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Are Early Investments In Computer Skills Rewarded In The Labor Market?

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Abstract
The paper assesses the relationship between investments in computer skills by adolescents and earnings at age 26. The heaviest investors earned 9 to 16 percent more than otherwise equivalent NELS-88 classmates. The payoff to early computer skills was substantial in jobs involving intense and complex uses of computers; negligible when computers were not used at work. It was non-gaming use of computers outside of school that enhanced future earnings, not playing video/computer games—which lowered earnings. Children in low SES families invested less in computer skills and thus benefited less from the job opportunities generated by the digital revolution.

Keywords
CAHRS, ILR, center, human resource, job, worker, advanced, labor market, satisfaction, employee, work, computer skills, earnings, payoff, school, video/computer games, digital revolution

Comments

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Abstract

The paper assesses the relationship between investments in computer skills by adolescents and earnings at age 26. The heaviest investors earned 9 to 16 percent more than otherwise equivalent NELS-88 classmates. The payoff to early computer skills was substantial in jobs involving intense and complex uses of computers; negligible when computers were not used at work. It was non-gaming use of computers outside of school that enhanced future earnings, not playing video/computer games—which lowered earnings. Children in low SES families invested less in computer skills and thus benefited less from the job opportunities generated by the digital revolution.

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Keywords: Wage Differentials by Skill; Computer Use, Computer Skills; digital Divide
JEL Classification: J24, J31, O33

Are Early Investments in Computer Skills Rewarded In The Labor Market?

1. Introduction

There is broad agreement that the diffusion of information technology (computers, communications, digital information, software) has transformed the modern workplace. The introduction of information and communication technology has increased the demand for more educated workers (Autor, Katz and Krueger, 1998; Acemoglu, 2002). There is a debate, however, about how this technological change has specifically changed the knowledge, skills and attitudes needed to be an effective worker[1].

A topic of special interest is whether computer skills are an important component of this set of skills. In 1993 Alan Krueger published a paper showing that employees using computers at work had a 10 percent higher wage (proxy for productivity) than non-users. A few years later, however, Krueger's interpretation of the computer use wage differential as a return to computer skills was challenged by DiNardo and Pischke (1997). Using German data they replicated Krueger's finding of a positive correlation between wages and computer use; but they also found that wages had positive relationships with using pencils, telephones and calculators at work (or even sitting down while working). Since everyone knows how to use pencils and telephones, tool specific skills cannot be the reason why those using these tools are better paid. There must be another explanation. DiNardo and Pischke conclude "that computer users possess unobserved skills that are rewarded in the labor market or that computers were introduced first in higher paying occupations and jobs." (1997, p.292) The reverse causation explanation assumes that workers allocated computers quickly learn the skills necessary to use them.

The controversy that followed has generated an apparent consensus that the coefficient on computer use in cross-section regressions is actually caused by unobserved worker heterogeneity in occupational position or in non-computer skills that the analyst failed to control for.[2] Reflecting this consensus, Levy and Murnane state: "What Krueger found was not a payoff to basic computer skills but a payoff to the unmeasured skills needed to excel at [*expert thinking and complex communication*] tasks (2004: 107)”.[3]

The absence of controls for expert thinking, complex communication and other unobserved skills clearly generates an upward bias in estimates of the wage effects of computer skills and computer use. This does not, however, prove that computer skills have no effect on productivity and wages. The basic skills necessary to get started in data entry or word processing are easy to learn and may no longer yield a wage premium. But, computer skills are multi-faceted competencies that grow and broaden as individuals gain experience and training. Only a few workers fail to add to the entry level basic skills and spend their entire career carrying out practiced routines. Most workers attain intermediate level skills by seeking help from co-workers, attending training courses and experimenting with the software to solve the problems they encounter at work. Workers with the strongest taste for learning about computers eventually become the go-to-guys or gals who assist co-workers encountering computer problems and significantly contribute to work group productivity. Many intermediate and advanced computer skills are useful at other firms, so the employer is forced to raise the wage of those who move beyond a basic level of computer skills. Pabilonia and Zoghi (2005) analysis of Canadian data indeed shows that wage premiums for experience are larger for workers who use computers.

This suggests that the best way to measure the payoff to computer skills is to study how continuous measures of computer skills relate to wages and productivity. Only a few studies have employed this strategy and all of them have used self-reported assessments of current skill levels. Respondents to the 1993 ABS TEES survey in Australia described their skill level (from none to advanced) in seven computing areas (word processor, data entry, etc). Borland, Hirschberg and Lye (2004) analysis of these data found a significant positive relationship between earnings and the number of types and average level of computer skills. Dickerson and Green (2004) examined the British Skills Surveys for 1997 and 2001 describing each respondent’s job and the importance, sophistication and effectiveness of his use of computers. They concluded that both computer skills and high-level communication skills generated positive wage premiums both in cross-section hedonic wage equations and in their analysis of within-cohort change.[4] However, two other studies--Borghans and ter Weel's (2005) analysis of the 1997 wave of the British Skills Survey and Sakellariou and Patrinos (2003) analysis of data on Vietnamese workers--conclude that that the higher wages of computer users are not generated by the user's computer skills.

Our approach to testing the hypothesis that computer skills influence earnings is very different from previous studies. We use micro data from the National Educational Longitudinal Study (NELS-88), a longitudinal data set that followed a nationally representative sample of 8th graders in 1988 through high school and then surveyed them once again eight years later in 2000 when most were working full-time.

We use five indicators of computer specific learning–by-doing and formal training during high school as proxies for (predictors of) later computer skills. The indicators are voluntary activities intended to develop computer skills or to use computers to learn other things. Consequently our indicators will pick up the effects of (1) an early start to developing computer skills, (2) the benefits of early computer skills in promoting the learning of academic (e.g. writing, statistics, mathematics), occupational and more advanced computer skills, (3) the effect of a taste for using computers as a tool on the development of academic and occupational skills and (4) the desire to learn about computers that is likely to lead to continuous updating and upgrading of computer skills over the next decade. We caution readers, therefore, against interpreting a coefficient on a single indicator as an estimate of the impact of that isolated activity on productivity eight years later. Think of the proxy variables as predictors of the cumulative impact of an unobserved process of developing computer and other skills that will be intense at first and then diminish as labor market experience accumulates. As in Becker's model of general OJT, the need to finance further on-the-job learning may initially prevent productivity benefits from showing up in wage increases. Eventually, however, effects cumulate and wage rates respond positively to the indicators of early investments in computer skills.

Consumption activities that use computers as a tool were not considered investments in computer skills. The literature on the effects of computers on learning has concluded that how computers are used is crucial. Playing computer games distracts from schoolwork, diminishes study time and academic achievement (Stinebrickner and Stinebrickner, 2004). Consequently, we do not expect game playing to teach skills that are rewarded by the labor market. Consequently, computer and video game playing is measured separately and included in some regression models as a control.

By studying the effects of pre-labor market investments in computer skill, we avoid the problem of reverse causation that most researchers feel contribute to the correlation between wages and contemporaneous measures of computer use and skills. It also means that unobserved occupational heterogeneity will not bias our analysis as it biases analyses that try to measure the effect of contemporaneous measures of computer use or skills on wage rates. We expect early investments in computer skills to influence occupational choice and sorting. Our regressions are intended to measure both these sorting effects and the effects of early investments in computer skills on within occupation wage differentials. Thus the Dinardo/Pishke critique of cross section studies relating wages and computer use does not apply to our main results. We will also present results for models that control for job characteristics, occupation and industry, but we do not view these results as fully controlling for occupational heterogeneity.

One threat to validity remains: student heterogeneity. Investments in computer skills are correlated with other determinants of earnings such as social class, family income, having a computer at home, IQ, GPA, ambition, course taking patterns, participation in learning opportunities outside of school and school quality. These traits must be controlled for if we are to obtain unbiased estimates of the effects of pre-labor market computer skills. We are fortunate in this regard. The NELS-88 survey obtained a wealth of data on parents, schools and the attitudes, behavior and achievement of 8th grade students, so we will have better controls for these characteristics then any previous study of computer skills.

To summarize our results, we found that students at the top of our scale of early investment in computer skills (EICS) earned 9 to 12 percent more in the year 2000 than others of equal ability, schooling and family background. Early investors were also more likely to be in high wage occupations at age 26, more likely to use a computer at work and more likely use their computer to perform complex tasks. If they did not use a computer at work, the payoff to early investments in computer skills was zero. Among those who were using computers in complex way, the early investors were paid at least 10 percent more.

