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The effects of home computers on school enrollment

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Abstract

Approximately 9 out of 10 high school students who have access to a home computer use that computer to complete school assignments. Do these home computers, however, improve educational outcomes? Using the Computer and Internet Use Supplement to the 2001 Current Population Survey, I explore whether access to home computers increases the likelihood of school enrollment among teenagers who have not graduated from high school. A comparison of school enrollment rates reveals that 95.2% of children who have home computers are enrolled in school, whereas only 85.4% of children who do not have home computers are enrolled in school. Controlling for family income, parental education, parental occupation and other observable characteristics in probit regressions for the probability of school enrollment, I find a difference of 1.4 percentage points. Although the evidence is mixed on whether the errors are correlated, I also estimate bivariate probit models for the joint probability of school enrollment and owning a home computer and find larger effects (7.7 percentage points). Use of computers and the Internet by the child's mother and father are used as exclusion restrictions. The estimates are not sensitive to alternative combinations of exclusion restrictions and alternative samples.

Keywords: School enrollment; Computers; Internet; Digital divide; Technology

1. Introduction

The impact of computers in the workplace and schools has been hotly debated by policy makers, academics, and the media. The well-known evidence on the relationship between computer use and earnings ranges from a sizeable wage premium (Krueger, 1993) to a potentially spurious correlation (DiNardo & Pischke, 1997).[1] Meta-analyses and surveys of recent studies find widely varying estimates of the effects of computer use in schools on academic performance (see Noll, Older-Aguilar, Rosston, & Ross, 2000; Kirpatrick & Cuban, 1998 for example), and recent evidence from a quasi-experiment in Israel schools indicates no improvement in math test scores (Angrist & Lavy, 1999). Interestingly, however, school principals and teachers overwhelmingly support the use of educational technology. In a recent national survey funded by the US Department of Education, nearly all principals report that educational technology will be important for increasing student performance in the next few years, and a clear majority of teachers report that the use of technology is essential to their teaching practices (SRI, 2002).

Policy makers also cannot agree on the importance of and solutions to disparities in access to information technology or the so-called "Digital Divide". The Department of Agriculture, Commerce, Education, Health and Human Services, Housing and Urban

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[1]See Freeman (2002) and Valletta and MacDonald (2004) for recent discussions of the impacts of information technology on the labor market.

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Development, Justice and Labor, each have programs addressing the digital inclusion of various groups, and spending on the E-rate program, which provides discounts to schools and libraries for the costs of telecommunications services and equipment, totaled $5.8 billion as of February 2001 (Puma, Chaplin, & Pape, 2000). More recently, however, the current Chairman of the Federal Communications Commission (2000), Michael Powell, referred to the digital divide as "a Mercedes divide. I'd like to have one; I can't afford one", and the funding for several technology-related programs affecting disadvantaged groups is in jeopardy (Servon, 2002).

The digital divide in access to computers at home poses a particularly controversial problem for policy makers. Should the digital divide be viewed simply as a disparity in utilization of goods and services arising from income differences just as we might view disparities in purchases of other electronic goods, such as cameras, stereos, or televisions? Or, should the digital divide be viewed as a disparity in a good that has important enough externalities, such as education, healthcare, or job training, that it warrants redistributive policies.[2] Although there is substantial disagreement over this issue, the consequences of access to home computers are relatively unknown. In particular, the literature on the educational impacts of home computers is especially sparse.[3]

Theoretically, we might expect home computers to exert a positive influence on academic performance directly through the use of educational software and indirectly by facilitating the completion of school assignments and learning. Access to a home computer may also familiarize the student with computers increasing the returns to computer use in the classroom (Underwood, Billingham, & Underwood, 1994). Estimates reported below indicate that approximately 9 out of 10 high school students who have access to a home computer use that computer to complete school assignments, and 46% of teachers report that student access to technology/Internet is a barrier to effective use of technology in the classroom (SRI, 2002).

Access to home computers may also have a direct effect on school enrollment or high school graduation that is independent of its effect on academic performance. In particular, the use of computers may "open doors to learning" and doing well in school (Cuban, 2001 and Peck, Cuban, & Kirkpatrick, 2002), and thus may encourage some teenagers to stay in school.[4] Home computers and the skills acquired using them may also alter the economic returns to completing high school. It is well known that information technology skills are becoming increasingly important in the labor market. For example, the US Department of Labor's 2002–2003 Occupational Outlook Handbook projects Computer Software Engineers-Applications, Computer Support Specialists, Computer Software Engineers-Systems Software, Network and Computer Systems Administrators, and Network Systems and Data Communications Analysts to be the fastest growing occupations from 2000 to 2010. Freeman (2002) also provides evidence that the share of employment in information technology industries and occupations and the share of employees using computers and the Internet at work have risen dramatically over the past decade and a large percentage of new hires are required to use computers (Holzer, 1996). Computer skills may be improve employment opportunities, but only in combination with a minimal educational credential such as a high school diploma.

On the other hand, home computers may have negative effects on educational outcomes. Computers have often been criticized for providing a distraction for children through video games and the Internet or for displacing other more active forms of learning (Giacquinta, Bauer, & Levin, 1993 and Stoll, 1995).[5] The Internet also makes it substantially easier to plagiarize and find information from non-credible sources. Theoretically, it is unclear as to which of the two opposing forces dominates, and therefore the question of whether access to home computers improves educational outcomes must be explored empirically.

To my knowledge, the only previous study that attempts to identify the effects of home computers on educational outcomes is provided by Attewell and Battle (1999). Using the 1988 National Educational Longitudinal Survey (NELS), they provide evidence that test scores and grades are positively related to home computer use even after controlling for differences in several demographic and individual characteristics. They find that students with home computers score 3–5% higher than students without home computers.

[2]See Noll et al. (2000) and Crandall (2000) for an example of the academic debate.

[3]Recent studies have explored other effects of computers. See Morton, Zettelmeyer, and Risso (2000), Bakos (2001), Borenstein and Saloner (2001), and Ratchford, Talukdar, and Lee (2001) for consumer beneifts, Kuhn and Skuterud (2000, 2004) and Stevenson (2003) for job search, Freeman (2002) for union membership, and Kawaguchi (2001) for employment and wages.

