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THE EFFECTS OF HOME COMPUTERS ON EDUCATIONAL OUTCOMES: EVIDENCE FROM A FIELD EXPERIMENT WITH COMMUNITY COLLEGE STUDENTS*

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There is no clear theoretical prediction regarding whether home computers are an important input in the educational production function. To investigate the hypothesis, we conduct a field experiment involving the random provision of free computers to low-income community college students for home use. Although estimates for a few measures are imprecise and cannot rule out zero effects, we find some evidence that the treatment group achieved better educational outcomes than the control group. The estimated effects, however, are not large and are smaller than non-experimental estimates. There is also some evidence that benefits from home computers increase with distance to campus.

The use of computers is ubiquitous in the US educational system. Nearly all instructional classrooms in US public schools have computers with Internet access, with an average of more than one instructional computer for every four schoolchildren (US Department of Education, 2006). A growing number of state, school district and individual school programmes have further increased the ratio of computers to students to as high as one-to-one through the provision of laptops to all schoolchildren and teachers (Warschauer, 2006; Silvernail and Gritter, 2007). The federal government has also played an active role in reducing disparities in access to technology, spending roughly $2 billion per year on the E-rate programme, which provides discounts to schools and libraries for the costs of telecommunications services and equipment (Puma *et al.*, 2000; Universal Services Administration Company, 2007). Schools themselves are spending more than $5 billion per year on technology (Market Data Retrieval, 2004).

Despite the efforts to improve computer access in schools, a total of 45 million households in the US (38% of all households) do not have computers with Internet access at home (US Department of Commerce, 2008). Access to home computers is also not evenly distributed across the population; large disparities exist by income and

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race.[1] For example, only 46% of the 50 million US households with less than $50,000 in annual income have computers with Internet access at home compared with 87% of households with more than $50,000 in income. These disparities in access to home computers – known as the Digital Divide – may contribute to educational inequality. There is no clear theoretical prediction, however, regarding whether home computers are likely to have a negative or positive effect on educational outcomes. Having access to a home computer is undoubtedly useful for completing school assignments because it increases and improves flexibility in access time to a computer for these purposes. On the other hand, home computers may crowd out schoolwork time because they are commonly used for games, networking, downloading music and videos, communicating with friends and other entertainment among youth (Jones, 2002; US Department of Commerce, 2004; Lenhart, 2009). A better understanding of the extent to which home computers have an effect on educational outcomes is critical because it sheds light on whether home computers are an important input in the educational production process and whether disparities in access to technology will translate into educational inequality.

Although an extensive literature examines the effectiveness of computer use in the classroom, very little research has focused on the question of whether *home* computers improve educational outcomes. The handful of previous studies examining the relationship between home computers and educational outcomes find somewhat mixed results (Attewell and Battle, 1999; Fuchs and Woessmann, 2004; Schmitt and Wadsworth, 2006; Fairlie, 2005; Fairlie *et al.*, 2010; Malamud and Pop-Eleches, 2011). A limitation of this literature, however, is that most of these previous studies may suffer from omitted variable bias – specifically that the most educationally motivated students and families are likely to be the same ones that purchase computers for school use.

To address this limitation, we conduct the first-ever field experiment involving the provision of free computers to students for home use.[2] Participating students were randomly selected to receive free computers and were followed for two years. The random assignment evaluation is conducted with 286 entering students receiving financial aid at a large community college in Northern California. We received enough funding to provide half of these students with computers. Although baseline and follow-up surveys were conducted, administrative data provided by the college for all students is primarily used for the analysis of educational outcomes eliminating concerns about non-response. The field experiment identifies the causal effects of home computers on educational outcomes and provides evidence on the potential mechanisms exerting both positive and negative influences on educational outcomes. The findings from this study shed light on whether home computers are an important educational input and whether we should view the remaining digital divide in the US as a difference in consumer preferences or a disparity in educational resources.[3]

[1] See US Department of Commerce (2008), Fairlie (2004), Goldfarb and Prince (2008), Ono and Zavodny (2003, 2007) and Warschauer (2003) for recent evidence on disparities in computer and Internet use.

[2] To our knowledge the only other study that conducts a random assignment evaluation of free computers for home use is that by Servon and Kaestner (2008), which studies the effects of computers on the use of financial services.

[3] See Noll *et al.* (2000) and Crandall (2000) for an example of the debate over this issue.

The results from the experiment also provide the first evidence in the literature on the effects of home computers for post-secondary students. The focus on the impact of computers on community college students is especially important. Community colleges enrol nearly half of all students attending public universities and an even larger share of disadvantaged students (US Department of Education, 2011). The share is even higher in states such as California where community colleges serve 2.9 million students a year, representing more than 70% of all public higher education enrolment (Sengupta and Jepsen, 2006; California Community Colleges Chancellor's Office, 2009*a*). The returns to community colleges are also high and, recently, President Obama proposed an unprecedented funding increase for community colleges that will boost enrolments by 5 million students by 2020.[4]

In addition to providing workforce training and basic skills education community colleges serve as an important gateway to four-year colleges, especially among low-income and minority students. The cost savings from spending two years at a community college before entering a four-year college can be substantial and are likely to rise – typical full-time tuition at a community college is $2,063 compared with $5,950 at a public university and $21,588 at a private university (US Department of Education, 2011). In some states with large community college systems, such as California, nearly half of all students attending a four-year college previously attended a community college (California Community Colleges Chancellor's Office, 2009*b*).[5] Finally, unlike four-year colleges where many students live on campus and have access to large computer laboratories, community college students often have limited access to on-campus technology. Data from an extensive survey of US colleges in 2004 indicates that 80% of four-year college students use their own computers compared with only 35% of two-year college students (Educause, 2005).

The findings from the experiment indicate that the treatment group of students receiving free computers had better educational outcomes than the control group along a few measures. Although a few of the estimates are imprecisely measured and cannot rule out zero effects, the point estimates are consistently positive and small in magnitude across several educational outcomes. 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 may have benefited more from home computers possibly by improving flexibility and total time using computers for schoolwork. Estimates from the random experiment are also found to be smaller than non-experimental estimates from matched Current Population Survey (CPS) data raising concerns that previously reported estimates of large, positive effects of home computers on educational outcomes may be overstated.

1. Previous Research

The educational production function commonly estimated in the literature relates student performance to student, family, teacher and school inputs measured directly or

[4] See Kane and Rouse (1999) and Leigh and Gill (2007) for reviews of the literature on the labour market returns to community colleges. See http://www.whitehouse.gov/issues/education/for President Obama's plan for expanding the role of community colleges in higher education.

[5] Transfers from California community colleges to the California State University (CSU) system are projected to increase by 25% over the next decade (California Postsecondary Education Commission, 2010).

as fixed effects (Rivkin *et al.*, 2005). The personal computer is an example of one of these inputs in the educational production process. The use of computers in US schools is now universal and has been studied extensively but the role of home computers as an input in educational production is not well understood.[6]

There are several reasons to suspect that home computers may represent an important educational input. 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, 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 provide the most benefits to the user (DiMaggio and Hargittai, 2001). Almost all students using home computers use these computers to complete school assignments and nearly three of every four use them for word processing (Fairlie *et al.*, 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; Warschauer and Matuchniak, 2010). Enhanced computer skills from owning a personal computer may also alter the economic returns to education, especially in fields in which computers are used extensively. Finally, the social distractions of using a computer in a crowded computer lab on campus may be avoided by using a computer at home.