We also conclude that how young people use a computer is probably more important than having a home computer. Time spent playing video/computer games significantly reduced earnings a decade later. Students from low-income families were less likely to have a computer and much less likely to take computer skills courses outside of school. They also tended to use their computer for game playing and not for learning. As a result, they developed fewer computer skills and benefited less from the job opportunities generated by the digital revolution.

The paper is organized as follows. Section 2 gives a detailed description of our measures of pre-market investments in computer skills and the extensive set of controls for characteristics of the student. In section 3 we present the main results and describe how we deal with various problems that may bias the estimates. In section 4 we relate our results with the existing literature and in section 5 we conclude, commenting on some caveats of our data and how can they affect our results. Policy implications are finally suggested.

2. Data description

We analyze micro data from the National Educational Longitudinal Study (NELS-88) of a nationally representative sample of young people who were in 8th grade in 1988. Students, parents and school principals were surveyed in 1988, 1990 and 1992, high school transcripts were obtained in 1994 and students were surveyed in 1994 and 2000, two and eight years after scheduled graduation. The student and parent interviews provide data on early investments in computer skills, on other types of skills, on family background and on student behavior and attitudes in 8^{th} grade. The two follow-ups after scheduled graduation from high school provide information on post-secondary schooling, employment and jobs including a detailed description (including how computers were used) of the job occupied in the first quarter of 2000. Everyone is roughly the same age, so our measures of early investments in computer skills come from the same stage of the life cycle for everyone. Measuring past investments in computer skills for people of widely varying ages is difficult because opportunities to learn depend on when you were in school and when you enter the labor market.

Our dependent variable is the predicted log of annual earnings in 2000 (we use "predicted" because interviews were conducted primarily during the first semester of the year 2000). We used this information (rather than the available information on income for the year 1999) because accurate measures of many key variables--school attendance, occupation and the characteristics of one's current job--were only available for the first quarter of 2000. Earnings not hourly wages were used as the dependent variable to minimize measurement error. Fifty three percent of the sample reported earnings in annual terms and another 29 percent reported earnings in monthly terms. Only 18% reported an hourly rate of pay. Respondents provided estimates of average hours per week so an estimate of hourly wages can be calculated.[5] However, dividing weekly, monthly and annual earnings by our measure of hours per week would have introduced measurement error that might bias our results. We dropped from the sample individuals who reported yearly earnings below $400 or over $200,000. We decided to include in our analysis part time workers and those who were working and studying at the same time (not necessarily working part time)[6].

Students with missing data on early investments in computer skills, test scores, curriculum or educational attainment in 2000 were excluded from the analysis. For the rest of the variables, we set missing values equal to the population mean and included a dummy variable indicating that the variable was missing. The analysis sample included students both from public and private high schools and those who dropped out before graduating. A description of the key control variables used in the different models estimated is provided in Appendix 1.

Computer Information in the NELS-88 Data

This data set contains unusually detailed information on both formal and informal investments in computer skills during high school. Measures of formal training in computer skills are available for both high school courses and for classes taken outside of high school.

1. Investment in formal computer training in school. Coded high school transcripts are the source of our data on courses completed during high school. They were measured in Carnegie Units (a course with roughly 150 hours of instruction). Courses in computer skills were disaggregated into two categories:

   Number of business related computer courses: courses intended to provide skills in how to use a computer in a business environment. Most popular courses: Keyboarding (65% of the total credit hours taken in business computer skills) Computer Aided Design (7%), Computers in Business (10%), and Business Computer Programming (11%).

   Number of computer science courses: courses intended to provide skills in the computer and information sciences. Most popular courses: Computer Appreciation (56% of the credit hours taken in computer science), Computer Applications (9%), Data Processing (6%), BASIC (9%), and other programming languages (13%).

In both groups, introductory courses account for over half of the credit hours in each category. We are not able to separate out advanced courses, so we cannot directly test whether advanced courses have bigger effects. What we do instead is include quadratic terms for business computer courses and for computer science courses. This tests whether the second and third full year course taken in each category have bigger effects on subsequent earnings than the first course. If the large number of students who take only a one semester (or a one year) computer course take only introductory courses, this is an indirect way of testing whether advanced courses have stronger effects.

2. Investment in formal computer training outside of school. The 1988 parents' questionnaire asked: "Has your eighth grader attended classes outside of his or her regular school to study computer skills?" It was coded as 1 if the answer was yes. These classes were often intended as much to spark interest and engagement (e.g. building your own computer or programming a robot in BASIC or LOGO) as to teach immediately useful skills such as word processing. Since participation was voluntary

and parents had to provide transportation, taking such a class reflected both a "taste" for getting involved with computers and parental encouragement of the focus on computers. Computer skills are also developed through learning-by-using. We defined the following variables to capture the effects of skills developed through informal investments:

3. Use of a home computer for educational purposes: we used the question "Do you have a computer in your home that your child uses for educational purposes?" from parents' questionnaire in 1988. No information on the extent of use was obtained so this variable is a zero-one dummy variable. Note that the 0 value can either be the absence of a computer in the home or the existence of a computer that is not used for educational purposes. Since a dummy variable indicating a computer that was not used for educational purposes was always included in models, the coefficient on the 'home computer for educational purposes' variable contrasts the earnings of those who did not have a home computer in 8th grade, to those who had one and used it for educational purposes.

4. Time spent using computers not for gaming: we derive a variable using the question "How often do you spend time using personal computers, not including school-related work or video/computer games outside of school?", included in the 1992 student questionnaire. The four categories of the response (rarely or never, less than once a week, once or twice a week, every day or almost) were recoded to 0, 0.33, 0.66 and 1, respectively[7].

2.2 Who gets an early start developing computer skills?

We begin by examining the extent of early investments in computer skills for the high school graduating class of 1992. Forty-three percent of 8th graders had a home computer but only 24 percent used one for educational purposes.[8] Fifty-six percent took at least a one-semester computer course during high school. Forty percent said they had used a computer outside of school for purposes other than games and schoolwork during their senior year. Clearly exposure was substantial. How did it vary by social background and ability? Did a digital-skills divide exist at the dawn of the PC age?

To address these questions Table 1 presents the weighted means of the five indicators of computer skill investment (and two control variables) for the whole sample and for selected sub-samples.[9] The first column presents the weighted means for the whole sample (recall that our sample excludes those not working in 2000). The means calculated for the bottom and top quartiles of the family socioeconomic status (SES) and mathematics test scores distributions are in columns 2 through 5. Relative to 8th graders in the bottom SES quartile, the top quartile was three time more likely to have a computer, six times more likely to use a home computer for education and 3.5 times more likely to have had computer skills training outside of school. By 12th grade, however, the digital divide by SES had moderated. The number of computer courses taken in high school was not related to SES and non-gaming computer use was now only 70 percent greater for the top SES quartile.

The effect of parental background on a child's development of computer skills comes not only from the greater availability of computers in wealthy homes but also from the tendency of their children to use computers differently. Seventy percent of high SES 8th graders with a home computer used it for education; only 40 percent of the low SES kids with home computers used it for education. High school seniors from low SES backgrounds spent 60 percent more time playing computer and video games--a way of using computers that lowers academic engagement and achievement. This implies that giving low income students computers will not eliminate the digital divide. Students from disadvantaged backgrounds must also be persuaded to use computers more for learning and less for playing games.

Math test scores also had strong relationships with 8th grade indicators of exposure to computers. As with SES, relationships were weaker for 12th grade indicators—time spent using computers not for games and the number of business computer courses taken. Not surprisingly, students in the top math achievement quartile took nearly double the number of computer science courses as students in the bottom math quartile and spent less time playing computer games. These results, once again, remind us that models assessing the effects of early investments in computer skills must have good controls for social background and prior academic achievement.

Table 1
Means of Variables Measuring Early Investment In Computer Skills By Family And Student Characteristics

		Family Socioeconomic status in 1988		*Mathematics test scores in 1988*		*Obtained at least a bachelor degree by 2000*		*Use of computer at job in 2000*	
	Full sample	*Below 25 percentile*	*Above 75 percentile*	*Below 25 percentile*	*Above 75 percentile*	*No bachelor*	*Yes bachelor +*	*Not used at work*	*Frequent use at work*
	Mean	*Mean*	*Mean*	*Mean*	*Mean*	*Mean*	*Mean*	*Mean*	*Mean*
Extent of computer use during 12th grade outside school	0.24	0.17	0.29	0.20	0.29	0.22	0.27	0.17	0.25
Computer at home USED for education $	0.24	0.07	0.46	0.11	0.41	0.18	0.38	0.13	0.28
Computer at home NOT USED for educa. $	0.19	0.11	0.21	0.17	0.19	0.18	0.20	0.16	0.20
Attended classes outside school to study computer skills (8th grade) $	0.10	0.05	0.17	0.07	0.16	0.09	0.15	0.07	0.12
# of computer science courses	0.34	0.29	0.34	0.22	0.40	0.29	0.43	0.26	0.37
# of computer business courses	0.17	0.17	0.15	0.16	0.17	0.17	0.17	0.13	0.19
# of hours per week playing computer or video games	3.25	3.93	2.44	3.60	2.73	3.78	2.35	3.96	2.93

Source: Analysis of NELS88. Weighted means for the sample of 8th graders interviewed in 1988 who were working in 2000. For the variable of hours playing with computer or video games the sample excludes drop-outs in 1992.