[4]The use of computers at home may also translate into more positive attitudes towards information technology potentially leading to long-term use (Selwyn, 1998). Many teachers report that educational technology increases outside class time initiative among students (SRI, 2002).

[5]The use of computers at home, even for these non-educational uses, may have an indirect effect on school enrollment by reducing criminal activities. Bjerk (2004) finds evidence of a negative relationship between criminal activity and the presence of a home computer.

Although Attewell and Battle (1999) control for several interesting and typically unobservable characteristics of the educational environment in the household, their estimates may be biased due to omitted variables.[6] In particular, if the most educationally motivated families are the ones that 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. Conversely, if the least educationally motivated families (after controlling for child and family characteristics) are the ones that are more likely to purchase computers then their estimates may understate the effects of home computers.

To address these concerns, I use data from the Computer and Internet Use Supplement to the 2001 Current Population Survey (CPS) to explore the relationship between home computers and school enrollment. Estimates from probit regressions for the probability of school enrollment and bivariate probit models for the joint probability of school enrollment and having a home computer are estimated. The Computer and Internet Use Supplement to the 2001 CPS provides detailed information on locations of computer and Internet use, which allows for the creation of several exclusion restrictions in the bivariate probit models. Computer and Internet use at work by the child's parents should affect the probability of the family purchasing a home computer, but should not affect academic performance (after controlling for other factors). There exists a strong correlation between using a computer at work by a household member and computer ownership by that household (US Department of Commerce, 2002), and it is unlikely that parental use of computers and the Internet at work have a strong effect on educational outcomes after controlling for family income, parental education and parental occupations. I provide evidence on these issues below.

The focus on school enrollment is also important because the effects of access to home computers on this outcome may differ from those on grades, test scores, and other direct measures of academic performance. Dropping out of school is also associated with a much lower probability of returning to and completing high school. For example, estimates from the NLSY indicate that 50% of dropouts from 1979–1986 returned to school by 1986 (Chuang, 1997), and estimates from the CPS indicate that only 42% of 22–24 year olds who did not complete high school received a GED (US Department of Education, 2001b). Furthermore, the labor market outcomes of GED recipients are worse than those of conventional high school graduates, and, at best, only slightly better than those of dropouts who did not receive a credential (see Cameron & Heckman, 1993 and Murnane, Willett, & Tyler, 2000).[7]

2. Data

I use data from the Computer and Internet Usage Supplement to the September 2001 Current Population Survey (CPS). The survey, conducted by the US Census Bureau and the Bureau of Labor Statistics, is representative of the entire US population and interviews approximately 50,000 households. It contains a wealth of information on computer and Internet use, including detailed data on types and location of use.

The main sample used in the following analysis includes only children ages 16–18 who have not graduated from high school and live with at least one parent. Parents living in the same household as the child are identified by using parent and spouse identification numbers provided by the CPS.[8] Parents living in a different household, however, cannot be matched to children. Mother's and father's education levels, occupations, ages and labor force statuses are obtained directly from matching parental records to child records. Of the total sample of children ages 16–18 who have not graduated from high school, 93.3% live with at least one parent.

3. Computer and Internet use

The presence of computers and the Internet in the nation's schools is ubiquitous. The National Center for Education Statistics reported that 100% of all public secondary schools in the fall of 2001 were connected to the Internet (US Department of Education, 2001c). In these schools, 88% of all instructional classrooms had Internet access, and there were 0.23 instructional computers per student on average. For the sample of high school students ages 16–18 from the 2001 CPS, reported rates of computer and Internet use reflect these high levels of access. Ninety percent of enrolled high school students report using a computer at school and 62% report using the Internet at school.

[6] They include measures of the frequency of child–parent discussions of school-related matters, parent's familiarity with the parents of their child's friends, attendance in "cultural" classes outside of school, whether the child visits science or history museums with the parent, and an index of the educational atmosphere of the home (e.g. presence of books, encyclopedias, newspapers, and place to study). The composite measure of socioeconomic status included in their analysis, however, may not adequately capture the independent effects of family income, parental education, and parental occupation.

[7] Murnane, Willett and Boudett (1997) also find that relatively few GED recipients obtain post-secondary education.

[8] Using this information, however, I cannot distinguish between biological parents and stepparents.

Access to computers and the Internet at home is not universal, but fairly high. Slightly less than 77% of children ages 16–18 who have not graduated from high school and live with at least one parent have access to a computer at home (see Table 1). Levels of access, however, vary tremendously across income, educational and racial groups (see US Department of Labor, 2003 and Fairlie, 2004).

Patterns of home computer use are revealing. Teenagers appear to be using their home computers—94.6% of children who have access to a home computer use it. Interestingly, 95.0% of children who are enrolled in school use their home computer compared to 87.1% of children who are not enrolled in school suggesting that computers may be useful for completing homework assignments. Examining this issue directly, estimates from the CPS indicate that of those children who use a home computer and are currently enrolled in school, 92.8% use their computer to complete school assignments.

Teenagers also use home computers for many other purposes. The most common uses of home computers among teenagers are for the Internet (88.0%), games (81.5%), email (80.9%), and word processing (72.2%). Use of home computers for graphics and design (32.5%) and spreadsheets or databases (25.0%) are also fairly common. None of these uses among high school students, however, is as prevalent as using home computers to complete school assignments. Furthermore, the large percentage of high school students, especially relative to the percentage of dropouts, using home computers for word processing provides additional evidence that home computers are useful for completing homework assignments. Concerns that home computers are only used for non-educational purposes such as playing games, listening to music, and emailing friends, seem exaggerated (Giacquinta et al., 1993).

Table 1
Home computer use among children ages 16–18 (Current Population Survey, 2001)

	All children	Enrolled in school	Not enrolled
Percent of children with access to a home computer	76.6%	78.5%	52.1%
Sample size	4281	4008	273
Percent of children with access to a home computer who use that computer	94.6%	95.0%	87.1%
Sample size	3370	3217	153
Percent of home computer users who: use computer for school assignments		92.8%	
Use computer for the Internet	88.0%	88.5%	78.5%
Use computer for games	81.5%	81.5%	82.8%
Use computer for electronic mail	80.9%	81.5%	67.4%
Use computer for word processing	72.2%	73.6%	43.5%
Use computer for graphics and design	32.5%	32.8%	24.2%
Use computer for spreadsheets or databases	25.0%	25.0%	25.4%
Sample size	3189	3056	133

Notes: (1) The sample consists of children ages 16–18 who have not graduated from high school and live with at least one parent. (2) All estimates are calculated using sample weights provided by the CPS.