On the other hand, home computers are often used for games, networking, downloading music and videos, communicating with friends and other forms of entertainment, potentially displacing time for schoolwork (Jones, 2002; US Department of Commerce, 2004).[7] Nearly three-quarters of home computer users use their computers for games, and a large percentage of these users report playing games at least a few times a week (Lenhart *et al.*, 2008; Fairlie *et al.*, 2010). Social networking sites such as Facebook and Myspace and other entertainment sites such as Youtube and iTunes have grown rapidly in recent years (Lenhart, 2009). The number of Facebook users alone increased from only 2 million users in 2004 to 150 million users in 2009.[8] Computers are also often criticised for displacing other more active and effective forms of learning and by emphasising presentation (e.g. graphics) over content (Giacquinta *et al.*, 1993; Stoll, 1995; 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, 2005). In the end, there is no clear theoretical prediction on the sign or magnitude of the effects of home computers on educational achievement, and thus an empirical analysis is needed.

To identify the effects of home computers, the starting empirical approach has been to regress educational outcomes on the presence of a home computer, controlling for

[6] A large literature examines the impact of computers, Internet subsidies and computer-assisted software in schools generally finding mixed results. See Kirkpatrick and Cuban (1998) and Noll *et al.* (2000) for reviews of this literature and Barrow *et al.* (2009), Machin *et al.* (2007) and Goolsbee and Guryan (2006) for examples of a few recent studies.

[7] Valentine *et al.* (2005) find that leisure use of home computers and the Internet is negatively associated with educational attainment. See Warschauer and Matuchniak (2010) for a review.

[8] The potential negative impact of the extensive use of Facebook among college students on academic outcomes has recently received some attention (Karpinski, 2009; Pasek *et al.*, 2009). These concerns are similar to those over television (Zavodny, 2006).

detailed student, family and parental characteristics. Studies using this approach generally find relatively large positive effects of home computers on educational outcomes (Attewell and Battle, 1999; Fairlie, 2005; Schmitt and Wadsworth, 2006; Fairlie *et al.*, 2010), although there is some evidence of negative effects (Fuchs and Woessmann, 2004). In some cases these controls include prior educational attainment, difficult-to-find detailed characteristics of the educational environment in the household and extracurricular activities of the student (Attewell and Battle, 1999; Schmitt and Wadsworth, 2006; Fairlie *et al.*, 2010). However, these estimates of the effects of home computers on educational outcomes may still be biased because of omitted variables. The main concern is that if the most educationally motivated students and families are the ones who are the most likely to purchase computers, then a positive relationship between academic performance and home computers may simply capture the effect of unmeasurable motivation on academic performance.[9]

Several studies have investigated this issue using instrumental variable (IV) techniques, future computer ownership, falsification tests, individual student fixed effects or regression discontinuity designs (RDD). Estimates from bivariate probits for the joint probability of an educational outcome and computer ownership reveal large positive estimates (Fairlie, 2005; Fairlie *et al.*, 2010). Another approach, first taken by Schmitt 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 suspicions that current ownership proxies for an unobserved factor, such as educational motivation. However, previous studies do not find a positive estimate for future computer ownership and do not find positive estimates for additional falsification tests (Schmitt and Wadsworth, 2006; Fairlie *et al.*, 2010). Malamud and Pop-Eleches (2011) address the endogeneity problem with an RDD based on the effects of a government programme in Romania that allocated a fixed number of vouchers for computers to low-income children in public schools. Estimates from the discontinuity created by the allocation of computer vouchers by a ranking of family income indicate that Romanian children winning vouchers have lower grades, but higher cognitive ability and better computer skills.

We take a new approach to address the problem of correlated unobservables by conducting the first random assignment field experiment providing free computers to students for home use. As noted before, the only previous study that randomly assigned free computers to individuals for home use was that by Servon and Kaestner (2008). Through a programme with a major bank, computers with Internet service were randomly assigned to low and moderate-income families to determine how they affect the use of financial services. Although there exist recent random experiments involving the provision of computer-assisted learning in schools (Barrow *et al.*, 2009; Mathematica Policy Research, 2009), to our knowledge, no previous study has randomly provided free computers to students for home use. Furthermore, no previous study explores the impact of home computers on the educational outcomes of college students.

[9] It may instead be the case that the least educationally motivated students and families (after controlling for individual and family characteristics) are the ones who purchase computers perhaps because of their entertainment value or because they substitute for more traditional and time-consuming forms of learning.

2. The Field Experiment

To study the educational impacts of home computers, we randomly assigned free computers to entering community college students who were receiving financial aid.[10] The students attended Butte College, which is located in Northern California and has a total enrolment of over 20,000 students. Butte College is part of the California Community College system, which is the largest higher educational system in the nation and includes 110 colleges and educates more than 2.6 million students per year (California Community Colleges Chancellor's Office, 2009*a*). Compared with the average community college in the US, Butte College is larger but does not differ substantially in the composition of its student body. For example, Butte College has a roughly similar share of female students as the US total (55.0% compared with 58.5%) and roughly similar share of non-minority students (65.4% compared with 60.8%).

The computers used in the study were provided by Computers for Classrooms, Inc., a computer refurbisher located in Chico, California.[11] To implement the study, we first obtained a list of all financial aid students with less than 24 units attending the college in fall 2006. The 24 unit cutoff was chosen to capture new and relatively new students as of fall 2006. It ensures that students in the study have less than two previous full-time semesters at the college. In fall 2006, there were 1,042 financial aid students and 6,681 students in total who met the course unit restriction. The Butte College Office of Financial Aid advertised the programme by mailing letters to all financial aid students. Participation in the programme involved returning a baseline questionnaire and consent form to release future academic records from the college for the study. Students who already owned computers were not excluded from participating in the lottery because their computers may have been very old and not fully functional with the latest software and hardware. The results presented next are not sensitive to the exclusion of these students who represented 29% of the sample. We received 286 responses with valid consent forms and completed questionnaires, and received enough funding to randomly provide free computers to 141 of these students. Eligible students were notified by mail and instructed to pick up their computers at the Computers for Classrooms warehouse. More than 90% of eligible students picked up their free computers by the end of November 2006. All correspondence with students was conducted through Butte College's Office of Financial Aid. We conducted a follow-up survey of study participants in late spring/summer 2008 with a response rate of 65%.[12] Butte College provided us with detailed administrative data on all students in July 2008.

[10] We did not provide Internet service as part of the experiment but found at the end of the study that more than 90% of the treatment group had Internet service. Previous research indicates that Internet subscription is very high among computer owners in the US making it difficult to identify separate effects (Fairlie *et al.*, 2010).

[11] The computers were refurbished Pentium III 450 MHz machines with 256 MB RAM, 10 GB hard drives, 17″ monitors, modems, ethernet cards, CD drives and Windows 2000 Pro Open Office (with Word, Excel and PowerPoint). The system also came with a 128 MB flash drive for printing student papers on campus and a two-year warranty on hardware and software. Computers for Classrooms offered to replace any computer not functioning properly during the two-year period.

[12] The baseline characteristics of the follow-up sample look roughly similar to those of the full sample (see Appendix). The response rate was 61% for the control group and 69% for the treatment group. The difference is not statistically significant.

2.1. *Who Applied for the Computer Giveaway?*

Table 1 reports administrative data from the original application to the college for students who applied to the computer-giveaway programme, all financial aid students and all entering students. The racial composition of study participants is very similar to that of all financial aid students, the group initially targeted for the study. A total of 60.1% of study participants are white compared with 61.3% of all financial aid students. The largest minority group, Latinos, comprise 16.8% of study participants and 15.6% of all financial aid students. A similar percentage of primarily English language students also participated in the study compared with all financial aid students. The one difference between study participants and the population of financial aid students is that a larger percentage of women applied for the computer lottery than men. Women comprise 62.6% of all study participants which is higher than the 54.7% for all financial aid students.

Information about students' educational goals was also collected on the application form. The most common response is 'undecided on goal', which represents 37.4% of study participants and 36.5% of all financial aid students. The second most common goal reported by applicants is to 'obtain an associate degree and transfer to a four-year institution'. Of the study participants, 20.6% reported this goal compared with 23.3% of all financial aid students. The next most common goal reported is to 'transfer to a four-year institution without an associate degree'. Slightly more than 10% of both study participants and all financial aid students reported this goal. Overall, the distributions of reported goals at the time of application are very similar.

