Are early investments in computer skills rewarded in the labor market?[1]

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Abstract – This paper uses longitudinal data from NELS-88 to test whether students who invested time in developing computer skills during high school earn more as young adults. We conclude that how one uses a computer is probably more important than access to computers. Holding schooling, achievement and social background constant, high school students who took computer skills courses and used personal computers for non-gaming purposes were, a decade later, more likely to have high-skilled well-paid jobs where computer skills were highly rewarded. Those who, instead, used computers to play video/computer games earned significantly less. Rewards for early investments in computer skills were generated largely by sorting such individuals into jobs where computer skills were needed and autonomy and cognitive complexity was greater.

In 1988 there was a substantial class related digital divide. Students from low-income families were much less likely to have home computers and much less likely to take computer skills courses outside of school. They also tended to use the computers they had access to 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.

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1. Introduction

There is broad agreement that the diffusion of information technology (computers, communications, digital information, software) has transformed the modern workplace. A debate is underway about how this has changed the knowledge, skills and attitudes needed to be an effective worker. A number of studies have found a direct relationship between the introduction of information and communication technology (ICT) and the increase in the demand of more educated workers (Autor, Katz and Krueger, 1998; Acemoglu, 2002). The economic payoffs to many of the skills learned at school are also rising. The productivity and wage payoffs for academic achievement have grown during the last 30 years (Bishop 1992; Murnane, Willett and Levy, 1995; Dolton and Vignoles, 2002). Other studies have shown that the wage premiums for school-based occupation training programs have also risen and are now quite high (Mane 1999; Bailey et al 2004; Bishop and Mane 2004).[2]

A topic of special interest that has generated much debate is whether computer skills have large effects on productivity and wages. 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. He also reported that temp agencies charge higher fees when they place workers with computer skills and were offering free computer skills training to job applicants. 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 those who use these tools are paid more. There must be another explanation.

The controversy that followed generated a "post DiNardo-Pischke consensus" (Dolton and Makepeace 2002:2) that basic computer skills are too easy to learn to generate the 10 percent plus pay differential found in so many studies. The consensus view appears to be that the apparent return to computer use is actually unobserved worker heterogeneity in occupational position or in non-computer skills

[2] Non-cognitive skills such as social skills, dependability and the tendency to follow the rules have also been shown to be important (Bishop 1998; Bowles, Gintis and Osborne, 2001; Heckman and Rubinstein, 2003).

that the analyst failed to measure and control for.[3] Levy and Murnane, for example, 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)".

Autor, Levy and Murnane (2003) are almost certainly correct that computer use is correlated with expert thinking and complex communication skills and that this contributed to Krueger's findings. However, this does not prove that computer skills have **<u>no</u>** effect on productivity and wages, only that coefficients on computer use are upward biased measures of computer skill effects. Skill at computers is not a dichotomy; it is a continuous and multi-faceted trait. While many workers have only rudimentary skills, others have developed high or intermediate-level skills and use them to improve the productivity of their work group.

This suggests that a better way to test Krueger's hypothesis 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 (2004) 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. Borghans and ter

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[3] For a detailed review of this literature see Katz and Autor (1999) and Handel (2003). It is interesting to note that there have been published very recently several papers claiming a "true" impact of computer use (Dolton and Makepeace, 2004; Jin-Tan Liu, Meng-Wen Tsou and James K. Hammitt 2004; Pabilonia and Zoghi, 2004).

[4] At a lower level of detail in the definition of computer skill we can find two more papers. Bel (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.

Weel (2005:1) argue that reverse causation is an important part of the explanation for the association between wages and self reported computer skills. High-wage firms make greater use of computers and high-wage workers are the first to be allocated computers because time-saving investments are more valuable when wages are high. Workers who are allocated computers then learn the skills necessary to use it.

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 8^{th} 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 (eg. 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 (Steinbrickner and Steinbrickner 2005). 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 potential problem of reverse causation that Borghans and ter Weel argue are contributing 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.