The Internet also appears to be useful for schoolwork. Nearly 90% of high school students who use the Internet use it to complete school assignments (see Table 2).[9] Perhaps this is not surprising given the proliferation of homework help sites on the web and high rates of access in schools (Lenhart, Simon, & Graziano, 2001). The Internet is also frequently used, however, for non-educational purposes such as playing games (58.3%), chat rooms (37.0%), viewing TV or movies or listening to music (27.3%), and shopping (22.5%).

At a minimum, estimates from the 2001 CPS indicate that home computers and the Internet are useful for completing school assignments. Whether these students wrote better reports or could have completed their school assignments at a library, community center or school, however, is unknown.[10] Furthermore, the prevalence of non-educational uses of information technology, such as games, chat rooms and music, suggests that home computers may also provide a distraction that lessens or negates their educational impact.

4. The effects of home computers on school enrollment

School enrollment among teenagers is positively associated with owning a home computer. Table 3 reports estimates of enrollment rates among children ages 16–18 who have not finished high school by access to home computers. Slightly more than 95% of children with home computers are enrolled in school. In comparison, only 85.4% of children without access to home computers are enrolled in school.[11] This represents

[9]The CPS does not distinguish between types of Internet use at home, school or other locations.

[10]Only 11.2% of teenagers who do not have access to a home computer, use the Internet at a library or community center. Furthermore, a higher percentage of teenagers who have access to a home computer (13.9%) use the Internet at these locations. Data on detailed location of use of computers is not available.

[11]Attewell and Battle (1999) also find large differences in academic performance based on access to home computers using the NELS. In particular, they find than eighth graders with home computers scored 6 points higher on reading and 5 points higher on math than eighth graders without home

Table 2
Internet use among children ages 16–18 (Current Population Survey, 2001)

	All children	Enrolled in school	Not enrolled
Percent of children who use the Internet anywhere	77.9%	80.1%	49.2%
Sample size	4281	4008	273
Percent of Internet users who: use the Internet to complete school assignments		89.2%	
Use the Internet for electronic mail	83.7%	84.0%	78.0%
Use the Internet for playing games	58.3%	58.0%	65.6%
Use the Internet to search for information about products and services	54.0%	54.2%	50.3%
Use the Internet to get news, weather or sports	53.3%	53.3%	52.6%
Use the Internet for chat rooms or LISTSERVs	37.0%	36.5%	46.8%
Use the Internet for viewing TV or movies, or listening to music	27.3%	27.2%	28.8%
Use the Internet to purchase products or services	22.5%	22.5%	22.8%
Sample size	3433	3298	135

Notes: (1) The sample consists of children ages 16–18 who have not graduated from high school and live with at least one parent. (2) All estimates are calculated using sample weights provided by the CPS.

Table 3
School enrollment among children ages 16–18 Current Population Survey, 2001

	Enrollment rate (%)	Sample size
School enrollment among children without access to home computer	85.4	911
School enrollment among children with access to home computer	95.2	3370

Notes: (1) The sample consists of children ages 16–18 who have not graduated from high school and live with at least one parent. (2) All estimates are calculated using sample weights provided by the CPS.

(*footnote continued*)
computers (average scores among NELS respondents on both tests were approximately 50).

a large difference, as only 7.1% of all children who live with at least one parent are not enrolled in school.[12] Furthermore, the 9.8 percentage point difference in enrollment rates is slightly larger than the difference in enrollment rates between teenagers who have college-educated and high-school dropout fathers (9.0 percentage points), but smaller than the difference between teenagers who have college-educated and high-school dropout mothers (13.8 percentage points). Although these estimates do not control for factors, such as the child's age or his/her family's income, they are suggestive of the direction and size of potential impacts.

To control for these factors and others, I first model the school enrollment decision.[13] Assume that school enrollment is determined by an unobserved latent variable,

$$Y_i^* = X_i'\beta + C_i'\delta + u_i \tag{4.1}$$

for person i, $i = 1,....,N$. Only Y_i is observed, which equals 1 if $Y_i^* \geqslant 0$, implying that person i chooses to enroll in school; Y_i^* equals zero otherwise. X_i is a vector of individual, family and geographical area characteristics, C_i is a dummy variable for the presence of a home computer, and u_i is the error term. Assuming that u_i is normally distributed, the data are described by the following probit model:

$$\text{Prob}(Y_i = 1) = \Phi(X_i'\beta + C_i'\delta), \tag{4.2}$$

where Φ is the cumulative normal distribution function. Although the normality assumption should only be taken as an approximation, the probit model provides a useful descriptive model for the binary event that a child enrolls in school.

Table 4 reports estimates from probit regressions for the probability of school enrollment among children ages 16–18 who have not graduated from high school. All specifications include the sex, race, and age of the child, number of children in the household, family income, mother's and father's presence in the household, education level, labor force status and occupation, region of the country, central city status, and the state-level unemployment rate, pupil–teacher ratio, average expenditures per pupil and dummy variables for the age requirements of compulsory schooling laws (means for most variables are reported in Appendix A).[14] As expected, family income and parental education have

[12]Nearly 50% of these non-enrollees are working, and 16.4% are unemployed and 34.6% are not in the labor force.

[13]A large literature on the determinants of high school enrollment and dropouts exists. See Card and Lemieux (2000), Eckstein and Wolpin (1999), Rees and Mocan (1997), and Ahituv and Tienda (2004) for a few recent examples.

[14]The state-level unemployment rate is from Bureau of Labor Statistics (2002), and the age requirements for compulsory schooling laws, pupil–teacher ratio and average expenditures per pupil are from US Department of Education (2001a).