2.3 Are early investors in computer skills more likely to complete college and to get jobs using computers?

Relationships between early investments in computer skills and the likelihood of getting a bachelors degree before 2000 are presented in column 6 and 7 of Table 1. A positive relationship is clearly evident. Those who later obtained bachelors degrees were twice as likely in 8th grade to use computers for learning and to get training in computer skills outside of school. They also took more computer science courses in high school and spent a lot less time playing computer/video games in 12th grade.

The final two columns of Table 1 compare people who frequently use computers on their job in 2000 to those who did not use a computer at work. As hypothesized computer use on the job is positively associated with the number of computer courses taken in high school and with time spent using computers for learning. It is also negatively associated with the time spent in 12th grade playing computer/video games.

3. Empirical Analysis

3.1 Basic Results

We build our empirical strategy upon the experience accumulated in the literature on the returns to different types of course work in high school (Altonji, 1995; Mane, 1999; Rose and Betts, 2004; Bishop and Mane, 2004) and on the theoretical discussion provided in Tyler (2004). We estimate the following linear model of the log of 2000 annual earnings for the student *i* in the school *s*:

*LnEarn*is = �+ �0*InvCompSk*is + �1*DemFam*is + �2*SchChar*is + �3*Abil*is +

�4*Activ* + �5*Ed*is + µis (1)

where *LnEarn*is is the log of yearly earnings in 2000; *InvCompSk* is a vector of indicators of pre-labor market investments in computer skills. *DemFam* and *SchChar* are, respectively, vectors of information on demographic/family background and school/local area characteristics. *Abil* is a vector describing the student's academic achievement in 8th grade and courses taken in high school; *Activ* is a vector describing school activities and attitudes: *Ed* is a series of dummy variables indicating the highest degree earned by 2000; and µis a classical i.i.d. error term.

A short description of the key variables included in each group can be found in Appendix 1. Equation 1 is estimated using Ordinary Least Squares. Standard errors are adjusted using the Huber-White “sandwich” estimator to account for the within-school correlation of the error term.

Table 2 presents the coefficients and standard errors from estimates of equation (1) with different sets of control variables. Column 1 presents results for a model that does not control for any individual, family or school characteristic (imposing all �=0, except �0). Except for the high school business computer courses, our key variables have the expected positive associations with earnings at age 25.

Since early investments in computer skills were positively correlated with family SES, mathematical skills and other traits known to influence later earnings, these associations do not establish a causal effect on earnings. In column 2 of table 2 we expand the basic model adding controls for *demographic characteristics*, *family background, school characteristics* and *characteristics of the local labor market*. Demographic characteristics include ethnicity, gender, handicapping condition, language minority condition, married in 2000, number of dependents in 2000 and interactions of both with the female dummy. Family background controls include: family SES, a dummy for single parent, parents divorced, # of siblings, index of parental involvement in education, index of technological goods at home and index of cultural goods in the home. The characteristics of the school the student attended during 10th grade (or had attended prior to dropping out) included were: Catholic School, secular private school, private school controlled by a church other than the Catholic church, teachers’ starting salary, percent student body white, percent free lunch, mean 8th grade test score, mean family SES and enrolment per grade (plus it’s square). Controls for characteristics of the regional labor market (SMSA or state) included the unemployment rate, mean weekly wage in retailing, the manufacturing wage, dummies for 4 Census regions, dummies for rural, central city and suburban residence.

Table 2
Effects Of Investment In Computer Skills On Log Earnings Estimates

	(1)	(2)	(3)	(4)	(5)	School fixed effect model
Extent of computer use during 12th grade outside school	0.110 (0.025)***	0.069 (0.023)***	0.064 (0.024)***	0.061 (0.023)***	0.065 (0.023)***	0.066 (0.026)***
Have computer at home that is used for education	0.159 (0.020)***	0.026 (0.020)	0.013 (0.020)	0.015 (0.020)	0.014 (0.020)	-0.002 (0.022)
Have computer at home that is NOT used for education	0.093 (0.024)***	0.034 (0.021)*	0.030 (0.021)	0.029 (0.021)	0.031 (0.021)	0.029 (0.023)
Attended computer skills classes outside regular school (8th grade)	0.097 (0.024)***	0.058 (0.023)***	0.053 (0.023)**	0.064 (0.023)***	0.062 (0.023)***	0.055 (0.026)**
# of computer science courses	0.024 (0.031)	-0.007 (0.028)	-0.036 (0.029)	-0.037 (0.029)	-0.040 (0.029)	-0.020 (0.037)
# of computer science courses squared	0.012 (0.016)	0.027 (0.014)*	0.032 (0.014)**	0.033 (0.015)**	0.032 (0.015)**	0.017 (0.018)
# of computer business courses	-0.036 (0.032)	-0.001 (0.032)	-0.020 (0.031)	-0.022 (0.031)	-0.016 (0.031)	–0.050 (0.032)
# of computer business courses squared	0.005 (0.008)	0.002 (0.008)	0.005 (0.007)	0.006 (0.006)	0.006 (0.007)	0.006 (0.009)
Demographic information	NO	YES	YES	YES	YES	YES
Family background characteristics	NO	YES	YES	YES	YES	YES
School characteristics	NO	YES	YES	YES	YES	NO
Ability Information	NO	NO	YES	YES	YES	YES
Personal Activities and Behaviour	NO	NO	NO	YES	YES	YES
Highest Education Degree	NO	NO	NO	NO	YES	YES
Observations	6526	6526	6294	6294	6294	6294
R-squared	0.025	0.148	0.161	0.171	0.199	0.180

Source: Analysis of NELS88. Sample is the 8th graders interviewed in 1988 who were working in 2000. Except when noted all control variables are measured in 1988. Demographic information contains: ethnicity, gender, handicapping condition, language minority condition, married in 2000, number of dependents in 2000 and interactions of both with the female dummy. Family background contains: family SES, single parent, parents divorced, # of siblings, parental involvement in education, index of technological goods at home and index of cultural goods at home. The following characteristics of the school the student attended during 10th grade (or had attended prior to dropping out) were also controlled: Catholic School, secular private school, private school controlled by a church other than the Catholic church, teacher salary, percent student body white, percent free lunch, mean 8th grade test score, mean family SES and enrolment per grade (plus it's square). The following characteristics of the state were controlled: unemployment rate, mean weekly wage in retailing, ratio of college graduate earnings to high school graduate earnings in 1989, ratio of tuition at four year public colleges to the weekly earnings in retailing and dummies for 4 Census regions. Ability information includes: test scores in mathematics, English, social studies and science, GPA, dummy for in advanced courses and number of credits in academic subjects, vocational education, introductory vocational education and electives (over high school period). Personal Activities and behaviour includes: hours watching TV, read for fun index, smoking, extracurricular in-school activities, indexes for involvement in sports, religious and arts activities outside school, self-efficacy (locus of control) index, self esteem index. Numbers in parenthesis below the coefficient are Huber-White standard errors that correct for clustering by school. * significant at 10%; ** significant at 5%; *** significant at 1%

State graduation requirements were also controlled: the total number of courses required to graduate, the number of academic courses required to graduate, a dummy for no state course graduation requirements and a dummy for a minimum competency test graduation requirement.

As expected adding these controls lowers the coefficients on indicators of early investment in developing computer skills (EICS), but the estimated effects for taking classes out of school and intensity of computer use as a senior remain substantively important and statistically significant. Seniors who used a computer every day not for gaming earned 6.9 percent more. The ten percent of students who got out-of-school computer training in 8th grade earned 6.2 percent more in 2000. The small group of students who did both earned 9 to 12 percent more than otherwise equal individuals who did neither[10]. These are large effects.

By contrast, the estimated effects of having a computer at home in 8th grade (whether used for educational purposes or not) fall significantly and lose statistical significance when family SES is controlled.[11] Thus having a home computer in 8th grade does not predict higher earnings in 2000 unless it leads the student becoming a frequent non-gaming user of computers during senior year.

