Review*, 73(2), 227-250.

DiNardo, John, and Jorn-Steffen Pischke. 1997. "The Returns to Computer Use Revisited: Have Pencils Changed the Wage Structure Too?" *Quarterly Journal of Economics*. 112:1, 291-304.

European Commission. 2013. “Survey of Schools: ICT in Education - Benchmarking Access, Use and Attitudes to Technology in Europe’s Schools.” Digital Agenda for Europe. Final Report: 1-159.

Falck, Oliver, Constantin Mang, and Ludger Woessmann. 2015. “Virtually No Effect? Different Types of Computer Use and the Effect of Classroom Computers on Student Achievement,” CESifo Working Paper No. 5266.

Fairlie, Robert W. 2004. "Race and the Digital Divide," *Contributions to Economic Analysis & Policy, The Berkeley Electronic Journals* 3(1), Article 15: 1-38.

Fairlie, Robert W. 2005. "The Effects of Home Computers on School Enrollment," *Economics of Education Review* 24(5): 533-547.

Fairlie, Robert W. 2012. "Academic Achievement, Technology and Race: Experimental Evidence," *Economics of Education Review* 31(5): 663-679.

Fairlie, Robert W. 2012. "The Effects of Home Access to Technology on Computer Skills: Evidence from a Field Experiment," *Information Economics and Policy* 24(3–4): 243–253.

Fairlie, Robert W., and Rebecca A. London. 2012. "The Effects of Home Computers on Educational Outcomes: Evidence from a Field Experiment with Community College Students.” *Economic Journal* 122(561): 727-753.

Fairlie, Robert W., and Jonathan Robinson. 2013. "Experimental Evidence on the Effects of Home Computers on Academic Achievement among Schoolchildren," *American Economic Journal: Applied Economics* 5(3): 211-240.

Federal Communications Commission. 2014. *The E-Rate Program*. http://www.fcc.gov/e-rate-update.

Figlio, David, Mark Rush, and Lu Yin. 2013. “Is it Live or Is It Internet? Experimental Estimates of the Effects of Online Instruction on Student Learning,” *Journal of Labor Economics* 31(4): 763-784.

Freeman, Richard B. 2002. “The Labour Market in the New Information Economy.” Oxford Review of Economic Policy 18:288–305.Figlio, David N. 1999. “Functional Form and the Estimated Effects of School Resources,” *Economics of Education Review* 18: 241–252.

Fiorini, Mario. 2010. “The Effect of Home Computer Use on Children’s Cognitive and Non-Cognitive Skills,” *Economics of Education Review* 29: 55-72.

Fuchs, Thomas, and Ludger Woessmann. 2004. "Computers and Student Learning: Bivariate and Multivariate Evidence on the Availability and Use of Computers at Home and at School," CESifo Working Paper No. 1321.

Giacquinta, Joseph, Jo Anne Bauer, and Jane Levin. 1993. *Beyond Technology’s Promise: An Examination of Children’s Educational Computing at Home*, New York: Cambridge University Press.

Goolsbee, Austan, and Jonathan Guryan. 2006. "The Impact of Internet Subsidies in Public Schools," *The Review of Economics and Statistics* 88(2): 336-347.

Goldfarb, Avi. and Jeff Prince. 2008. Internet adoption and usage patterns are different: implications for the digital divide,” *Information Economics and Policy*, 20(1): 2–15.

Grimes, Douglas, and Mark Warschauer. 2008. “Learning With Laptops: A Multi-Method Case Study,*” Journal of Computing Research* 38(3): 305-332.

Hanushek, Eric A. 1979. “Conceptual and Empirical Issues in the Estimation of Educational Production Functions,” *The Journal of Human Resources* 14(3): 351-388.

Hanushek, Eric A. 1986. “The Economics of Schooling: Production and Efficiency in Public Schools,” *Journal of Economic Literature* 24(3): 1141-1177.

Hanushek, Eric A., Steven G. Rivkin, and Lori L. Taylor. 1996. “Aggregation and the Estimated Effects of School Resources,” *Review of Economics and Statistics* 78(4): 611-627.

Hanushek, Eric A. 2006. “School Resources,” In Eric A. Hanushek and Finis Welch (Ed.). *Handbook of the Economics of Education, Volume 2*, Amsterdam: North Holland: 865-908.

Rivkin, Steven G., Eric A. Hanushek, and John F. Kain. 2005. “Teachers, Schools, and Academic Achievement.” *Econometrica*. 73(2): 417–458.

Hoffman, Donna L. and Thomas P. Novak. 1998. "Bridging the Racial Divide on the Internet." *Science* 17 April: 390-391.

