REEVALUATING THE EFFECT OF EDUCATION ON EARNINGS IN THE UNITED STATES

Chau Thanh Nguyen
Hoa Thanh Duong
Department of Mathematics
Illinois State University

Abstract

This paper estimates the return to schooling in the US at individual level using the NLSY97 data. Quarter of birth and parental education will be used as instrument for education. An additional instrument is introduced to estimate the return to schooling. I follow the study of Arkes (2010) to exploit the idea that economic conditions during the high school time of students might affect the expected educational attainment. The single treatment model with propensity score matching method is employed to estimate the return to high education.

Keywords: Education, Return to schooling, Instrumental variable, Quarter of birth, Parental education, Unemployment rate, Propensity score matching

I. Introduction

Estimating the return to schooling has been attracting interest of many researchers. Understanding the return to education is important for individuals because though schooling provides people with necessary knowledge and develops competitive skills that will help them to compete and increase their earnings in labor market, it involves many expenses especially opportunity cost. For country as a whole, the human capital in the form of education is one of the determinants of economic growth and can be a solution for inequalities in society. In the developed country like the US, the rapid increase school enrollment leads to concern about the relative cost between benefit of education (Card, 2001).

However, the causal effect of education on earnings is not easy to uncover due to the endogenous schooling and the unobservable characteristics. Many estimation methods have been employed to deal with the endogeneity problem of education: family fixed effect (Behrman and Rosenzweig, 1999; Miller, Mulvey and Martin, 2001; and Bonjour et al., 2002), matching (Branda and Xieb, 2010; Blundell, 2005), control function (Blundell, 2005), regression discontinuity (Fan et al., 2010 and Devereux et al., 2010). Instrumental variable is the most widely used method. There are many different instrumental variable are used. Some instruments are from supply side of education such as tuition of college (Kane and Rouse, 1993), change in schooling system (Harmon and Walker, 1995) and quarter of birth (Angrist and Krueger, 1991). Some others from demand side: parental education (Lemke and Rischall, 2003; Plug, 2001)) and Spouse's smoking (Arabsheibani and Mussurov, 2007).

Despite a number of empirical studies using alternative instrumental variable, estimating the return to schooling is needed to be estimated with updated data set because of the rapid growth in the number of college students leads to the change in the relative cost and benefit of education. Heoling et al (2014) found that the returns to both bachelor's and master's degree have fallen over the years. Particularly, return to bachelor's degree was 24.54% in 1997, 19.45% in 2005 and only 17.85% in 2013.

In this paper, we will estimate rate of return to schooling in the US at individual level using the NLSY97 data. Following the traditional studies, quarter of birth and parental education will be used as instrument for education. An additional instrument is introduced to estimate the return to schooling. I follow the study of Arkes (2010) to exploit the idea that economic condition during the high school time of students might affect the expected educational attainment. The single treatment model with propensity score matching method will be employed to estimate the return to college versus non-college individuals

The outline of the remainder of the paper is as follow. Section II briefly highlights the relevant literature on estimating return to schooling using instrumental variable and propensity score matching method. In section III, theoretical framework for my model is constructed. In section IV and V, model and data description is specified. Section VI presents the estimation results for OLS, instrumental variable and propensity score matching. Section VII concludes.

II. Literature Review

Assuming the exogeneity of education, the ordinary least square (OLS) estimation method carries several potential sources of bias. The most widely concerned bias in estimating the return to schooling is the bias due to unobservable ability. Individuals with higher ability can earn more money and also tend to have higher educational attainment. The positive correlation between ability and education induces the upward bias in the estimated average return of education. Moreover, the measurement error in the schooling variable may cause the measurement error bias. Individuals tend to report the higher education than they actually got. The upward report will cause the underestimation of the return to schooling. In the case of continuous education variable, the estimation of return by OLS might carry downward bias because individuals tend to report higher years of schooling. OLS estimation ignores the fact that education should not be treated as exogenous and hence the estimated coefficient of education is not the rate of return but only the correlation between schooling and income.

In order to deal with endogenous nature of education, many researches have adopted different methods to discover the causal link between education and labor market outcomes. The most popular estimation method is instrumental variables. The endogeneity of education was first encountered by Angrist and Krueger (1991) who used quarter of birth as an instrument for schooling. Angrist and Kruger observed that people born in the beginning of the year meet the compulsory schooling requirement earlier and hence tend to drop out from school earlier than people born later in the year. They found that the instrumental variables estimate of the return to education (10%) is close to OLS estimate (7%) suggesting that there is a little bias in conventional estimates. Bound, Jaeger, and Baker (1995) claimed that the IV used by Angrist and Krueger used is weak due to the weak correlation between quarter of birth and education; therefore IV estimation is asymptotically biased toward the corresponding OLS estimates. Kane and Rouse (1993) used distance to the nearest 2-year and 4-year colleges and state-specific tuition rates as instruments. Using the NLSY79 data, their IV estimates based on these instruments are 15-50% above the corresponding OLS. Blackburn and Neumark (1993) used parental education as the instrument for schooling and also found that instrument for schooling leads to considerably higher estimates of the return to schooling only for wages at labor market outcome. Harmon and Walker (1995) studied the return to schooling in Britain using changes in the legal minimum school-leaving age as instruments for completed education. The IV estimate is 15.4% and considerably above the corresponding OLS estimate of 6.1%. Lemke and Rischall (2003) revisited the NLSY79 data but controlled for ability and parental income using three different instruments: parental education, quarter of birth and college proximity. They found that parental education is the most valid and useful instrument. Also the weak correlation between instruments and education produces imprecise and likely biased estimates of the return to schooling. In 2010, Arkes investigated the 1980 Census data set and introduced a new instrument – state unemployment rates during a person's teenage years to estimate the returns to schooling. He argued that higher unemployment rates reduce the opportunity costs of attending schools and thus are positively correlated with educational attainment. The estimates using the unemployment rate and the ones using the quarter of birth are almost identical (9.6% and 9.8%) and larger than OLS estimates (6.6%).

