# The effects of home access to technology on computer skills: Evidence from a field experiment

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### ABSTRACT

Computer skills are important for educational and labor market success. This paper examines whether disparities in access to home computers are limiting the acquisition of computer skills. To address problems with selection bias, I use data from a randomized field experiment providing free computers for home use to community college students. I find that the treatment group of low-income students receiving free computers has significantly higher levels of computer skills than the control group of low-income students not receiving free computers. The "intent-to-treat" estimates indicate an increase in high-level computer skills of 17% points, and the LATE estimates indicate a range of 19–23% points. The results are robust to estimation strategy, measurement of the dependent variable, and inclusion of different sets of controls. The benefits appear to be the strongest among young, minority, low-income, and female students.

## 1. Introduction

Thirty-five million households in the United States do not have Internet access at home (National Telecommunications and Information Administration, 2011). These households that do not have access to home computers are predominately poor. For example, only 58% of the 50 million US households with less than $50,000 in annual income have Internet access at home. In contrast, nearly 92% of households with more than $50,000 in income have Internet access.[1] What are the consequences, if any, of these large disparities in access to home technology often referred to as the "Digital Divide"? The small and growing literature on this question provides some evidence of positive effects of home computers on educational, labor market and other outcomes raising concerns about the potential consequences of the digital divide.[2]

Inequality in access to home computers may have an especially negative effect on creating disparities in computer skills. The increased use time, flexibility and autonomy offered by having access to a home computer may result in enhanced computer skills for home users relative to non-home users. Home computers should improve skills among the general population, however, for groups with alternative access, such as students, they might have only a marginal effects on skills. This link between computer ownership and computer skills, however, has not been carefully examined, which may be an important omission from the literature because of its broader implications for potential consequences of the digital divide. Indeed, previous researchers have identified disparities in computer skills as an understudied and important aspect of the

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[1] Rates of computer ownership are also substantially lower among minority families. See US Department of Commerce (2008), Goldfarb and Prince (2008), Ono and Zavodny (2003, 2007), and Fairlie (2004) for example.

[2] See Attewell and Battle (1999), Schmitt and Wadsworth (2006), Fairlie (2005), Beltran et al. (2010), Kawaguchi (2006), Fiorini (2010), and Balboni et al. (2011) for a few recent examples. See also Fuchs and Woessmann (2004), Malamud and Pop-Eleches (2011), and Vigdor and Ladd (2010).

digital divide and have referred to them as the "second-level" of the digital divide (see Hargittai (2002) and Servon (2002) for example).

In this paper, I address this limitation in the literature by exploring whether having access to home computers improves computer skills. A major problem in estimating the causal relationship between home computers and computer skills is that those individuals who are inherently good at using computers may also be the ones that are most likely to purchase them. This selection bias may lead to an overstatement of the effects of having access to a home computer on computer skills from standard regression analysis. To address this problem, I use data from the first-ever randomized field experiment providing free computers to students for home use.[3] Participating students were randomly selected to receive free computers to use at home and their computer skills and academic outcomes were measured at the end of the second academic year. The random-assignment evaluation is conducted with 286 entering students receiving financial aid at a large community college in Northern California. Previous findings from the field experiment provide some evidence that the randomly selected group of community college students receiving free computers achieved modestly better educational outcomes than the control group that did not receive free computers (Fairlie and London, 2012).[4] The effects of home computers on the computer skills of students, however, have not been previously examined. Although examining the impacts of home computers on college performance is clearly important, examining the impacts on computer skills is also important because of the possible independent effects on other outcomes such as job skills, communication, and the ability to acquire information. This study represents the first test of the hypothesis that having a home computer improves computers skills using a randomized control experiment.