Table 4
Probit and bivariate probit regressions for school enrollment and home computer (Current Population Survey, 2001)

	Specification			
Explanatory variables	(1)	(2)	(3)	
Dependent variable	Enrollment	Enrollment	Computer	Enrollment
Model type	Probit	Probit	Bivariate	Bivariate
Female	0.1975 (0.0709)	0.1797 (0.0750)	0.0941 (0.0541)	0.1819 (0.0780)
Black	0.2062 (0.1179)	0.1945 (0.1232)	−0.6869 (0.0842)	0.3501 (0.1399)
Latino	0.0364 (0.1233)	0.0006 (0.1291)	−0.4218 (0.0882)	0.1320 (0.1429)
Native American	0.1593 (0.2397)	0.3016 (0.2664)	−0.6420 (0.1830)	0.2941 (0.2944)
Asian	0.3489 (0.2443)	0.4850 (0.2890)	0.1748 (0.1474)	0.3130 (0.2808)
Age 17	−0.3067 (0.0873)	−0.3107 (0.0930)	−0.0493 (0.0589)	−0.2963 (0.1016)
Age 18	−1.3409 (0.0904)	−1.3088 (0.0958)	−0.2435 (0.0780)	−1.2604 (0.1113)
Family income: missing	0.2490 (0.1643)	0.2891 (0.1711)	0.3419 (0.1261)	0.1376 (0.1826)
Family income: $10,000–$15,000	0.0171 (0.1825)	0.0052 (0.1887)	0.1218 (0.1469)	−0.0070 (0.1933)
Family income: $15,000–$20,000	0.0841 (0.2036)	0.1519 (0.2149)	0.3185 (0.1541)	−0.0030 (0.2082)
Family income: $20,000–$25,000	0.1071 (0.1811)	0.2128 (0.1904)	0.1514 (0.1406)	0.0565 (0.1921)
Family income: $25,000–$30,000	0.0891 (0.1921)	0.0413 (0.1982)	0.3772 (0.1453)	−0.0127 (0.2063)
Family income: $30,000–$35,000	0.0401 (0.1947)	0.1586 (0.2078)	0.4234 (0.1549)	−0.0721 (0.2173)
Family income: $35,000–$40,000	0.1737 (0.2115)	0.1649 (0.2214)	0.6257 (0.1631)	0.0168 (0.2334)
Family income: $40,000–$50,000	0.3246 (0.1818)	0.3282 (0.1896)	0.6831 (0.1402)	0.1327 (0.2258)
Family income: $50,000–$60,000	0.1380 (0.1904)	0.2582 (0.2038)	0.7657 (0.1528)	−0.0357 (0.2151)
Family income: $60,000–$75,000	0.4841 (0.2042)	0.5443 (0.2187)	0.8480 (0.1542)	0.2890 (0.2334)
Family income more than $75,000	0.3810 (0.1845)	0.3364 (0.1943)	0.9684 (0.1505)	0.1960 (0.2117)
Mother-high school graduate	0.2413 (0.1103)	0.2855 (0.1148)	0.2681 (0.0848)	0.1584 (0.1230)
Mother-some college	0.2529 (0.1224)	0.2891 (0.1283)	0.5511 (0.0949)	0.1268 (0.1480)
Mother-college graduate	0.4199 (0.1602)	0.4342 (0.1701)	0.5436 (0.1266)	0.2984 (0.1780)
Father-high school graduate	−0.0134 (0.1278)	−0.0940 (0.1361)	0.0565 (0.0922)	−0.0294 (0.1352)
Father-some college	0.0150 (0.1406)	−0.0186 (0.1509)	0.1989 (0.1047)	−0.0318 (0.1489)
Father-college graduate	0.2428 (0.1775)	0.2538 (0.1953)	0.5248 (0.1453)	0.1991 (0.1879)
Home computer	0.1878 (0.0864)	0.2115 (0.0904)		0.8562 (0.3152)
Marginal effect	0.0138	0.0166		0.0767
Mother uses computer at work			0.0924 (0.0885)	
Father uses computer at work			0.1433 (0.1117)	
Mother uses the Internet at work			0.2251 (0.0982)	
Father uses the Internet at work			0.4034 (0.1335)	
Mother's occupation controls	Yes	Yes	Yes	Yes
Father's occupation controls	Yes	Yes	Yes	Yes
ρ			−0.3958 (0.1790)	
Mean of dependent variable	0.9358	0.9321	0.7860	0.9358
Sample size	4239	3607	4239	

Notes: (1) The sample consists of youth ages 16–18 who have not graduated from high school and live with at least one parent. (2) The sample in Specification 2 excludes children in families obtaining their newest home computer in 2001. (3) All equations also include a constant, number of children in the household, dummy variables for region, central city status, mother's and father's presence in the household and labor force status, and the state-level unemployment rate, pupil–teacher ratio, average expenditures per pupil, and dummy variables for the age requirements of compulsory schooling laws.

large positive effects on school enrollment. Older children and boys have lower probabilities of attending school, all else equal.

Owning a home computer appears to increase the probability of high school enrollment. The coefficient estimate on the home computer variable is large, positive, and statistically significant. The marginal effect evaluated at the mean characteristics of the sample, which is reported below the coefficient estimate, implies that having a home computer is associated with a 1.38 percentage point higher probability of being enrolled in school.[15] The effect of this variable on the probability of school enrollment is comparable in size to that implied

[15]The average treatment effect, which equals $1/n\,\Sigma\Phi(X_i'\beta+\delta)-\Phi(X_i'\beta)$, is larger (0.0195).

by being a girl and is slightly smaller than that implied by having a high-school- or "some college-" educated mother (relative to a high school dropout). The effect, however, is much smaller than that implied by being 18 years old (relative to 16), having a college-educated mother, or moving from the bottom of the family income distribution to the top.

An immediate concern with these estimates is that some families may have purchased their computers after or near the time that the school enrollment decision was made, and thus may be caused directly by the school enrollment decision in the survey month. Furthermore, computers purchased close to the survey month may have a limited effect on school enrollment. Although the CPS does not provide information on the timing of when all computer purchases were made, it provides information on when the newest computer was obtained by the family. Therefore, as a check of these results I estimate a probit model that excludes all observations for which the newest computer was obtained in 2001. This exclusion is likely to be over-restrictive, however, because a computer purchased in 2001 may represent a replacement for an older model or may have been purchased several months prior to the survey date, which is in September. The results are reported in Specification 2 of Table 4. The coefficient estimate on home computer is slightly larger in this specification.

