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McMaster University

DEPARTMENT OF ECONOMICS

The Roles of Education, Skill and Parental Income in Determining Wages

Isaac C. Rischall[1]
Department of Economics
McMaster University
1280 Main St. West
Hamilton, Ontario, Canada L8S 4M4
(905)-525-9140 ext. 23211
fax: (905)-521-8232
rischall@mcmaster.ca
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ABSTRACT: This study attempts to examine how much of the correlation in incomes across generations can be explained by education and skill. I find two different answers to this question depending on how I instrument for years of schooling. Using quarter of birth and proximity to a local college as instruments, I find high returns to schooling, low returns to skill, and most of the intergenerational mobility coefficient explained. However, these instruments are poorly correlated with years of education. Thus, the estimates are imprecise and potentially biased. Furthermore, using family background variables as instruments, I find the opposite results. Moreover, if one excludes family income or skill as control variables then the estimates of the returns to schooling are upwardly biased.

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The Roles of Education, Skill and Parental Income in Determining Wages

I. Introduction

From the intergenerational mobility and returns to education literatures, one comes away with two conclusions: a father's permanent income is highly correlated with his son's permanent income and people with more education receive higher wages. Undoubtably a portion of the first conclusion is explained by the second. Part of the reason why a son's permanent income is correlated with his father's permanent income is because a father with a high income can provide a child with more human capital investments such as education. However, this might not fully explain the role of a father's income in determining a son's wage. This paper combines the returns to education literature and the intergenerational mobility literature to ascertain how much of the correlation of income across generations can be attributed to wealthy parents providing their children with more education and skills.

In a study of intergenerational mobility Corcoran et al. (1991) include respondent's education in one model specification. After controlling for education, they find that a son's earnings are still highly influenced by family background variables including parent's income, and that the estimated returns to education is six percent which is in line with the education literature. This is evidence that education cannot fully explain family income's role in determining a child's earnings. However, since this study was asking predictive questions one cannot take their estimates as the effect of family income and education on earnings. In other words, this paper did not take into account the possible endogeneity of the schooling decision.

Alternatively, Neal and Johnson (1996) find that controlling for skill as measured by the

Armed Forces Qualification Test (AFQT) score explains much of the wage gap between blacks and whites. If there is a channel transmitting income from fathers to sons other than education or skill then there should be a wage gap between whites and blacks after controlling for AFQT.

Rischall (1998) estimates returns to education using instrumental variables under two specifications, one where family income is accounted for and a second where it is not. Under the specification where family income is included, the returns to education are approximately four and a half percent for males. Alternatively, when not controlling for family income the estimate increases to fourteen percent. In the specification that controls for family income there is evidence of low income mobility across generations. Also, the black-white wage differential declines after controlling for family income. However, the estimate of the differential is not statistically significant in either specification.

Building on Rischall (1998), this essay compares the estimated returns to education using different instrumental variables. It shows how these instruments relate to family income and how the estimated returns to education change when family income and skill measures are included as determinants of wage. Section II provides a simple model of how education and wages are related. Section III describes possible instruments for education. These instruments include quarter of birth[2], proximity to a local college[3] and family background variables[4]. Section IV describes the data used in this paper. Section V contains results. The results differ greatly depending on the instruments used. If one uses solely quarter of birth as an instrument then the

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[2] See Angrist and Krueger (1991).

[3] See Card (1995a)

[4] See Willis and Rosen (1979)

returns to schooling are large. The returns to skill are small, and most of the correlation between income across generations is explained by these human capital investments. However, these instruments are poorly correlated with education and potentially bias the returns to education estimates. Alternatively, if one uses family background variables as instruments then one sees that returns to education are small, the returns to skill are high and much of the correlation between incomes across generation left unexplained. Furthermore, not controlling for family income and skill causes one to overestimate the returns to schooling. Section VI compares the results of this paper with other results in the returns to education literature. Section VII provides concluding remarks.