Some school sponsored computer courses had no effects on earnings in 2000; others had positive effects. Business computer courses (keyboarding, word processing) had tiny non-significant coefficients. The first half-credit computer science course (which is the modal number of CS courses taken) also had no effect on earnings. However, the second semester of CS courses increased earnings by 2 percent and a second full-year course significantly increased earnings by another 7.6 percent. The third Carnegie unit of computer science also had large positive effects. Apparently, only the more advanced computer science courses were associated with higher earnings in 2000.

3.2 Ability bias and other sources of omitted variable bias

Are there other confounding variables that might account for our results? Might differences in student ability, behavior and attitudes be the real explanation of the wage premium in year 2000 for those with a strong interest in computers in 1988? The very rich NELS-88 data set allows us to test this hypothesis by adding measures of student ability and course taking patterns as control variables. The model presented in column 3, contains the following additional control variables: test scores in mathematics, English, social sciences and sciences, grade point average (GPA) and a dummy for taking 'advanced', 'enriched' or 'accelerated' courses in English, mathematics, sciences or social studies. All these variables were measured when the student was in 8th grade. We also added controls for the number of Carnegie units awarded in four different fields: academic, introductory vocational, occupation-specific vocational and personal interest (art, music, health, physical education, etc). Comparing column 3 to column 2, we see that coefficients hardly change at all. Clearly, we must reject the hypothesis that the positive relationship between EICS and earnings is really an effect of other cognitive abilities (measured in 8th grade) not the effect of skills and tastes that are computer related.

How about other "personal" traits? Ambition, self esteem, self-efficacy, hard work, reliability, dedication, leadership, time management, career planning skills and social skills all contribute to one's career. These traits are developed in part during secondary school and have been found to be reasonably stable over time. If they are positively correlated with early investments in computer skills, they might be the "true" explanation for the positive effects of EICS on earnings. To test this hypothesis we included in the model as control variables, scales describing *attending (participating in) religious activities or instruction outside of school*; *sports classes outside of school;* and *art, music and dance classes outside of school* (see Appendix 1 for a detailed description). Note that this insures that the 'computer training outside of school' variable captures the effect of computer classes not the family's propensity to arrange for non-school instruction in religion, sports or the creative arts. We will thus be able to compare returns to participation in extracurricular activities, sports and out of school classes in religion and creative arts to our estimates of the returns to early investments in computer skills.

Results of a model that includes the added controls for non-cognitive and social abilities are presented in column 4. Once again, the coefficients of interest remain practically unchanged, leading us to reject the hypothesis that EICS coefficients reflect a spurious correlation with non-cognitive traits that are valued by the labor market. The stability of the EICS coefficients as measures of ability, course taking, attitudes and after-school activities are added to the model implies that better measurement of these traits would be unlikely to change the finding that the EICS variables are significant predictors of earnings 8 years after high school graduation.

The only noticeable change is a 22 percent increase in the coefficient on the dummy for taking computer training outside of school. The probable explanation for this pattern is the addition to the model of a variable--taking out-of-school classes in music, art and dance--that is positively correlated with computer course taking and negatively related to future earnings. A two standard deviation increase in the arts activities predicts a 1.7 percent reduction in earnings. Since a large share of students taking out-of-school computer courses also took arts classes, the regression is now estimating the effect of the computer courses from a lower base—the reduced earnings of those who took the art and music courses outside of school.

What happens to our estimates of the effects of early investments in computer skills (EICS) when educational attainment is held constant? This question is addressed in column 5 of Table 2 where we present the results for a model that now includes a series of dummy variables indicating the highest educational degree attained by 2000. The EICS coefficients remain quite stable. This implies that the positive effects of early investments in computer skills on earnings are not caused by a positive association between EICS and later educational attainment.[12] Investments in computer skills appear to have direct effects on productivity and wages that are independent of years of schooling.

Finally, we estimated a model with school fixed effects (as in Rose and Betts, 2004) to test whether unmeasured differences in local labor markets and school quality might be contaminating our estimates of the effect of early investments in computer skills. Results are presented in column 6 and once again the estimated effects of computer training taken outside of school and the frequency of non-gaming uses of your home computer do not change. School fixed effects do however, shrink the estimated benefits of taking many advanced computer science courses at school and cause the estimated effects of business computer courses to become significantly negative. In the model presented in column 5, two CS courses boosted earnings by 6 percent and the third CS course kicked them up another 12 percent. In the fixed effect model in column 6, two CS courses boost earnings by 4.2 percent and the third course adds another 7 percent. This decline in the estimated effects of high school CS courses suggests that schools that offered advanced computer courses in 1990 were also doing many other things right that benefited all their graduates regardless of whether they took CS courses or not.

3.3 Do Early Investments in computer skills help you get cognitively demanding jobs that pay more?

How much of the substantial earnings premium received by those who invested in computer skills during high school is due to getting better jobs? How much is due to getting higher rates of pay in essentially the same job? We address this issue by entering characteristics of the individual's job in 2000 to the model presented in column 5 of Table 2 and repeated in column 1 of Table 3.

We have two different ways of describing the individual's job: 65 dummy variables for occupation and industry and a vector of variables describing the autonomy exercised on the job and the tasks performed. The year 2000 follow-up survey asked "how often [on your job] do you" (never, occasionally, or a lot) "read letters, memos, or reports"; "write letters, memos, or reports"; "read manuals or reference books, including catalogues"; "read or fill out bills, invoices, spreadsheets, or budgets"; "measure or estimate the size or weight of objects"; or "calculate prices, costs, or technical specifications." We also have a self-assessment of how much autonomy the worker had in the job[13].

Results of a model including job characteristics are presented in column 2 of Table 3. The job characteristics variables substantially improve the fit of the model. R square increases from .20 to .26. Almost all of the job characteristics had significant positive relationships with earnings. Those with the highest level of job autonomy were paid 8 percent more [not shown]. Jobs that required one to frequently "read letters, memos or reports" were paid 20 percent more. The only job characteristic associated with lower pay was "measure or estimate the size or weight of objects."

Table 3
The Effects Of Investment In Computer Skills
On Log Earnings – Robustness Checks

	(1)	(2)	(3)	(4)
Extent of computer use during 12th grade outside school	0.065 (0.023)***	0.033 (0.022)	0.036 (0.022)*	0.009 (0.021)
Have computer at home that is used for education	0.014 (0.020)	0.009 (0.019)	0.020 (0.017)	0.016 (0.017)
Have computer at home that is NOT used for education	0.031 (0.021)	0.012 (0.020)	0.031 (0.019)	0.028 (0.019)
Attended classes outside regular school to study computer skills (8th grade)	0.062 (0.023)***	0.060 (0.022)***	0.031 (0.020)	0.039 0.020)*
# of computer science courses	-0.040 (0.029)	-0.041 (0.029)	-0.059 (0.025)**	-0.059 (0.025)**
# of computer science courses squared	0.032 (0.015)**	0.033 (0.015)**	0.034 (0.012)***	0.034 (0.012)***
# of computer business courses	-0.016 (0.031)	-0.012 (0.031)	-0.015 (0.031)	-0.017 (0.031)
# of computer business courses squared	0.006 (0.007)	0.003 (0.007)	0.001 (0.007)	0.001 (0.007)
Demographic, Family, School Inf., Ability, Personal Activities and Behaviour and Highest Education Degree	YES	YES	YES	YES
42 Occupation Dummies and 23 Industry Dummies	NO	NO	YES	YES
Job Characteristics	NO	YES	NO	YES
Observations	6294	6291	6526	6291
R-squared	0.199	0.257	0.327	0.364

Source: Analysis of NELS88. Sample is the 8th graders interviewed in 1988 who were working in 2000. Except when noted all control variables are measured in 1988. Controls included in Demographic, Family, School information are the same as in previous models. Information included in Job Characteristics is: self perceived autonomy at work, read letters, write letters, read manuals, read bills, measure size and calculate specifications. Numbers in parenthesis below the coefficient are Huber-White standard errors that correct for clustering by school. Models 1, 2 and 3 estimated by OLS. Model 4 estimated by fixed effects.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

How did the job characteristics variables change the estimated effects of EICS variables? There were no real changes in the estimated effects of computer courses taken in school or outside of school. The only major change was a 46 percent decline in the coefficient on the time spent in non-gaming uses of computer.