OUR RESULTS SHOW THAT…………

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 yield very useful data on early investments in computer skills (see next part of the section), on other types of skills, on family background and on student behavior and attitudes in 8th 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.[5]

We use the log of monthly earnings in early 2000 (times 12) as our primary dependent variable. 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.[6] 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 used earnings in 2000 (rather than 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. 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

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[5] 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 how opportunities for learning on the job have evolved over time.

[6] The results from models predicting the log of hourly wages were very similar to the earnings regressions presented. In the Substantively important differences will be mentioned in them in the paper.

those who were working and studying at the same time (not necessarily working part time)[7].

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 variables used in the different models estimated is provided in Appendix 1.

2.1 Computer information in the NELS-88 data

This data set contains 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. Coded high school transcripts are the source of our data on courses completed during high school. We created four control variables describing the non-computer courses taken—academic courses, introductory vocational courses, occupation-specific vocational courses and all other courses (art, music, health, physical education, etc.). Courses in computer skills were disaggregated into two categories.
    - **Number of business related computer courses** taken in high school eg. Keyboarding (65% of the credit hours taken in business computer skills) Computer Aided Design (7%), Computers in Business (10%), and Business Computer Programming (11%). They were measured in Carnegie Units (a course with roughly 150 hours of instruction). Appendix B provides a detailed list of the courses included in each category.
    - **Number of computer science courses**: courses intended to provide skills in the computer and information sciences: Computer Appreciation (56% of the credit hours taken in computer science), Computer Applications (9%), Data Processing (6%), BASIC (9%), and other programming languages (13%).

[7] 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.

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.

Students who take computer classes are also more likely to take classes in religion, sports, art, music and dance outside of school. NELS-88 questionnaires asked about participation in these other types of classes during 8th, 10th and 12th grade, so scales describing participation in *religious instruction outside of school*, *sports classes outside of school* and *art, music and dance classes outside of school* were constructed (see Appendix A) and included in the regressions as control variables. 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 other subjects--religion, sports and the creative arts.

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[8].

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.[9] 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

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

[9] 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.

and for selected sub-samples.[10] The first column presents the weighted means for the whole sample (recall that our sample excludes those

[INSERT TABLE 1]

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.

[10] In the Annex we present descriptive statistics for the complete set of variables.

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). This way we estimate the following linear model of the log of 2000 annual earnings for the student *i :*

$$\boldsymbol{LnEarn}_{is} = \alpha + \beta_0 \boldsymbol{InvCompSk}_{is} + \beta_1 \boldsymbol{DemFam}_{is} + \beta_2 \boldsymbol{SchChar}_{is} + \beta_3 \boldsymbol{Abil}_{is} + \beta_4 \boldsymbol{Activ} + \beta_5 \boldsymbol{Ed}_{is} + \mu_{is} \qquad (1)$$

where $\boldsymbol{LnEarn}_{is}$ 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 of variables describing the student's academic achievement; ***Activ*** is a vector of variables describing her school activities and attitudes: ***Ed*** is a series of dummy variables indicating the highest degree earned by 2000; and μ is a classical i.i.d. error term. We describe below the variables includedin each group. 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 (imposing all β=0, except β_0) that does not control for any individual, family or school characteristic. Except for the high school business computer courses, our key variables have the expected positive associations with earnings at age 25.

[INSERT TABLE 2]

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. 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 estimates remain substantively important and statistically significant. Seniors who used a computer every day but not for gaming earned 6.9 percent more. The ten percent of students who got out-of-school computer training in 8^{th} grade earned 5.8 percent more in 2000. Thus the small group of students who did both earned 8 to 13 percent more than otherwise equal individuals who did neither[11]. These are large effects.

When controls are added for family and school characteristics, the estimated effect of having a computer at home (that is used for educational purposes) drops by roughly 85 percent and becomes insignificant.[12] Adding SES controls also lowered coefficients on non-school courses and time spent using computers outside of school for non-gaming purposes by roughly one-third. This pattern suggests that having a home computer allows students to get an early start learning computer skills but does not assure that the computer will be used for this purpose. Long-term labor market benefits accrued to those who did not use their home computer solely for entertainment and game playing.