Though using different data sets, most papers using IV found higher returns to education than the OLS estimate. These findings are counterintuitive to the argument that correction for ability bias should produce lower estimated return to schooling. However, some twin studies correcting for these biases in estimating the return to schooling cross-sectional OLS estimate is higher than estimate based on difference across twins such as Behrman & Rosenzweig (1999). Miller, Mulvey and Martin (2001) and Bonjour et al (2002) found similar result but the result became opposite when they apply IV for the education differences within twin.

For the single treatment model compares the earnings of high education versus non-high education, Branda and Xieb (2010) used propensity score strata method to study the effects of completing college on earnings with data from the National Longitudinal Survey of Youth 1979 and the Wisconsin Longitudinal Study and found that individuals most likely to benefit from a college education are the least likely to obtain one. Blundell (2005) used different methods including propensity score matching to estimate the return to high education in UK. The average return of 27% for those completing higher education versus anything less was found.

The following part of the paper will explain the relationship and the literature on the correlation between chosen instruments and educational attainment.

Season of Birth and Education

Season of birth can affect educational attainment through two channels: *relative age effect* and *compulsory schooling effect*. The relative age effect is obvious in sports due to the physically developmental advantage of players who are born before others in the same age group. Helsen et al (2005) used information of youth soccer players across ten European countries and found that players with a greater relative age are more likely to be identified as ‘‘talented’’ because of the likely physical advantages they have over their ‘‘younger’’ peers. The relative age effect can also affect cognitive development differences within an age group (Mortimore et al. 1988). Many studies have demonstrated that students younger in their cohorts perform worse than children older in their cohort. Carroll (1992) noted the relatively poorer school attendance of these younger children and Sharp et al. (1994) found that they had scored significantly lower than their older peers in English, Math and Science Standard Assessment Tasks (SATs) scores. A more recent study found evidence of benefits to being among the oldest in one’s age-grade cohort (Robertson 2011). The admission cutoff dates (usually at the ages of 5 to 7 in the US education system) contribute to the relative age effect. The children born after the cut-off date enter school with some months older than their classmates. Hence, they would have relative age effect advantages and are more likely to achieve higher education.

Angrist and Krueger (1991) observed another channel that season of births can affect educational attainment through *cutoff date at the end of school career.* The compulsory schooling law in the US requires students to stay in school until a certain age. The age that the students can legally drop out from school varies across states from 16 to 18. They argued that children born right after the admission cutoff date, entered school at the older age and therefore can drop out from school earlier than their friends.

The total effect of season of birth is the sum of two effects: relative age effect and compulsory schooling effect. Because these effects are opposite, the net effect depends on which effect dominates. Angrist and Krueger (1991) found a negative net effect. Some studies using other countries data, controlling for compulsory schooling effect, found a positive effect of birth season (Plug, 2001).

Parental Education and Children's Educational Attainment

Parental educational level was proved to be an important predictor of children's educational outcomes (Haveman and Wolfe (1995); Dearing, McCartney and Taylor (2002)). Parental education should influence parent's skills and knowledge of the education system, which in turns would influence their practice at home and the skills children learn from their parents. The evidence for this argument is the early language and reading interaction between parents and their children. Highly educated parents expect more from their children. They would make sure that their children are exposed to the maximum education opportunities. They are more likely to send their children to better school and enroll in music lesson, computer class and summer camp. (Hoff (2003))

Another explanation for the correlation between parental education and children education is the influence of where the family live and the types of jobs parents work. The parental income depends on parental education will decide where the family will live, which in turn will determine which types of school the children attend. The school and neighborhood characteristics should affect the children's educational attainment (Furstenberg et al. (1999)).

State Unemployment Rates and Education

State unemployment rates during one's teenage years as instrument for education was first introduced by Arkes (2010). He argued that economic conditions can affect school enrollment through two forces: income effect and substitution effect. Because higher unemployment rate may reduce household income, the family may not be able to afford child education expenses and teenage children may have to quit school and go to work to support their family. The opposite effect happens when unemployment rate decreases.