The third and fourth columns of Table 3 present models containing the vector of 65 occupation and industry dummies. Occupation is clearly a powerful predictor of earnings; R square rises to .36 when the dummy variables are added. Adding the occupation/industry dummy variables substantially reduces the coefficients on EICS variables. When both job characteristics and occupation/industry dummies are used, the coefficient on out-of-school computer courses falls by 42 percent and the coefficient on non-gaming uses of computers falls by 80 percent. The estimated effects of computer science courses in high school also fall. This suggests that somewhat more than half of the effect of early investments in computer skills on earnings operates through the occupation, industry and skill demands of one's job. This was to be expected. There is wide variation across occupations in how computers are used, so one would expect those who bring computer skills to the market to be recruited for jobs that have the greatest need for those skills. We will test this presumption in section 4.2.

4. Robustness checks

4.1 Playing video/computer games as a source of learning-by-using

From the very beginning of computer gaming, it has been claimed that game playing generates important learning, not just entertainment (see Greenfield (1984) for an early example and Mitchell and Savill-Smith (2004) for a recent review of the literature). It is argued that computer games generate a positive attitude towards computers and give youth confidence in their ability to make a computer work for them (Levine and Donitsa-Schmidt, 1998). It often stimulates youth to learn more about computer hardware (e.g. how to install memory and video card upgrades). It is also believed to stimulate the learning of programming skills and understanding the logic and internal construction of software (Gailey, 1993).

Others, however, argue that game playing inhibits the development of productive skills. Stinebrickner and Stinebrickner (2004) have demonstrated that college students who are randomly assigned to a freshman roommate who brings video games to campus do less homework and get lower grades. Secondly, playing computer games may cause youth to turn inward, avoid engagement with peers and prevent the development of "social" skills needed to be a successful worker. Finally, depending on the type of game, you can develop some bad social behaviors such as aggressiveness (Griffiths, 1997) or lack of understanding that in the real world one cannot control what happens.

The NELS-88 data set allows us to directly test the relationship between video game playing and subsequent labor market success. The 1992 student questionnaire asked: "During the school year, how many hours a day do you USUALLY play video or computer games, such as Nintendo?"[14] There were separate questions for weekdays and weekends that we summed to create a variable measuring the total number of hours per week that the student played video or computer games during senior year. Those who had dropped out of high school were not asked this question, so dropouts are not included in the data set in which we analyze the effects of game playing. The analysis of the effects of playing computer/ video games is presented in table 4.

Table 4
Effects Of Playing Games On Log Earnings

	(1)	(2)	(3)	(4)
# of hours per week playing computer or video games	-0.0013 (0.0012)	-0.0036 (0.0012)***	-0.0032 (0.0013)***	-0.0041 (0.0015)***
Extent of computer use during 12th grade outside school				0.067 (0.024)***
Have computer at home that is used for education				0.020 (0.021)
Have computer at home that is NOT used for education				0.027 (0.022)
Attended classes outside regular school to study computer skills (8th grade)				0.068 (0.023)***
# of computer science courses				-0.036 (0.030)
# of computer science courses squared				0.033 (0.015)**
# of computer business courses				-0.027 (0.032)
# of computer squared business courses				0.007 (0.006)
Demographic, Family and School Information	NO	YES	YES	YES
Ability information	NO	NO	YES	YES
Personal Activities and Behaviour	NO	NO	YES	YES
Highest Education Degree	NO	YES	YES	YES
Observations	7791	7791	7498	5671
R-squared	0.001	0.169	0.183	0.189

Source: Analysis of NELS88. Sample is the 8th graders interviewed in 1988 who were working in 2000. Except when noted all control variables are measured in 1988. Controls included in Demographic, Family, School, Ability and Personal information are the same as in previous models. Numbers in parenthesis below the coefficient are Huber-White standard errors that correct for clustering by school. Models estimated by OLS.
* significant at 10%; ** significant at 5%; *** significant at 1%

The first three columns present models where the video game variable substitutes for the EICS variables. The hypothesis that gaming generates computer or other types of skills that are rewarded by the labor market clearly receives no support from our analysis. The coefficient on game playing is always negative and becomes more negative and statistically significant when controls for gender, social class and educational attainment are added to the model. Unexpectedly, the inclusion of controls for ability and personal characteristics does not change the value of the coefficient.

4.2 Early Investment in computer skills and the later use of computers

Clearly early investments in computer skills have a positive relationship with earnings eight years after high school graduation even when family background, ability, personality, courses taken, school quality and educational attainment are held constant. Much of that relationship arises from the success of early investors in competing for entry into high wage occupations. Because of the number and quality of the controls used in these analyses, we conclude that the taste for and the act of investing in computer skills during the high school years had significant causal effects on earnings a decade later.[15] Generic problem solving skills that are positively correlated with the EICS variables, but in fact causally independent of enhanced computer skills, do not appear to be the real cause of the EICS wage premiums.

We now offer two additional robustness tests of the computer specific nature of these relationships. The first test examines whether people who invested in computer skills prior to entering the labor market are more likely to get jobs using computers. If, as some researchers have argued, required computer skills are easy to learn on the job or are firm specific, prior training in computer skills should have no effect on whether one uses a computer at work. Our alternative hypothesis is that the computer skills of new hires help them become immediately productive when the job requires the use of a computer and this will tend to result in those who got an early start developing computer skills being sorted into jobs where computer skills are important.

To test this hypothesis, we used the information provided in the survey about computer use at work. The respondents reported whether they were frequent computer users, occasional computer users or did not use a computer at work. We estimated a logit model predicting "frequent use of computers at work" using the EICS variables and our comprehensive set of pre-labor market characteristics of the students and her school (job characteristics and occupation were not included). The indicators of early investments in computer skills significantly influenced the probability of using a computer frequently (not shown for simplicity). Most of the EICS variables had positive and significant effects. For instance, daily non-gaming use of computers in 12th grade was associated with a 22 percent increase in the probability of frequently using a computer at work. Each computer science course increased the probability of frequently using computers by roughly 12 percent. The first business computer course had a small non-significant (four percent) impact. The square term is positive so the second and third course had larger effects.

The second robustness test examines how the effects of early investments in computer skills on wages vary across jobs that do and do not require high level computer skills. If the EICS variable truly reflects computer skills (not just generic 'expert thinking and complex communication skills'), EICS should effect earnings in jobs where computers are used but not effect earnings in jobs where computers are not used. Furthermore, the effect of the EICS variable on wages should be strongest in jobs where the complexity of the computer tasks is high. [16]

We created a measure of the complexity of computer tasks from the answers to several questions in our data set. Complexity depends on a variety of factors: the types and number of software programs used, the frequency of using these software programs, and discretion in decision over one's tasks. We included all three factors in our measure of complexity in computer use (see Appendix 2 for a detailed definition). This index was used to split the sample into 3 groups: those not using computers at work; those using computers but at low level of complexity (below the mean on the complexity index among those using computers) and those with an above average complexity index.

To get more reliable estimates in these smaller samples, a composite was created based on the three EICS variables (spending time using computer outside school in 12th grade, taking some extra training in 8th grade and having a computer at home used for educational purposes in 8th grade). All three variables range from zero to one. The new variable has a mean of 0.61 and a standard deviation of 0.72. We also excluded from the model the square terms in the high school computer courses. We estimated a model predicting earnings for each group with the new variables and the detailed controls used previously.

Results are presented in table 5. They clearly indicate that early investments in computer skills generate no pay off when the individual does not use a computer at work. On the other hand, when she does use a computer at work, there is a significant earnings payoff to early investments in computer skills. Furthermore, the magnitude of the payoff is particularly large when the job involves particularly complex uses of computers. This result is important. It implies that the skills signaled by the EICS variables are indeed computer skills, not generic skills useful in many occupations where computers are not used or where only low-level computer skills are required.

This also provides an explanation for the tendency of early investors in computer skills to sort themselves jobs that involve using high-level computer skills. The coefficients on formal course work and having a home computer are all non-significant and similar in magnitude to the results reported in Column 3 of Table 3 where occupation and industry are controlled.

5. Caveats and policy implications

The specific instances of CS learning described in the NELS-88 questions are incomplete and imperfect proxies for the cumulative sum of all investments in computer skills from 1988 through 1999. Going to computer skills classes outside of school in 1988 (before the advent of email and web browsers) signals that the youth had a special curiosity and taste for learning about computers. This trait is likely to have led to continuing investments in computer skills after high school graduation. Consequently, the reader is warned against interpreting individual coefficients as structural estimates of the value added of a particular type of investment in computer skills.