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 1.8 percent and a second full-year course significantly increased earnings by another 6.6 percent. The third Carnegie unit of computer science also had large positive effects. Apparently, only the more advanced computer science courses generated earnings payoffs in 2000.

3.2 Ability bias and other sources of omitted variable bias

We have seen that including controls for socio-economic status and characteristics of the school, labor market and state significantly reduced the coefficients on our indicators of early investment in computer skills (EICS). The EICS coefficients, however, remained significant and substantively important. Are there other confounding variables that might account for our results? The students who were "into" computers on 1988 were better at mathematics, more likely to take creative arts classes outside of school and devoted more time to extra curricular activities than other

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

[12] We tested the effect of a single dummy for having a computer at home. Results (not provided for simplicity) show a 2.9% positive effect statistically significant at 10% level.

students from comparable family backgrounds. Might these 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 added 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 8^{th} 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 can see that coefficients fall by only ten percent or so. Clearly, we must reject the hypothesis that the positive relationship between EICS and earnings is really an effect of other cognitive abilities 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. Here again the rich NELS-88 data set allows us to test this hypothesis. NELS-88 has scales for self-esteem and self-efficacy in 8^{th} grade and data on a variety of activities (after-school extracurricular activities, out-of-school sports, time watching TV, reading for pleasure, religious activities and art/music/dance courses and activities that both proxy for personal traits and measure investments in skills that may be rewarded by the labor market. 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 underlying concepts 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 21 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, music and dance 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.

College attendance and completion is positively correlated with some of our EICS variables. 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 student's 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.[13] 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

[13] Using a comprehensive set of control variables, we estimated probit 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.

home computer do not change. School fixed effects do, however, lower the estimated effects of business computer courses and they become significantly negative.

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

[INSERT TABLE 3]

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[14].

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 7.4 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."

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

[14] 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

taken in school or outside of school. The only major change was a 60 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 .364 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 38 percent and the coefficient on non-gaming uses of computers falls by 86 percent. The estimated effects of computer science courses in high school also fall. This suggests that substantially more than half of the effects of early investments in computer skills on earnings operate through the occupation, industry and the 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 (Clayson, 1983; Greenfield, 1984). 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, 1995). 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 argue that game playing inhibits the development of productive skills. Steinbrickner and Steinbrickner (2005) 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?"[15] 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.

[INSERT TABLE 4]

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 high school had significant causal effects on

[15] 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 encyclopaedias, 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.

earnings a decade later.[16] Generic 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 needed computer skills are easy to learn on the job or are firm specific, prior training in computer skills will have no effect on whether one uses a computer at work. Alternatively, if prior skills contribute to productivity in jobs that use computers, those who develop computer skills in high school will tend to be sorted into these jobs.

To test this hypothesis, we classified workers in 2000 into three groups: non users, occasional computer users and frequently computer users. We predicted "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 exercise to test the direct relationship between computer skills and the use of computer is derived from Borghans and ter Weel (2005). They suggest that if prior computer skills raise productivity and wages, the relationship should be stronger the more difficult and complex the computer tasks are. They propose measuring the effects of computer skills by studying how payoffs vary within-group of jobs that have similar levels of computer complexity.

[16] Remember that the coefficients on EICS variables are not structural estimates of the earnings effects of specific types of computer skill development. They are also capturing the impacts of later computer training and the computer talents and tastes that led students to take computer courses outside of school and to become heavy non-gaming users of computers in their senior year.