The focus on low-income community college students may be of special interest because of the growing importance of community colleges in higher education and the limited access to on-campus technology at community colleges relative to 4-year colleges. Community colleges enroll nearly half of all students attending public universities, and an even larger share of low-income and minority students (US Department of Education, 2009). The share is even higher in some states, such as California, where community colleges serve 2.5 million students a year representing more than 70% of all public higher education enrollment (Sengupta and Jepsen, 2006), and President Obama recently proposed an unprecedented funding increase for community colleges that will boost graduates by 5 million by 2020.[5]

The findings from this study are especially important because of the increasing reliance on technology in the labor market and educational system.[6] Computer skills are undoubtedly useful for success in the labor market. More than 80% of all jobs require the use of computers in the workplace and 95% of jobs held by college graduates require their use (Madden and Jones, 2008).[7] Information technology jobs are some of the best paid and fastest growing occupations in the United States (US Department of Labor, 2008; US Bureau of Labor Statistics, 2009). Home computers also appear to increase the benefits to using computers at school possibly through the enhanced computer skills of home users (Mitchell Institute, 2004). Related to this issue, higher levels of Internet skills are found to be associated with types of Internet use that potentially have the most economic benefits to the user (Hargittai and Hinnant, 2008).

## 2. The field experiment

Free computers were randomly assigned to entering financial aid students at Butte Community College located in Northern California. Butte College has a total enrollment of over 15,000 students and 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, 2008). The computers used in the study were provided by Computers for Classrooms, Inc. a computer refurbisher located in Chico, California.[8]

To implement the field experiment letters advertising the computer giveaway program were sent to all financial aid students with less than 24 units attending the college in Fall 2006 (see Fairlie and London, 2012 for more details on the field experiment). In Fall 2006, there were 1042 financial aid students and 6681 students in total who met the course unit restriction. Participating students were required to return a baseline questionnaire and consent form releasing 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 old, unreliable, and not fully functional with the latest software and hardware.[9] There were 286 students who participated in the study with 141 of these students receiving free computers. Internet service was not provided as part of the experiment, but I found at the end of the study that more than 90% of the

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

[4] Additionally, a comparison of the experimental estimates to non-experimental estimates of the effects of home computers on educational outcomes from the CPS suggests that non-experimental estimates may be upwardly biased (Fairlie and London, 2012).

[5] See http://www.whitehouse.gov/issues/education.

[6] The National Research Council (1999) has proposed that information technology fluency be a minimum standard for college graduates.

[7] Among college-educated workers using computers at work, 87% use computers for spreadsheets/data bases, 47% use computers for graphics/design, and 24% use computers for programming, all of which require skills beyond word processing, email and Internet search (US Department of Education, 2007).

[8] 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). Computers for Classrooms offered to replace any computer not functioning properly during the 2-year period.

[9] Twenty-eight percent of students reported already owning a computer. The results presented below are not sensitive to the exclusion of these students.

treatment group had Internet service.[10] No training or assistance with the computers was provided and students were not restricted in what they used the computers for to focus on the effects of home computers instead of a broader (or more defined) policy intervention. More than 90% of eligible students picked up their free computers by the end of November 2006.

Information on computer skills used in the analysis was gleaned from a follow-up survey conducted in late Spring/Summer 2008. The follow-up survey had an overall response rate of 65% among study participants. The surveys were conducted by mail and phone, although eight surveys were conducted by email after repeated attempts by mail and phone failed. The results presented below are not sensitive to the exclusion of these observations.

## 2.1. Hawthorne effects

As with any random experiment, there exists the possibility that the treatment group has a positive outcome partly because the interest being shown in them by researchers through the experiment leads to a change in their behavior (i.e. Hawthorne effect). This might be of special concern for the measure of computer skills because it is self-reported on the follow-up survey. The cost of exaggerating computer skills on a survey because students receiving free computers through the experiment felt like they should have learned something is relatively small (especially compared to obtaining better grades or graduating with a degree).

There are several reasons, however, for why this might not represent too substantial of a problem for the experiment. First, the computers were handed out to students at the Computers for Classrooms warehouse in Chico, California. No one from Butte College or from the research team was present during the handout and none of the surveys were conducted by Computers for Classrooms (consent, baseline or follow-up). Second, the students receiving free computers were never told that they were part of an experiment and that they were going to be compared to students who did not receive free computers. Third, computer skills were measured 1.5 years after the receipt of the computer and there was no contact with study participants until this point (and only through the mailed out follow-up survey). Researchers and college administrators did not have any correspondence with study participants about the project between computer handout and follow-up survey. Fourth, the title of the follow-up survey was "Butte College Student Questionnaire" with Butte College and University of California logos at the top. Nowhere on the follow-up questionnaire were students reminded of the computer handout that occurred 1.5 years earlier, that this was a follow-up survey, or that this was an experiment. The questions about computer ownership and hours of use were also intentionally made general and did not ask students how they obtained computers. Although Hawthorne effects cannot entirely ruled

out it does not seem like they are too problematic for the experiment given its design and the design of the follow-up survey.