We do claim, however, that it is the taste for developing computer skills and/or the skills themselves that caused the higher pay eight years after graduating from high school. The early investors may have also developed enhanced expert thinking and complex communication skills (as Levy and Murnane suggest), but they either (a) developed those skills through a learning process made more efficient by computer software (that those without computer skills did not take advantage of) or (b) their enhanced expert thinking and communication skills derive to a significant extent from their skill at using computer software. Either way the individuals who got an early start learning computer skills developed a portfolio of skills by the year 2000 that was very well rewarded by employers.[17]

How well rewarded were they? That is not an easy question to answer because the coefficients on the EICS variables and the high school computer science course variables are not structural estimates of the effects particular training programs. We view them, instead, as proxies for a taste to learn about computers and a history of training and learning about computers some of which occurred after high school graduation. The best way to finesse this problem is to standardize the EICS index used in Table 5 and to compare it's half standardized coefficient to half standardized coefficients for other variables such as GPA, math test scores, hours spent in extracurricular activities, sports lessons outside of school, religious activities, artistic activities, self efficacy and self esteem.

The results of this exercise are presented in Table 6. Column 1 presents the percentage change in earnings for all workers that results from a one standard deviation change in each of the student skill/activity variables listed above. The composite indicator of early investment in computer skills (EICS) had a bigger effect (3.0 percent per SD] than any of the other skill indicators— math ability, GPA, locus of control and extracurricular activities. This large effect is all the more impressive when we recognize that the half standardized EICS coefficient is biased towards zero by measurement error.

For the other skills and activities, the half-standardized coefficients were 2.6 percent for extracurricular activities, 2.3 percent for self-efficacy (external locus of control), 2.1 percent for self-esteem and 2.2 percent for GPA, for sports lessons outside of school and for occupation specific vocational courses. All of these relationships are statistically significant at the 5 percent level or better. The positive effect of extracurricular activities and sports appears to be a return to the social, teamwork and leadership skills that are developed or signaled by these activities.

Math achievement raised earnings by 1.8 percent per SD on the math test. Religious activities and time spent watching TV had no relationship with future earnings. Reading for pleasure, artistic activities and computer game playing had significant negative relationships with future earnings. The half standardized coefficients were -2.3 percent for computer game playing, -2.0 percent for reading for pleasure and -1.6 percent for fine and performing arts classes outside of school (not shown in tables). The negative relationship between fine and performing arts classes and earnings probably reflects the low wage levels of jobs in these fields. We do not have an explanation for the negative relationship between reading for pleasure and earnings.[18]

We also estimated the model separately for workers who did not use a computer at work and by complexity of use for those who used a computer. The results of these models are shown in columns 2, 3 and 4 of Table 6. As predicted computer skills had no effect on earnings in jobs where computers were not used and very large effects on earnings in jobs that required high level computer skills. This was also true for grade point average and mathematics achievement. These results support the consensus view that the falling price and growing power of computers have increased the demand for mathematical skills and the cognitive abilities signaled by GPA. But they also are strong evidence against the conventional wisdom that the computer skills used by most workers can be easily learned after they get a job requiring them. Our results imply that developing computer skills early in life both helps one get better jobs and also enhances one’s productivity on jobs where computers are used extensively. This finding is not driven by the obvious need for computer skills in jobs like programming and computer systems analysis. When we re-estimated our models without the 461 computer technicians and professionals in our year 2000 data, the coefficients on EICS variables fell only slightly. We conclude that medium and high level computer skills are needed in a host of occupations that do not have computer in the job title. Those seeking managerial and professional jobs would be well advised to invest in these skills before entering the labor market.

Self esteem had the opposite pattern--large (4.4 percent) positive effects for jobs not involving computers and small non-significant effects for jobs where computers were used. Extra curricular activities and sport lessons had small but comparable positive effects on earnings in all three types of jobs. Lessons in art and music were negatively related to earnings in all three categories. Reading for fun had a strong negative (-4.4 percent) relationship with earnings in jobs where computers were not used and no relationship with earnings in jobs where complex computer skills were required. For the jobs employing complex computer skills, the half standardized coefficient were 3.7 percent for the EICS index, 3.2 percent for math achievement, 2.7 percent for GPA and 2.2 percent for self-esteem and 2.1 percent for extracurricular activities.

Clearly, even when we condition on whether and how computers are used on the job, early investments in computer skills are very important predictors of earnings eight years after high school graduation. In contrast, playing video games appears not to have developed the kind of computer skills that employers valued. A one standard deviation increase in game playing lowered predicted earnings by 2.3 percent.

There was a significant digital divide in 1990. Sophomores in the top SES quartile were nearly three times more likely to use a home computer at least once a week than students in the bottom SES quartile (NCES, Tab. 138, 2005). High SES students were also more likely to use their home computers for learning rather than gaming. Seventy percent of high SES 8th graders with home computers in 1988 used them for education; only 40 percent of the low SES students with home computers did so. During senior year students from low SES backgrounds spent 60 percent more time playing video games than their high SES classmates. Opportunities for computer skills training at school were more equally distributed but this training appears to have had smaller effects on later earnings than self-initiated learning. As a result, low SES students developed fewer computer skills and benefited less from the job opportunities generated by the digital revolution.

The digital divide is now smaller but still substantial. In 2003 ninety-seven percent of families with incomes above $100,000 had a computer at home and 95 percent had internet connections. For families near the poverty line, less than half owned a home computer and less than a third had internet connections. As in 1990, children growing up in high income families were also more likely to use home computers for learning and work and less likely to use them for gaming.[19] Students from high income families devote less time to gaming. The proportion of students who spend more than an hour a day gaming is 19 percent in the high SES quartile and 29 percent for the bottom SES quartile (NCES, Tab. 138, 2005). The number of young people getting an early start on developing computer skills is growing, but the kids from disadvantaged backgrounds still lag behind their advantaged classmates.

Some argue that modern multi-player simulation games are less damaging than first generation video games such as Mario Brothers, Tetrus and PacMan. That speculation, however, is contradicted by the Steinbrickner and Steinbrickner (2005) study. Being assigned a gamer as a roommate in freshman year, significantly lowered homework completion and GPA. Consequently, our advice to parents is to try to discourage gaming and use the home computer instead for email, instant messaging, research on the internet, word processing, etc. Our analysis suggests that sports, extracurricular activities and completing homework are much better uses of a youth's time than gaming.

Table 5
Effects of Investment in Computer Skills On
Log Earnings by Levels of Complexity in Computer Use

	(1)	(2)	(3)
	Non computer users	*Computer users below mean complexity level*	*Computer users above mean complexity level*
Composite measuring pre-labor investment in computer skills market	-0.017 (0.032)	0.021 (0.016)	0.053 (0.016)***
Have computer at home that is NOT used for education	0.055 (0.053)	0.018 (0.027)	0.063 (0.030)**
# of computer science courses	-0.041 (0.049)	0.013 (0.020)	0.022 (0.020)
# of computer business courses	0.105 (0.054)**	0.007 (0.026)	-0.056 (0.053)
Demographic, Family, School, Ability, Personal Information and Highest Education Degree	YES	YES	YES
Observations	1033	2935	2326
R-squared	0.281	0.183	0.197

Source: Analysis of NELS88. Sample is the 8th graders interviewed in 1988 who were working in 2000. Controls included in Demographic, Family School, Ability, Personal information are the same as in previous models. Numbers in parenthesis below the coefficient are Huber-White standard errors that correct for clustering by school. Models estimated by OLS.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6
Comparing the Effect on Earnings Of
A One Standard Deviation Increase in Different Skills

	(1)	*(2)*	*(3)*	*(4)*
	Complete sample	*Non computer users*	*Computer users below mean complexity level*	*Computer users above mean complexity level*
Composite measuring market investment in skills pre-labor computer	0.030 (0.008)***	-0.010 (0.023)	0.014 (0.012)	0.037 (0.011)***
Grade Point Average in 8th grade	0.022 (0.010)**	0.002 (0.025)	0.012 (0.013)	0.027 (0.016)*
Mathematics test score	0.019 (0.010)*	0.009 (0.031)	0.001 (0.014)	0.032 (0.015)**
Extracurricular hours per week	0.026 (0.008)***	0.024 (0.029)	0.024 (0.011)**	0.021 (0.011)**
Sports lessons outside of school	0.022 (0.007)***	0.015 (0.023)	0.023 (0.009)***	0.015 (0.010)
Religious activities	-0.004 (0.008)	-0.012 (0.021)	-0.002 (0.011)	0.006 (0.012)
Classes outside of school music, theatre or dance in art,	-0.016 (0.008)*	-0.006 (0.029)	-0.012 (0.011)	-0.008 (0.012)
Index of self-efficacy locus of control or external	0.023 (0.009)***	0.007 (0.023)	0.018 (0.013)	0.016 (0.014)
Index of self-esteem	0.021 (0.009)**	0.044 (0.024)*	0.006 (0.012)	0.022 (0.015)
Watch TV Index	-0.005 (0.010)	0.023 (0.023)	-0.018 (0.013)	-0.001 (0.019)
Reading for Fun Index	-0.020 (0.008)***	-0.041 (0.024)*	-0.027 (0.011)**	-0.006 (0.011)
Demographic, Family, School, Ability, Personal Information and Highest Education Degree	YES	YES	YES	YES
Observations	6331	1039	2948	2344
R-squared	0.195	0.272	0.182	0.193