The findings from the probit model for school enrollment are consistent with the findings from previous research on the relationship between home computers and other educational outcomes using the 1988 National Educational Longitudinal Survey. Attewell and Battle (1999) provide evidence that test scores and grades are positively related to home computer use. As noted above, even after controlling for differences in several demographic and individual characteristics, students with home computers were found to score 3–5% higher than students without home computers.

4.1. Bivariate probit results

Although the findings presented in Attewell and Battle (1999) and those presented above are based on regression models that include numerous controls for individual, parental, and family characteristics, estimates of the effects of home computers on educational outcomes may be biased. For example, if children with higher levels of academic ability or children with more "educationally motivated" parents are more likely to have access to home computers, then the probit estimates may overstate the effect of home computers on school attendance. On the other hand, if parents of children with less academic ability or time to spend with their children are more likely to purchase computers, then the probit estimates may understate the effect. In either case, the effects of unobserved factors, such as academic ability and parental motivation, may invalidate the causal interpretation of the previous results.

A potential solution to this problem is to estimate a bivariate probit model in which equations for the probability of school enrollment and the probability of having a home computer are simultaneously estimated. This model is equivalent to an instrumental variables or two-stage least squares model and is preferred when both the dependent variable and endogenous variable are binary.

Similar to (4.1), assume that home computer ownership is determined by an unobserved latent variable,

$$C_i^* = X_i'\gamma + Z_i'\pi + \varepsilon_i, \tag{4.3}$$

where only C_i equal to 0 or 1 is observed, Z_i is a vector of variables that are not included in (4.1), and ε_i is the error term. In this case, u_i and ε_i are distributed as bivariate normal with mean zero, unit variance, and $\rho = \mathrm{Corr}(u_i, \varepsilon_i)$. The bivariate probit model is appropriate when $\rho \neq 0$.

The choice of Z_i is of paramount importance. I use information on whether the child's mother and father use a computer and the Internet at work. Computer and Internet use at work by the child's parents appear to be good exclusion restrictions—they affect the probability of purchasing a computer, but do not affect academic performance (after controlling for other factors). There exists a strong correlation between using a computer at work by a household member and computer ownership by that household (US Department of Commerce, 2002). In addition, we do not expect the use of a computer at work by the child's mother or father to have a strong effect on educational outcomes after controlling for family income, parental education, and parental occupations. Computer use at work may be associated with higher earnings, but this effect should be controlled for by the inclusion of family income.

Estimates from the bivariate probit model for the probability of school attendance and having a home computer are reported in Specification 3 of Table 4.[16] As expected, parental education is an important determinant of owning a home computer (reported in the first column). The probability of owning a home computer generally increases with both mother's and father's education. Education may be a proxy for wealth or permanent income and have an effect on the budget constraint or may have an effect on preferences for computers through pure tastes, exposure, perceived usefulness, or conspicuous consumption. Family income is also important in determining who owns a home computer. The relationship between the home computer probability and income is almost monotonically increasing across the listed categories. It is likely to be primarily

[16]The model correctly predicts school enrollment and home computers 83.2% and 80.8% of the time, respectively.

due to its effect on the budget constraint, however, it may also be due its effect on preferences.

Race and ethnicity are also important determinants of computer ownership. Black, Latino, and Native American children have lower probabilities of having a home computer than do white children. In addition to these control variables, age, number of children, and regions also have statistically significant effects on the home computer probability.

All four excluded variables have positive coefficients in the home computer equation. Only mother's use of the Internet at work and father's use of the Internet at work, however, are statistically significant at conventional levels. The coefficients on these variables imply large effects on the probability of having a home computer. In particular, if the father uses the Internet at work then the probability of having a home computer is 8.11 percentage points higher, all else equal. The stronger effects of Internet use compared to computer use at work may imply that communication and information retrieval uses of computers at work are associated with purchasing home computers and not other uses, such as appointment scheduling, database entry, and production.

The second column in Specification 3 reports the bivariate probit results for the school enrollment equation. Having a home computer has a large, positive and statistically significant effect on school enrollment. The coefficient estimate implies that the presence of a home computer increases the probability of school enrollment among children by 7.67 percentage points.[17] This effect is quite large as the average probability of school enrollment among teenagers who do not have a computer is 85.4%. Interestingly, this estimate lies between the probit estimate (1.38 percentage points) and the raw difference in school enrollment rates between children who have access to home computers and those who do not (9.8 percentage points), which is consistent with the negative estimate of ρ.

The point estimate of estimate of ρ indicates a negative correlation between the unobserved factors affecting home computers and school enrollment. Formal tests of the hypothesis that $\rho = 0$, however, reveal mixed results. The Wald statistic for the hypothesis is 4.89, which is larger than the chi-squared critical value of 3.84, whereas the likelihood ratio statistic is 2.37, which is smaller than the critical value. Thus, the evidence is not clear on whether the errors are correlated and estimation of the bivariate probit model is needed. Given the uncertainty in these results, however, I continue the approach of accounting for the potential correlation in errors.

The negative point estimate of ρ implies that the unobserved factors affecting home computers and school enrollment are negatively correlated. In other words, the two outcomes are negatively correlated after controlling for age, race, family income, parental education, parental occupation, and other factors. Although it is unclear what causes this relationship, one possibility is that the least "educationally motivated" families after controlling for observables are the ones that are most likely to purchase computers perhaps motivated by the many recreational uses of computers. Also, conditioning on family income and parental education, parents who have less time to spend helping their children with homework may be more likely to purchase computers. Another possibility is that excluded variables are correlated with u_i, which I investigate below.