On the other hand, the substitution effect suggests a positive relationship between high unemployment rate and high rate of enrollment; higher unemployment rates reduce the opportunity cost of studying and so they encourage students to stay in school. The net effect of unemployment rates will depend on which effect is larger. However, the literature reveals a negative net effect of unemployment to educational attainment. For example, Betts and McFarland (1995) found that 1% increase in unemployment rates is associated with rises in full time attendance of about 0.5% in late 1960s and 4% in mid-1980s. Goldin (1999) shows that the biggest increase in high-school enrollment and graduation rates in the US took place between 1928 and 1938, the time of Great Depression with high unemployment rates.

The criteria for unemployment rate to be a good instrument for education in an earning model is that unemployment rates during teenage years affect individual earnings only through educational attainment. The criteria can be checked using an over-identification test. Most of literature focuses on the effect of an individual's experience with unemployment but not the aggregated unemployment rate on future earnings. And even in these studies, the explanation for the difference in earnings is from the change of investment in education due to unemployment. Mroz and Sarage (2004) using the NLSY79 data found that unemployment experienced can affect future earnings as long as 10 years despites the catch up response. However, Kawaguchi and Murao (2014) using OECD countries during 1960–2010, they found a persistent effect of unemployment in the ages 16–24. The persistence of this negative effect is stronger in countries with stricter employment protection legislation. Therefore, the validity of unemployment rate as an instrumental variable for education needs to be further tested.

Arkes (2010) used 1980 Census data with the income data of individual at the age of 37-46. At that age, the unemployment rates 20-30 years ago when the individual was teenager may not no longer affect the individual income and hence there should not be the correlation between state unemployment rate during teenage years to the error term in earnings equation.

III. Theoretical Framework

The theoretical framework for this paper is Mincer (1974) model which explains the return to education by focusing on life-cycle dynamics and the relationship among observed earnings, expected earnings and human capital investments. According to Mincer, the earnings at time t+1 depends on the investment in the previous time period (t). Let E_t be the potential earnings at time t. The investment in education can be written as a fraction of potential earnings.

$$E_{t+1} = E_t + C_t\rho_t = E_t(1 + k_t\rho_t)$$

where C_t is the investments in education, ρ_t is the return to investments and k_t is the invested fraction of income. Repeat the substitution, we have:

$$E_{t+1} = \prod_{j=0}^{t-1}(1 + \rho_j k_j)E_0$$

Mincer separated two types of human capital investments: formal schooling investment is defined as years spent in full time schooling ($k_t = 1$) and post-school investment. Assume that the rate of return on formal schooling investment is $\rho_t = \rho_s$ and ρ_s is constant for all years of schooling. Similarly, the rate of return on post-school investment is $\rho_t = \rho_o$ and ρ_o is constant overtime and across individuals. Then we have:

$$lnE_t = lnE_0 + s\ ln(1 + \rho_s) + \sum_{j=s}^{t-1}\ln(1 + \rho_o k_j)$$

The approximation version of the above equation is:

$$lnE_t \approx lnE_0 + s\ \rho_s + \rho_o\sum_{j=s}^{t-1}k_j$$

Assuming the linearly declining rate of post-school investment, Mincer also showed that the logarithm of earnings depends on the level and quadratic terms of labor market experience. The standard form of the Mincer earnings model can be written as:

$$\ln(w) = \alpha_0 + \rho_s\ s + \beta_0\ x + \beta_0\ x^2 + \varepsilon$$

IV. Methodology

To deal with endogenous nature of education, we use two methods to estimates the schooling's contribution. First of all, we revisit instrumental variable method to evaluate the rate of return to schooling in the US. Following the traditional studies, quarter of birth and parental education will be used as instrument for education. An additional instrument is introduced to estimate the return to schooling. We follow the study of Arkes (2010) to exploit the idea that economic condition during the high school time of students might affect the expected educational attainment. The economic condition is represented by the state unemployment rates. The second method is propensity score matching to estimate to return to high education.

The earnings, which is measured by the log of hourly wages, is a function of education and experience, personal characteristics (gender, race, tenure, ability, marital status, number of children in household) and state unemployment rates as the indication of economic conditions.

$$lnwage_{it} = \alpha S_{it} + \beta X_{it} + \varepsilon_{it}$$

where S is the year of schooling and X is the personal characteristics and economic conditions, and ε is the random component. S is not exogenous because of omitted ability and other unobservable characteristics. We find instrumental variable for S which is highly correlated with one's schooling but not correlated with the error term ε. The first stage estimation is

$$S_{it} = \gamma X_{it} + \delta Z_{it} + v$$

where Z is chosen instrument variables. Z is a good instrument for schooling if Z is highly correlated with S but not correlated with ε. This implies that instrument affects earnings through schooling only.

Instruments are valid if the following two requirements are satisfied: Instrument exogeneity and instrument relevance.

For instrument exogeneity, valid instruments must be uncorrelated with the error term meaning that the valid instruments affect earnings through schooling only. This requirement needs a strong theoretical argument. The Hansen J statistic over-identification test indicates whether the instruments are exogenous or not.