Source: Analysis of NELS88 8th graders who were working in 2000. Controls included in Demographic, Family School, Ability, Personal information are the same as in previous models. Numbers in parenthesis below the coefficient are Huber-White standard errors that correct for clustering by school. Models estimated by OLS.
* significant at 10% on a two tail test; ** significant at 5%; *** significant at 1%

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Appendix 1
Key Control Variables Used in the Regressions

Grades and test scores

Grades: average of the self-reported grades in English, mathematics, science and social studies in 8^{th} grade. Five points scale where mostly As is 4 and mostly below D is 0.5.
Tetamat: mathematics test score in 8^{th} grade. The IRT Theta "T" score was used because it has a normal distribution. Theta has a mean of 50 and a standard deviation of 10 where the standardization was carried out on the weighted panel sample.
Tetaeng: English test score in 8^{th} grade.
Tetasoc: Social Science test score in 8^{th} grade.
Tetasci: Science test score in 8^{th} grade.
Advanced: mean of four dummies measuring whether the student is attending at least once a week advanced, enriched or accelerated courses in English, mathematics, sciences or social studies in 8^{th} grade. Missing values were replaced by the mean of the variable.

Personal and Family Characteristics

Locus: psychological scale created by NELS measuring respondent's sense of locus of control. Missing values were replaced by the mean of the variable.
Self: psychological scale created by NELS measuring respondent's self esteem. Missing values were replaced by the mean of the variable.
handicap: dummy variable measuring in 1988 current or past participation in a program for the orthopedically handicapped or learning disabled. Information comes from the parents and teachers questionnaires. Note that the eligibility criteria and participation patterns used in NELS-88 tended to eliminate most severely handicapped students from the sample. Missing values were replaced by the mean of the variable.
Ses88: composite created by NELS measuring the family socioeconomic status when the student was in 8th grade. They used father's and mother's education level and occupation and family income.
famsize: composite created by NELS estimating family size from both the parent and student questionnaires. Missing values were replaced by the mean of the variable.
Readfun: number of hours per week the student read on his/her own outside school--NOT in connection with schoolwork. Missing values were replaced by the mean of the variable.
Tvhours: number of hours per day watching television. Missing values were replaced by the mean of the variable.
Parinvol: variable measuring parent's involvement in student school activities when she/he was in 8th grade. It was created using two questions: how often student discuss with parents what is done in class and how often parents check on the student's homework. It runs from low values (checking often) to high values (not checking at all). Missing values were replaced by the mean of the variable.
divor: household composition reported by the student in 1988. In this case, the student lives with either the biological father or mother and, respectively, a female or male guardian. Missing values were replaced by the mean of the variable.
Singfem: household composition reported by the student in 1988. In this case the student only lives with the biological mother. Missing values were replaced by the mean of the variable.
homecapital: sum of five dummy variables indicating whether the household has a: dishwasher, VCR, microwave, washing machine and clothes dryer in the year 1988. Missing values were replaced by the mean of the variable. *homeculture*: sum of seven dummy variables indicating whether the household has: newspapers, magazines, an encyclopedia, atlas, dictionary, more than 50 books and a place for the student to study in the year 1988. Missing values were replaced by the mean of the variable.

Extracurricular: Response to 10th and 12th grade question: “In a typical week, how much time do you spend in all SCHOOL-SPONSORED extracurricular activities?” It was measured in hours per week. Drop-outs were assigned a 0 value. The index is a simple mean of the sum of the two years. Missing values were replaced by the mean of the variable.

Compositeart: Composite created using information from the 8th, 10th and 12th grade questionnaires. In 8th grade students were asked whether they were attending classes outside of school in music, art or dance. We created dummy variables for each of them. In 10th and 12th grade students and dropouts were asked: “How often do you spend time on the following activities outside of school…taking classes (music, art or dance). The four possible responses (from never to very often) to this question were coded 0, .33, .66 and 1. The index is a simple sum of these five (three dummies for 1988 and two variables for 1990 and 1992) and ranges from 0 to 5. Missing values were replaced by the mean of the variable.

Compositereli: Composite created using information from the 8th, 10th and 12th grade questionnaires. In 8th grade students were asked whether they were attending classes outside of school in religion. We created a dummy variable. In 10th and 12th grade students and dropouts were asked: Students were asked in 10th and 12th grade “How often do you spend time…attending (participating in) religious activities…outside school?.” The four possible responses to this question were coded 0, .33, .66 and 1. The index is a simple sum of these three variables (one for each year) and ranges from 0 to 3. Missing values were replaced by the mean of the variable.

Outsidesport: Students were asked in 10th and 12th grade, “How often do you spend time…outside of school?…. taking sports lessons: karate, tennis, etc.” The four possible responses (from never to very often) to these questions were coded 0, .33, .66 and 1. The index is a simple sum of these two variables (one for each year) and ranges from 0 to 2. Missing values were replaced by the mean of the variable.

Appendix 2
Complexity of Computer Use Index

To create the Complexity of Computer Use Index we used information from several questions included in the survey. First, we used a series of questions indicating how often respondents used the computer at their jobs to perform four specific tasks: for word processing; to search on the internet; to perform technical activities such as data entry and access, spreadsheets, and other computer programs; and to write software or applications for the computer. For each task the respondent could answer: "never," "occasionally" and "a lot." We created four dummy variables indicating occasional use (where no use and frequent use have a 0 value) and four additional dummies to indicate frequent use (where no use and occasional use have a 0 value). We did not incorporate information on the frequency of email use in the index because most researchers do not view email as requiring significant computer skills. We then summed the four dummy variables for occasional use and the four dummies for frequent use.

Index of occasional use (IOS) = (word occasionally + internet occasionally + technical occasionally + programme occasionally)

Index of frequent use (IFS) = (word a lot + internet a lot + technical a lot + programme a lot)

Secondly, to create our Complexity of Computer Use Index, we also used the information regarding respondents' perceived job autonomy. They were asked to choose among four situations:

In your job…
1 … someone else decides what you do and how you do it,
2 … someone else decides what you do, but you decide how to do it,
3 … you have some freedom in deciding what you do and how to do it
4 … you are basically your own boss

We created an Autonomy Index (AI) as a dummy variable with value 1 if the respondent picked up answer 3 or 4, and 0 otherwise.

Adding the Index of occasional use and the Index of frequent use and applying a weighting scheme depending on the value in the Autonomy Index, we have:

Complexity of Computer Use Index (CCUI)= IOS + (IFS*2) if AI = 0 or

Complexity of Computer Use Index (CCUI)= (IOS + (IFS*2)) * 2 if AI = 1

The weighting scheme intends to reflect that complexity of use depends both on intensity and on the autonomy one's has in the job. We conducted several sensitivity tests with different weighting schemes, producing results similar to the ones obtained with this scheme.