A comparison of all students reveals that study participants are more likely to be women than the total student body. Women comprise 55.3% of all students attending the college. Study participants as well as all financial aid students are more likely to be

Table 1

Application Information for Study Participants, Financial Aid Students and All Students

	Study participants	All financial aid students	All entering students
Gender (%)			
Female	62.6	54.7	55.2
Male	35.7	43.6	43.6
Missing	1.7	1.7	1.2
Race/ethnicity (%)			
White	60.1	61.3	65.2
Asian and Pacific Islander	8.0	8.2	7.0
African-American	3.1	3.2	2.6
Latino	16.8	15.6	13.1
Native American	2.1	2.9	2.2
Other	1.0	1.2	1.2
Unknown	8.7	7.6	8.7
English language (%)			
English	81.8	83.7	80.1
Not English	7.0	6.7	7.8
Unknown/uncollected	11.2	9.6	12.1
Sample size	286	1,042	6,681

Note. Based on administrative data provided by Butte College for entering students in fall 2006.

from minority groups than all students but are less likely to be non-primary English language students, which may be related to applying for financial aid. These differences, however, are small.

Although study participants are a self-selected group from all financial aid students, they do not appear to be very different from either financial aid students or the entire student body along observable characteristics. They may differ, however, along dimensions directly related to participation in the study. Specifically, they may have less access to computers and disposable income than other financial aid students. These differences have implications for our ability to generalise the results based on study participants to all community college students receiving financial aid. But, students with limited access to computers and financial resources are the population of most interest for any policy intervention involving the provision of free or subsidised computers.

2.2. *Comparability of Treatment and Control Groups*

Table 2 reports a comparison of background characteristics for the treatment and control groups. All study participants were given a baseline survey that included detailed questions on gender, race, age, high school grades, household income,

Table 2

Background Characteristics of Study Participants

	All study participants (%)	Treatment: computer eligible		Control: computer ineligible (%)	p-value for treatment (all eligible)/control difference
		All (%)	Received computer (%)		
Female	63.3	64.5	64.3	62.1	0.666
Latino	17.8	15.6	15.5	20.0	0.333
Other minority	18.2	21.3	20.9	15.2	0.182
Age	25.0	24.9	24.9	25.0	0.894
Parent some college	37.8	41.8	42.6	33.8	0.161
Parent college graduate	22.0	18.4	16.3	25.5	0.150
High school grades As and Bs	30.4	32.6	31.0	28.3	0.426
High school grades Bs and Cs	56.6	55.3	58.1	57.9	0.657
Live with own children	27.3	27.7	27.9	26.9	0.885
Live with parents	34.6	31.2	31.0	37.9	0.234
Household income: \$10,000–\$19,999	31.5	30.5	32.6	32.4	0.728
Household income: \$20,000–\$39,999	25.9	27.7	26.4	24.1	0.498
Household income: \$40,000 or more	16.8	14.9	15.5	18.6	0.401
Takes most classes at Chico Center	25.2	25.5	26.4	24.8	0.891
Takes most classes at Glen/other	8.4	7.8	7.8	9.0	0.724
Has job	55.0	52.2	54.0	57.6	0.358
Application goal: get AA/transfer	20.6	19.1	19.4	22.1	0.543
Application goal: transfer no AA	10.8	10.6	10.1	11.0	0.915
Application goal: degree no transfer	7.7	7.8	7.0	7.6	0.946
Application goal: other	16.8	18.4	20.2	15.2	0.462
Application goal: unknown	37.4	36.9	36.4	37.9	0.855
Application goal: missing	6.6	7.1	7.0	6.2	0.765
Complete follow-up survey	64.7	68.8	68.2	60.7	0.153
Sample size	286	141	129	145	286

Note. Based on baseline survey administered to all study participants.

parents' education and other characteristics. The average age of study participants is 25 years. More than half of the students have a parent with at least some college education, and about one-third of students received mostly grades of A and B in high school. A little over one-quarter of study participants have children and one-third live with their parents. As would be expected among financial aid students, study participants have low income levels with only 17% having current household incomes of $40,000 or more. The majority of study participants have household incomes below $20,000 and more than half are employed. The treatment and control groups are also similar along the educational goals reported at the time of application.

The similarity of the mean values of these baseline characteristics confirms that the randomisation created comparable treatment and control groups for the experiment. We do not find large differences for any of the characteristics, and none of the differences is statistically significant.

2.3. *First-stage Results for Computer Use*

If distributing free computers has an impact on educational outcomes, we might expect to see more hours of computer use by the treatment group than the control group. Home computers, however, only increase the *potential* for more computer use and actual use may decline if home computers allow for more efficient use of computers than school computers. Efficiency gains may result from increased familiarity and better suited software on home computers, but may also result from fewer distractions or less interrupted time than found in crowded campus computer labs. Roughly, one-quarter of students report experiencing wait times when using computers at the college. Nevertheless, it is useful to compare total hours of computer use before exploring the impacts on educational outcomes.

To investigate this issue we examine data from the follow-up survey which was conducted in spring 2008. Although these data are not as comprehensive in terms of coverage of students as the administrative data that we use to examine educational outcomes (which are available for all study participants), they provide some suggestive information on first-stage effects. Table 3 reports the total number of hours of computer use for the treatment and control groups for the 185 students completing follow-up surveys.[13] The treatment group reports using computers 16.1 hours per week on average compared with 13.4 hours per week for the control group. The estimated difference of 2.7 hours is large, representing 20% more hours, but is not statistically significant at conventional levels for a two-tailed test (the p-value is 0.15). Controlling for baseline characteristics we find a similar difference in hours of computer use between the treatment and control groups.

Another first-stage result is to examine whether home computers allow students increased flexibility in the times when they use computers. Table 3 reports the percentages of students who reported using computers at various times of the day to complete school assignments. Students who received home computers were more likely

[13] Among follow-up survey respondents the treatment and control groups have similar baseline characteristics. The main exception is that we find that a larger percentage of the control group live with their parents (see Appendix).

Table 3

Computer Use among Study Participants

	Treatment group	Control group	Treatment-control Difference	Treatment-control SE	Regression adjusted Difference	Regression adjusted SE
Total number of hours of computer use per week	16.1	13.4	2.7	1.8	2.3	1.9
Times of day for computer use to complete school assignments (%)						
Early morning (6:00AM–8:00AM)	18.3	19.5	−1.3	5.9	−2.4	6.2
Daytime (8:00AM–5:00PM)	55.9	49.4	6.5	7.5	6.2	7.8
Early evening (5:00PM–10:00PM)	61.3	62.1	−0.8	7.3	−2.4	7.4
Late evening (10:00PM–12:00AM)	37.6	29.9	7.7	7.1	9.8	7.3
Nighttime (12:00AM–6:00AM)	14.0	6.9	7.1	4.5	6.9	4.5
Sample size	97	88				

Notes. The data are based on follow-up survey conducted in spring 2008. Regression-adjusted treatment-control differences control for gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents and family income.

to report using computers in the daytime, late evening and night-time than students who did not receive computers although the differences are not precisely measured. The treatment and control groups are equally likely to use computers in the early morning and early evening. Although certainly not conclusive, the estimated differences provide some suggestive evidence that the provision of the home computers increased the total time of use of computers and flexibility of use.

3. Estimating the Effects of Home Computers on Educational Outcomes

To examine whether the home computers improved educational outcomes we start by briefly examining the full distribution of grades received in courses taken by the two groups of students. Figure 1 displays grade distributions for all courses taken by study participants after fall 2006 (when computers were distributed) through spring 2008. Grade information was provided by Butte College in their administrative data and is available for all students and all quarters in the study period. Butte College assigns letter grades of A, B, C, D and F, and non-letter grades of CR and NC. The CR grade is considered the same as a C or higher, and C grades and higher are considered satisfactory. D grades are considered passing, but unsatisfactory, and an NC grade is considered unsatisfactory or failing. The treatment group appears to be more likely than the control group to receive B and C grades and less likely to take courses for non-letter grades (i.e. CR/NC) than the control group. The treatment group also appears less likely to receive an NC grade than the control group.