## 2.2. Who applied for the computer lottery?

Table 1 reports administrative data from the original application to the college for students applying to the computer-giveaway program, all financial aid students, and all entering students.[11] 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 to 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 to 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.

A comparison to all students reveals that study participants are more likely to be female 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 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.

Overall, 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 generalize 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 subsidized computers.

## 2.3. 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, parents' education, and other characteristics. The average age of study participants is 25. 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

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[10] Previous research indicates that Internet subscription is very high among computer owners in the United States making it difficult to identify separate effects (Beltran et al., 2010).

[11] Baseline and follow-up survey data is only available for study participants.

**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 | 1042 | 6681 |

*Note*: Based on administrative data provided by Butte College for entering students in Fall 2006.

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

As noted above 65% of study participants responded to the follow-up survey, which provides information on computer skills at the end of the study period. The group of students responding to the follow-up survey appears to be representative of the full sample. Table 3 reports a comparison of the baseline characteristics. The follow-up sample has a similar racial, gender, parental education, income, and family composition as the full sample. The follow-up sample also has a similar average age and grade distribution as the full sample. Additionally, regression analysis reveals very little explanatory power for predicting response to the follow-up survey based on the baseline characteristics.

Table 3 also reports a comparison of baseline characteristics for the treatment and control groups within the follow-up sample. Sixty-nine percent of the treatment group responded to the follow-up survey and 61% of the control group responded. The difference is not statistically significant. The treatment and control groups appear to be similar for most characteristics. None of the differences are statistically significant with the exception of living with parents. The control group is more likely to live with their parents than the treatment group. We would expect some statistically significant differences due to chance when making this many comparisons given standard significance levels. All of these baseline characteristics are controlled for in the regressions reported below to further insure

**Table 2**
Background characteristics of study participants.

|  | Treatment:computer | | | | | P-Value for control difference |
|---|---|---|---|---|---|---|
|  | All study participants | Eligible | | Treatment/computer ineligible | |  |
|  |  | All | Control: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 |
| Sample size | 286 | 141 | 129 | 145 | |  |

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

**Table 3**
Background characteristics of follow-up survey respondents.

| | All study participants | Follow-up survey respondent | Follow-up sample | | P-Value for treatment/control difference |
| | | | Treatment group | Control group | |
|---|---|---|---|---|---|
| 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.

the comparability of the treatment and control groups in the analysis. I also check the robustness of the regression results to using weights that adjust for differential non-response rates.

### 2.4. Computer use and flexibility

The follow-up survey provides information on total hours and flexibility of computer use which provides some evidence on "first-stage" effects of the experiment (see Fairlie and London, 2012 for more details). The treatment group reports using computers 16.1 h per week on average compared to 13.4 h per week for the control group. The estimated difference of 2.7 h 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). The follow-up survey also provides evidence on whether the home computers allowed students increased flexibility in the times when they use computers. The estimates indicate that students who received home computers are more likely to report using computers in the daytime, late evening, and nighttime 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. These results 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 computer skills

Does having access to a home computer improve computer skills? This question is explored by using information on self-reported computer skills on 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 "inade-

quate". This self-reported, five-point scale is similar to previously used measures of technology skills. Hargittai (2005) finds that self-reported Internet use skill measures have good predictive power for actual Internet skills, and much more predictive power than either the amount of time spent per week or the number of years of use. Using the follow-up survey results from the experiment, I find that self-reported skills are positively correlated with several types of computer use, such as for work, searching for job opportunities, searching for health information, and searching for political information. Although a measure of computer skills based on a detailed test of would still be preferable, the costs and logistics of conducting these tests with the sample of community college students receiving financial aid were prohibitively expensive.

Fig. 1 displays the full distribution of responses for self-reported computer skills for the treatment and control groups. Only one student reported having "inadequate" computer skills so this category is combined with "satisfactory". Students winning free computers were more likely to report their computer skills as "excellent" or "very good" and less likely to report their skills as "good" or "satisfactory".