Instead of using a self-reported assessment of complexity of computer use (as in the paper cited above), we created a measure from the answers to several questions in our data set. The complexity of use derives from the type and number of software programs used; intensity of use of computers; and discretion in decision over one's tasks. We included all three of these factors in our measure of complexity of computer use. We added up a series of 8 dummy variables for using the computer either occasionally or a lot for: word processing; to search the internet; to perform technical activities as data entry, access and spreadsheets; and to write software or applications for the computer[17]. To reflect different complexities in use, we used a weighting scheme. Specifically, we weighted the word, internet and technical occasional use with 1; programming occasionally with 1.5; word, internet and technical frequent use with 2; and programming a lot with 3. Finally, we re-weighted the total by 2 if the worker reported having autonomy at work[18]. This variable was used to create 3 groups: those not using computers at work (with a 0 value in the measure of complexity), those who were below the mean (with the mean calculated just for those with values over 0) and those who were above the mean. 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. The square terms of the computer course variables were dropped. We estimated models predicting earnings for each of the three groups with the new variables and the detailed controls used previously.

Results are presented in table 5. They clearly indicate that early investment in computer skills generates no pay off when the individual does not use a computer at work. On the other hand, when he 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

[17] There also was information on the use of e-mail, but we decided no to include it as it has been mentioned that it is not necessary to have computer skills to use efficiently an e-mail program.
[18] We conducted several sensitivity tests with different weighting schemes, producing results similar to the ones obtained with this scheme.

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 between 1988 and 1999. We had no way of controlling for the curiosity and the taste for learning about computers that led some high school students to risk a reputation as a computer geek in order to develop computer skills. 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 much 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.[19]

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 variable 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

[19] Our earnings data is for a period when demand for workers with advanced computer skills was growing rapidly. The dot-com bubble has since burst and many programming jobs have moved overseas, so the shortage of computer skills that bid up wages in 2000 may have ended and returns to advanced computer skills may now be significantly lower.

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 had a bigger effect (3.5 percent per SD) than any of the other student characteristics. Math achievement came in a close second with a 3.3 percent increase in earnings per SD on the math test. Half-standardized coefficients were 2.4 percent for GPA and time devoted to extracurricular activities, 2.3 percent for sports lessons outside of school and self-esteem and 2.1 percent for self-efficacy (external locus of control). Artistic activities and computer game playing had significant negative relationships with future earnings. All of these relationships are statistically significant at the 5 percent level or better.

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 the table. Since we are now conditioning on computer use at work, the estimated effects of early computer skill development become smaller. Coefficients on some of the other student characteristics go down as well. In the jobs that use computers but the complexity is below average, a one standard deviation increase in the EICS index raises earnings by 2.4 percent. Only sports lessons outside of school had equally large standardized effects. When the complexity of computer use is above average, the half standardized coefficient is 3.5 percent for the EICS index, 4.6 percent for math achievement, 2.9 percent for GPA and 2.3 percent for self-esteem and 2.0 percent for extracurricular activities. Another thing to note is how the effects of student skills and activities vary by the importance of computers in the job held in 2000. Indicators of early leadership, teamwork and social skills--extracurricular activities, sports and self esteem—have larger effects on pay in jobs that do not involve high level computer skills. Other indicators--grade point average, self-efficacy and computer skills--had bigger effects in jobs that require high-level computer skills.

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. Playing video games did not develop the kind of computer skills that employers valued. A one standard deviation increase in game playing lowers predicted earnings by 2.3 percent. These results provide powerful support for the thesis that 'all uses of computers are not equal.' Schools should encourage parents to buy a home computer but it should be used for email, word processing and research on the internet; not for playing computer games. Sports, extracurricular activities and completing homework are much better uses of a youth's time than video game playing.

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.