II. Model

For the purposes of this paper, I propose a simple model of how education and wages are related.[5] Individuals choose education level to maximize the following utility function.

$$\begin{aligned} U(y,S,X,Z,\epsilon,\nu) &= \ln(y) - f(S,Z,\nu) \\ &= \ln(g(S,X,\epsilon)) - f(S,Z,\nu). \end{aligned} \qquad \textbf{(1)}$$

Let y be the present discounted value of lifetime earnings of the individual which is a function (g(•)) of schooling (S), a vector of observable covariates (X) and an unobserved variable (ϵ). The costs of schooling are an increasing, convex function (f(•)) of schooling, a vector of observable covariates (Z) and an unobserved variable (ν). One important note is that there are variables included in Z that are included in X. Specifically, I assume that family income and skill

[5] See Card (1995b) or Ashenfelter and Rouse (1998) for similar model specifications.

influence both the cost of education and the earnings an individual receives. Maximizing utility in Equation (1) requires that optimal schooling (S*) satisfy the first order condition,

$$\frac{\partial g}{\partial S}\frac{1}{g} = \frac{\partial f}{\partial S}. \qquad \textbf{(2)}$$

Equation (2) states that the marginal benefit of schooling equals the marginal costs. In order to implement this model empirically, one must choose functional forms for the marginal benefits and costs. I assume the following:

$$\begin{aligned} MB &= \frac{\partial g}{\partial S}\frac{1}{g} = b. \\ MC &= \frac{\partial f}{\partial S} = \alpha S + \theta' Z + \nu. \end{aligned} \qquad \textbf{(3)}$$

Solving MB = MC and integrating the marginal benefit equation yield the following results:

$$S^{*} = \gamma' Z + \xi. \qquad \textbf{(4)}$$

$$\ln(y) = bS^{*} + \beta' X + \epsilon. \qquad \textbf{(5)}$$

ξ and γ are linear transformations of ν and α.

To estimate the returns of education, one can estimate b from Equation (5). If it is the case that ϵ are ξ uncorrelated then ordinary least squares (OLS) estimation of Equation (5) yields consistent estimates of b and β. However, this is an assumption that many are unwilling to make.

In other words, many assume that there exists unobserved ability that affects both schooling and earnings. An alternative assumption is that there is a variable in Z that is not a member of X and that this variable in Z is uncorrelated with ,. If this is the case, one can estimate Equation (5) by using the variable in Z as an instrument for S*. This will yield consistent estimates of b and $. However, now the problem becomes finding a valid instrument.

III. Possible Instruments

In the returns to education literature many variables have been considered as possible instruments for schooling. In particular, this paper considers three types of instruments from this literature: quarter of birth, proximity to a two or four-year college and family background variables.

Quarter of birth: Angrist and Krueger (1991) use quarter of birth as an instrument for schooling. The theory behind this variable as an instrument comes from compulsory schooling laws. These laws require students to remain in school until they reach a specific age. All students start school at the same time. However, students who are born in the first quarter of the year reach the compulsory schooling age first, and are able to drop out of school earlier. Quarter of birth should be uncorrelated with any unobserved ability variables. It should not directly affect wages, but it should affect schooling. Thus, it should be a valid instrument.[6]

Proximity to a two or four-year college: Card (1995a) uses proximity to a two or four-year college as an instrument for schooling. The theory behind this variable as an instrument is that students who live in a county with a two or four-year college face lower costs of college

[6] Bound and Jaeger (1996) provide evidence that quarter of birth may actually be correlated with unobserved ability.

attendance. Thus, living in a county that contains a college will affect a student's enrollment decision. Furthermore, living in a county with a college should be uncorrelated with the student's unobserved ability and should not directly affect his or her wages.[7]

Family background variables: Willis and Rosen (1979) use family background variables such as the education of the individual's parents as instruments. The validity of these instruments is questionable because many believe that these variables have a direct effect on wages. Furthermore, Card (1998) shows that even if family background variables do not have an independent causal effect on earnings, using them as instruments may cause even further bias of OLS results. This occurs if the family background variables are correlated with unobserved ability. Card shows that if this is the case, controlling for the family background variables and using OLS produces estimates of the returns to education with less bias than the OLS results without controlling for background variables. However, if one uses the family background variables solely as instruments than the bias is worse than OLS. The approach that I take is that certain family background variables are valid instruments (parent's education) if one controls for other family background variables (family income) and skill (AFQT).

Nevertheless, family background variables should have a large effect on schooling. An advantage of these instruments over the other two sets of instruments is that the correlation between schooling and parents' schooling is very high relative to the correlation between schooling and the other possible instruments. Thus, if these variables are valid instruments the precision of the instrumental variables estimation will be better using family background variables rather than (or along with) quarter of birth or proximity to a college.

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[7] This instrument may not be valid because communities with colleges may draw in families with high ability children. Thus, it is possible that proximity to a local college will be correlated to unobserved ability.