International Telecommunications Union. 2014. "Core indicators on access to, and use of, ICT by households and individuals, latest available data," http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

International Telecommunications Union. 2014. "Key ICT indicators for developed and developing countries and the world (totals and penetration rates)," http://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx.

Jones, Steve. 2002. *The Internet Goes to College: How Students are Living in the Future with Today's Technology*, Washington, D.C.: Pew Internet and American Life Project.

Joyce, Ted, Sean Crockett, David A. Jaeger, Onur Altindag, Stephen D. O'Connell. 2014. “Does Classroom Time Matter? A Randomized Field Experiment in Principles of Microeconomics”. Working paper.

Junco, Reynol. 2012. "Too much face and not enough books: The relationship between multiple indices of Facebook use and academic performance," *Computers in Human Behavior* 28(1): 187–198.

Kaiser Family Foundation. 2010. *Generation M^2: Media in the Lives of 8- to 18-Year Olds*. Kaiser Family Foundation Study.

Kirkpatrick, H., and L. Cuban. 1998. "Computers Make Kids Smarter--Right?" *Technos Quarterly for Education and Technology* 7:2.

Kirschner, Paul A., and Aryn C. Karpinski. 2010. "Facebook® and academic performance," *Computers in Human Behavior* 26(6): 1237–1245.

Koedinger, K. R., Anderson, J. R., Hadley, W. H., and Mark, M. A. 1997. “Intelligent Tutoring Goes To School in the Big City,” *International Journal of Artificial Intelligence in Education* 8: 30-43.

Kremer, Michael, Conner Brannen, and Rachel Glennerster. 2013. “The Challenge of Education and Learning in the Developing World,” *Science*, 340: 297-300.

Krueger, Alan B. 1993. "How Computers Have Changed the Wage Structure: Evidence from Micro Data." *Quarterly Journal of Economics*. 107:1, 35-78.

Kulik, Chen-Lin, and James Kulik. 1991. “Effectiveness of Computer-Based Instruction: An Updated Analysis,” *Computers in Human Behavior* 7: 75–94.

Lenhart, Amanda, Maya Simon, and Mike Graziano. 2001. *The Internet and education: findings from the Pew Internet & American Life Project.* Washington, DC: Pew Internet & American Life Project.

Lenhart, Amanda, Kahne, J., Middaugh, E., Macgill, A.R., Evans, C. and Vitak, J. 2008. *Teens, Video Games, and Civics: Teens' Gaming Experiences are Diverse and Include Significant Social Interaction and Civic Engagement*, Washington, DC: Pew Internet and American Life Project.

Leuven, E., Lindahl, M., Oosterbeek, H., and Webbink, D. 2007. "The Effect of Extra Funding for Disadvantaged Pupils on Achievement," *Review of Economics and Statistics* 89(4): 721-736.

Liao, Yuen-Kuang. 1992. “Effects of Computer-Assisted Instruction on Cognitive Outcomes: A Meta-Analysis.” *Journal of Research on Computing in Education* 24(3): 367-380.

Linden, Leigh L. 2008. "Complement or Substitute? The Effect of Technology on Student Achievement in India," Working paper.

Lowther, Deborah L., Steven M. Ross, and Gary M. Morrison. 2003. “When Each One Has One: The Influences on Teaching Strategies and Student Achievement of Using Laptops in the Classroom,” *Educational Technology Research & Development* 51(3): 23-44.

Machin, Stephen, Sandra McNally, and Olmo Silva. 2007. "New Technology in Schools: Is There a Payoff?" *Economic Journal* 117(522): 1145-1167.

Maine Education Policy Research Institute. 2007. *Maine's Middle School Laptop Program: Creating Better Writers*, Maine Education Policy Research Institute, University of Southern Maine.

Malamud, Ofer, and Cristian Pop-Eleches. 2011. "Home Computer Use and the Development of Human Capital," *Quarterly Journal of Economics* 126: 987-1027.

Mathematica. 2007. “Effectiveness of Reading and Mathematics Software Products: Findings from the First Student Cohort,” Report for U.S. Department of Education.

Mathematica. 2009. "Effectiveness of Reading and Mathematics Software Products: Findings from Two Student Cohorts," Report for U.S. Department of Education.

McEwan, Patrick J. 2014 “Improving Learning in Primary School of Developing Countries: A Meta-Analysis of Randomized Experiments,” *Review of Educational Research*.

Mo, D., Swinnen, J., Zhang, L., Yi, H., Qu, Q., Boswell, M., and Rozelle, S. 2012. "Can One Laptop per Child Reduce the Digital Divide and Educational Gap? Evidence from a Randomized

Experiment in Migrant Schools in Beijing," Rural Education Action Project, Stanford University, Working Paper 233.