Separating the four potential responses into two categories, I find that half of the control group reported having "excellent" or "very good" computer skills. In contrast, nearly two-thirds of the treatment group reported having computer skills at this level. The increased access to computers offered by receiving a free home computer appears to have improved students' skills at using computers. To investigate this question more carefully I turn to a regression analysis.

### 3.1. Regression results

Table 4 reports estimates from several regressions using the probability of having "excellent" or "very good" computer skills (defined here as high-level skills) as the depen-
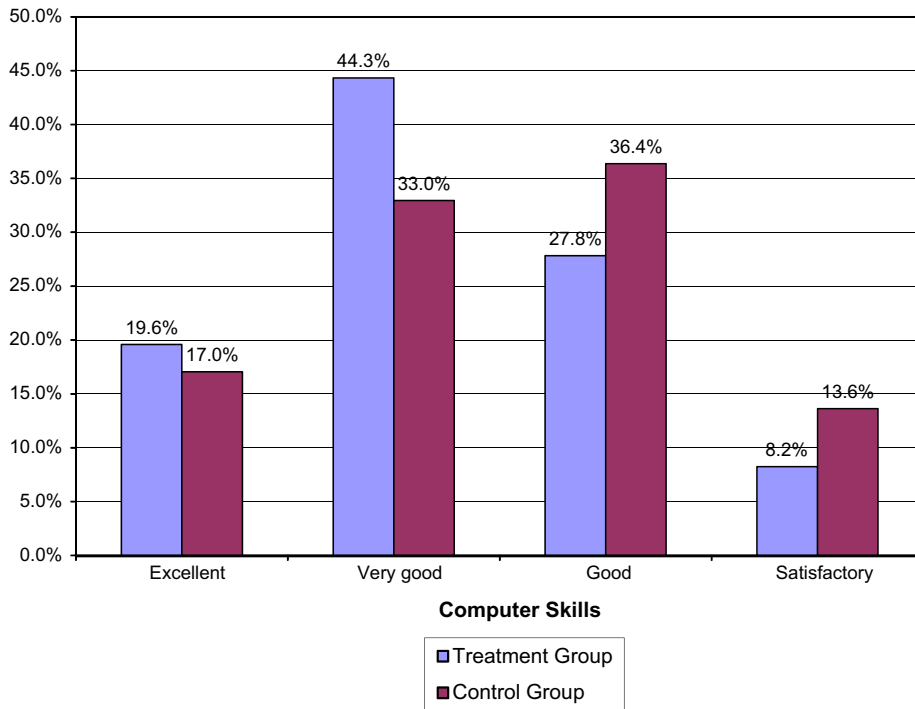
**Fig. 1.** Computer skills.

**Table 4**
Probit regressions for the probability of having high-level computer skills.

|  | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.1375 | 0.1505 | 0.1558 | 0.1699 |
|  | (0.0720) | (0.0714) | (0.0726) | (0.0733) |
| Main controls | No | Yes | Yes | Yes |
| Campus and job activity | No | No | Yes | Yes |
| *Assessments and English* |  |  |  |  |
| Language (administrative data) | No | No | No | Yes |
| Mean of dependent variable | 0.5730 | 0.5730 | 0.5714 | 0.5714 |
| Sample Size | 185 | 185 | 182 | 182 |

*Notes*: (1) The dependent variable is having high-level (or "very good" or "excellent") computer skills. (2) Marginal effects and their standard errors are reported. (3) Main controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, and family income. (4) Assessments include math, English and reading.

dent variable. The regression equation for the probability of having high-level computer skills is straightforward in the context of the random-assignment experiment:

$$\text{Prob}(y_i = 1) = \Phi(\beta X_i + \delta T_i), \qquad (4.1)$$

where $y_i$ is whether the student has high-level computer skills, $X_i$ includes baseline characteristics, $T_i$ is the treatment indicator, and $\Phi$ is the cumulative distribution function for the standard normal distribution. The effect of winning a free computer or the "intent-to-treat" estimate is captured by $\delta$. All specifications are estimated using a probit model and marginal effects and their standard errors are reported. Marginal effects estimates are similar for logit and OLS models.[12]

Specification 1 reports estimates of the treatment effect without any controls. The point estimate for $\delta$ implies that the treatment group of students receiving free computers has a 13.8% point higher likelihood of having high-level computer skills than the control group not receiving free computers. Including detailed controls for gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, and family income does not change the conclusion of a large, positive treatment effect (Specification 2). These variables are taken from the baseline survey administered to all study participants before receiving free computers. The treatment group has a 15.1% point higher likelihood of having high-level computer skills than the control group.