Instrument relevance checks whether the correlation between the instruments and schooling is not weak. Instruments with low correlation with the endogenous regressors are called weak instruments, with the IV estimation performing potentially worse than OLS (Stock et al., 2002). The relevance of the instruments is tested in the first-stage regression. As a rule of thumb, the F-statistic of a joint test whether all excluded instruments are significant should be bigger than 10. In case of a single instrument and a single endogenous regressor, this implies that the t-value for the instrument should be bigger than 3.2 or the corresponding p-value below 0.0016.

The second part of my paper estimates single treatment model and considers high education as a dummy variable. The high education group is the group includes individuals with college education or higher. This model helps to estimate returns to college or higher education versus no college.

$$lnwage_{it} = \alpha HE_{it} + \beta X_{it} + \varepsilon_{it}$$

Propensity score matching (PSM) is a matching method to estimate the effect of a treatment or policy. PSM helps to reduce the bias by simply comparing outcomes among individuals who received high education versus who did not receive this treatment. This method deal with the endogeneity bias bias because the difference in the outcome between treated and non-treated groups may depend on characteristics that affect whether or not the individual goes to college instead of due to the effect of obtaining college degree. The matching method mimics randomization by creating the sample of highly educated individuals that is comparable to the sample of the not highly educated individuals. In this method, each individual has his own probability of getting high education given a set of observed characteristics. This probability is called propensity score. In the other words, the propensity score p(x) is the conditional probability of HE given background variables.

$$p(x) = \Pr(HE = 1|X = x)$$

Let lnw(0) and lnw(1) denote the potential wages under non-HE and HE respectively. Then we match observations from HE group and non-HE group based on their propensity score so that potential earnings are independent of HE conditional on background variables X

$$lnw(0), lnw(1) \perp HE|X$$

Thus, we have:

$$lnw(0), lnw(1) \perp HE|p(x)$$

There are several available matching methods. In this paper, three of them will be used: nearest neighbor, kernel and radius matching. Nearest neighbor matches treated and untreated individual taking each treated unit and searching for the control individual with the closest propensity score. Kernel matching uses weighted averages of all individuals in the control group to construct the counterfactual outcome. Thus, one major advantage of these approaches is the lower variance which is achieved because more information is used. However, possibly observations are used are bad matches and give the incorrect estimates. In radius matching, each treated individual is matched only with the control individual whose propensity score falls into a predefined neighborhood of the propensity score of the treated individual.

V. Data and Variables

My study uses panel data from The National Longtitudinal Survey of Youth 1997 (NLSY97), which follows American youth born from 1980 to 1984. Respondents were ages 12-17 when first interviewed in 1997 and then interviewed on an annual basis. The sample used in my study is from 1997 to 2011. The unemployment rates during teenage years that we used as instrument for education is the average of state unemployment rates in the years when individual reaches the ages of 15, 16 and 17. Therefore, the observations younger than 18 years old are excluded from my sample. After dropping the missing variables, the sample includes 25,543 observations.

Table 1 summarizes the estimated sample. The earnings are represented by the hourly wage of individual's current main job. Hourly wages are inflation adjusted to real wages using the CPI index with the base year of 2010. The average wage is $14.20/hour. Years of schooling is the highest grade that the individual ever completed. The maximum of years of schooling is 20 representing individuals with 8 years or more in college. Parental education is also in continuous form.

Race is categorized into three groups: white, black and others. The sample has 69% white, 20% black and 11% of other races. Experience is the accumulated number of years the respondent worked at any job during the year. Tenure is the number of years at the current main job as of the survey date. In order to capture individual ability, we use the 1997 PIAT standardized math score as a proxy. Marital status is controlled for by including a dummy variable with the value of 1 for married individuals and 0 otherwise. High education (HE) has the value of 1 for college or higher and 0 for high school or lower education. About 20 percent of the sample has high education.

As the instrument, quarters of birth variables are created as dummy variables. Parental education is the years of schooling of father and mother, with the mean of 12.82 and 12.98 respectively. The last instrument is the state unemployment rate during the teenage years of the respondents. We take the average unemployment rates when the respondents reach the age of 15, 16 and 17 at the state that he or she was living. The current state unemployment rates reflect the economic conditions. We control for the current state unemployment rate to avoid the correlation between the instrument and the error term of earnings equation. They range from 2.3 to 13.8%.

Table 2 is the summary statistics comparing two groups: high education and non- high education. On average higher education group has hourly wages $6 more than non-high education group. Female has higher education with 57% in high education group compare with 43% of male and White people on average have higher education than other races. Higher education group also has longer experience, tenure and more likely to be married because older people are more likely to have higher education, longer experience and more likely to be marred as well. Higher education group has higher math score (103.4 and 95.08) implying the positive correlation between ability and educational attainment.

VI. Findings

6.1. Returns to years of schooling

Table 3 shows the results of the first stage estimation of the return to years of schooling. The first column shows the correlation between quarter of birth and educational attainment. The first quarter (January to March) is dropped from equation. The coefficient of quarter 2 is statistically significant showing that individuals born in the second quarter attain higher education, but individuals born in the other two quarters (from July to December) do not have statistically different education than those born in the first quarter. Though the quarter of birth dummy variables are jointly significant at 1% level, the F-test (7.26) indicates a weak correlation between instruments and years of education. The second column uses parental education as instrument. The coefficients of both father and mother years of schooling are statistically significant at 1% level. They are jointly significant with F-statistics of 138.78. The high F-statistic implies a strong correlation between instrument and education. In contrast, the coefficient of state unemployment rate during teenage years in the third is not statistically significant showing no correlation between state unemployment rates during teenage years and educational attainment.