Mo, D., Zhang, L., Luo, R., Qu, Q., Huang, W., Wang, J., Qiao, Y., Boswell, M., and Rozelle, S. 2014. "Integrating Computer Assisted Learning into a Regular Curriculum: Evidence from a Randomized Experiment in Rural Schools in Shaanxi." Working Paper.

Mossberger, K., C. Tolbert, and M. Stansbury. 2003. *Virtual Inequality: Beyond the Digital Divide*. Georgetown University Press, Washington, DC.

Mossberger, K., C. Tolbert, and M. Gilbert. 2006. "Race, Place, and Information Technology," *Urban Affairs Review*, 41(5): 583-620.

Noll, Roger G., Dina Older-Aguilar, Gregory L. Rosston, and Richard R. Ross. 2000. "The Digital Divide: Definitions, Measurement, and Policy Issues," paper presented at Bridging the Digital Divide: California Public Affairs Forum, Stanford University.

OECD. 2014. *OECD Factbook 2014: Economic, Environmental and Social Statistics*, http://www.oecd-ilibrary.org/economics/oecd-factbook-2014_factbook-2014-en.

Ono, Hiroshi, and Madeline Zavodny. 2007. "Digital Inequality: A Five Country Comparison Using Microdata," *Social Science Research,* 36 (September 2007): 1135-1155.

Pasek, Josh, and Eszter Hargittai. 2009. "Facebook and academic performance: Reconciling a media sensation with data," *First Monday* 14: Number 5 - 4.

Patterson, Richard W. 2014. "Can Behavioral Tools Improve Online Student Outcomes? Experimental Evidence from a Massive Open Online Course". Working paper.

Peck, Craig, Larry Cuban, and Heather Kirkpatrick. 2002. "Technopromoter dreams, student realities," *Phi Delta Kappan*, 83(6), 472–480.

Rainie, Lee, and Paul Hitlin. 2005. *The Internet at School*, Washington, DC: Pew Internet and American Life Project.

Rouse, Cecilia E., and Alan B. Krueger. 2004. Putting computerized instruction to the test: a randomized evaluation of a "scientifically based" reading program," *Economics of Education Review* 23(4): 323–338.

Schmitt, John, and Jonathan Wadsworth. 2006. "Is There an Impact of Household Computer Ownership on Children's Educational Attainment in Britain?" *Economics of Education Review*, 25: 659-673.

Stoll, Clifford. 1995. *Silicon Snake Oil: Second Thoughts on the Information Highway*, New York: Doubleday.

Suhr, Kurt. David Hernandez, Douglas Grimes, and Mark Warschauer. 2010. “Laptops and Fourth-Grade Literacy: Assisting the Jump over the Fourth-Grade Slump.” *The Journal of Technology, Learning, and Assessment*. 9(5): 1-45.

Texas Center for Educational Research. 2009. *Evaluation of the Texas Technology Immersion Pilot: Final Outcomes for a Four-Year Study (2004-05 to 2007-08)*.

Todd, Petra E., and Kenneth I. Wolpin. 2003. “On the Specification and Estimation of the Production Function for Cognitive Achievement.” *The Economic Journal*. 113(2): 3–33.

UNESCO Institute for Statistics. 2009. “Guide to Measuring Information and Communication Technologies in Education,” Technical Paper No. 2: 1-140.

UNESCO Institute for Statistics. 2014. “ICT in Education in Asia: A comparative analysis of ICT integration and e-readiness in schools across Asia” Information Paper No. 22: 1-64.

U.S. Census Bureau. 1988. *Computer Use in the United States: 1984. Current Population Reports Special Studies, Series P-23, No. 155*.

U.S. Department of Education. 2013. *Digest of Education Statistics 2012 (NCES 2014-015)*. National Center for Education Statistics, Institute of Education Sciences, U.S. Department of Education. Washington, DC.

Universal Services Administration Company. 2010. *Annual Report*.

U.S. Census Bureau. 2012. Computer and Internet Access in the United States: 2012, Table 1. Reported Internet Usage for Individuals 3 Years and Older, by Selected Characteristics: 2012, http://www.census.gov/hhes/computer/publications/2012.html

Vigdor, Jacob L., Helen F. Ladd, and Erika Martinez. 2014. “Scaling the Digital Divide: Home Computer Technology and Student Achievement,” Economic Inquiry. 52(3): 1103–1119.