TABLE 2- EFECTS 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	0.069	0.064	0.061	0.065	0.066
	(0.025)***	(0.023)***	(0.024)***	(0.023)***	(0.023)***	(0.026)***
Have computer at home that is used for education	0.159	0.026	0.013	0.015	0.014	-0.002
	(0.020)***	(0.020)	(0.020)	(0.020)	(0.020)	(0.022)
Have computer at home that is NOT used for education	0.093	0.034	0.030	0.029	0.031	0.029
	(0.024)***	(0.021)*	(0.021)	(0.021)	(0.021)	(0.023)
Attended computer skills classes outside regular school (8th grade)	0.097	0.058	0.053	0.064	0.062	0.055
	(0.024)***	(0.023)***	(0.023)**	(0.023)***	(0.023)***	(0.026)**
# of computer science courses	0.024	-0.007	-0.036	-0.037	-0.040	-0.020
	(0.031)	(0.028)	(0.029)	(0.029)	(0.029)	(0.037)
# of computer science courses squared	0.012	0.027	0.032	0.033	0.032	0.017
	(0.016)	(0.014)*	(0.014)**	(0.015)**	(0.015)**	(0.018)
# of computer business courses	-0.036	-0.001	-0.020	-0.022	-0.016	-0.050
	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)	(0.032)
# of computer business courses squared	0.005	0.002	0.005	0.006	0.006	0.006
	(0.008)	(0.008)	(0.007)	(0.006)	(0.007)	(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%

TABLE 3- THE EFECTS 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	0.033	0.036	0.009
	(0.023)***	(0.022)	(0.022)*	(0.021)
Have computer at home that is used for education	0.014	0.009	0.020	0.016
	(0.020)	(0.019)	(0.017)	(0.017)
Have computer at home that is NOT used for education	0.031	0.012	0.031	0.028
	(0.021)	(0.020)	(0.019)	(0.019)
Attended classes outside regular school to study computer skills (8th grade)	0.062	0.060	0.031	0.039
	(0.023)***	(0.022)***	(0.020)	(0.020)*
# of computer science courses	-0.040	-0.041	-0.059	-0.059
	(0.029)	(0.029)	(0.025)**	(0.025)**
# of computer science courses squared	0.032	0.033	0.034	0.034
	(0.015)**	(0.015)**	(0.012)***	(0.012)***
# of computer business courses	-0.016	-0.012	-0.015	-0.017
	(0.031)	(0.031)	(0.031)	(0.031)
# of computer business courses squared	0.006	0.003	0.001	0.001
	(0.007)	(0.007)	(0.007)	(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%

TABLE 4- EFECTS OF PLAYING GAMES ON LOG EARNINGS

	(1)	*(2)*	*(3)*	*(4)*
# of hours per week playing computer or video games	-0.0013	-0.0036	-0.0032	-0.0041
	(0.0012)	(0.0012)***	(0.0013)***	(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 business courses squared				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%

TABLE 5- EFECTS 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 market investment in computer skills	-0.017	0.021	0.053
	(0.032)	(0.016)	(0.016)***
Have computer at home that is NOT used for education	0.055	0.018	0.063
	(0.053)	(0.027)	(0.030)**
# of computer science courses	-0.041	0.013	0.022
	(0.049)	(0.020)	(0.020)
# of computer business courses	0.105	0.007	-0.056
	(0.054)**	(0.026)	(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 pre-labor market investment in computer skills	0.030	-0.010	0.014	0.037
	(0.008)***	(0.023)	(0.012)	(0.011)***
Grade Point Average in 8th grade	0.022	0.002	0.012	0.027
	(0.010)**	(0.025)	(0.013)	(0.016)*
Mathematics test score	0.019	0.009	0.001	0.032
	(0.010)*	(0.031)	(0.014)	(0.015)**
Extracurricular hours per week	0.026	0.024	0.024	0.021
	(0.008)***	(0.029)	(0.011)**	(0.011)**
Sports lessons outside of school	0.022	0.015	0.023	0.015
	(0.007)***	(0.023)	(0.009)***	(0.010)
Religious activities	-0.004	-0.012	-0.002	0.006
	(0.008)	(0.021)	(0.011)	(0.012)
Classes outside of school in art, music, language or dance	-0.016	-0.006	-0.012	-0.008
	(0.008)*	(0.029)	(0.011)	(0.012)
Index of self-efficacy or external locus of control	0.023	0.007	0.018	0.016
	(0.009)***	(0.023)	(0.013)	(0.014)
Index of self-esteem	0.021	0.044	0.006	0.022
	(0.009)**	(0.024)*	(0.012)	(0.015)
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. 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%

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APPENDIX 1

VARIABLES USED IN THE REGRESSIONS

Dependent Variable

Lnwag00: hourly wage rate in current / most recent job in 2000 (individuals who did not work in 2000 are excluded). This variable was not reported directly by all respondents, so we had to create it by dividing reported income from job by number of hours in a typical week.