Table 4 includes the second stage results for the effects of schooling on hourly wages. The first column shows the OLS estimation assuming the exogeneity of education. Column 2-4 displays the results from the instrumental variable method that uses the instruments of quarters of birth, parental education and state unemployment rate at the age of 15-17, respectively.

Under OLS estimation, an additional year of schooling increases hourly wages by 4.98%. The estimation results under the three instrumental variables are different. When quarter of birth is used as an instrument, education has a low effect on wages (0.96%) and state unemployment rates indicate a schooling effect of 16.98%. However, both of them are not significant. Only with parental education as an instrument, schooling has a statistically significant effect on wages (5.23%). This result is very close to the OLS estimation.

Validity of Instruments

For instrument exogeneity, the Hansen J statistic over-identification test indicates whether the instruments are exogenous or not. An insignificant F-test supports the validity of instrument. I found that quarter of birth and parental education satisfy this requirement. The state unemployment rates during teenage years has significant F-test in Hansen J statistics shows that state unemployment rates during teenage years have direct effect to earnings after 18 years old.

For instrument relevance, joint F-test of excluded instrument variables in table 3 implies that only parental education satisfies the test. The state unemployment rates during teenage years are not significantly correlated with education. There is correlation between seasons of birth and education but this is a very weak because the F-test is about 7, smaller than rule of thumb that F-test need to be higher than 10.

From instrument exogeneity and instrument relevance tests, we can conclude that parental education outperforms other variables as a good instrument for education. This is consistent with previous papers. (Plug, 2001; Lemke and Rischall, 2003)

6.2. Returns to higher education

Table 2 summarizes the difference between the groups of HE and non-HE. On average, HE individuals receive hourly wages that are by 5$ higher than the one of non-HE. Female and white people tend to have HE than others. HE people have higher math score (103 to 95).

Because HE is dummy variable, the first stage estimation using instrumental variable method is a probit estimation. The marginal effects of the first stage estimation are reported in Table 5. Similar to the model with the continuous education variable, the first stage in this model shows no correlation between HE and state unemployment rate during teenage years, strong correlation between HE and parental education, and weak correlation between HE and quarters of birth.

Table 6 represents the second stage of the return of high education on wages. The first column is the OLS estimation and the next three columns treat HE as endogenous for each of the potential instrument. Consistent with the estimation of years of schooling, the coefficient of HE when using quarter of birth and state unemployment rate during teenage years are statistically insignificant. Meanwhile, the return to HE using parental education as instrument has a statistically significant coefficient of 9.74%. This is very different to the OLS estimation of 26.35% return to HE.

As a robustness check, we estimate the return to HE using propensity score matching method. The results are reported in Table 7. Three matching methods are used. With nearest neighbor matching methods, the return to high education is 25.65% on treated (ATT) and 18.61% on untreated (ATU) individuals and the average treatment affect (ATE) is 20.26%. Kernel matching method is very similar to nearest neighbor matching method results (22.34%). However, estimation using radius matching method gives much higher return to HE with the ATT, ATU and ATE of 37%.

The propensity score matching estimations results are similar to OLS estimation ranging from 20% to 37% but much higher than the IV method with only 9.74% using parental education as instruments. This is consistent with the findings of Blundell (2005). He found the return to HE from 20% to 50% varies to different models. He also shows that the IV method did not give consistent estimation (5% to 117.1%). Though IV method requires instrument for every observation, the chosen instrument does not have enough power to predict all the interactions well and brings to the poor performance of IV model. Therefore, the IV estimation for the return to HE is not reliable.

VII. Conclusion

In this paper we have estimated the return of years of schooling in the U.S. using different instrumental variables and tested the validity of different instruments. Our study supports the invalidity of quarter of birth and unemployment rates during teenage years as instrument for years of schooling. The test results show no correlation between unemployment rates during teenage years and future earnings. The parental education again is proved as the best instrument for educational attainment. Controlling for ability and economic conditions, IV and OLS estimation results are very close, an additional year of schooling contributes to 5% increase in the earnings.

The single treatment model of education corroborated that college and higher educated people earn about 20% to 37% more than non-college people. The instrumental variable method is not appropriate for single treatment model. The propensity score matching estimation and OLS have close results.

Reference

Angrist D. J. and Krueger B.A. (1991), Does Compulsory School Attendance Affect Schooling and Earnings?, Quarterly Journal of Economics, 106(4), 979-1014.

Arkes, J. (2010). Using unemployment rates as instruments to estimate returns to schooling. *Southern Economic Journal*, 711-722.

Behrman R. J. and Rosenzweig R. M. (1999), “Ability” biases in schooling returns and twins: a test and new estimates, *Economics of Education Review*, 18(2), 159–167.