The primary measure used by the college to gauge the success and eligibility of students for various programmes is the percentage of courses in which students receive a satisfactory or higher grade (i.e. C, B, A or CR grade), referred to as the 'course success rate'. Panel I of Table 4 reports estimates for the course success rate by treatment status. For the treatment group, 82.6% of courses received a successful

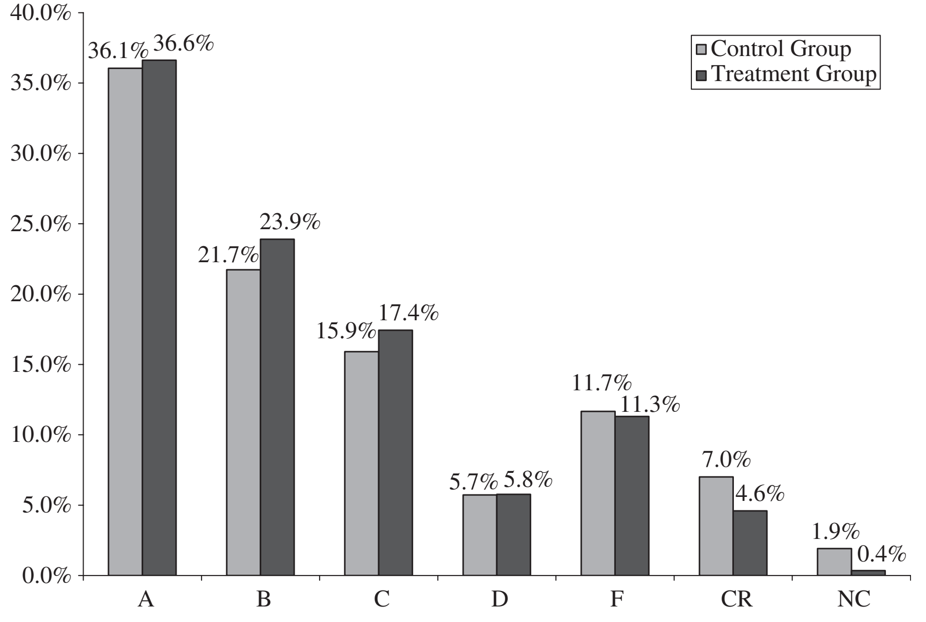

Fig. 1. *Grade Distribution for Study Participants*

Table 4

Treatment-Control Differences in Educational Outcomes

	Control mean	Treatment mean	Treatment-control difference	Regression-adjusted treatment-control difference (1)	(2)	(3)
I. Successfully pass course (course success rate)	0.807	0.826	0.019 (0.030)	0.020 (0.029)	0.021 (0.029)	0.029 (0.029)
II. Take course for grade	0.911	0.951	0.040* (0.021)	0.033** (0.014)	0.026** (0.013)	0.029** (0.013)
III. Take transfer course for CSU or UC campus	0.740	0.803	0.063** (0.032)	0.060** (0.028)	0.060** (0.028)	0.070** (0.028)
IV. Graduate with degree or certificate	0.159	0.184	0.026 (0.045)	0.019 (0.045)	0.019 (0.045)	0.017 (0.045)
V. Educational outcome index	0.000	0.137	0.137** (0.057)	0.117** (0.048)	0.101** (0.046)	0.105** (0.043)
Baseline controls			No	Yes	Yes	Yes
Quarter and course department fixed effects			No	No	Yes	Yes
Maths, English and reading assessments			No	No	No	Yes

Notes. The dependent variables are whether the grade was a C, CR or better in panel I, whether the course was taken for a letter grade in panel II, whether the course is transferable to the California State University (CSU) or University of California (UC) systems in panel III, whether the student received an associates degree, vocational degree or vocational certificate in panel IV and an equally weighted average of z-scores from the four reported educational outcomes in panel V. z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation. Robust standard errors are reported and adjusted for multiple courses taken by study participants. *, ** and *** denote statistical significances at the 0.10, 0.05 and 0.01 levels, respectively. Baseline controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, family income, initial campus location, has a job and primarily speaks English. The sample size is 1,792 courses taken by 286 study participants.

grade. The control group has a course success rate of 80.7%.[14] Another important educational outcome is the percentage of courses taken for grades, which may be an indicator of student confidence in doing well in courses and the future possibility of transferring to other community colleges or four-year colleges. Among the treatment group, 95.1% of courses are taken for letter grades compared with 91.1% of courses taken by the control group (see panel II of Table 4).

In addition to the effects on grades, receiving a free computer may affect longer-term outcomes such as transferring to a four-year college or graduating with a degree from the community college. Although Butte College and other community colleges in California do not collect information on whether their students transfer to four-year colleges, we can examine whether students take transferable courses. Transfer course enrolment is tracked by the California Community Colleges Chancellor's Office (2009*a*) as a measure of community college performance. In addition, previous research using a special cohort of students linked through California state system-wide administrative data indicates that enrolment in transferable courses in the first and second years of study is a major predictor of who eventually transfers to four-year universities (Sengupta and Jepsen, 2006). All courses offered at the college can be identified as being transferable to the CSU or University of California (UC) systems. Panel III of Table 4 reports estimates for the treatment/control difference in the probability of taking transferable courses. Of the courses taken by the control group, 74% are transferable. The percentage of courses that are transferable taken by the treatment group is 6.3 percentage points higher at 80.3%.

The college also provided us with information on whether students received a degree or certificate by summer 2008. Students may have received an associates degree, vocational degree or vocational certificate. Estimates of the treatment-control differences are reported in panel IV in Table 4. We find that 18.4% of computer-eligible students received a degree by summer 2008, compared with 15.9% of non-computer-eligible students.[15]

The estimates reported in Table 4 provide evidence of positive and statistically significant effects of home computers on two of the reported educational outcomes. Although the treatment estimates are imprecisely measured for the course success and graduation rates, the direction and rough magnitude of these point estimates are consistent with the other educational outcomes. To provide additional evidence on the overall effects of home computers on educational outcomes we create a summary index that aggregates information over multiple treatment effect estimates following the approach recently taken by Kling *et al.* (2007) and Karlan and Zinman (2008). Specifically, we create an index of educational outcomes that combines the four educational measures reported before. By aggregating the separate educational outcomes we improve the statistical power to detect treatment effects that work in the same

[14] For a related measure also tracked by the community college, which includes withdrawals in the denominator, we find similar results for treatment-control differences. In addition, examining the pass rate among courses taken for letter grades we find a similar positive treatment effect, and we find a very large positive difference (14.3 percentage points) conditioning on courses taken for non-letter grades.

[15] In addition, we find for the sample of students who have not graduated by the end of the sample period that the treatment group is 6.1 percentage points more likely to plan to continue the next year than the control group (48.7% compared with 42.6%).

direction, which is the case here. To create the index, we first calculate z-scores for each of the dependent variables by subtracting the control group mean and dividing by the control group standard deviation. Thus, each dependent variable has mean zero and standard deviation equal to one for the control group. The educational outcome index is then calculated from an equally weighted average of the z-scores for the four dependent variables. The treatment effect estimate for this index indicates where the mean of the treatment group is in the distribution of the control group in terms of standard deviation units.

Panel V of Table 4 reports estimates for the educational outcome index. By definition, the control group mean for the index is 0. The treatment group index is 0.1368 which captures the treatment effect. It implies that the treatment group mean is 0.1368 standard deviations higher than the control group mean. This difference between the treatment and control groups in the educational summary index is statistically significant.[16] The treatment effect estimate for the summary measure of educational outcomes confirms the findings across educational outcomes from the experiment. We consistently find positive point estimates for treatment effects across educational outcomes although some estimates are statistically insignificant.