4.2. Exclusion restriction results

The evidence from the bivariate probit model suggests that access to home computers increase the likelihood of staying in school. As noted above, this interpretation depends on the assumption that work computer and Internet use by parents are correlated with the home computer probability (after netting out X_i), but are not correlated with the school enrollment probability (i.e. uncorrelated with u_i). Internet use at work by the child's mother and father, at least, appear to be consistent with the first requirement. The coefficient estimates in the home computer equation are positive and statistically significant. The coefficient estimates, however, on the mother's and father's computer use at work variables are not statistically significant in the bivariate probit model.[18]

Because of concerns about the effects of weekly correlated instruments (e.g. Bound, Jaeger, & Baker, 1995 and Staiger & Stock, 1997), I estimate a bivariate model that only includes mother's and father's use of the Internet at work as exclusion restrictions. I am also concerned about the interdependence of these variables. Of those mothers and fathers who use a computer at work, 65.5% and 77.3% also use the Internet at work, respectively. Estimates are reported in Specification 1 of Table 5. The coefficient estimate on having a home computer is slightly larger and remains statistically significant. As expected, the implied effects of mother's and father's use of the Internet at work on having a home computer are now larger and more significant.

I also estimate a model that only includes a dummy variable for whether either parent uses the Internet at work (Specification 2). Approximately, 40% of children who have one parent who uses the Internet at work also have another parent who uses the Internet at work. The

[17] The average treatment effect is 0.1173.

[18] The coefficient estimates and statistical significance for the excluded variables are very similar in a probit model for the probability of having a home computer.

Table 5
Additional bivariate probit regressions using alternative combinations of exclusion restrictions (Current Population Survey, 2001)

	Specification			
	(1)	(2)	(3)	(4)
Home computer	0.9014 (0.3051)	0.9509 (0.2966)	0.8029 (0.3380)	0.8655 (0.3224)
Marginal effect	0.0820	0.0881	0.0710	0.0783
Exclusion restrictions				
Mother uses the Internet at work	0.2783 (0.0846)			
Father uses the Internet at work	0.5103 (0.1005)			
Either parent uses the Internet at work		0.4879 (0.0730)		
Mother uses computer at work			0.2132 (0.0757)	
Father uses computer at work			0.3794 (0.0838)	
Either parent uses computer at work				0.3311 (0.0674)
ρ	−0.4212 (0.1713)	−0.4506 (0.1666)	−0.3638 (0.1952)	−0.3994 (0.1849)
Mean of dependent variable	0.9358	0.9358	0.9358	0.9358
Sample size	4239	4239	4239	4239

Note: See notes to Table 4.

coefficient estimate on home computer is slightly larger than the estimate in the main specification. Another test of the sensitivity of results is to estimate the probit model only including the computer at work variables. The results are reported in Specifications 3 and 4. In both cases, the coefficient estimates are similar to the original estimates. The coefficients on mother's and father's use of computers at work are now statistically significant. The estimates reported in Table 5 indicate that the estimated effect of home computers on school enrollment is quite robust to alternative specifications of instruments, such as the exclusion of "weaker" instruments or correlated instruments.

Are computer and Internet use at work by the child's parents uncorrelated with u_i? One method of exploring this issue is to estimate a standard probit model for school enrollment that includes the four excluded variables. Although not reported, I find that none of the instruments is statistically significant. Mother's and father's use of computers at work have negative coefficients, and mother's and father's use of the Internet at work have positive coefficients. I also estimate probit models for school enrollment that includes all four combinations of instruments listed in Table 5. In each of the specifications, none of the instruments has a statistically significant coefficient estimate. Although this is not a formal test of the validity of the instruments, it suggests that computer and Internet use at work by the child's parents do not have a large effect on the probability of being enrolled in school after controlling for family income, parental education, parental occupation, and other factors.

Additional evidence on the validity of the exclusion restrictions can be provided by examining how sensitive the coefficient on home computers is to the inclusion of family and parental characteristics. Assuming that unobserved factors such as "educational motivation" are correlated with family income, parental education and parental occupations then the finding that the coefficient on home computers is insensitive to the inclusion of home computers lends at least some credibility to the instruments. As expected, there are strong positive relationships between computer and Internet use at work, and family income and education. Computer and Internet use at work also differ substantially by occupation (estimates are reported in Appendix B). The coefficient estimate on home computer, however, is not overly sensitive to the exclusion of these variables (see Specifications 1 and 2 of Table 6). I find that the coefficient estimate on home computer actually decreases slightly after excluding the parental occupational controls (Specification 1). The coefficient estimate on home computer increases by 16.7% after excluding family income, parental education and parental occupations (Specification 2). In both cases, however, the coefficient on home computer remains large, positive, and statistically significant.

To further check the sensitivity of my results, I add another exclusion restriction to the model. If network effects exist in the adoption of computers and the Internet then the rate of computer ownership in the local area should affect the probability of owning a computer. At the same time, local levels of computer ownership should not have a large effect on school enrollment after controlling for family income, parental education, school quality and unemployment rates. Therefore, I use computer ownership and Internet rates in the metropolitan area as an additional exclusion restriction in the bivariate probit. Estimates are reported in Specification 3 of Table 6. The coefficient estimate on home computer is very similar to the original estimate and remains large, positive and statistically significant.

Table 6
Additional bivariate probit regressions using alternative controls, exclusion restrictions, and samples (Current Population Survey, 2001)

	Specification				
	(1)	(2)	(3)	(4)	(5)
Home computer	0.7612 (0.3269)	0.9991 (0.2540)	0.7955 (0.3248)	0.9071 (0.3236)	0.9532 (0.3138)
Marginal effect	0.0681	0.1030	0.0699	0.0832	0.0903
Exclusion restrictions					
Mother uses computer at work	0.1332 (0.0829)	0.2906 (0.0790)	0.0979 (0.0891)		0.1214 (0.0905)
Father uses computer at work	0.1287 (0.1066)	0.3211 (0.1029)	0.1427 (0.1117)		0.1134 (0.1155)
Mother uses the Internet at work	0.2360 (0.0955)	0.3452 (0.0915)	0.2169 (0.0989)		0.2206 (0.1002)
Father uses the Internet at work	0.4171 (0.1280)	0.6018 (0.1210)	0.3963 (0.1337)		0.4294 (0.1372)
MSA-level home computer rate			1.6732 (1.1206)	1.8817 (1.1022)	
MSA-level Internet access rate			−0.6848 (1.0639)	−0.8145 (1.0489)	
ρ	−0.3435 (0.1850)	−0.3942 (0.1364)	−0.3610 (0.1861)	−0.4203 (0.1828)	−0.4500 (0.1775)
Mean of dependent variable	0.9358	0.9358	0.9358	0.9358	0.9345
Sample size	4239	4239	4239	4239	3926

Note: (1) See notes to Table 4. (2) Specification 1 excludes parental occupation controls, and Specification 2 excludes family income, parental education and parental occupations. The sample in Specification 5 excludes children in households in which the newest home computer is more than 4 years old.