Betts J. R. and McFarland L. L. (1995), Safe Port in a Storm: The Impact of Labor Market Conditions on Community College Enrollments, *The Journal of Human Resources*, 30 (4), 741-765.

Blackburn L. M. and Neumark D. (1993), Are OLS Estimates of the Return to Schooling Biased Downward? Another Look, NBER working paper, 4259.

Blundell R. (2005), Evaluate the effect of education on earnings: models, methods and results from National Child Development Survey, *Journal of the Royal Statistical Society*, 168(3), 473-512.

Bonjour, D., Cherkas, L., Haskel, J., Hawkes, D., & Spector, T. (2002). Estimating returns to education using a new sample of UK twins. Queen Mary and Westfield College, London.

Bound J., Jaeger A.D. and Baker M. R. (1995), Problems with Instrumental Variables Estimation when the Correlation between the Instruments and the Endogenous Explanatoly Variables is Weak, *Journal of the American Statistical Association*, 90, 443-450.

Branda E. J. and Xieb Y. (2010), Who benefits most from college? Evidence for negative selection in heterogeneous economic returns to higher education, *American Sociological Review*, 75(2), 273-302.

Card, D. (2001). Estimating the return to schooling: Progress on some persistent econometric problems. *Econometrica*, 69(5), 1127-1160.

Carroll, H. C. M. (1992). Season of birth and school attendance. *British Journal of Educational Psychology*, 62(3), 391-396.

Dearing E., McCartney K. and Taylor B.A. (2001), Change in family income matters more for children with less, *Child Development,* 72:1779–1793.

Devereux, P. J., & Hart, R. A. (2010). Forced to be Rich? Returns to Compulsory Schooling in Britain. *The Economic Journal*, 120(549), 1345-1364.

Furstenberg F.F., Cook D.T., Eccles J. (1999) and Elder Jr. G. H., Managing to Make It: Urban Families and Adolescent Success, Chicago (University of Chicago Press)

Goldin G. (1999), A brief history of education in the United States, Working paper.

Harmon C. and Walker I. (1995), Estimates of the Economic Return to Schooling for the United Kingdom, *The American Economic Review,* 85(5), 1278-1286.

Haveman R, Wolfe B. (1995). The determinants of children’s attainments: A review of methods and findings. *Journal of Economic Literature*. 33:1829–1878.

Heckman, J., & Navarro-Lozano, S. (2004). Using matching, instrumental variables, and control functions to estimate economic choice models. *Review of Economics and statistics,* 86(1), 30-57.

Helsen, W. F., Van Winckel, J., & Williams, A. M. (2005). The relative age effect in youth soccer across Europe. *Journal of sports sciences*, 23(6), 629-636.

Hoff, E. (2003). The specificity of environmental influence: Socioeconomic status affects early vocabulary development via maternal speech. *Child development*, 74(5), 1368-1378.

Kane J.T. and Rouse E.C. (1993), Labor Market Returns to Two- and Four-Year Colleges: Is a Credit a Credit and Do Degrees Matter?, NBER working paper, 4268.

Kawaguchi D. and Murao T. (2014), Labor-Market Institutions and Long-Term Effects of Youth Unemployment. *Journal of Money,* 46, 95-116.

Kawaguchi, D., and Murao, T. (2014). Labor-Market Institutions and Long-Term Effects of Youth Unemployment. *Journal of Money, Credit and Banking*, 46(S2), 95-116.

Lemke, R. J., & Rischall, I. C. (2003). Skill, parental income, and IV estimation of the returns to schooling. *Applied Economics Letters,* 10(5), 281-286.

Miller P., Mulvey C. and Martin N. (2001), Genetic and environmental contributions to educational attainment in Australia, Economics of Education Review, 20(3), 211–224.

Mincer, J. (1974). Schooling, Experience, and Earnings. *Human Behavior & Social Institutions* No. 2.

Mortimore, P., Sammons, P., Stoll, L., Lewis, D., and Ecob, R. (1988). School matters: The junior years. Open Books.

Mroz T. A. and Savage T. H. (2006), The Long-Term Effects of Youth Unemployment, *The Journal of Human Resources*, 41(2), 259-293.

Plug, E. J. (2001). Season of birth, schooling and earnings. *Journal of Economic Psychology*, 22(5), 641-660.

Robertson E. (2011), The effects of quarter of birth on academic outcomes at the elementary school level, *Economics of Education Review,* 30, 300–311.

Sharp, C., Hutchison, D., & Whetton, C. (1994). How do season of birth and length of schooling affect children's attainment at key stage 1?. *Educational Research*, 36(2), 107-121.

Stock, J. H., Wright, J. H., & Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4).