Appendix 3
Descriptive Statistics
Correspond to Model 5 of Table 2

Variable	Obs	Mean	Std. Dev.	Min	Max
Log annual earnings	6294	10.19575	.628060	6.39693	12.2060
Using computer outside school	6294	.2377931	.3237389	0	1
Computer home education	6294	.26136	.4394106	0	1
Computer home no education	6294	.2000318	.4000556	0	1
Classes in computer	6294	.1121703	.315601	0	1
# courses computer science	6294	.3613346	.5190815	0	3.5
# courses comp. Business	6294	.1720734	.3984802	0	9
Hispanic	6294	.1132825	.316963	0	1
Black	6294	.0738799	.2615961	0	1
Indian	6294	.0085796	.0922353	0	1
Asian	6294	.0651414	.2467948	0	1
female	6294	.5028599	.5000315	0	1
married	6294	.3973872	.4890859	0	1
dependents	6294	.5149349	.8831362	0	5
married *female	6294	.2168397	.4120331	0	1
dependent *female	6294	.2848745	.7005276	0	5
lang. Minority	6294	.1255164	.3313298	0	1
handicap	6294	.2113124	.4082719	0	1
SES	6294	-.0382386	.7575109	-2.414	1.854
Family size	6294	4.572	1.317.776	2	11
divorced	6294	.1040173	.3042189	0	1
single mother	6294	.1255105	.3300892	0	1
par. Involvement	6294	.6531946	.2446748	0	1
# appliances at home	6294	4.173	1.070.315	0	5
# culture at home	6294	5.351	1.306.028	0	7
urban	6294	.2287893	.4200867	0	1
rural	6294	.3427073	.4746523	0	1
central	6294	.3063235	.4610024	0	1
south	6294	.3261837	.4688527	0	1
west	6294	.1922466	.3940971	0	1
catholic school	6294	.0637115	.2442576	0	1
private Religious school	6294	.0182714	.1339417	0	1
private Non religious school	6294	.0390848	.1938122	0	1
mean math test school	6294	45.861	4.026	30.62594	63.86
mean SES school	6294	-.0543922	.4891728	-1.65	1.666
enrolment school	6294	3.095067	2.231527	.2	13
pupil teacher ratio	6294	15.960	3.881519	10	30
% white body	6294	.7597422	.2853735	0	1
% free lunch school	6294	.1843047	.1954509	0	1
Annual salary new teacher	6294	20.101	3.226	14	34.167
State MCE	6294	.3479504	.4755233	0	1
State units to grad	6294	18.6503	3.351	13	24
State academic to grad	6294	10.36688	1.7413	7	13
No mandatory units	6294	.0826184	.2753264	0	1
Mean unemployment state	6294	.0682257	.0120763	276667	.1086667
Mean wage state	6294	5.5752	.110066	5.3403	5.8171
Mean wage manufacturer	6294	6.1521	.118075	5.8760	6.3986
GPA	6294	3.035854	.710076	.5	4
Math test score	6294	46.27966	8.435288	24.48	67.23
English test score	6294	47.44917	8.385853	24.14	63.49
social test score	6294	46.22367	8.649698	21.13	66.07
science test score	6294	46.56939	8.237817	22.51	69.42
# credits vocational	6294	1.138796	1.538843	0	7.5

Appendix 3
Descriptive Statistics
Correspond to Model 5 of Table 2

Variable	Obs	Mean	Std. Dev.	Min	Max
# credits academic	6294	14.94352	4.248792	0	22.5
# credits other vocational	6294	.3554899	.7260575	0	4
# credits other courses	6294	5.820569	2.489736	0	12
Enrolled in advanced courses	6294	.317859	.3730378	0	1
# extracurricular activity	6294	4.484679	5.016864	0	22.5
Sports outside school	6294	.1867561	.388349	0	2
Religion outside school	6294	1.006369	.821802	0	3
Art outside school	6294	.7925727	.9767919	0	5
Locus of control	6294	.0526881	.592102	-2.51	1.52
Self esteem	6294	.0168944	.634929	-2.91	1.23
Hours read no school	6294	2.018848	1.9302	0	7
Hours television week	6294	3.076804	1.4973	0	6
Hours playing games week	5671	3.20067	5.627888	0	35
autonomy	6348	.6841525	.4648891	0	1
read letters a lot	6294	.4783499	.4995704	0	1
read letters occasionally	6294	.3942686	.4887315	0	1
write letters a lot	6294	.3142812	.4642655	0	1
write letters occasionally	6294	.421351	.4938145	0	1
read manuals a lot	6294	.2971186	.4570252	0	1
read manuals occasionally	6294	.5096835	.4999456	0	1
read bills a lot	6294	.3295544	.4700884	0	1
read bills occasionally	6294	.2936545	.4554714	0	1
measures size a lot	6294	.2771217	.4476124	0	1
measures size occasionally	6294	.2372855	.4254522	0	1
calculate specif. A lot	6294	.3859235	.486851	0	1
calculate specif. Occasionally	6294	.3053063	.4605733	0	1
uses word a lot	6294	.3869038	.4870818	0	1
uses word occasionally	6294	.2516204	.4339803	0	1
uses internet a lot	6294	.285192	.4515433	0	1
uses internet occasionally	6294	.2481303	.4319637	0	1
technical a lot	6294	.4129965	.4924131	0	1
technical occasionally	6294	.2454712	.430402	0	1
programming a lot	6294	.0516783	.2213951	0	1
programming occasionally	6294	.1078431	.310208	0	1

Endnotes

[1] See Heckman et al. (2006) for a discussion on the effects of cognitive and noncognitive abilities on labor market outcomes. Bishop and Mane (2004) analyze the impact of technical abilities.

[2] For a detailed review of this literature see Katz and Author (1999) and Handel (2003). For recent papers claiming a "true" impact of computer use, see Dolton and Makepeace (2004) and Pabilonia and Zoghi (2005).

[3] Autor, Levy and Murnane (2003) proposes a very plausible explanation of why computers are "substitutes for workers in performing tasks that can be accomplished by following explicit rules and…complements [of] workers performing nonroutine problem-solving and complex communications tasks (p. 1279). Their empirical work shows that labor demand shifts during the 1980s and 90s favoring nonroutine tasks were concentrated in industries where IT investment was extensive.

[4] At a lower level of detail in the definition of computer skill we can find two more papers. Bell (1996) uses a dummy variable using information on people claiming they have (or not) ability to use computers. Hamilton (1997) uses the High School & Beyond data set to create a variable indicating whether an individual has ever used software packages or a computer language to program. In both papers, the authors report that computers skills payoff in the labor market.

[iv] The results from models predicting the log of hourly wages were very similar to the earnings regressions presented.

[6] Student status and part time worker was self reported. 40% of part time workers worked 35 or more hours per week. Two-thirds of those enrolled in higher education worked 35 hours per week or more.

[7] Alternative ways of coding this variable did not change our results.

[8] We compared CPS and NELS-88 estimates of the availability of computers at home. In the 1989 CPS 30% of the youth aged 14 reported having a computer at home (www.census.gov/population/ www/socdemo/computer.html). The parent questionnaire generated the higher figure of 38% for the entire sample (including those who did not work in 2000). It is not clear which data set is more accurate.

[9] In the Appendix 3 we present descriptive statistics for the complete set of variables.

[10] The positive values for "Time using a home computer not for gaming" ranged from 0.33 to 1.0. Taking computer courses is a dummy. The share of the sample with a positive value for both simultaneously was 6.3 percent.

[11] We tested the effect of a single dummy for having a computer at home. Results show a 2.9% positive effect statistically significant at 10% level.

[12] Using a comprehensive set of control variables, we estimated logit models predicting college attendance 1, 2, 3 and 4 semesters after scheduled graduation and obtaining of a bachelors degree or better by interview date in 2000. Taking computer science courses in high school predicted higher college attendance and completion rates. Additional computer science courses had slightly larger effect on college attendance than academic courses. The other EICS variables did not have significant effects on the college attendance or attainment.

[13] Respondents could choose between four possibilities: someone else decides what you do and how you do it; someone else decides what you do, but you decide how to do it; you have some freedom in deciding what you do and how to do it; you are basically your own boss

[14] All of these games ran on a computer but often the computer was dedicated to gaming (with a video link to a television set). This meant that ownership of video game equipment did not create opportunities to use a computer for word processing, spread sheet work, accessing encyclopedias, etc. As personal computers have become more capable and less expensive, game playing has migrated to home

computer platforms. The opportunity to use the platform in other ways exists, but the opportunity is not always exercised.

[15] Remember that the coefficients on EICS variables are not structural estimates of the earnings effects of specific types of computer skill development. They are capturing the effects of an early start developing computer skills through learning by doing and the taste to learn more about computers signaled by their 1988 decision to take a computer course outside of school and to become heavy non-gaming users of computers in 1992 prior to the spread of email and web browsers.

[16] Borghans and ter Weel (2005) also assess the wage effects of computer skills by studying how payoffs vary within-group of jobs that have similar levels of computer complexity.

[17] Our earnings data are for the peak of the dot-com bubble. It could be that returns to advanced computer skills may now be lower.

[18] The result is not a fluke. We estimated a similar model in High School and Beyond data and got the same result. Reading for pleasure has substantial positive correlations with homework, grades and test scores. It's correlation with most other variables is low. With TV time the correlation is -.07, with time spent playing video games it's -.047, with extracurricular activities it's .04 and with self-esteem it's .03. This pattern of correlations casts doubt on the hypothesis that reading for fun is a proxy for weak social skills.

19 More than half of 3 to 17 year old students from high income families with computers used the computer for word processing and email. In the low income families with computers, by contrast, less than 40 percent of children did word processing and less than a third did email (DeBell, M., and Chapman, Table 2A & 8A, 2005).