However, the recent instrumental variable literature finds that imprecise estimates is not the problem one should be concerned with when dealing with instruments that are poorly correlated with the endogenous explanatory variable. Nelson and Startz (1990a and 1990b) show that if an instrument is poorly correlated with the endogenous explanatory variable the resulting instrumental variables estimate is biased. This bias is potentially worse than the bias from using OLS. Also, in the finite sample, asymptotic standard errors provide poor estimates for the true standard errors. Bound et al. (1995) considers multiple instruments and finds that even using large samples does not protect one from the problems of small sample bias. Furthermore, adding more poorly correlated instruments may decrease the asymptotic standard errors, but it will also increase the potential for small sample bias.[8] Therefore, if family background variables are valid instruments they will be more likely to give unbiased estimates of the returns to schooling.

Now the question becomes whether the family background variables have a direct effect on wages, making them invalid instruments. One argument for the direct effect of family background variables comes from a networking argument. If one comes from a highly educated family, it is likely to that his or her parents will know other highly educated families and that using this networking will lead to a higher paying job for the individual. However, this argument also works for a family's permanent income. Connections and networking will increase the wages of a child coming from a family with high permanent income. Also, if an individual comes from a family with high permanent income then this can decrease the opportunity cost of job search, increase the

[8] Staiger and Stock (1997) deal with this problem in regard to the Angrist and Krueger (1991) study. Angrist and Krueger found IV estimates that are higher than OLS estimates. When Staiger and Stock correct for the poor instrument bias they find estimates that are even higher than Angrist and Krueger's IV estimates. One possibility is that if Bound and Jaeger (1995) are correct and quarter of birth is correlated with unobserved ability then one should see IV estimates higher than OLS estimates because of this correlation.

reservation wage and increase the observed wages of individuals. This leads to an argument where the effect of parental education on wages goes through parental income. Thus, if one includes parental income in the wage equation, other family background variables can be used as instruments for schooling.

In other words, if family income is included it is considered both a member of X and Z, a variable that affects the cost of education and earnings. Other family background variables are members of Z. They only affect the cost of education and are valid instruments for education in the earnings equation. However, if parental income is excluded, it is part of the unobserved term in both the cost of education and the earnings equations. Since parental income is correlated with other family background variables, the exclusion of parental income implies that other family background variables are correlated with the unobserved term of the earnings equation. Therefore, the other family background variables are no longer valid instruments. Validity of family background variables as instruments depends on the inclusion of parental income as a member of X.

IV. Data

Data for this paper come from the National Longitudinal Survey of Youth. The data contain information on youth whose ages ranged from 14 to 22 in 1979. These respondents have been tracked in subsequent years, and I have information up to 1996. The original sample contains information on 5404 black and white males. Of this original sample, I restrict my sample to those who are 17 or younger and live with at least one parent in 1979. I make this restriction because I am interested in the relationship between family income and future wages and I do not want the family income measure corrupted by the respondent's own earnings. Also, Neal and Johnson (1996) argue that AFQT score is an exogenous measure of skill for those under 17. This reduces my sample by 3132. Further, I drop 467 observations with missing information on family background variables including parent income and education. I drop 867 observations with missing wage data[9], 22 observations with missing education data, 31 observations with missing skill data and four observations with missing information on whether the respondent lives in the South. This leaves me with a final sample of 881 observations. Variable definitions are contained in Table 1. Table 2 contains summary statistics.[10] I will discuss variables of special interest within the text.

Wage is the 1995 wage of the individual measured in 1992 dollars. **Family Income** is the income of the respondent's family in 1979 measured in 1992 dollars. **AFQT** is the AFQT test score of the respondent. It is used as the measure of skill of the respondent.

Dadedu and **Momedu** represent father's and mother's education in years. **Dadhouse** and **Momhouse** are indicators of whether there is a father (or stepfather) present in the respondent's household and whether there is a mother (or stepmother) in the respondent's household in 1979. These four variables are the family background variables used as instruments.

4year and **2year** are indicators of whether there is a 4 or 2 year college in the respondent's 1979 county of residence. The variables are obtained by merging the NLSY with the Higher Education General Information Survey (HEGIS) from 1983-84.

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[9] This includes 20 observations where the respondent reported a wage below $1 or greater than $75.

[10] Since I have omitted so many observations due to missing family background variables, I also report the summary statistics of these observations for comparison. The summary statistics indicate that the omitted group does have lower wages, education and AFQT score. These individuals also come from lower income families.

Table 3 shows the correlation matrix between possible instruments, ln(**Wage**), **Education** and ln(**Family Income**). Notice the small correlation between the presence of a 4-year college in the county of residence and **Education**. The correlation is approximately 0.03, which would suggest that even if this variable is a valid instrument, that using it for IV estimation will lead to imprecise and biased results. A similar story is true for the indicator of being born in the first quarter. The correlation between this indicator and **Education** is only 0.09. Also, theory would suggest that there be a negative correlation between being born in the first quarter and education. Lastly, the correlation between parent education variables and **Education** is relatively large, on the order of 0.4. This would suggest that if these variables are valid instruments, then using these variables as instruments would lead to fairly precise results.

