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Impact of Childhood Computer Access on Wage Determination

ECON 599 - Applied Econometrics

1 Introduction

Traditional definitions of human capital, such as education, have been well studied concerning their improvement in economic outcomes. Many studies, such as Card in 1999, have linked higher educational attainment to higher wages. This result makes complete economic sense, as higher educated workers differentiate themselves from the rest of the labour market. The relatively lower supply of educated individuals drives up their wages.

In this paper, I consider alternative forms of human capital formation. Workers can differentiate themselves along several axes in today's economy, not just through traditional means such as education. This paper focuses on the effects of technological education. A paper by Autor et al. in 1998 showed a rapidly increasing presence of computer usage in the workplace between 1983 and 1994, even for blue-collar jobs and those with low education levels. This increase in computer usage indicates an increased demand for technologically competent individuals over that period. Likely, this trend has only continued upwards since, and technological competency is even more critical to wage determination.

The Organisation for Economic Cooperation and Development (OECD) recognized in 2001 a digital divide between individuals and their access to information through technology. In particular, they outline that the primary cause of this digital divide is income and education differences. However, a study by Mossberger and Tolbert in 2006 suggests that even after controlling for income and education, black individuals are less likely to have technological access and skills as a youth. They theorize that this results mainly due to environmental differences, such as the quality of one's childhood community. Therefore, it will be quite important to control for childhood differences in my sample. I include a variety of variables that control for observable factors such as household income and several variables that attempt to control for unobservable differences in the overall 'quality' of childhood.

Wealth inequality between race (Bhutta et al., 2020) and sex (Denton and Boos, 2007) has been studied extensively in economic literature. Since demand has grown for technologically skilled workers, and black youth are disproportionately unable to access technology, this digital divide may further inequality. In particular, white individuals may learn lasting, necessary skills for the job market in childhood through technology availability. In contrast, black individuals with systematically lower access may enter the job market relatively unprepared.

Krueger has studied research into how computer usage affected wages in 1993. Controlling for various factors, he finds that computer usage correlates with higher wages. While this is a significant result, it makes perfect economic sense. Individuals that can use computers differentiate themselves and are more attractive to employers, thus earning higher wages. The effect of childhood access does not appear well studied in the literature.

The proposed question of this paper, if childhood access affects adulthood wages, leads to two main questions. First, does childhood access lead to a lasting effect on adulthood wages? Secondly, can these skills be learned later in life and leave workers as well off? If individuals do not develop these skills as children before they enter the labour market, then if they develop these skills at all, they must do it while in the labour market. Therefore, an important question is if this delayed technological education negatively impacts lifetime earnings. This paper deals primarily with the first question, establishing a baseline relationship between childhood access and wages.

There are several questions to consider when determining if childhood access affects wages. For instance, one should consider how individuals use computers in their youth. A youth that uses the computer as a child to learn 'employable' skills such as programming may benefit more from computer access than those using it for recreation, such as video games. To consider this specification, I include variables that attempt to measure the type of usage and the corresponding increase in their technical skill as an alternative model. Finally, the documented lower access of black youths to technology may imply that they benefit disproportionately from technological access. Therefore to model this, I consider a third model with interaction terms.

This paper seeks to establish a baseline relationship between computer access and wages, with a primary concern being its impact on racial inequality. A positive and significant relationship could motivate studies to answer question two; if these skills can be learned later in life with no effect on lifetime earnings. If this result is valid and the relationship is causal, this may motivate policy to reduce wealth inequality.