Specification 3 includes additional controls from the baseline survey. The campus locations, where the student took the majority of his/her courses and whether the student was working at the time of the baseline survey

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[12] Estimates are also similar after adjusting for survey non-response by using the inverse of the predicted probabilities of completing the follow-up survey as sample weights. See the Appendix for estimates.

**Table 5**
Ordered probit regressions for computer skills.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.2541 | 0.3207 | 0.3201 | 0.3226 |
| | (0.1577) | (0.1646) | (0.1667) | (0.1725) |
| *Treatment marginal effects for:* | | | | |
| $y = 0$: Satisfactory skills | −0.0469 | −0.0535 | −0.0540 | −0.0508 |
| | (0.0299) | (0.0288) | (0.0293) | (0.0286) |
| $y = 1$: Good skills | −0.0526 | −0.0720 | −0.0713 | −0.0754 |
| | (0.0332) | (0.0379) | (0.0381) | (0.0412) |
| $y = 2$: Very good skills | 0.0329 | 0.0456 | 0.0445 | 0.0474 |
| | (0.0220) | (0.0256) | (0.0253) | (0.0275) |
| $y = 3$: Excellent skills | 0.0667 | 0.0799 | 0.0808 | 0.0788 |
| | (0.0413) | (0.0412) | (0.0423) | (0.0424) |
| Main controls | No | Yes | Yes | Yes |
| Campus and job activity | No | No | Yes | Yes |
| Assessments and English | | | | |
| Language (administrative data) | No | No | No | Yes |
| Mean of dependent variable | 1.6486 | 1.6486 | 1.6484 | 1.6484 |
| Sample Size | 185 | 185 | 182 | 182 |

*Notes*: (1) The dependent variable equals 0 for "satisfactory", 1 for "good", 2 for "very good", and 3 for "excellent" computer skills. (2) Marginal effects and their standard errors are reported. (3) Main controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, and family income. (4) Assessments include math, English and reading.

are included as additional controls. The coefficient on the treatment dummy variable remains similar. In Specification 4, I add administrative information on basic assessment tests collected by the college for most entering students.[13] Assessments in math, English and reading are available. These assessment scores are used for student placement in courses. Administrative data collected at the time of application also provide information on whether the student primarily speaks English. Given the importance of English language ability for educational outcomes I include this as an additional control variable. The coefficient on the treatment variable is 17.0% points.

Overall, the treatment group has a substantially higher likelihood of having high-level computer skills than the control group. Attesting to the power of the randomization, the estimated effect does not change after the inclusion of several sets of baseline controls. Receiving a free computer increases the computer skills of students.

### 3.2. Ordered probits

The previous regressions model the probability that a student has "excellent" or "very good" computer skills relative to "good" or "satisfactory" skills. This dichotomy identifies higher than average computer skills relative to lower than average computer skills as evidenced by the split in the control group into equal shares. Do the results from an estimation technique that models the full distribution of computer skills provide the same conclusion regarding the positive effects of home computers on improving computer skills? To examine this question I estimate ordered probits for a dependent variable that takes on four possible values for computer skills: $y = 0$ for "satisfactory", $y = 1$ for "good", $y = 2$ for "very good", and $y = 3$ for "excellent". The specification is:

$$\text{Prob}(y_i = 0) = 1 - \Phi(\beta X_i + \delta T_i),$$
$$\text{Prob}(y_i = 1) = \Phi(\mu_1 - \beta X_i - \delta T_i) - \Phi(-\beta X_i - \delta T_i),$$
$$\text{Prob}(y_i = 2) = \Phi(\mu_2 - \beta X_i - \delta T_i) - \Phi(\mu_1 - \beta X_i - \delta T_i),$$
$$\text{Prob}(y_i = 3) = 1 - \Phi(\mu_3 - \beta X_i - \delta T_i),$$

(4.2)

where the $\mu$'s capture the cutoffs for the underlying latent variable measuring computer skills.