Independent Variables

High school courses (information comes from Transcript data files):

newvoca: number of Carnegie units of non-computer occupation specific courses taken in high school.

homeintr: number of Carnegie units of beginning vocational courses (including all home economics courses) taken during high school.

Academic: total number of Carnegie units taken in English, foreign languages, mathematics, science and social studies during high school.

othercor: total number of Carnegie units of personal interest courses taken during high school.

High School Completion and College Attendance Variables

Educa: number of years of schooling, where 10 is assigned to those without a high school diploma.

Part2000: dummy variable indicating whether or not the respondent was a part-time student at the time of the interview, (working for pay).

Grades and test scores

Grades1: 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.

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 8th grade. Missing values were replaced by the mean of the variable.

Dumyadva: dummy variable with value =1 when advanced was missing.

Tetamat: mathematics test score in 8th 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.

Geographic Region during high school

Urban1: dummy variable for school located in a urban community.

Rural1: dummy variable for school located in a rural community (default is suburban).

West1: dummy variable for school located in the west region.

South1: dummy variable for school located in the south region. *Central1*: dummy variable for school located in the west region (default is Northeast).

Personal characteristics

Female: dummy variable for being male.

Black: dummy variable for being black, non Hispanic.

Asian: dummy variable for being Asian.

Hispanic: dummy variable for Hispanic.

NatAmer: dummy variable for being Native American (default is white, non hispanic).

Mishand: 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.

dumyhand: dummy variable with value =1 when mishandi was missing.

langmino: dummy variable with value =1 when mishandi was missing.

Family Background (all variables measured in 8th grade)

Ses88: composite created by NELS measuring the family socieconomic status. 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.

parinvol: variable measuring parents involvement in student school activities. 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).

divor: household composition reported by the student. In this case the student lives with either the biological father or mother and, respectively, a female or male guardian.

Singfem: household composition reported by the student. In this case the student only lives with the biological mother.

Singmale: household composition reported by the student. In this case the student only lives with the biological father.

other: household composition reported by the student. In this case the student lives with a relative or non-relative other than his/her father or mother (default is living with student's father and mother).

homecapital: sum of five dummy variables indicating whether the household has a: dishwasher, VCR, microwave, washing machine and clothes dryer.

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,.

Classes outside of school in art, music, language and dance: Parents were asked "Has your 8th grader attended classes outside of her regular school to study…[Art; Music; Dance]. Yes answers for each type of class were coded as 1.0; zero otherwise. The 10th and 12th grade questionnaires asked students and dropouts: "How often do you spend time on the following activities outside of school…taking classes (music, art, language or dance). The four possible responses to this question were coded 0, .33, .66 and 1.0. The index is a simple sum of these five variables. It ranges from zero to 5.0.

Religious activities not sponsored by school: Parents were asked "Has your 8th grader attended... religion...classes outside of school?" 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 1.0. The index is a simple sum of these three variables and ranges from 0 to 3.0.

Sport lessons outside of school: Students were asked in 10th and 12th grade, "How often do you spend time...outside of school?.... taking sports lessons: karate, tennis, etc." Answers ranged from zero to five in 10th grade and zero to seven in 12th grade. The index is the average of the 10th and 12th grade responses.

Extracurricular hours per week: Response to 10th grade question: "In a typical week, how much time do you spend in all SCHOOL-SPONSORED extracurricular activities?"

School Background (all variables measured in 1990 and provided by the principal)

Sallowte: salary paid to a first year full-time teacher.

Pupteara: pupil-teacher ratio in the school.

Whitsch: percentage of white (non of Hispanic origin) students among tenth graders.

Luncfree: percentage of students over the total student body that receives free or reduced-price school lunch program.