3.1. *Regression-adjusted Estimates*

To improve precision and confirm the robustness of the results to randomisation, we estimate several regressions for the educational outcomes. The regression equation is straightforward in the context of the random experiment:

$$y_{ij} = \alpha + \boldsymbol{\beta X}_i + \delta T_i + \lambda_t + \lambda_d + u_i + \varepsilon_{ij}, \tag{1}$$

where y_{ij} is the outcome for student i in course j, $\boldsymbol{X}_i$ includes baseline characteristics, T_i is the treatment indicator, λ_t are quarter fixed effects, λ_d are department fixed effects and $u_i + \varepsilon_{ij}$ is the composite error term. The effect of becoming eligible for a free computer or the 'intent-to-treat' estimate of the giveaway programme is captured by δ. All specifications are estimated using ordinary least squares (OLS) and robust standard errors are reported with adjustments for multiple observations per student (i.e. clustered by student). Marginal effects estimates are similar from probit and logit models, and are thus not reported.

Specification 1 of Table 4 reports estimates of the treatment effect after controlling for gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, family income, initial campus location, has a job and primarily speaks English. These detailed controls are taken from the baseline survey administered to all study participants or from the application form to the college, which are both measured prior to the receipt of the free computers. The inclusion of these controls results in similar treatment effect estimates for all the educational outcomes. The precision of the estimates also improves with the inclusion of these baseline controls.

One concern is that students may have taken different types of courses which ultimately are responsible for differences in grades. A comparison of course departments

[16] Using various combinations of these and additional educational outcomes, we consistently find positive and statistically significant treatment-control differences for the summary index.

Table 5

Departments of Courses Taken by Study Participants

	Treatment group (%)	Control group (%)
Administration of justice	3.7	1.7
Anthropology	2.5	2.4
Biology	5.1	3.7
Business computer information systems	8.5	10.5
Child development and family relations	4.2	2.9
English	7.7	6.7
History	4.0	3.5
Mathematics	11.5	11.1
Political Science	2.4	2.6
Psychology	4.4	3.6
All other departments	46.2	51.3

Notes. Data are based on administrative data provided by Butte College for study participants. The largest 10 departments for study participants are reported. The sample sizes are 849 courses taken by 141 students in the treatment group and 943 courses taken by 145 students in the control group.

between the treatment and control groups, however, reveals similar distributions. Table 5 reports distributions for the 10 most popular departments. The most popular department for taking courses is mathematics. A similar percentage of treatment and control students take mathematics courses (11.5% compared with 11.1%, respectively). The next most popular department is business computer information systems, representing 8.5% of the treatment group and 10.5% of the control group. To investigate this concern further, we estimate regressions that add fixed effects for course departments and the quarter in which the course was taken (specification 2 of Table 4). The coefficient estimates on the treatment variable remain similar for all of the educational outcomes.

In specification 3, we add administrative information on basic assessment tests collected by the college for most entering students.[17] Assessments in mathematics, English and reading are available. These assessment scores are used for student placement in courses. Adding more confidence to the results we find similar treatment effect estimates after the inclusion of these assessment scores which are generally strong predictors of educational outcomes. Overall, we find that the treatment-control differences in educational outcomes are not sensitive to controlling for detailed student characteristics and other factors.

3.2. *Compliance and Local Average Treatment Effects*

We next address the potential problem of impartial compliance in both the treatment and control groups. All the estimates discussed thus far include the full sample of computer-eligible students in the treatment group. We first start by noting again that 92% of eligible students pick up their free computers (see Table 2). To check that the 'treatment-on-the-treated' estimate does not differ substantially from the previous

[17] Not all the students take the assessment tests when entering the college, and thus a small percentage of students may have taken the tests after the start of the study.

'intent-to-treat' estimate, we estimate an IV regression.[18] Specifically, we use computer eligibility as an IV for whether the student picked up the free computer. The first-stage regression for the probability of computer receipt is:

$$C_i = \omega + \boldsymbol{\gamma X}_i + \pi T_i + \lambda_t + \lambda_d + u_i + \varepsilon_{ij}. \tag{2}$$

The second-stage regression is:

$$y_{ij} = \alpha_2 + \boldsymbol{\beta}_2 \boldsymbol{X}_i + \varphi \hat{C}_i + \lambda_t + \lambda_d + u_i + \varepsilon_{ij}, \tag{3}$$

where $\hat{C}_i$ is the predicted value of computer ownership from (2). In this case, φ provides an estimate of the 'treatment-on-the-treated' effect. The IV estimates are reported in specification 2 of Table 6 (specification 1 reports the OLS estimates for convenience). As expected given the high compliance rate, the estimates are only slightly larger than the intent-to-treat estimates and approximate the simple OLS coefficients divided by 0.92.

Table 6

Local Average Treatment Effect Estimates for Educational Outcomes

	Treatment-control difference		
		IV estimates	
	OLS estimate (1)	Lower bound (2)	Upper bound (3)
I. Successfully pass course (course success rate)	0.029	0.031	0.039
	(0.029)	(0.031)	(0.039)
II. Take course for grade	0.029**	0.031**	0.039**
	(0.013)	(0.015)	(0.018)
III. Take transfer course for UC or CSU	0.070**	0.077**	0.096**
	(0.028)	(0.030)	(0.038)
IV. Graduate with degree or certificate	0.017	0.018	0.024
	(0.045)	(0.050)	(0.064)
V. Educational outcome index	0.105**	0.115**	0.143**
	(0.043)	(0.047)	(0.059)
Baseline controls	Yes	Yes	Yes
Quarter and course department fixed effects	Yes	Yes	Yes
Maths, English and reading assessments	Yes	Yes	Yes

Notes. The dependent variables are whether the grade was a C, CR or better in panel I, whether the course was taken for a letter grade in panel II, whether the course is transferable to the California State University (CSU) or University of California (UC) systems in panel III, whether the student received an associates degree, vocational degree or vocational certificate in panel IV and an equally weighted average of z-scores from the four reported educational outcomes in panel V. z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation. Robust standard errors are reported and adjusted for multiple courses taken by study participants. *, ** and *** denote statistical significances at the 0.10, 0.05, and 0.01 levels, respectively. Baseline controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, family income, initial campus location, has a job and primarily speaks English. The sample size is 1,792 courses taken by 286 study participants. The dependent variable in the first-stage regression in the instrumental variable (IV) model is obtaining a new computer. The lower (upper) bound estimate assumes that all control group non-compliers obtained computers at the end (beginning) of the study period. OLS, ordinary least squares.

[18] The intent-to-treat estimates are relevant for potential policy conclusions drawn from the results. Any computer giveaway or price subsidisation programme will likely not experience full compliance. There will always be some students who do not participate in a programme even though they showed initial interest, and some students who purchase computers independent of the programme.

Similar to most social experiments, it is not possible to prevent the control group from receiving an intervention that potentially has the same effect as the treatment intervention. In this case, the control group may have purchased computers on their own during the study period. From the follow-up survey taken at the end of the study period, we find that 29% of the control group reports getting a new computer but no information is available on when they purchased the computer. Although students in the control group who purchased their computers near the end of the study period are not likely to have a large effect on the estimates, students in the control group purchasing computers at the beginning of the study period may dampen estimated differences between the treatment and control groups.

To investigate these issues further we expand on the 'treatment-on-the treated' results to estimate the more general local average treatment effect (LATE). The estimates reported in specification 2 implicitly assume that all students in the control group received a computer at the end of the study period. The other extreme is to assume that all the students in the control group reporting obtaining a computer in the follow-up survey received that computer at the beginning of the study period. In this case, control group students obtaining computers contribute to the estimation of (2) with $C_i = 1$. Specification 3 in Table 6 reports estimates.[19] The new IV estimates are now larger than the treatment-on-the-treated (TOT) estimates and are roughly 35–40% larger than the original OLS estimates.