Table 5 reports estimates for ordered probits using the same set of specifications as reported in Table 4. The treatment coefficient captures movement from lower to higher values in the distribution of computer skills. The treatment coefficient is large and positive in all specifications. Focusing on Specification 4 which includes all of the control variables I find a treatment coefficient of 0.323.

Table 5 also reports marginal effects for each categorical level of computer skills. These marginal effects indicate the effect of the treatment on the probability of having computer skills at each of the four reported levels. Focusing on the results for Specification 4, I find that the treatment decreases the probability of being in the lowest skills category (i.e. having "satisfactory" computer skills) by 5.1% points. Receiving a free computer also decreases the probability of being in the next lowest skill category. The treatment has the opposite effect on higher level skills. It increases the probability of having "very good" skills by 4.7% points and having "excellent" skills by 7.9% points. The unambiguous effect of home computers is to shift the distribution of computer skills to the right (toward higher levels). The previous results for the effects of home computers on high-level skills summarize these distributional effects well.

### 3.3. Compliance and local average treatment effects

I next address the potential problem of non-compliance in the both the treatment and control groups. All of the estimates discussed thus far include the full sample of

[13] Not all students take the assessment tests when entering the college, and thus may have taken the test after the start of the study.

computer eligible students in the treatment group, and therefore represent estimates of the "intent-to-treat" as noted above. Among the follow-up sample, 91% of eligible students picked up their free computers. Among the control group, 28% report having a computer on the follow-up survey at the end of the study period. Similar to interventions in most social experiments, it was not possible to prevent the control group from obtaining a computer which might have the same effect as the computers provided to the treatment group through the experiment. One complication, however, is that no information is available on when students in the control group purchased their computers. 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, but 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 I expand on the "intent-to-treat" results to estimate the more general local average treatment effect (LATE). The LATE estimator adjusts for non-compliance in the treatment and control groups and identifies the effect of having a computer on computer skills (for those whose computer ownership was affected by whether they won a free computer) instead of the effects of receiving the option to get a free computer through the giveaway program. The LATE estimator is obtained from an instrumental variables regression. Specifically, computer eligibility (randomly winning a free computer) is used as an instrumental variable for whether the student reports having a home computer at follow-up. The first-stage regression for the probability of computer ownership is:

$$C_i = \gamma X_i + \pi T_i + u_i. \tag{4.3}$$

The second-stage regression is:

$$y_i = \beta_2 X_i + \Delta \widehat{C}_i + \varepsilon_i, \tag{4.4}$$

where $\widehat{C}_i$ is the predicted value of computer ownership from (4.2). A linear specification is used to simplify the two-stage estimation and is the common approach taken in the literature (Wooldridge, 2010). In this case, $\Delta$ provides an estimate of the LATE. Note that as we get closer to 100% compliance in both the treatment and control groups, $\widehat{C}_i$ becomes very similar to $T_i$, and $\Delta$ closely approximates the ITT estimator.

IV estimates are reported in Specifications 3 and 4 of Table 6. Specifications 1 and 2 report OLS coefficients for a benchmark for the IV estimate. The OLS coefficients are similar to the marginal effects for the probit regressions reported in Table 4. Specification 3 reports the LATE estimate assuming that all students in the control group reporting having a computer at follow-up actually obtained those computers at the very end of the study period. Although this is unlikely it provides a lower bound on the LATE estimate. It represents a special case of the LATE estimator when no one in the control group is treated and is often referred to as the "treatment on the treated" estimator because it only adjusts for non-compliance in the treatment group (Duflo and Rachel Glennerster, 2008). As expected given the high compliance rate in the treatment group, the estimate of the treatment effect is only slightly larger than the intent-to-treat estimate and approximates the simple OLS coefficient divided by 0.91.

Specification 4 of Table 6 reports the LATE estimate making the opposite extreme assumption that all of the students in the control group reporting a computer at follow-up obtained that computer at the very beginning of the study period (i.e. when students in the treatment group received their computers). The new IV estimate is 20% larger than the IV estimate reported in Specification 3 and is 30% larger than the ITT estimate. Given this range of IV estimates, the LATE estimate is between 0.188 and 0.226, which represents a sizeable increase in having high-level computer skills.