The computer ownership and Internet rates, however, are statistically insignificant.[19] I also estimated an additional specification in which I used only metropolitan-area computer ownership and Internet rates as exclusion restrictions (reported in Specification 4). The coefficient estimate on home computer increased to 0.9071 and is statistically significant. Overall, the use of these alternative exclusion restrictions does not change the previous conclusions regarding the relationship between home computers and school enrollment.

4.3. Quality of home computers

The effects of home computers on school enrollment are likely to differ by the quality of these computers. Unfortunately, the CPS does not include information on processing speed, available RAM, hard disk space, or other measures of computer quality. As noted above, however, the CPS includes information on when the newest household computer was purchased. With rapid improvements in technology, older computers are typically lower quality on average, and thus should have less of an impact on educational outcomes than newer computers. To test whether the previous estimates are sensitive to inclusion of old computers, I estimate a bivariate probit that excludes children living in households in which the newest home computer is more than 4 years old. This excludes 7.4% of the sample. Estimates are reported in Specification 5 of Table 6. The coefficient on home computer is now larger and remains statistically significant. I also estimate a specification with the more restrictive exclusion of newest computers purchased more than 3 years ago, representing 11.6% of the sample. The coefficient on home computer is now 0.7362, which is smaller than before, but continues to imply a large effect. These results indicate that the bivariate probit estimates are not sensitive to exclusion of older computers.[20]

4.4. Additional estimates

I investigate the sensitivity of the results to several alternative samples. First, similar to above, I estimate a specification that excludes all children living in households in which the newest computer was obtained in 2001. The exclusion of these children rules out the possibility that some families may have purchased their computers after or near the time that the school

[19] I also find statistically insignificant coefficient estimates on these variables in standard probit regressions for the probability of school enrollment.

[20] I also estimate a standard probit model in which I include interactions for the age of the newest purchased computer. None of the interaction coefficients is statistically significant, and the point estimates do not reveal a clear pattern of effects. This may partly be due to the offsetting effects of newer computers having less potential influence on school enrollment because of the length of time of use.

Table 7
Additional bivariate probit regressions using alternative samples (Current Population Survey, 2001)

	Specification			
	(1)	(2)	(3)	(4)
Sample restrictions	Removes computers purchased in 2001	Adds children living without parents	Compulsory schooling sample	Removes missing income observations
Home computer	1.1198 (0.2630)	0.9958 (0.2637)	0.7088 (0.4291)	0.8868 (0.3467)
Marginal effect	0.1214	0.1060	0.0740	0.0774
ρ	−0.5341 (0.1451)	−0.4484 (0.1526)	−0.2677 (0.2539)	−0.3991 (0.1947)
Mean of dependent variable	0.9321	0.9213	0.9147	0.9363
Sample size	3607	4548	2720	3644

Notes: (1) See notes to Table 4. (2) See text for a more detailed description of the sample restrictions used in each specification.

enrollment decision was made. Specification 1 of Table 7 reports results. The coefficient estimate implies a slightly larger effect and remains statistically significant.

Another concern regarding the robustness of estimates is the exclusion of children who do not live with their parents. The main justification for removing these children is that they do not have parents who are ‘‘at risk’’ of using a computer and/or the Internet at work for use as instrumental variables. One method of addressing this concern is to add these children back to the sample and set mother’s and father’s use of computers and the Internet at work to zero. Estimates are reported in Specification 2. The coefficient estimate for home computer is not sensitive to the inclusion of these children.

The age requirements for compulsory schooling laws differ across states ranging from 16 to 18 (US Department of Education, 2001a). I currently include dummy variables for whether the age requirements are 17 or 18 years of age (with age 16 being the left out category). However, I am concerned that the process determining school enrollment may differ between children under the age cutoff and children above the age cutoff.[21] To address this issue, I estimate a bivariate probit model that excludes all children under the age requirement of the compulsory schooling law in their state. Estimates are reported in Specification 3. The coefficient estimate implies a similar size effect although it is no longer statistically significant.

In all previous specifications I include a dummy variable for missing family income, which represents 14.0% of the sample. Specification 4 reports estimates for a sample that excludes these missing values. The coefficient estimate is not sensitive to this change. Overall, the coefficient estimate on home computer in the bivariate probit is quite robust to alternative specifications and samples.

Although not reported, I also investigate whether the coefficient estimates are sensitive to the inclusion of additional occupational dummies and stratifying the sample by occupation. The inclusion of additional dummies for mother’s and father’s occupation has very little effect on the coefficient estimate.[22] I also identified two sets of occupations—low computer-use and high computer-use occupations.[23] I estimated separate bivariate probits excluding these two groups. The home computer coefficients (and standard errors) in the mother’s low-computer use and high-computer use specifications are 0.6839 (0.6354) and 0.8959 (0.3779), respectively. The home computer coefficients in the father’s low-computer use and high-computer use specifications are 0.5484 (0.4720) and 1.4781 (0.2645), respectively. Although the coefficients differ somewhat, especially using father’s occupation, they suggest that large differences in computer use across occupations are not driving the results.

[21] School enrollment rates are not 100% for children who are younger than the age requirement for compulsory schooling in their state. For example, less than 97% of 17-year olds living in states with age 18 compulsory schooling laws are enrolled in school.

[22] I include additional dummies for professional services, other services, management-related occupations, teachers, retail and personal services sales workers, secretaries, mechanics, and construction trades. Several of these groupings for mother’s or father’s occupation were collapsed, however, because of small sample sizes.

[23] Low computer-use occupations include service, precision production, machine operator, transportation, handlers, and farming. High computer-use occupations include executive, professional specialty, technician, sales, and administrative support.