2 Econometric Model

My three models attempt to determine how technological access, type of access, and access by group, impact adulthood wages. I utilize a pooled OLS model for each of these models, employed in similar wage determination studies. In particular, Castex and Dechter used pooled OLS to model education and cognitive ability returns to wages across time. To determine the relationship between access and wages, I estimate model 1.

$$\ln(\text{Wage}_{it}) = \alpha + \beta_1 \text{Comp Access}_i + \beta_2 Z_i + \beta_3 X_{it} + \varepsilon_{it} \tag{1}$$

Where Z_i represents a matrix of time invariant fixed effects, and X_{it} represents a matrix of time varying effects. I refer to Z and X as childhood and adulthood controls, respectively. To determine how types of access benefit wages, I estimate model 2.

$$\ln(\text{Wage}_{it}) = \alpha + \beta_1 \text{Comp Access}_i + \beta_2 \text{Comp Skill}_i + \beta_3 Z_i + \beta_4 X_{it} + \varepsilon_{it} \tag{2}$$

Where computer skill contains three possible computer related courses individuals could take during high school. I still include computer access to determine if these courses remove any significance. Finally, to model impact on different groups, I estimate model 3.

$$\ln(\text{Wage}_{it}) = \alpha + \beta_1 \text{Comp Access}_i + \beta_2 \text{Comp Skill}_i + \beta_3 \text{Interaction}_i + \beta_4 Z_i + \beta_5 X_{it} + \varepsilon_{it} \tag{3}$$

Where interaction contains two interactions. The first for interactions between black individuals and computer access, and the second for the interaction between women and computer access. Again, I nest models 1 and 2 in model 3 to determine if the inclusion of the interaction terms alters significance.

A naive regression without appropriate controls will likely exaggerate the effect of computer access on wages. Childhood computer access is likely to correlate with factors such as high family income, which may provide more opportunities and raise an individual's potential wage. Childhood controls control for individual-specific effects, ideally controlling for every significant characteristic variable, with the only difference being computer access. Finally, adulthood controls are necessary to isolate time-varying effects, such as industry of employment, union and urban status.

In this model, I expect there to be an unobserved individual effect, α_i.[1] This presence of α_i implies a fixed-effects model is suitable. However, computer access as a child is time-invariant; therefore dropped from fixed-effect models. Fixed-effect models are unsuitable as they do not lead to an estimated coefficient for childhood computer access. Therefore, following papers such as Castex and Dechter, I utilize a pooled OLS model and attempt to add enough controls to attempt to estimate α_i as much as possible. If α_i is estimated sufficiently, then $\beta_2 Z_i + \beta_1 \text{Comp Access} = \alpha_i$, and there is essentially no individual-specific effect, and therefore OLS is suitable. The biggest issue for pooled OLS models is that if unobserved individual effects, α_i, are correlated with regressors, the estimated coefficients are biased. To reduce this correlation, I include many demographic and childhood controls to reduce this correlation as much as possible. In particular, I control for parental education, income, and other variables that represent childhood quality. On top of this, I use several variables that proxy individual attitude, such as delinquency.[2]

Finally, there are likely to be clustered errors which will cause standard test statistics to be invalid. I use clustering robust standard errors with each person's unique ID as a cluster to correct this.

2.1 Endogeneity

If sufficient controls are not present, I will likely obtain omitted-variable bias. For instance, childhood computer access may correlate highly with childhood income. If childhood income is not controlled for and has a significant effect on adulthood wages, I have endogeneity. The addition of a variety of control variables will reduce the likelihood of omitted variable bias. However, while this paper takes extensive care to include various control variables, an omitted variable may be unobservable and therefore cannot be controlled. For instance, overall childhood 'quality' is relatively unobservable and would likely be correlated with technological access. I utilize several variables to proxy this childhood quality, such as household structure, parental income and education. However, these variables may be poor proxies, in which case I will not be able to observe childhood quality and control it successfully.

Due to the significant amount of controls utilized, I feel that I am likely able to control for any omitted variable bias. However, given the possibility that these variables do not successfully represent unobservable variables, it is necessary also to include an IV estimation.

[1]This comes directly from the paper's proposal that computer access, an individual effect, may determine wage.
[2]Section 3 provides a more detailed discussion of these variables.