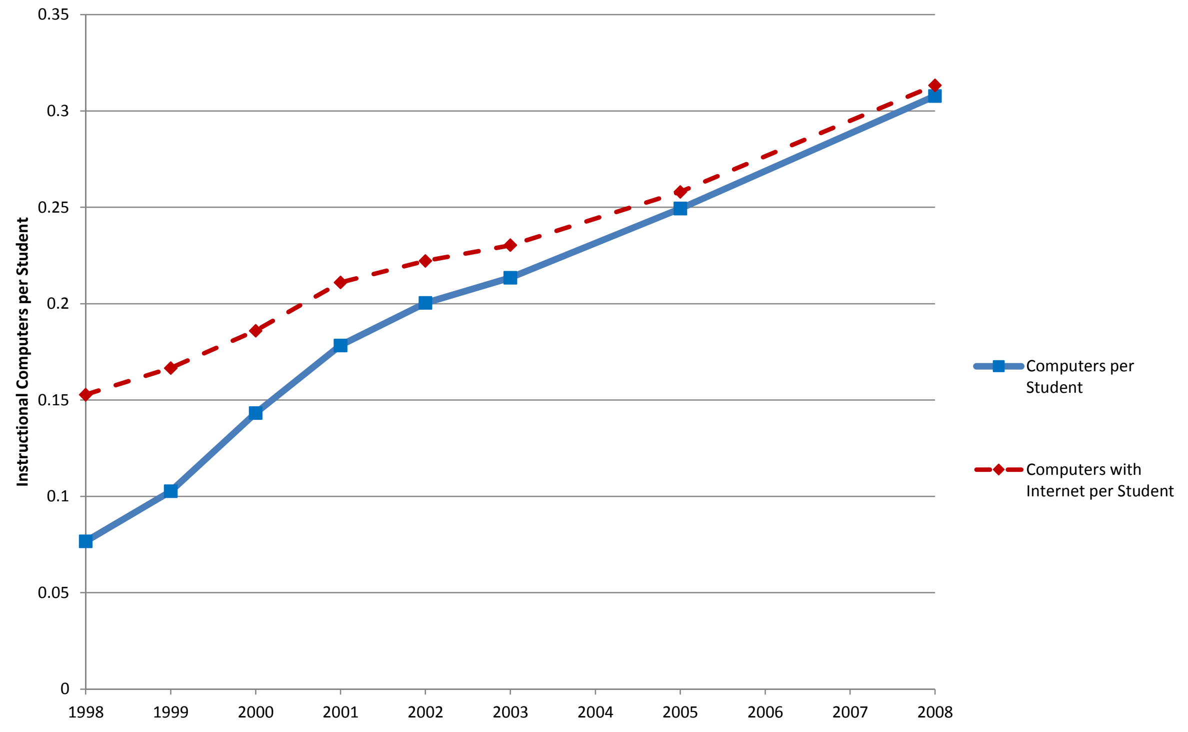
Wallsten, S. 2005. "Regulation and internet use in developing countries," *Economic Development and Cultural Change*, 53: 501–23.

Warschauer, Mark. 2003. *Technology and Social Inclusion: Rethinking the Digital Divide*, MIT Press: Cambridge.

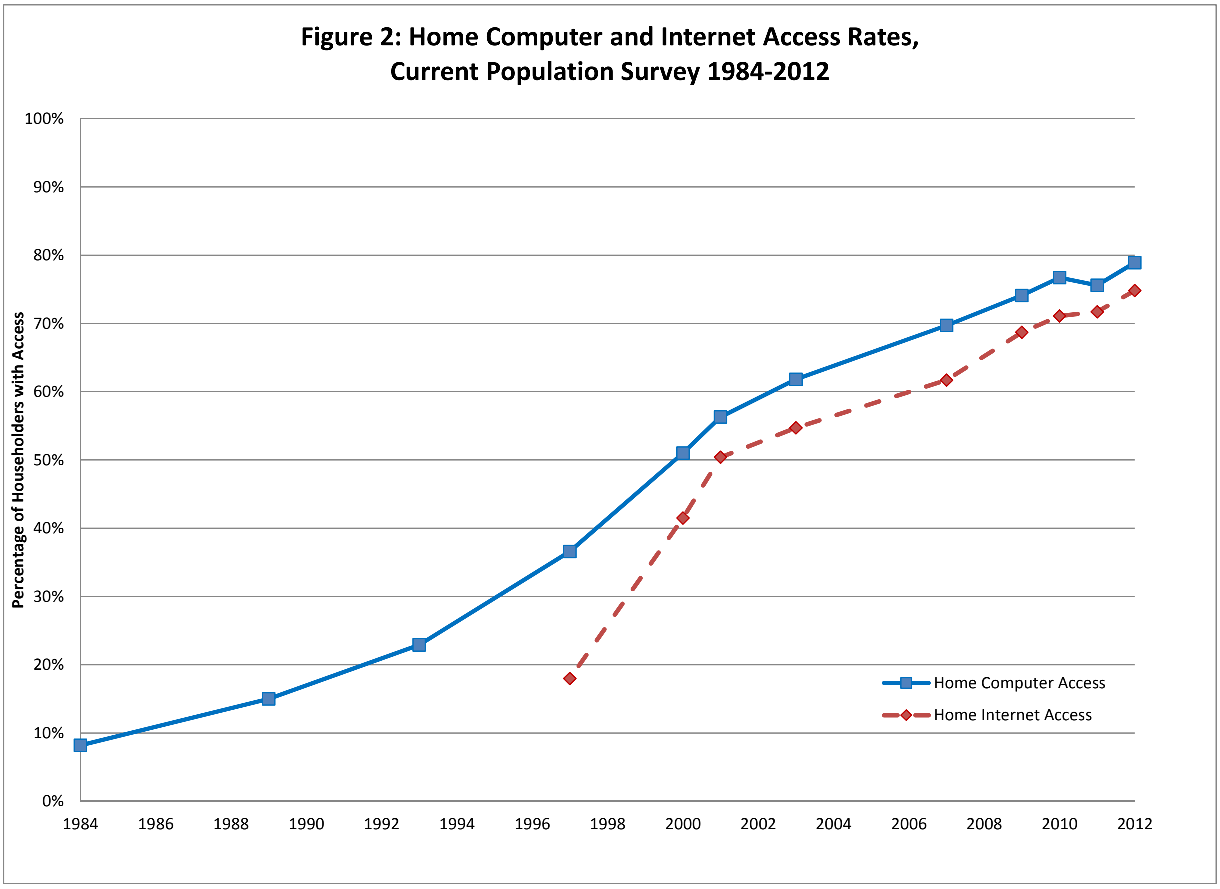
Warschauer, Mark. 2006. *Laptops and Literacy: Learning in the Wireless Classroom*, Teachers College Press.