The effects of home computers on computer skills for students complying with the experiment are large. Because compliance in the treatment and control groups is relatively high these estimates do not differ substantially from the "intent-to-treat" estimates that capture the effects of offering free computers to students. These estimates are useful from a policy perspective because any computer giveaway or price subsidization program will likely not

**Table 6**
OLS and IV regressions for having high-level computer skills.

| | OLS estimates (ITT) | | IV Estimates (LATE) | |
| | | | Lower bound | Upper bound |
| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.1392 | 0.1742 | | |
| | (0.0726) | (0.0787) | | |
| Obtain new computer | | | 0.1884 | 0.2263 |
| | | | (0.0846) | (0.1157) |
| Main controls | No | Yes | Yes | Yes |
| Campus and job activity Assessments and English | No | Yes | Yes | Yes |
| Language (administrative data) | No | Yes | Yes | Yes |
| Mean of dependent variable | 0.5730 | 0.5714 | 0.5714 | 0.5714 |
| Sample Size | 185 | 182 | 182 | 182 |

*Notes*: (1) The dependent variable is having high-level (or "very good" or "excellent") computer skills. (2) Robust standard errors are reported. (3) Main controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, and family income. (4) Assessments include math, English and reading. (5) The dependent variable in the first-stage regression in the 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 survey period.

**Table 7**
Probit regressions for having high-level computer skills by gender, race, income.

|  | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment * female | 0.1695 (0.0886) |  |  |  |
| Treatment * male | 0.1136 (0.1236) |  |  |  |
| Treatment * minority |  | 0.2164 (0.1267) |  |  |
| Treatment * non-minority |  | 0.1180 (0.0877) |  |  |
| Treatment * high income |  |  | 0.0059 (0.1041) |  |
| Treatment low income |  |  | 0.2690 (0.0962) |  |
| Treatment * age ⩾25 |  |  |  | 0.1067 (0.1157) |
| Treatment * age <25 |  |  |  | 0.1725 (0.0948) |
| Mean of dependent variable | 0.5730 | 0.5730 | 0.5730 | 0.5730 |
| Sample size | 185 | 185 | 185 | 185 |

*Notes*: (1) The dependent variable is having high-level (or "very good" or "excellent") computer skills. (2) Marginal effects and their standard errors are reported. (3) Controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, and family income.

experience full compliance. There will always be some students who do not participate in a program even though they showed initial interest, and some students who purchase computers independent of the program.

### 3.4. Heterogeneity of treatment effects

Demographic groups may have been affected by the computer giveaway program differently. Although the sample size does not allow for an extensive analysis of the heterogeneity of treatment effects, I investigate differences in treatment effects across a few main groups. I focus on treatment effects by gender, race, income, and age. Table 7 reports probit regressions for the probability of having high-level computer skills. Separate treatment effects are included for men and women in Specification 1. The treatment coefficients are positive for both men and women, but the point estimate is larger for women.

Examining differences by race, the point estimates suggest that the improvement in computer skills from home computers is larger for minorities than for non-minorities, but the difference is not statistically significant. The finding of a larger, positive point estimate for the effects of home computers on educational outcomes for minorities may be related to previous exposure patterns (Fairlie, 2012). Minorities have much lower rates of computer ownership than non-minorities (US Department of Commerce, 2008). Less than half of minority households have access to computers with the Internet at home compared with two-thirds of white households. These results are consistent with previous research indicating large racial disparities in access to computers, the Internet and broadband at home (US Department of Commerce, 2008; Goldfarb and Prince, 2008; Ono and Zavodny, 2003, 2007, Fairlie, 2004). Lower rates of computer ownership among family,

friends, and relatives may provide fewer alternatives for places to access computers for minority students than non-minority students. More limited opportunities for computer use may result in larger impacts of receiving a free computer on computer skills for minority students. Fairlie (2012) finds generally stronger positive effects on school outcomes for minority students than non-minority students.

Separate treatment effects for higher-income students ($20,000 or more in household income) and lower-income students (less than $20,000 in household income) are also estimated. I find a large, positive coefficient estimate on the treatment variable for the low-income group, but essentially no effect for the high-income group (the *P*-value for the difference is 0.064). These estimates are consistent with low-income students having fewer opportunities to access computers at alternative locations and less previous exposure to computers. Low-income families are considerably less likely to have access to home computers. Estimates from the 2010 CPS indicate that only 58% of US households with less than $50,000 in annual income have computers with Internet access at home compared to 92% of households with more than $50,000 in income (National Telecommunications and Information Administration, 2011).