I propose using parental education as an instrument for childhood computer access. I suggest this variable as high parental education is likely to be associated with being able to provide technological access. Likely, even after controlling for income, high education parents might recognize the necessity of technological access,[3] and may have a significant effect. Next, since I use both parents' education levels, I have over-identification and can test for the exogeneity of the instruments directly. Finally, it is unlikely, with sufficient controls, that parental education affects your adulthood wage. If adequate controls are not present, parental education may significantly affect wages. For instance, I do not control for childhood income, but if parental education is, then parental education may be highly significant since it is likely to correlate with childhood income. I would expect high childhood income, generally, leads to living in better neighbourhoods, going to better schools, and possibly higher wages. Parental education does not directly provide these benefits to wages.

3 Data

My data comes from the 1997 cohort of the National Longitudinal Study of Youth, referred to as NLSY97.[4] NLSY97 was created to represent the overall United States population. 8984 youth aged 12 to 16 as of December 31, 1996, participated in the survey. An additional oversample of 2236 black and hispanic individuals is available to represent these groups specifically. Since I wish to consider population effects, I omit those in the oversample and consider only the sample representative of the United States population. I exclude Individuals currently enrolled in school and those missing key childhood variables.

My panel runs from 2003 to 2011, with several childhood variables derived from earlier periods. These childhood variables are time-invariant and individual-specific and attempt to estimate the individual effect, α_i. Section 3.1 describes the variables included in Z and their construction, and section 3.2 describes the variables included in X and their construction. Table 1 presents summary statistics on critical variables for my panel. The table demonstrates that black youth had lower childhood computer access than the total sample. However, despite this lower access, they are more likely to have taken a childhood programming class than the total sample. Along these lines, black households have significantly lower incomes than the total sample. There are few disparities between women and the total sample, but many differences exist between black individuals and the overall sample.

[3]This may be because high education, white-collar jobs are more likely to use computers at work, and low education blue-collar jobs might not.

[4]This was the same data source as used by Castex and Dechter, who also utilized a pooled OLS approach, with extensive attention to control variables.

Table 1: Summary Statistics by Race and Sex

	Black		Women		Full Sample	
	Mean	SD	Mean	SD	Mean	SD
Real Wage	7.11	0.56	7.17	0.56	7.24	0.54
Poor Health	0.01	0.09	0.01	0.08	0.00	0.07
High Scool	0.82	0.39	0.86	0.35	0.83	0.38
Bachelors	0.12	0.33	0.28	0.45	0.23	0.42
Graduate Degree	0.02	0.14	0.04	0.20	0.03	0.18
Married	0.01	0.11	0.03	0.18	0.03	0.18
Experience	282.15	137.36	316.14	141.95	318.78	144.30
Union	0.19	0.39	0.10	0.29	0.11	0.31
Childhood Variables:						
Both Parents	0.44	0.50	0.61	0.49	0.63	0.48
Hard Times	0.07	0.26	0.05	0.21	0.04	0.19
Mother Education	12.64	2.14	13.08	2.48	13.03	2.54
Father Education	12.32	2.19	12.86	2.94	12.85	3.40
Delinquency	0.96	1.17	0.72	1.10	0.97	1.34
Substance Abuse	0.72	0.78	1.12	0.93	1.08	0.89
Household Income	38649.80	28543.60	60443.16	49204.67	60771.35	48372.18
Computer Access	2.04	1.53	2.77	1.43	2.77	1.43
Computer Programming	0.40	0.47	0.19	0.23	0.24	0.30
Computer Literacy	0.61	0.53	0.50	0.49	0.51	0.50
Other Computer Course	0.45	0.38	0.48	0.46	0.46	0.47
Demographics:						
Women	0.51	0.50	1.00	0.00	0.47	0.50
Black	1.00	0.00	0.13	0.34	0.12	0.33
Age	24.45	2.56	24.54	2.55	24.51	2.56
Urban	0.87	0.43	0.81	0.46	0.81	0.47
N	1161		4420		9438	

Note: Real wage is real log wage in 2015 dollars. Graduate represents a master's, Ph.D., or other professional degrees. Experience is weeks worked since 1997. Both parents indicate if both parents were present in the household in 1997. Hard times indicate if youth experienced 'hard times.' Parental education is given in years of schooling. Delinquency and substance abuse are indices, with higher values indicating more delinquency and substance abuse. Household income is also in 2015 dollars. Computer access is years of computer access.