Zavodny, Madeline. 2006. “Does Watching Television Rot Your Mind? Estimates of the Effect on Test Scores,” *Economics of Education Review* 25: 565-573.

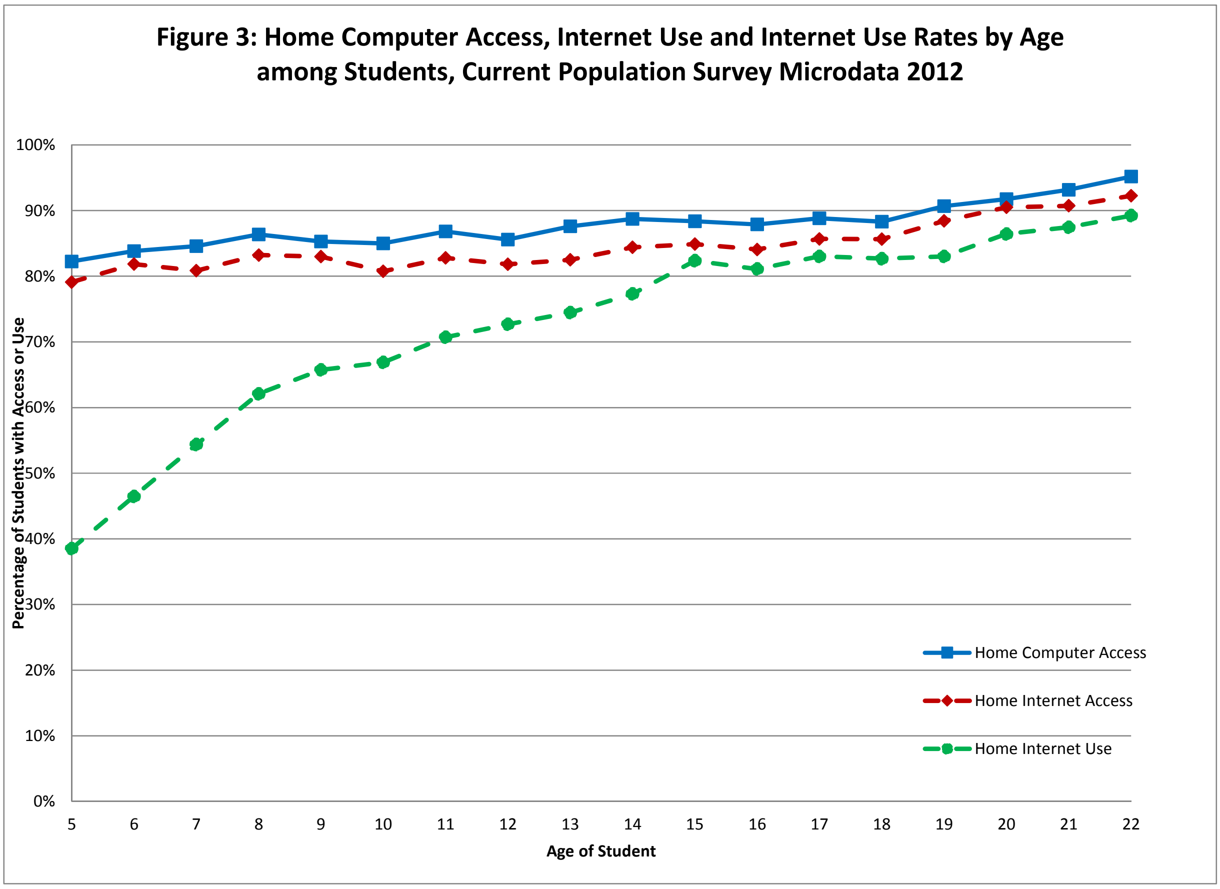
Figure 1: Number of Instructional Computers and Instructional Computers with Internet Access per Public School Student, National Center for Educational Statistics