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
Hourly wage (cent)	1419.72	4611.28	1	346287.80
Log(wage)	6.93	0.86	0	12.76
Years of schooling	12.84	2.32	6	20
High education (HE)	0.19	0.39	0	1
Female	0.49	0.50	0	1
Male	0.51	0.50	0	1
White	0.69	0.46	0	1
Black	0.20	0.40	0	1
Other races	0.11	0.32	0	1
Experience (years)	5.05	3.35	0	21.40
Tenure (years)	1.69	1.92	0	21.40
Standard math score	96.62	13.88	55	145
Child	0.30	0.70	0	6
Married	0.16	0.36	0	1
State unemployment rates	5.9968	2.1178	2.30	13.80
Quarter 1 (Jan-Mar)	0.2269	0.4188	0	1
Quarter 2 (Apr-May)	0.2084	0.4061	0	1
Quarter 3 (June-Sep)	0.2762	0.4471	0	1
Quarter 4 (Oct-Dec)	0.2885	0.4530	0	1
Father’s education (years)	12.82	3.07	2	20
Mother’s education (years)	12.96	2.73	1	20
State unemployment rates during teenage years	4.2773	0.8531	2.55	8.2

Note: Number of observation = 25,543

Table 2: Descriptive Statistics of Higher Education Sample

Variables	Non Higher Education	Higher Education
Hourly wage (cent)	1307.83	1910.45
Log(wage)	6.85	7.28
Female	0.47	0.57
Male	0.53	0.43
White	0.66	0.77
Black	0.22	0.12
Other races	0.11	0.10
Experience (years)	4.45	7.64
Tenure (years)	1.54	2.34
Standard math score	95.08	103.40
Child	0.32	0.22
Married	0.13	0.28
State unemployment rates	5.75	4.23
Number of observations	20,784	4,745

Table 3: First Stage estimate - Effect of Instruments on Years of Schooling (Dependent Variable is Years of schooling)

	Instrumental Variables		
	Quarter of Birth	Parental Education	State Unemployment Rates
Constant	5.0102 (0.0000)***	3.5783 (0.0000)***	5.3630 (0.0000)***
Female	0.7078 (0.0000)***	0.6915 (0.0000)***	0.7133 (0.0000)***
Black	0.1741 (0.0560)*	0.2179 (0.0110)**	0.1754 (0.0540)*
Other races	-0.0307 (0.7620)	0.2400 (0.0140)**	-0.0405 (0.6910)
Experience	0.1410 (0.0000)***	0.1504 (0.0000)***	0.1413 (0.0000)***
Experience Square	-0.0038 (0.0430)**	-0.0043 (0.0170)**	-0.0038 (0.0400)**
Tenure	0.0375 (0.1770)	0.0292 (0.2710)	0.0380 (0.1810)
Tenure Square	-0.0080 (0.0300)**	-0.0059 (0.0970)*	-0.0078 (0.0400)**
Standard math score	0.0492 (0.0000)***	0.0372 (0.0000)***	0.0493 (0.0000)***
Children	-0.8277 (0.0000)***	-0.7390 (0.0000)***	-0.8281 (0.0000)***
Married	0.2966 (0.0000)***	0.3280 (0.0000)***	0.2971 (0.0000)***
State unemployment rates	0.0022 (0.9210)	0.0037 (0.8630)	0.0031 (0.8890)
Quarter 2	0.3509 (0.0000)***		
Quarter 3	0.0014 (0.9870)		
Quarter 4	0.0856 (0.2990)		
Father education		0.1179 (0.0000)***	
Mother education		0.0859 (0.0000)***	
State unemployment rate during teenage years			-0.0562 (0.3800)
R-squared	0.4192	0.4573	0.4160

Partial R-squared	0.0057	0.0709	0.0002
F-statistic of excluded instruments	F(3, 2871) = 7.26	F(2, 2871) = 138.78	F(1, 2871) = 0.77
Prob > F	0.0001	0.0000	0.3801

Note: Dependent variable in each specification is the years of education. The t-statistics are shown in parenthesis. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 4: Second stage estimation - Effect of Years of Schooling on Earnings (Dependent Variable is Natural Logarithm of Hourly Wages)

	OLS	Instrumental Variables		
		Quarter of Birth	Parental Education	State Unemployment Rates
Constant		6.4410 (0.0000)***	6.2242 (0.0000)***	5.6272 (0.0010)***
Years of schooling	0.0498 (0.0000)***	0.0096 (0.8700)	0.0523 (0.0010)***	0.1698 (0.5950)
Female	-0.1423 (0.0000)***	-0.1155 (0.0100)***	-0.1461 (0.0000)***	-0.2301 (0.3190)
Black	0.0174 (0.4320)	0.0124 (0.601)	0.0050 (0.8190)	-0.0153 (0.8000)
Other races	0.0153 (0.5510)	0.0119 (0.6460)	0.0139 (0.5940)	0.0193 (0.5530)
Experience	0.0111 (0.1370)	0.0111 (0.3870)	0.0051 (0.6080)	-0.0114 (0.8040)
Experience Square	0.0018 (0.0000)***	0.0016 (0.0320)*	0.0018 (0.0130)	0.0022 (0.1180)
Tenure	0.0493 (0.0000)***	0.0665 (0.0000)***	0.0649 (0.0000)***	0.0604 (0.0000)***
Tenure Square	-0.0053 (0.0000)***	-0.0065 (0.0000)***	-0.0062 (0.0000)***	-0.0053 (0.0570)*
Standard math score	0.0002 (0.7400)	0.0023 (0.4540)	0.0001 (0.8790)	-0.0057 (0.7200)
Children	0.0084 (0.3980)	-0.0173 (0.7280)	0.0181 (0.2710)	0.1157 (0.6640)
Married	0.0878 (0.0000)***	0.1114 (0.0000)***	0.0988 (0.0000)***	0.0641 (0.5150)
State unemployment rates	-0.0327 (0.0000)***	-0.0330 (0.0000)***	-0.0331 (0.0000)***	-0.0334 (0.0000)***
R-squared	0.0940	0.0898	0.0949	0.0288
Hansen J statistic		0.1819	0.3912	0.0000