3.1 Childhood Variables

Computer access was a yearly survey question from 1997 to 2002; however, the question was not asked in 2001. To not introduce any possible errors from a discontinuity such as this, I only considered computer access for 1997 through 2000. I define childhood to be the years between birth and 18. Individuals aged 15 and 16 would be 19 and 20 by 2000. Therefore they are removed. I form computer access as the summation of access for 1997 through 2000.[5] However, computer access is measuring access at different ages for every age group. Therefore, I include birth year in the models to adjust for this.

To measure computer skills and differentiated usage, I utilize whether the youth have taken computer literacy, computer programming, or other computer-related courses in high school. These series are available from 1998 to 2000, and I sum their values for each individual to measure their computer skill as a child.

I used average household income from 1997 to 2000 as household income as a child. It was then put in 2015 dollars using the all-item CPI for the United States obtained from the federal reserve bank of St. Louis.

To represent individual effects,[6] I measured delinquency and substance abuse, as well as 'hard times.' In 1997 and 1998, NLSY97 provided a delinquency index for the youths. These range from zero to ten, with higher scores indicating higher incidents of delinquency. I average these values together. For 1997 through 2000, a substance use index is provided. This index ranges from zero to three, and I once again average. Hard times is a question posed in 1997 and varies between zero and one. One indicates that the youth experienced 'hard times' as a child.

Household status ranges from one to ten and indicates a variety of possible household structures. The both parents variable is assigned a 1 if both biological parents were present in 1997. Finally, I used father and mother education in 1997, given by years of schooling.

3.2 Adulthood Variables

The real wage is the real log wage from the youth's first job of that year. Nominal wages are converted to real terms using the all item CPI obtained from the Federal Reserve of St. Louis. I do not calculate the average between all jobs. It is unlikely that wage changes will be significantly large without changes in education, industry, or other factors, which the model will pick up in the next observable period.

I measure experience through total weeks worked, from 1997 to the year of estimation. Since NLSY provides weeks worked for that year, each year is a cumulative summation of all weeks worked in previous years, plus the weeks worked in the current year. Along with experience, I control the youth's employment industry by using the four-digit industry classification for their first. Industry

[5] IE, if an individual had a computer for all four years, their computer access as a child is given by four.

[6] As opposed to household effects.

for more than one job is not considered, following the same rationale as above with wages.

I also include several demographic variables,[7] as well as education. I measure education through four factors. I classify individuals as either having no degree, high school, a bachelor's, or a graduate/professional degree.

4 Results

4.1 Pooled OLS Model

Table 2 presents the results of a regression of various forms of computer access on wages. Model 1 only considers computer access, with no differentiation in usage or interaction terms. Method 2 adds to model 1 by adding differentiation in usage and skill. Finally, model 3 adds interaction terms to determine if computer access is beneficial to black individuals or women. Many additional controls, such as health, degree, marriage, urban and union status, employment industry, family structure as a youth, substance abuse and delinquency as a youth, and youth household income, are included in the regression. Overall, each model has approximately the same R^2 of 0.397. This R^2 is higher than in models presented by Castex and Dechter, who worked on the same dataset.

Model 1 suggests that each additional year of computer access as a youth increases adulthood wages by 1.29% and is significant at the 5% level. This result supports the hypothesis that computer access as a child has a lasting impact on wages. However, this is a moderately small effect, and despite my best efforts to control for as many factors as I can, it may be influenced by missing or unobservable variables. In model 2, the effect of computer access remains essentially unchanged, and none of the measures of computer usage are statistically significant. This result could be due to a variety of reasons. First and most simply, the type of computer usage may not matter so much as access. Second, the youth take these courses at school, and individuals without computer access at home may take these courses. Finally, these measures may simply not be sufficient in representing different uses of computers by the youth. Lastly, the addition of interaction terms in model 3 removes the significance of computer access, with no computer access variable being significant. Overall, the insignificance of the interaction term implies that black individuals and women do not disproportionally benefit from computer access.