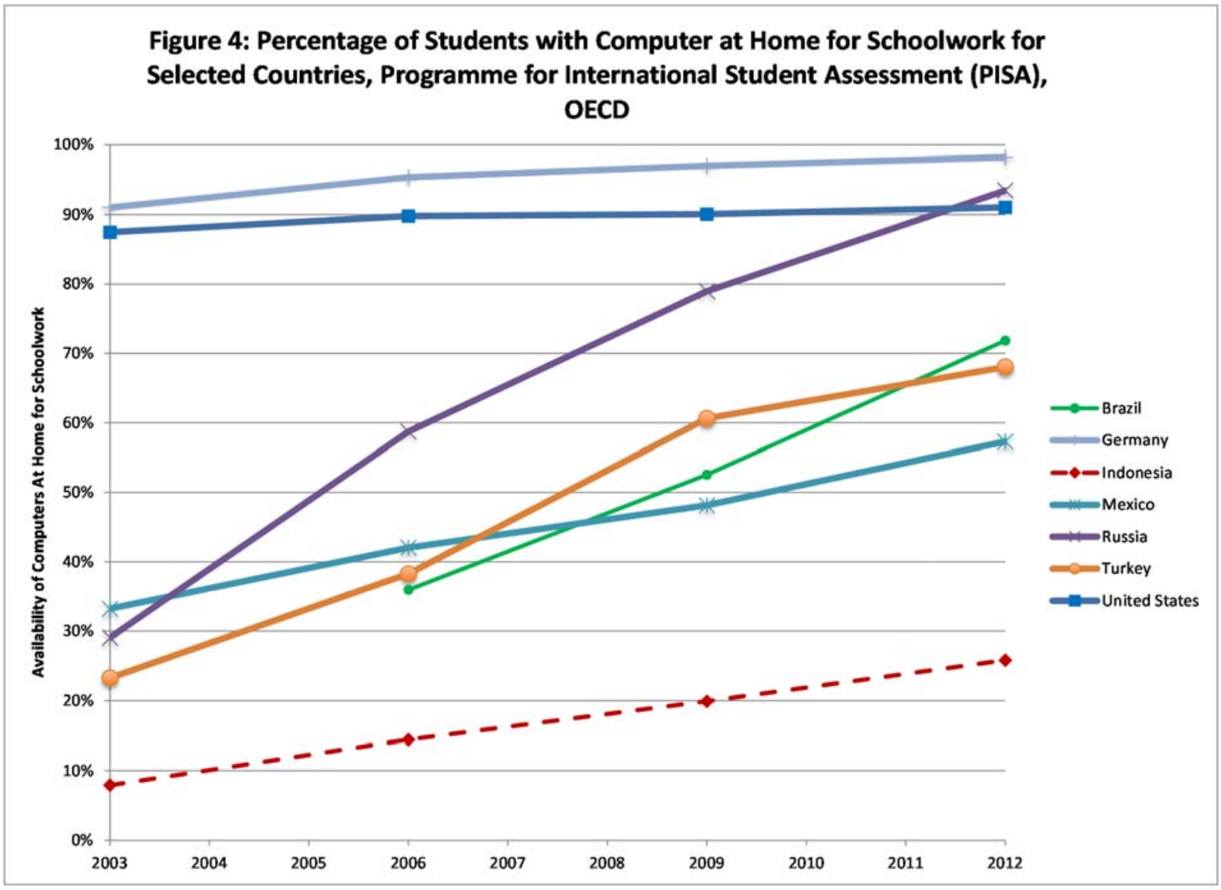
Source: U.S. National Center for Educational Statistics, from various years of the Digest of Educational Statistics.



Source: U.S. Census Bureau, Computer and Internet Use: Table 4. Households with a Computer and Internet Use: 1984 to 2012, from various years of the Current Population Survey.



Source: Author's calculations from Current Population Survey microdata 2012.