Gr10enro: tenth grade enrolment in hundreds.

Sq10enro: square of the tenth grade enrolment deviated from the mean.

Newtest: clustering students by 1990 high school, mean of the average (four items) test score obtained in 1988.

Newses: clustering students by 1990 high school, mean of the family socio-economic status in 1988.

Value Scores and Attitude Toward Work in 8th grade

Locus: psychological scale created by NELS measuring respondent's sense of locus of control.

Self: psychological scale created by NELS measuring respondent's self esteem.

Mistv: number of hours per day watching television. Missing values were replaced by the mean of the variable.

Dumytv: dummy variable with value =1 when mistv was missing.

Misread: number of hours per week the student read for fun. Missing values were replaced by the mean of the variable.

Dumyread: dummy variable with value =1 when misread was missing.

Missmoke: variable indicating student's smoking behaviour, where 0 means not smoking at all, 1 means smoking between one to five cigarettes per day and 2 means more than half a pack per day. Missing values were replaced by the mean of the variable.

Dumysmok: dummy variable with value =1 when missmoke was missing.

Variables describing state policies and local/regional labor markets

mcestate: a dummy variable for states where students must pass a minimum competency exam to receive a regular high school diploma. The states that required students to pass a minimum competency exam to graduate in 1992 were Alabama, Florida, Georgia, Hawaii, Louisiana, Maryland, Mississippi, Nevada, New Mexico, New Jersey, New York, North Carolina, South Carolina, Tennessee, and Texas. Thirty-six percent of our sample lived in states that mandate the MCE and set the graduation standard on the exam.

Nounit, statunit, acadunit: Three variables characterize course graduation requirements: a one-zero dummy variable identifying states without state-set minimum course graduation requirements, the minimum number of Carnegie units required to get a diploma, the number of core academic courses (English, math, science and social studies) required to get a diploma. States without statewide minimum course graduation requirements were assigned a value of 13—the lowest minimum total Carnegie unit requirement for the states with a requirement.

U93unemp, meanunem: unemployment rate in the local labor market—available in restricted data.

Logret93: Log of the state's weekly wage in retailing—available in restricted data.

Logman93: Log of the weekly wage in manufacturing—available in restricted data.

APPENDIX 2

COMPUTER COURSES IN THE BUSINESS AREA

Business Data Processing and Related Programs, Other	3	0,1%
Computers In Business	495	9,4%
Business Data Processing 1	300	5,7%
Business Data Processing 2	57	1,1%
Business Computer Programming 1	575	11,0%
Business Computer Programming 2	24	0,5%
Key Punch Operator	1	0,0%
Data Entry Operator 1	16	0,3%
Keyboarding	3415	65,2%
CAD	355	6,8%

COMPUTER COURSES IN THE COMPUTER SCIENCE AREA

General	51	0,5%
Computer Appreciation	6271	55,8%
Computer Mathematics 1	496	4,4%
Computer Mathematics 2	43	0,4%
Computer Applications	971	8,6%
Computer Applications, Independent Study	72	0,6%
Computer Science, Advanced Placement	114	1,0%
Computer Programming, Other	9	0,1%
Computer Programming 1	832	7,4%
Computer Programming 2	155	1,4%
Computer Programming 3	37	0,3%

FORTRAN, Introduction	21	0,2%
PASCAL, Introduction	317	2,8%
Advanced PASCAL	76	0,7%
BASIC, Introduction	983	8,7%
Advanced BASIC	84	0,7%
COBOL, Introduction	21	0,2%
LOGO, Introduction	12	0,1%
RPG Programming, Introduction	1	0,0%
Data Processing, Other	6	0,1%
Data Processing, Introduction	568	5,1%
Data Processing, Intermediate	50	0,4%
Data Processing, Advanced	11	0,1%
Computer Programming - Cooperative Education	1	0,0%
Information Sciences and Systems, Other	6	0,1%
Systems Analysis, Other	2	0,0%
Computer and Information Sciences, Other	27	0,2%