Women earn lower wages even after controlling for many variables typically used to explain the gender pay gap, such as their job industry. In particular, women experience 7.69% to 9.16% lower wages, which are all significant at the 99% level. Likewise, black individuals experience lower individuals than their peers. This difference varies from 4.73% to 9.14% lower. Models 1 and 2

[7] These include age, indicators for black individuals and women, urban-rural status, union participation, health and marriage status at the time of that period's estimation.

Table 2: Effect of Childhood Computer Access on Wages, Ordinary Least Squares

	(1)	(2)	(3)
Constant	6.428***	6.429***	6.451***
	(0.404)	(0.404)	(0.405)
Women	-0.0771***	-0.0769***	-0.0916***
	(0.0168)	(0.0168)	(0.0328)
Black	-0.0473*	-0.0475*	-0.0914**
	(0.0241)	(0.0243)	(0.0405)
Mother Education	-0.00335	-0.00329	-0.00332
	(0.00386)	(0.00386)	(0.00386)
Father Education	0.00366	0.00365	0.00381
	(0.00310)	(0.00309)	(0.00311)
Age	0.0267	0.0266	0.0257
	(0.0329)	(0.0329)	(0.0330)
Age^2	-0.000660	-0.000657	-0.000635
	(0.000676)	(0.000676)	(0.000677)
Experience	0.000814***	0.000814***	0.000809***
	(0.0000845)	(0.0000846)	(0.0000849)
Computer Access	0.0129**	0.0127**	0.00720
	(0.00589)	(0.00591)	(0.00795)
Computer Programming		0.00330	0.00306
		(0.0126)	(0.0126)
Computer Literacy		-0.00434	-0.00422
		(0.00998)	(0.00997)
Other Computer Course		0.00491	0.00540
		(0.0108)	(0.0107)
Computer Access $\times$ Black			0.0198
			(0.0145)
Computer Access $\times$ Women			0.00490
			(0.0103)
N	9422	9422	9422
R^2	0.397	0.397	0.397
Adjusted R^2	0.380	0.380	0.380

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Wages are log wages in 2015 dollars. Parental education is given in years of schooling. Experience is weeks worked since 1997. Computer access is years of computer access as a child. Computer programming, literacy, and other computer courses =1 if the respective course was taken in high school. Other control variables include health, degree, employment industry, marriage, urban and union status, family structure as a youth, substance abuse and delinquency, and youth household income.

suggest this difference is only significant at the 10% level, and model 3 at the 5% level.

Parental education is not statistically significant in any model, suggesting that it does not directly explain wages, which is key to its use as an instrument.[8] Since parental education does not explain wages, I move forward with it as my instrument of choice.

Both age and age squared are not statistically significant, which are typically influential variables in other labour literature. However, these variables are likely not significant as the panel has a relatively small variation in age. Experience is highly significant in all three models, suggesting that each additional week of work raises wages by 0.0814% or 4.23% per year.

4.2 Pooled IV Model

Table 3 presents the IV estimated form of model 1, with two auxiliary OLS regressions to test the instrument. Specifically, to be a good IV, parental education should be closely correlated with computer access and not correlate with the error term. Models 2 and 3 test these assumptions. Model 1 estimates model 1 from table 2, using parental education as the instrument. The IV estimation of this model removes the significance of computer access. The coefficient is not significantly different, but the standard errors are much larger. Model 2 regresses parental education on computer access and suggests that parental education is highly significant. Finally, in model 3, regressing the instruments on model 1s error term. In model 3, the father's education is significant at the 5% level, suggesting that the instruments may correlate with the error term.