5. Conclusions

Estimates from the Computer and Internet Use Supplement to the 2001 Current Population Survey, provide evidence on whether access to home computers increases the likelihood of school enrollment among teenagers who have not graduated from high school. A comparison of school enrollment rates reveals that 95.2% of children who have home computers are enrolled in school, whereas only 85.4% of children who do not have home computers are enrolled in school. Controlling for family income, parental education, parental occupation and other observable characteristics in probit regressions for the probability of school enrollment, I find a difference of 1.4 percentage points. Although formal tests of the hypothesis of uncorrelated errors reveal mixed results, I also estimate bivaratiate probit models for the joint probability of school enrollment and computer ownership. Use of computers and the Internet at work by the child's mother and father are the main exclusion restrictions. The coefficient estimates imply that the probability of school enrollment is 7.7 percentage points higher in the presence of a home computer. I interpret the results as providing evidence that home computers increase the likelihood of being enrolled in school with estimated effects ranging from 1.4 to 7.7 percentage points.

Although the bivariate probit results are exceptionally robust to alternative specifications and samples, there is the possibility that the large positive estimates of the effect of home computers on school enrollment are due to a correlation between the instruments and the error term in the enrollment equation. One potential problem is that parents with Internet access at work may be more able to communicate via email with teachers regarding their child's academic, attendance or behavior problems in school resulting in better educational outcomes. Only 28% of parents, however, report using email to communicate with their children's teachers (Lenhart et al., 2001). Furthermore, the majority of email communication between parents and teachers may occur at home instead of work.

Unfortunately, the CPS does not include information on other aspects of work (e.g. the use of pencils) that would allow for a "reality check" of the results using computer or Internet use at work as exclusion restrictions. In the end, however, there is no obvious reason to suspect that parental use of computers or the Internet at work is strongly correlated with educational outcomes after controlling for family income, parental education and parental occupations. Although more research is needed, the estimates presented above suggest that the household consumption of computers may provide positive externalities to families through better educational outcomes among children.

Table 8
Sample means of selected variables (Current Population Survey, 2001)

Variable	Mean	Standard deviation
School enrollment	0.9358	0.2451
Home computer	0.7860	0.4102
Female	0.4735	0.4994
Black	0.1151	0.3192
Latino	0.0979	0.2972
Native American	0.0198	0.1394
Asian	0.0373	0.1895
Age 17	0.4084	0.4916
Age 18	0.1314	0.3379
Number of children in household	2.1515	1.2240
Family income: missing	0.1404	0.3474
Family income: \$10,000–\$15,000	0.0422	0.2011
Family income: \$15,000–\$20,000	0.0342	0.1818
Family income: \$20,000–\$25,000	0.0533	0.2247
Family income: \$25,000–\$30,000	0.0465	0.2105
Family income: \$30,000–\$35,000	0.0495	0.2170
Family income: \$35,000–\$40,000	0.0429	0.2027
Family income: \$40,000–\$50,000	0.0937	0.2914
Family income: \$50,000–\$60,000	0.0896	0.2857
Family income: \$60,000–\$75,000	0.1064	0.3084
Family income more than \$75,000	0.2574	0.4372
Lives only with father	0.0559	0.2298
Mother-not in the labor force	0.1925	0.3943
Lives only with mother	0.2404	0.4274
Mother-high school graduate	0.3218	0.4672
Mother-some college	0.2880	0.4529
Mother-college graduate	0.2232	0.4164
Father-high school graduate	0.2406	0.4275
Father-some college	0.1984	0.3988
Father-college graduate	0.2241	0.4170
Father-not in the labor force	0.0446	0.2064
Mother uses computer at work	0.4343	0.4957
Father uses computer at work	0.3711	0.4832
Mother uses the Internet at work	0.2843	0.4511
Father uses the Internet at work	0.2869	0.4523
Sample size	4239	

Note: The sample consists of youth ages 16–18 who have not graduated from high school and live with at least one parent.

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Appendix A

The sample means of selected variables are listed in Table 8.

Appendix B

Estimates of parental computer and Internet use at work rates by selected explanatory variables are shown in Table 9.

Table 9
Parental computer and Internet use at work by selected explanatory variables (Current Population Survey, 2001)

	Mother uses computer at work	Mother uses Internet at work	Sample size	Father uses computer at work	Father uses Internet at work	Sample size
Family income						
Less than $10,000	0.1237	0.0538	186	0.0753	0.0538	186
$10,000–$15,000	0.1508	0.0503	179	0.0224	0.0168	179
$15,000–$20,000	0.1724	0.0897	145	0.0621	0.0345	145
$20,000–$25,000	0.2699	0.1858	226	0.0620	0.0310	226
$25,000–$30,000	0.2944	0.1624	197	0.1574	0.0914	197
$30,000–$35,000	0.3333	0.1810	210	0.2143	0.1286	210
$35,000–$40,000	0.4176	0.2363	182	0.1978	0.1264	182
$40,000–$50,000	0.4408	0.2595	397	0.2569	0.1688	397
$50,000–$60,000	0.5211	0.3500	380	0.4474	0.3132	380
$60,000–$75,000	0.5610	0.3526	451	0.5078	0.4102	451
Greater than $75,000	0.6050	0.4482	1,091	0.6737	0.5655	1091
Education						
High school dropout	0.0934	0.0297	471	0.1149	0.0611	409
High school graduate	0.3974	0.2273	1,364	0.3157	0.1931	1020
Some college	0.5184	0.3284	1,221	0.5422	0.4019	841
College graduate	0.6575	0.5074	946	0.7874	0.6905	950
Occupation (mother's or father's)						
Executive	0.7991	0.6074	433	0.7832	0.6539	549
Professional specialty	0.7441	0.5482	633	0.8389	0.7450	447
Technician	0.6434	0.3217	143	0.7105	0.5658	76
Sales	0.5771	0.3902	305	0.7254	0.5831	295
Administrative support	0.7407	0.4521	752	0.5738	0.4344	122
Service	0.1899	0.0874	595	0.3886	0.2085	211
Precision production	0.3600	0.1733	75	0.3068	0.2021	678
Machine operator	0.2645	0.0744	121	0.2402	0.1006	179
Transportation	0.1282	0.0513	39	0.1681	0.0905	232
Handlers	0.1579	0.1184	76	0.1908	0.0992	131
Farming	0.2703	0.1351	37	0.2750	0.1917	120

Note: The sample consists of youth ages 16–18 who have not graduated from high school and live with at least one parent.

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