Note: The t-statistics are shown in parenthesis. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 5: First Stage estimation - Effect of Instruments on HE (Dependent Variable is HE)

	Instrumental Variables		
	Quarter of Birth	Parental Education	State Unemployment Rates
Female	0.0932 (0.0000)***	0.0922 (0.0000)***	0.0049 (0.0851)*
Black	-0.0380 (0.0000)***	-0.0254 (0.0010)***	-0.0379 (0.0000)***
Other races	-0.0064 (0.4520)	0.0267 (0.0020)***	-0.0084 (0.3280)
Experience	0.0177 (0.0000)***	0.0213 (0.0000)***	0.0177 `(0.0000)***
Experience Square	-0.0005 (0.0260)**	-0.0007 (0.0020)***	-0.0005 (0.0220)**
Tenure	-0.0023 (0.3780)	-0.0032 (0.2230)	-0.0023 (0.3810)
Tenure Square	-0.0003 (0.3010)	0.0000 (0.9520)	-0.0002 (0.4110)
Standard math score	0.0060 (0.0000)***	0.0045 (0.0000)***	0.0060 (0.0000)***
Children	-0.1037 (0.0000)***	-0.0894 (0.0000)***	-0.1044 (0.0000)***
Married	0.0677 (0.0000)***	0.0699 (0.0000)***	0.0681 (0.0000)***
State unemployment rates	0.0038 (0.2680)	0.0051 (0.1270)	0.0040 (0.2500)
Quarter 2	0.0446 (0.0000)***		
Quarter 3	-0.0130 (0.0650)*		
Quarter 4	0.0014 (0.8430)		
Father education		0.0163 (0.0000)***	
Mother education		0.0096 (0.0000)***	
State unemployment rate during teenage years			0.0014 (0.7710)

Note: The t-statistics are shown in parenthesis. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 6: Second stage estimation - Effect of HE on Earnings (Dependent Variable is Natural Logarithm of Hourly Wages)

	OLS	Instrumental Variables		
		Quarter of Birth	Parental Education	State Unemployment Rates
Constant	6.5627 (0.0000)***	7.2205 (0.0000)***	7.3500 (0.0000)***	7.5196 (0.0000)***
HE	0.2635 (0.0000)***	0.0844 (0.1230)	0.0974 (0.0000)***	0.1160 (0.1060)
Female	-0.1314 (0.0000)***	-0.1559 (0.0000)***	-0.1632 (0.0000)***	-0.1700 (0.0000)***
Black	0.0305 (0.1670)	0.0264 (0.3100)	0.0264 (0.3680)	0.0330 (0.2490)
Other races	0.0130 (0.6140)	0.0447 (0.1500)	0.0456 (0.0770)**	0.0459 (0.1550)
Experience	0.0170 (0.021)*	0.0198 (0.0800)*	0.0176 (0.1110)	0.0179 (0.1520)
Experience Square	0.0014 (0.0040)***	0.0013 (0.0850)*	0.0014 (0.0660)*	0.0014 (0.0700)*
Tenure	0.0496 (0.0000)***	0.0601 (0.0000)***	0.0604 (0.0000)***	0.0603 (0.0000)***
Tenure Square	-0.0052 (0.0000)***	-0.0064 (0.0000)***	-0.0064 (0.0000)***	-0.0064 (0.0000)***
Standard math score	0.0013 (0.0250)**	0.0008 (0.5730)	0.0003 (0.6890)	0.0001 (0.9660)
Children	0.0004 (0.9700)	0.0195 (0.5250)	0.0244 (0.1400)	0.0351 (0.3510)
Married	0.0779 (0.0000)***	0.0652 (0.0370)**	0.0603 (0.0040)***	0.0552 (0.0970)*
State unemployment rates	-0.0333 (0.0000)***	-0.0325 (0.0010)***	-0.0334 (0.0000)***	-0.0331 (0.0020)***

Note: The t-statistics are shown in parenthesis. *** significant at the 1% level, ** significant at the 5% level, * significant at the 10% level

Table 7: Propensity Score Matching estimation of the Return to HE compare with less than HE. ATE: average treatment effect, ATT: average treatment effect on the treated, ATU: average treatment effect on the untreated.

Method of matching	ATT	ATU	ATE
Nearest Neighbor	0.2565 (0.0000)***	0.1861 (0.0000)***	0.2026 (0.0000)***
Kernel matching	0.2697 (0.0000)***	0.2092 (0.0000)***	0.2234 (0.0000)***
Radius matching	0.3697 (0.0000)***	0.3697 (0.0000)***	0.3697 (0.0000)***