The IV estimates indicate that the effects of having a home computer on educational outcomes are non-trivial but are not extremely large. The estimates indicate that the effects of having a home computer are 3–4% relative to the control group means for the taking courses for grades rate. For taking CSU- and UC-eligible transfer courses, the effects of having a home computer range from 10% to 13% of the control group mean. Although not statistically significant, the point estimates for the course success rate imply a 4–5% effect relative to the control group mean, and the point estimates for the graduation rate imply home computer effects from 12% to 15%. The summary index estimates indicate that the treatment group mean is 0.12–0.14 standard deviation units higher than the control group mean. As discussed further next, these estimates of the magnitude of home computers on educational outcomes are smaller than those typically found in non-experimental studies.

The IV estimates for the effects on graduation are useful for generating a rough, back-of-the-envelope estimate of the value of a computer. Although estimates of the returns to obtaining an associate's degree relative to not obtaining one vary widely, they appear to be in the range of 5–11% (Kane and Rouse, 1995, 1999). Using the mid-point of this range implies that the returns to an associate's degree are 8% or \$2,500 per year, and the gain in the present value of lifetime earnings is \$32,000.[20] The average LATE point estimate on the graduation rate of 0.021 implies that the computer is worth \$675 in present value of lifetime earnings. If the value of the computers is \$500 then there may be some under-investment of personal computers although it does not appear to be extremely large. Financial constraints may bind for some students, especially low-income students, limiting the educational purchases of computers even when it

[19] For all educational outcomes, the first-stage coefficients on the treatment variable are large and highly significant.

[20] These estimates assume a discount rate of 5%, tax rate of 25% and average earnings of \$31,000 (US Census Bureau, 2008).

would otherwise be optimal, but there might also be technical and informational constraints due to having less previous experience with computers.

4. Potential Mechanisms

In this Section, we attempt to identify the underlying mechanisms that are responsible for the estimated positive effects of home computers on educational outcomes. As noted previously, we find some evidence that home computers increase the total amount of time use of computers and flexibility of use of computers by students. Estimates from our follow-up survey conducted at the end of the study period indicate that the treatment group uses computers nearly 3 hours more per week than the control group. We also found that receiving a free computer appears to be associated with increased flexibility in the times of the day students use computers to complete their school assignments. If one of the main effects of having a home computer is providing longer and more flexible access to computers then we should find that students living farther away from campus benefit the most from receiving a free computer to use at home. As a result of lower time costs, students living near the college campus would benefit less from receiving home computers because on-campus computer labs are more accessible.

On the baseline survey, which was conducted before the computers were handed out, we asked students how far they lived from the campus. Using this information, we estimate regressions for educational outcomes that include interactions between treatment and distance from campus. To start, we include separate treatment indicators for students living close to campus and students living far from campus. Living close to campus is defined as being within 15 miles, which represents the median distance to campus among all study participants. The community college does not provide on-campus housing. Table 7 reports estimates for the four educational outcomes and the summary index. The treatment effects are positive and large for the group of students living more than 15 miles from the campus for the course success rate and graduation rate. The treatment point estimates are also positive, but smaller in magnitude and insignificant, for the other two educational measures. The summary index of educational outcomes indicates a positive and statistically significant treatment coefficient for students living farther from campus. In contrast to these results, we find both positive and negative estimates of the effects of home computers on educational outcomes for the group of students living close to campus at the beginning of the study. The treatment estimate for the summary index is essentially zero.

We also estimate regressions in which we include an interaction between the treatment effect and baseline distance to campus. In all specifications we also include a treatment dummy and the distance variable. We find a positive treatment/distance interaction in most of the specifications including the summary index providing some evidence that the positive effects of receiving a free computer increase with how far students live from the campus. The results from both sets of distance interactions are consistent with home computers providing more educational benefits to students who live farther from the campus. These students experience higher costs associated with relying primarily on using on-campus computers to complete schoolwork. The median distance to the campus is 15 miles and the average distance is 18 miles suggesting that there might be a non-trivial time savings from not having to go to campus to work on computers.

Table 7

Treatment-Control Differences in Educational Outcomes Interacted with Baseline Distance from Campus and Having a Job

	Course success (1)	Take course for grade (2)	Take transfer course (3)	Graduate with degree or certificate (4)	Educational outcome index (5)
I. Distance to campus					
Treatment × far from campus	0.063*	0.029	0.048	0.119**	0.213***
(more than 15 miles)	(0.034)	(0.020)	(0.035)	(0.059)	(0.061)
Treatment × close to campus	−0.047	0.038*	0.081*	−0.127*	−0.034
(less than 15 miles)	(0.051)	(0.023)	(0.048)	(0.070)	(0.076)
II. Work status					
Treatment × has job	0.041	0.050**	0.098**	0.055	0.194***
	(0.038)	(0.018)	(0.038)	(0.068)	(0.063)
Treatment × no job	−0.007	0.010	0.011	−0.026	0.018
	(0.048)	(0.023)	(0.042)	(0.062)	(0.080)

Notes. The dependent variables are whether the grade was a C, CR or better in specification (1), whether the course was taken for a letter grade in specification (2), whether the course is transferable to the California State University or University of California systems in specification (3), whether the student received an associates degree, vocational degree or vocational certificate in specification (4) and an equally weighted average of z-scores from the four reported educational outcomes in specification (5). z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation. Robust standard errors are reported and adjusted for multiple courses taken by study participants. *, ** and *** denote statistical significances at the 0.10, 0.05 and 0.01 levels, respectively. Baseline controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, family income, initial campus location, has a job and primarily speaks English. The sample size is 1,792 courses taken by 286 study participants. Dummy variables for living far from campus and having a job are also included in the regressions. Distance from campus and having a job are measured prior to when computers are handed out to students.

Table 7 also reports separate treatment effect estimates for students who have a job and for students who do not have a job. We find some evidence suggesting that students who had a job at baseline have better educational outcomes in the treatment group than in the control group. We find no evidence, however, that students who did not have a job experienced better educational outcomes for the treatment group. This finding is consistent with the argument that home computers provide more flexibility in computing access times. Students who are working are likely to have the least amount of spare and flexible time and might benefit the most from the increased availability and flexibility of having a home computer. Overall, the results presented in Table 7 provide some suggestive evidence that an important mechanism by which home computers exert a positive influence on educational outcomes may be by increasing total access time and flexibility in using computers to complete schoolwork.

Home computers may have improved educational outcomes partly through improving computer skills. The importance of disparities in computer skills in contributing to educational and overall economic inequality has been noted in the literature (Hargittai, 2002; Servon, 2002; Warschauer, 2003). If the increased use time, flexibility and autonomy offered by having access to a home computer improves the computer skills of students, then students may be more efficient at using and expanding the range of uses of computers for schoolwork (Warschauer and Matuchniak, 2010). We explore this question by using information on self-reported computer skills from the follow-up survey. Students were asked: 'How would you rate your computer skills?', and were given the possible responses of 'excellent', 'very good', 'good', 'satisfactory' and 'inadequate'. This self-reported, 5-point scale is similar to previously used measures of technology skills (Hargittai, 2005). Self-reported skill measures such as this one have been found to have good predictive power for actual skills and much more predictive power than either the amount of time spent per week or the number of years of use (Hargittai, 2005). Figure 2 displays the full distribution of responses for self-reported computer skills for the treatment and control groups. Roughly half of the control group reported having 'excellent' or 'very good' computer skills compared with nearly two-thirds of the treatment group. The difference of roughly 15 percentage points holds after controlling for the baseline variables and is statistically significant. An ordered probit for the full distribution of computer skills also reveals a positive and statistically significant treatment effect. The improvement in computer skills from receiving free computers is one possible method by which home computers could have a positive effect on educational outcomes although the effect might not be large.