I utilize Hanson's J-test of overidentification to test the hypothesis that the error terms correlate with the instruments. In particular, the null hypothesis is that all instruments are uncorrelated with the IV models error term. I present the formulation of the test statistic below.

$$J = N \times R^2$$

The J-statistic is distributed χ^2, with $m - k$ degrees of freedom, where m represents the number of instruments and k the number of endogenous variables. Table 4 presents the results of the J-test and suggests the null hypothesis that the instrument does not correlate with the error term can be rejected at the 5% level.

Overall, while the instrument correlates highly with computer access, and it is unlikely that parental education directly affects wages since the instrument is correlated with the error term, IV is inconsistent. This result invalidates the results from model 1 in table 3. Particularly, I cannot conclude that IV estimation removes the significance of computer access. Alternative instruments should be considered as a means of further research.

[8] I discuss this argument in section 2.1.

Table 3: Effect of Computer Access, IV Regression

	(1: IV) Real Wage	(2: OLS) Computer Access	(3: OLS) Model 1's Error Term
Constant	6.437***	0.0962	0.00342
	(0.399)	(1.079)	(0.0282)
Computer Access	0.0156		
	(0.0244)		
Women	-0.0777***	-0.0594	
	(0.0168)	(0.0624)	
Black	-0.0461*	-0.461***	
	(0.0260)	(0.0960)	
Mother Education		0.115***	-0.00352
		(0.0138)	(0.00216)
Father Education		0.0428***	0.00330**
		(0.0123)	(0.00161)
N	9637	9422	9422
R^2	0.360	0.396	0.001

Robust standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Note: Model 1 is an IV specification of model 1 from table 2, using parental education as an instrument for childhood computer access. Model 2 regresses computer access on parental education, with the same controls used in model 1. Model 3 regresses model 1's error term on the instruments.

Table 4: Hanson's J-test for Parental Education as Instruments

	J Statistic	1% Critical Value	5% Critical Value
H_0: Instrument not correlated with IV Error Term	5.571	6.635	3.841

Note: R^2 and observations, which form the test statistic, are obtained from model 3. Robust standard errors are used.

5 Conclusion

In this paper, I analyzed several forms of the hypothesis that childhood computer access affects wages. In particular, the analysis focused on its impact on adulthood wages, if differentiated usage or skill played a factor, and if computer access disproportionately affected individuals of specified race or sex.

Controlling for various factors, each additional year of computer access as a child correlated with an approximately 1.29% increase in wages. The selected measures of computer usage, which aimed to identify the presence of 'employable' skills, were not significant. Likewise, there was no disproportionate effect of computer access for either black individuals or women. However, this correlation only holds for this sample and this time. Even if the relationship between computer access and wages is causal, the exact magnitude of this effect will change over time. In particular, the demand for digital workers has only continued to rise. Due to this continuously increasing usage and reliance on technology, the relationship may be stronger today. However, this sample is inadequate to answer questions such as this. In particular, youths in this sample experienced their childhood on the 'cusp' of the technological age. Today's youth, firmly in the technological age, may exhibit a different relationship to childhood access. Further studies could be conducted when new longitudinal studies are available to examine how this effect changes over time.

I included various controls to reduce the possibility of omitted variable bias; however, as a robustness measure, an IV regression was employed. Utilizing parental education as an instrument led to computer access losing its significance. However, the instrument correlated with the error term, and therefore, IV gives biased estimates. Further research could focus on alternative instruments.

Overall, these results suggest a significant correlation between higher computer usage and higher wages. At best, these results suggest causation in this sample. However, this is only the case if the control variables are sufficient to isolate the effect of computer access. A causal study could motivate policy, given the relationship between computer access and wages. For instance, if the causal analysis determines that computer usage causes higher wages, technological access could be given to low-income and marginalized groups to improve their economic conditions. This policy could be beneficial in reducing inequality between groups, as those with technological access would earn higher wages, and low-income households, many of which are black families and other marginalized groups, will be left with lower wages. This difference in technological access only perpetuates an already existing and established pay gap. In this sample, black youths had lower childhood household income and lower computer access, and successfully identifying a causal link could establish a means to reduce wealth inequality.

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