Source: OECD, Programme for International Student Assessment (PISA).

Table 1: Number of Available Computers in School for Each Student, Programme for International Student Assessment (PISA), OECD 2012

Country	Available Computers per Student	Proportion of Computers with Internet
Argentina	0.49	0.71
Australia	1.53	1.00
Austria	1.47	0.99
Belgium	0.72	0.97
Brazil	0.20	0.92
Bulgaria	0.56	0.97
Canada	0.84	1.00
Chile	0.49	0.95
Colombia	0.48	0.71
Costa Rica	0.53	0.83
Croatia	0.32	0.96
Czech Republic	0.92	0.99
Denmark	0.83	0.99
Finland	0.46	1.00
France	0.60	0.96
Germany	0.65	0.98
Greece	0.24	0.99
Hong Kong	0.73	1.00
Hungary	0.64	0.99
Indonesia	0.16	0.56
Ireland	0.64	1.00
Israel	0.38	0.91
Italy	0.48	0.96
Japan	0.56	0.97
Jordan	0.35	0.84
Kazakhstan	0.80	0.57
Korea (South)	0.40	0.97
Malaysia	0.19	0.87
Mexico	0.28	0.73
Netherlands	0.68	1.00
New Zealand	1.10	0.99
Norway	0.79	0.99
Peru	0.40	0.65
Poland	0.36	0.98
Portugal	0.46	0.97
Romania	0.54	0.95
Russia	0.58	0.82
Serbia	0.24	0.83
Singapore	0.67	0.99
Slovak Republic	0.77	0.99
Spain	0.67	0.99
Sweden	0.63	0.99
Switzerland	0.68	0.99
Thailand	0.48	0.95
Tunisia	0.51	0.63
Turkey	0.14	0.96
United Arab Emirates	0.69	0.83
United Kingdom	1.02	0.99
United States	0.95	0.94
Vietnam	0.24	0.80

Note: To create the measure of computers per student, PISA uses responses to the following two questions: "At your school, what is the total number of students in the <national modal grade for 15-year-olds>?," and "Approximately, how many computers are available for these students for educational purposes?"

Table 2: Number of Computers in School per Student, European Commission 2012

Country	4th Grade	8th Grade	11th Grade General	11th Grade Vocational
Austria	0.13	0.23	0.55	0.18
Belgium	0.13	0.24	0.35	0.29
Cyprus	0.16	0.29	0.64	0.29
Czech Republic	0.18	0.21	0.29	0.20
Denmark	0.33	0.31	0.22	0.51
Estonia	0.24	0.28	0.26	0.21
European Union	0.16	0.20	0.33	0.24
Finland	0.17	0.21	0.52	0.25
France	0.13	0.19	0.38	0.29
Greece	0.06	0.05	0.06	0.08
Hungary	0.16	0.18	0.24	0.19
Ireland	0.14	0.21		0.21
Italy	0.06	0.09	0.18	0.09
Latvia	0.15	0.17	0.20	0.16
Lithuania	0.11	0.20	0.27	0.17
Luxembourg	0.23			
Malta	0.32	0.12		0.15
Poland	0.13	0.14	0.17	0.13
Portugal	0.12	0.18	0.29	0.18
Slovakia	0.16	0.17	0.27	0.19
Slovenia	0.13	0.13	0.73	0.22
Spain	0.31	0.31	0.45	0.23
Sweden	0.29	0.70		0.89

Note: Data from Digital Agenda for Europe: A Europe 2020 Initiative, European Commission.

Table 3: Percentage of Students wih Computer at Home for Schoolwork and Internet Connection at Home, Programme for International Student Assessment (PISA), OECD 2012

Country	Computer at Home for Schoolwork	Internet Connection at Home
Argentina	84%	
Australia	98%	98%
Austria	98%	99%
Belgium	97%	99%
Brazil	72%	
Bulgaria	93%	
Canada	97%	
Chile	86%	78%
Colombia	63%	
Costa Rica	74%	71%
Croatia	94%	96%
Czech Republic	97%	98%
Denmark	99%	100%
Finland	99%	100%
France	97%	
Germany	98%	99%
Greece	92%	88%
Hong Kong	99%	99%
Hungary	94%	94%
Indonesia	26%	
Ireland	95%	98%
Israel	94%	96%
Italy	97%	97%
Japan	70%	89%
Jordan	83%	75%
Kazakhstan	66%	
Korea (South)	95%	95%
Malaysia	68%	
Mexico	57%	52%
Netherlands	98%	99%
New Zealand	94%	94%
Norway	99%	99%
Peru	52%	
Poland	97%	95%
Portugal	97%	96%
Romania	87%	
Russia	93%	93%
Serbia	95%	90%
Singapore	95%	98%
Slovak Republic	92%	94%
Spain	96%	96%
Sweden	99%	99%
Switzerland	98%	99%
Thailand	63%	
Tunisia	57%	
Turkey	68%	59%
United Arab Emirates	93%	
United Kingdom	97%	
United States	91%	
Vietnam	40%	