Another mechanism by which receiving a free computer could affect educational outcomes is through an income effect. At the beginning of the study, the free computers were estimated to be worth \$500. This transfer implicitly creates an income shock which might be partly responsible for better educational outcomes. The income effect would only be realised, however, for students who subsequently sold the free refurbished computer (which might be for much less on the used market) or were intending to purchase a computer. Perhaps the most important channel by which an income shock could have a measurable effect on educational outcomes is by reducing how much time students need to work, thus freeing up more time to study. At a wage rate of \$10 per hour (the California minimum wage is \$8 per hour), a student could

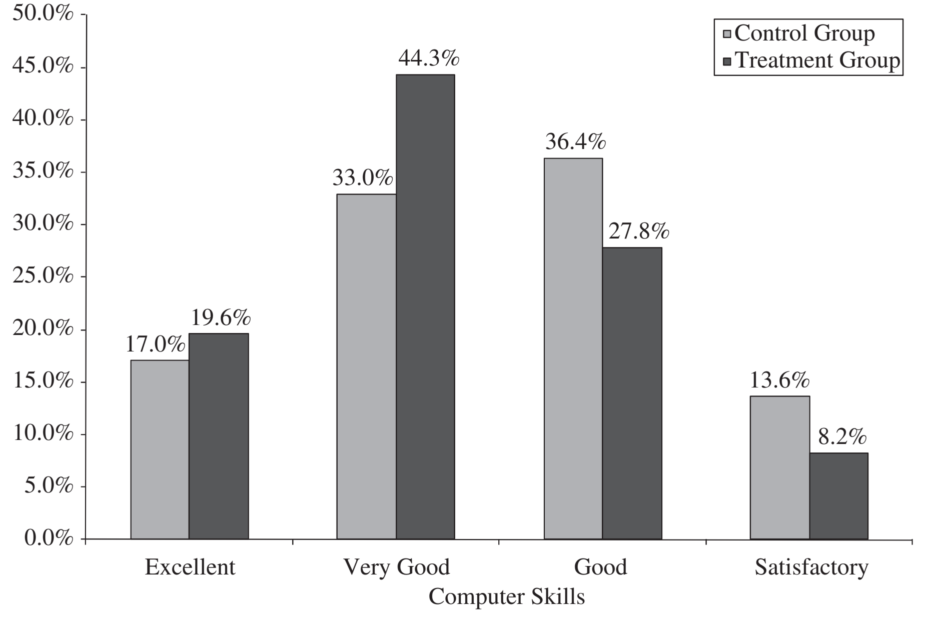

Fig. 2. *Computer Skills for Study Participants*

work 50 hours less over the two-year study period. Although the income transfer and the potential hours worked reduction are not large, we checked to see if the total number of hours worked were different between the treatment and control groups in the follow-up survey. We find that students in the treatment group worked 16.8 hours per week on average and students in the control group worked 17.1 hours per week on average. The difference in hours is very small (less than 2%). Students do not appear to have worked less because of receiving free computers. An income effect might also affect their living situation allowing students to live in less crowded housing which might result in better educational outcomes. In the follow-up survey, however, we do not find evidence that the average number of people living in the household in the treatment group (3.6) is lower than for the control group (3.4). Although we cannot rule out the possibility of an income effect it is unlikely that it is primarily responsible for the effect of free computers on educational outcomes for these students.

Home computers increase the total potential use for non-educationally productive activities, such as games, social networking and other forms of entertainment. The use of computers for these purposes may be restricted in on-campus computer labs, but there are no restrictions on the use of home computers for entertainment-related activities at home. The unregulated use of home computers by students for entertainment may offset some of the potential positive effects on educational outcomes by displacing time devoted to schoolwork. Game use is extensive among young adults and there has been a particularly rapid growth in the use of social networking sites, such as Facebook, over the past few years (Lenhart *et al.*, 2008; Lenhart, 2009).

In the follow-up survey, we asked students how many hours per week they use computers for games, chat rooms, videos (YouTube), networking software (Facebook, MySpace), music and other entertainment. As expected, we find that game, networking and entertainment use is higher among the treatment group than the control group. The control group reports using computers for games, networking and entertainment 2.2 h per week, whereas the treatment group reports using computers for these activities 2.8 h more per week. The 2.8 h per week that the treatment group uses computers for entertainment purposes represents nearly one-fifth of the total time they use computers. Although these estimates are imprecisely measured and the treatment-control difference is not statistically significant, increased game, social networking and entertainment use associated with having a home computer could explain why we only find modest-sized effects of home computers on educational outcomes.

In sum, home computers appear to have increased the total hours and time flexibility of computer use, improved the computer skills of their owners, and have the largest benefits for students with more limited on-campus access. All these factors may contribute to how home computers exert a positive influence on educational outcomes. On the other hand, we do not find evidence suggesting that the positive effects simply capture an income effect.

5. Non-experimental Estimates

Previous non-experimental studies generally indicate very large positive effects of home computers on educational outcomes. In contrast, the estimates from this study indicate more modest-sized effects even from the IV estimates. But, it is difficult to make comparisons because the previous research does not focus on the effects of home computers on community college students. To remedy this problem we estimate regressions for community college graduation using the latest Computer and Internet Supplements from the Current Population Survey (October 2007 and 2009) to compare with the experimental estimates.[21] Fortunately, the October 2007 and 2009 CPS also includes the annual Education and Enrollment Supplement, which includes information on enrolment in community college.

A limitation of the CPS, however, is that the cross-sectional data cannot be used to examine whether computer ownership among enrolled community college students affects subsequent educational outcomes. To address this limitation we link the October 2007 CPS to the October 2008 CPS and the October 2009 CPS to the October 2010 CPS to create longitudinal data. Households in the CPS are interviewed each month over a four-month period. Eight months later they are re-interviewed in each month of a second four-month period. The rotation pattern of the CPS makes it possible to match information on individuals in a CPS who are in their first four-month rotation period (e.g. October 2007) to information from the same month in their second four-month rotation period (e.g. October 2008). Thus, a two-year panel can be created for up to half of the original October 2007 and October 2009 respondents. To match these data, we use household and personal identification codes provided in the CPS and remove false matches using age, race and sex codes.

In Table 8, we report estimates from regressions of the probability of graduating from community college. The variable of interest is whether the individual has a computer with Internet access at home, which is measured in the first survey year (October 2007 and 2009).[22] The sample is limited to students enrolled in community college in this year and graduation is measured in the second survey year (October 2008 or 2010). Using this definition, we find that 16.7% of students graduate. Including the detailed controls available in the CPS for gender, race/ethnicity, immigrant status, age, family income, home ownership, region, central city status and year of survey, we find a large, positive and statistically significant coefficient on having a computer with Internet access at home on graduation. The point estimate indicates that the graduation rate is 9.1 percentage points higher for community college students who have home computers with Internet access than for students who do not have access after controlling for income, race and other demographic characteristics.

One concern about the comparability of graduation rate estimates from our study sample and the CPS is that the two measures cover different time period lengths. The CPS analysis sample includes students in their first year of study and measures graduation from community college one year later. The Butte College study sample is also in their first full year of study but graduation is measured in the spring of their second year. We would expect that the graduation rate for first-year students in the study sample to be higher than the CPS sample simply because of the two-year window instead of the one-year window. To address this concern, we remove first-year students from the CPS sample to make the measures more comparable. Panel II of Table 8 reports estimates.

[21] The CPS, conducted by the US Census Bureau for the Bureau of Labor Statistics, is representative of the entire US civilian non-institutional population and interviews approximately 50,000 households.

[22] The 2007 and 2009 CPS do not include information on computer ownership without Internet service. As noted before, however, nearly all individuals with home computers have Internet access.