Finally, I estimate separate treatment effects by age using 25 as the cutoff. For both groups of students, I find positive treatment effect estimates, although the point estimate is larger for students under age 25. Although the difference is not significant, younger students may benefit more from free computers in computer skills because they are more likely to experiment with the computers at home. Older students may have more time commitments limiting the amount of time they have to learn more advanced features on the computer.

## 4. Conclusions

Computer skills are becoming increasingly important for success in education and the labor market. Nearly all instructional classrooms in US public schools have computers with Internet access, 95% of all jobs held by college-educated workers require the use of computers, and online job search has become the primary method of job search among college-educated job seekers (US Department of Education, 2007; Madden and Jones, 2008).[14] Individuals who do not have access to home computers may be at risk of having inadequate computer skills to adapt to the ever-increasing technological requirements of the labor market and society in general. In this paper, I use data from the a randomized field experiment providing free computers to students to estimate the previously unexplored effects of home computers on computer skills. I find that the treatment group of students receiving free computers to use at home has better computer skills than the control group of students not receiving free computers. Two-thirds of the treatment group has high-level computer skills compared

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[14] See Kuhn and Mansour (2011) and Stevenson (2009) for more evidence on the importance of Internet job search.

with only half of the control group. Controlling for baseline demographic characteristics does not change the conclusion – the treatment group of students receiving free computers has a 17% point higher likelihood of having high-level computer skills than the control group. Addressing non-compliance with the random experiment I find larger estimated effects of home computers on complying students ranging from 19% to 23% points.

The finding of positive effects of home computers on computers skills is also robust to using the full distribution of skill levels. Results from ordered probit models indicate a large, positive effect of receiving free computers on computer skills throughout the distribution. Examining potential heterogeneity of effects across groups I find that a few groups experience strong effects. In particular, young, minority, low-income and female students appear to benefit the most from access to home computers.

The findings from this experiment suggest that differences in access to home computers translate into disparities in computer skills which may have negative consequences for future educational, labor market and other economic outcomes. Given the potentially large returns to computer skills in the labor market, students may be under-investing in personal computers. For some students, especially low-income students, the primary cause of this suboptimal level of investment in technology may be financial constraints.[15] Tax breaks or special loans for educational computer purchases, an expansion of computer refurbishing programs that provide low-cost machines, and school laptop checkout programs may increase access for low-income students.[16] For any proposed policy solution, low-income community college students should be one of the groups of primary focus. Community colleges are growing in importance in higher education and access to on-campus technology at community colleges is very limited relative to access at 4-year colleges. Limited computer skills among some low-income community college students may place them at a major disadvantage when entering the labor market or transferring to 4-year colleges.

## Appendix A. Probit regressions for the probability of having high-level computer skills adjusting for non-response

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Treatment | 0.1201 | 0.1355 | 0.1414 | 0.1606 |
| | (0.0508) | (0.0542) | (0.0548) | (0.0580) |
| | | | | |
| Main controls | No | Yes | Yes | Yes |
| Campus and job activity | No | No | Yes | Yes |
| Assessments and English language (administrative data) | No | No | No | Yes |
| Mean of dependent variable | 0.5714 | 0.5714 | 0.5714 | 0.5714 |
| Sample size | 182 | 182 | 182 | 182 |

*Notes*: (1) The dependent variable is having high-level (or "very good" or "excellent") computer skills. (2) Estimates are adjusted for non-response by using inverse probability weights based on predicted probability of responding to follow-up survey from all baseline characteristics. (3) Marginal effects and their standard errors are reported. (4) Main controls include gender, race/ethnicity, age, parents' highest education level, high school grades, presence of own children, live with parents, and family income. (5) Assessments include math, English and reading.

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[15] Technical and informational constraints may also be important for low-income students because they are likely to have had less previous experience with computers. Nearly half of all non-computer owners report "cost/too expensive" as the reason for not having a home computer, and 20% report "do not know how to use it" or "do not really know about computers" as the reason (Baldassare and Dean Bonner, 2009). Another potential reason for suboptimal investment in personal computers is that forward-looking behavior 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.

[16] See Servon (2002) for a discussion of policies addressing the digital divide.

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