Table 4: Overview: Studies of Technology Use in Schools

ICT Study	Country	Investment	Grade	Design	Funding	Intensity	Results
Angrist and Lavy (2002)	ISR	computers	4, 8	policy d-in-d	supplemental	goal: 10:1 comp-stud ratio	insign, neg
Fuchs and Woessmann (2004)	Many	computers	10	cross-section	N/A	N/A	insign
Goolsbee and Guryan (2006)	USA	internet	K-12	policy d-in-d	subsidy	20-90% Internet discount	insign
Leuven et al. (2007)	NLD	computers, software	8	policy RD	supplemental	$90 ICT per pupil	insign, neg
Machin, McNally, and Silva (2007)	GBR	computers	K-6	policy d-in-d	supplemental	various (avg 5% ICT)	lang pos, math insign
Maine Ed Policy Research (2007)	USA	laptop	7,8	single diff		1-1 laptop	positive
Grimes and Warschauer (2008)	USA	laptop	K-8	policy d-in-d	supplemental	1-1 laptop	mixed
Barrera-Osorio and Linden (2009)	COL	computers	3-11	RCT	supplemental	avg 8.3 computers/school	insign
Texas Center for Ed Research (2009)	USA	laptop	6,7,8	policy d-in-d	supplemental	1-1 laptop	insign, pos
Suhr et al. (2010)	USA	laptop	4,5	policy d-in-d	supplemental	1-1 laptop	insign, pos
Cristia et al. (2012)	PER	laptop	K-6	RCT	supplemental	1-1 laptop	insign
Cristia et al. (2014)	PER	computers, internet	K-7	policy d-in-d	supplemental	~40% ICT increase	insign
Belo, Ferreira, and Telang (2014)	POR	internet	9	IV	supplemental	various	neg
CAI Study	**Country**	**Investment**	**Grade**	**Design**	**Instr. Time**	**Intensity**	**Results**
Rouse and Krueger (2004)	USA	language	K-6	RCT	supplemental	6-8 wks, 7-8 hrs/wk	insign
Banerjee, Cole, Duflo, Linden (2007)	IND	math	4	RCT	supplemental	2 yrs, 2 hrs/wk	positive
Mathematica Research (2007, 2009)	USA	math, language	K-12	RCT	substitute	1 yr, various	insign
Barrow, Markman and Rouse (2009)	USA	math	7-12	RCT	substitute	1 yr, daily class	positive
Carrillo, Onofa and Ponce (2010)	ECU	math, language	3-5	RCT	substitute	2 yrs, 3 hrs/wk	math pos, lang insign
Mo et al. (2014)	CHN	math	3,5	RCT	supplemental	1.5 yrs, 1.5 hrs/wk	positive

Table 5: Overview: Studies of Computer Use at Home

Study	Country	Investment	Grade/Age	Design	Data	Outcome	Results
Attewell, Battle (1999)	USA	computer	grade 8	cross-section	NELS	test scores	positive
Fuchs, Woessmann (2004)	Many	computer	teenagers	cross-section	PISA	test scores	negative
Fairlie (2006)	USA	computer	teenagers	cross-section	CPS	enrolled	positive
Schmitt,Wadsworth (2006)	GBR	computer	age 15-17	cross-section	BHPS	A-level exams	positive
Beltran, Das, Fairlie (2010)	USA	computer	teenagers	cross-sect, FE, IV	CPS - NLSY	graduate, grades, suspension	positive
Fiorini (2010)	AUS	computer use	age 4-7	cross-sect, IV	LSAC	cognitive skills	positive
Malamud, Pop-Eleches (2010)	ROM	computer	school aged	RD	survey	grades/cognitive skills	negative/positiv e
Vigdor, Ladd (2010)	USA	computer, internet	grades 5-8	cross-sect, FE	NC records	test scores	negative
Beuermann et al. (2012)	Peru	computer	grades 1-6	RCT	survey	cognitive skills	mixed
Fairlie, London (2012)	USA	computer	college	RCT	CC records	grades, transfer courses	positive
Mo et al. (2012)	CHN	computer	grade 3	RCT	survey	test scores/television	positive/negativ e
Fairlie, Robinson (2013)	USA	computer	grades 6-10	RCT	CA records	grades, test scores, attend	insign
Bauernschuster, Falck, Woessman (2014)	DEU	internet	age 7-16	IV	GSOEP	social activities	insign, pos