Table 8

Non-Experimental Regression Results for the Graduation Rate, Matched Current Population Surveys, October 2007–8 *and* 2009–10

	(1)	(2)	(3)	(4)	(5)
I. All community college students					
Home computer with Internet	0.091**	0.095**	0.120**	0.081*	0.110**
	(0.038)	(0.038)	(0.046)	(0.041)	(0.048)
Mean of dependent variable	0.167	0.169	0.176	0.177	0.168
Sample size	681	681	681	475	274
II. Excludes first-year students					
Home computer with Internet	0.203**	0.211**	0.217**	0.199**	0.220**
	(0.076)	(0.075)	(0.091)	(0.083)	(0.102)
Mean of dependent variable	0.266	0.268	0.292	0.283	0.273
Sample size	350	350	350	237	139
Sample	Full	Full	Full	Family income ≤ $75,000	Family income ≤ $40,000
Weights	N/A	Predicted financial aid	Ratio of income distributions	N/A	N/A

Notes. The sample includes individuals enrolled in two-year colleges in the first-survey year in the matched CPS data. The dependent variable is whether the student received an associates degree in the second survey year. Specification 2 weights observations by their predicted probability of being a financial aid student based on gender and race/ethnicity. Specification 3 weights observations by the ratio of the income distribution in the study sample relative to the income distribution in the CPS. Specifications 4 and 5 exclude students living in households with $75,000 or more in income and $40,000 or more income, respectively. Robust standard errors are reported. *, ** and *** denote statistical significances at the 0.10, 0.05 and 0.01 levels, respectively. All specifications include controls for gender, race/ethnicity, immigrant status, age family income, home ownership, region, central city status and year of survey.

As expected, the graduation rate increases (16.7% to 26.6%) and the estimate of the effect of home computers doubles in size (0.0909 to 0.2028). The information in the CPS on the year of study, however, is not entirely clear for community college students because the possible responses to the question appear to be written primarily for four-year college students (i.e. possible responses include Year 1-freshman, Year 2-sophomore, Year 3-junior and Year 4-senior). Owing to the uncertainty of how community college students respond to the year in college question we report both estimates using the full CPS sample and the sample excluding first-year students.

Estimates of the relationship between home computers and graduation rates are not sensitive to the inclusion of students living in high-income households in the CPS. In specification 2 of Table 8, we weight the CPS sample by the probability of being a financial aid student at Butte College. Using administrative data on gender and race/ethnicity for all students at Butte College, we estimate a regression for the probability of being a financial aid student and use the coefficients to calculate weights for each observation in the CPS sample making it more representative of financial aid population. The coefficient estimates for the full and restricted samples are similar to the unweighted estimates. We also weight the CPS sample by the ratio of the income distribution of the study sample relative to the CPS sample, thus making the CPS sample mimic the income distribution of the study sample. Specification 3 reports these estimates which show slightly larger estimates for the relationship between home computers and graduation rates. Finally, we report two sets of estimates in which we exclude the upper part of the income distribution to examine the sensitivity of our estimates. We report separate regression estimates for samples that exclude family incomes of $75,000 or more (specification 4) and $40,000 or more (specification 5). Although these income cutoffs remove a large portion of the CPS sample, we continue to find similarly large point estimates.

These estimates of the effect of home computers using the CPS are much larger than the range of estimates from our experiment. The LATE estimates for the graduation rate range from 1.8 to 2.4 percentage points. In the CPS, we find estimates ranging from roughly 10 to 20 percentage points with the most comparable estimates likely being at the high end of that range. These findings justify concerns that there might be positive selection in computer ownership and that non-experimental estimates may overstate the effects of home computers on educational outcomes.

6. Conclusions

This study provides the first field experiment involving the random provision of free computers to students for home use. We find some evidence that the randomly selected group of students receiving free computers has better educational outcomes than the control group that did not receive free computers. Although treatment effect estimates for a few outcomes are imprecise and cannot rule out zero effects, the point estimates of the effects of home computers are consistently positive across different measures of educational success. Creating a summary index that aggregates information over multiple treatment effect estimates, we find a positive and statistically significant effect of home computers on educational outcomes. The estimated impacts of home computers on educational performance, however, are not large – the educational outcome summary index implies that the treatment group is 0.14 standard deviations higher than the control group mean. These estimates from the random experiment are smaller than those found from an analysis of matched CPS data raising concerns that previously reported estimates of large, positive effects of home computers on educational outcomes may be overstated.

Findings from the experiment also provide some suggestive evidence on the underlying mechanisms responsible for positive effects. Home computers appear to improve flexibility in when computers are used for schoolwork and may represent an important substitute for on-campus use. We find some evidence that students living farther from the campus benefitted more from the computers than those living closer to the campus, although the estimates were not entirely consistent across outcome measures. Home computers also appear to improve computer skills possibly leading to more efficient and a wider range of uses of computers to complete schoolwork. One factor that may dampen any positive effects of home computers on educational outcomes is the displacement from non-educational uses such as for games, social networking and entertainment. We find evidence that is consistent with high levels of game, social networking and entertainment use among students receiving free computers, but more research is clearly needed on the potential displacement effect of entertainment uses of home computers on schoolwork time.

With the concern that home computers may provide a distraction in terms of games, networking and other entertainment for many students, the findings from this experiment suggest that disparities in access to home technology may translate into future disparities in educational, labour market and other economic outcomes. Given the large returns to education (Card, 1999), students may be under-investing in personal computers for educational purposes. For some students, especially low-income students, the primary cause of this sub-optimal level of investment in technology may be financial constraints.[23] Tax breaks or special loans for educational computer purchases, and an expansion of computer refurbishing programmes that provide low-cost machines may increase access for disadvantaged youth. Another potential solution is to expand the relatively new programmes that allow students to check out school laptop computers for home use (Warschauer, 2006). Although there are large-scale programmes that subsidise the school use of technology as an input in educational production (e.g. the E-Rate programme) and that provide subsidies for computer purchases among low-income youth in other countries (Department for Children, Schools and Families, 2008), programmes encouraging personal investment in educational technology are currently limited in the US (Servon, 2002; Warschauer, 2003). Addressing the remaining US digital divide in home access is likely to become even more important over time as schools, professors and financial aid sources are increasingly using technology to provide information, communicate with students and deliver course content.

Appendix

Background Characteristics of Follow-up Survey Respondents

	All study participants (%)	Follow-up survey respondent (%)	Follow-up treatment group (%)	Sample control group (%)	p-value for treatment/control difference
Female	63.3	64.9	65.0	64.8	0.980
Latino	17.8	18.4	15.5	21.6	0.285
Other minority	18.2	16.8	19.6	13.6	0.282
Age	25.0	25.6	26.1	25.0	0.444
Parent some college	37.8	41.1	46.4	35.2	0.125
Parent college graduate	22.0	21.6	18.6	25.0	0.290
High school grades As and Bs	30.4	35.7	36.1	35.2	0.904
High school grades Bs and Cs	56.6	53.0	52.6	53.4	0.911
Live with own children	27.3	28.1	28.9	27.3	0.811
Live with parents	34.6	33.0	25.8	40.9	0.029
Household income: $10,000–$19,999	31.5	30.8	26.8	35.2	0.217
Household income: $20,000–$39,999	25.9	26.5	29.9	22.7	0.272
Household income: $40,000 or more	16.8	18.9	15.5	22.7	0.210
Takes most classes at Chico Center	25.2	22.7	23.7	21.6	0.733
Takes most classes at Glen/other	8.4	8.6	8.3	9.1	0.840
Has job	55.0	56.0	51.1	61.4	0.164
Sample size	286	185	97	88	

Note. Based on follow-up survey conducted in spring 2008.

[23] Technical and informational constraints may also be important for low-income students because they are likely to have had less previous experience with computers. Another potential reason for suboptimal investment in personal computers is that forward-looking behaviour suggests that consumers may wait until a better model arrives (Prince, 2009). Students currently enrolled in college, however, are unlikely to postpone the purchase of a computer for a better model for very long.

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