Also, one should note the high correlation between ln(**Family Income**), parent education variables and the presence of a 4-year college. This would suggest that if ln(**Family Income**) belongs in the wage equation and it is omitted, then using parent education variables and the presence of a 4-year college as instruments will lead to inconsistent results.

To show the consistency of my data with respect to similar data sets, Table 4[11] presents log wage regressions that can be compared to previous research. From this table one sees a 32 percent wage gap between blacks and whites. This gap is larger than the 24 percent gap reported by Neal and Johnson (1996). The gap becomes about six percent after controlling for AFQT score. Neal and Johnson (1996) report a seven percent gap after controlling for AFQT score.

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[11] I have also estimated the regressions presented in the first three columns of Table 4 with the observations that are missing family background variables. In general, the results are similar to the results where I have family background variables. The returns to education for the regression in column 2 is 8.5 percent. The black-white wage gap estimates are about 4 percent lower in the first two columns, but half a percent higher in the third column.

Controlling for family income, as well as AFQT, causes the black - white wage gap to disappear in my sample.

With respect to the intergenerational income mobility literature, my estimate of the mobility coefficient is quite small. The coefficient on ln(**Family Income**) is 0.26. Solon (1992) and Zimmerman (1992) report that the estimate should be approximately 0.4. However, my estimate is not out of line with the estimate of 0.15 reported by Sewell and Hauser (1975) or the 0.18 reported by Behrman and Taubman (1985). My estimate is probably downward biased because of measurement error. Ideally, I would be estimating wage as a function of parent's permanent income. Since, I only observe parent's income one year, I have a poor measure of permanent income. Furthermore, I want to observe parent's income. The studies I have cited look at father's income. It is unclear how mobility will change when also accounting for mother's income. To account for measurement error I have also estimated the mobility coefficient using instrumental variables. The estimate increases to a range of 0.36 to 0.47, which is in line with the Solon (1992) and Zimmerman (1992) estimates.

Overall, Table 4 implies that my data are similar to that used in other studies. The following section considers how the returns to education change under various specifications that include and exclude ln(**Family Income**) and **AFQT**. The wage equation is estimated by OLS, and IV using various instruments.

V. Results

Tables 5A and 5B[12] present OLS estimates of the returns to schooling under different

[12] I estimated the regressions in the first two columns of Tables 5A and 5B with the observations that are missing family background information. The results do not change much when I use this subsample. The returns to

specifications. The estimates of the returns to schooling are relatively consistent across specifications, only changing when controlling for **AFQT**. The estimates range from 7.5 percent to 8.7 percent when not controlling for **AFQT**. When controlling for AFQT, the estimates decline to a range of 4.5 percent to 4.9 percent. One interesting feature of these estimates is that the only family background variable that has a coefficient estimate significantly different than zero at a ten percent level is ln(**Family Income**). Furthermore, one cannot reject the joint hypothesis that the parental education variables equal zero. The estimates that are positive are small. Thus, the OLS estimates show that there is little predictive power for earnings in family background variables other than family income. Another feature of the wage regressions to consider is the black-white wage gap. When not controlling for either AFQT or family income, the black-white wage gap is statistically significant at a five percent level and approximately 25 percent. Controlling for AFQT causes the gap to decline to approximately twelve percent. Furthermore, when one also controls family income the gap declines to below 6.5 percent and is not statistically significant at a five percent level. Finally, the results are consistent with Corcoran et al. (1991) where OLS estimates of returns to education change little when family income is included in the estimating equation.

Tables 6A and 6B[13] present Instrumental Variables estimates of the returns to schooling, where quarter of birth dummies are used to instrument for education. I use the quarter of birth

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education estimates are about 8 percent when one does not control for AFQT and they decrease to 4.5 percent if one does control for AFQT.

[13] I estimated the regressions in the first columns of Tables 6A and 6B with the observations that are missing family background information. The returns to education estimates is about 12.3 percent when one does not control for AFQT and they decrease to 9.4 percent if one does control for AFQT. Both these estimates have standard errors that are approximately the size of the estimate.

dummies first, because I believe that this variable is least likely to be correlated with unobserved ability and omitted family background variables. The estimates for returns to schooling are larger than the ones obtained by OLS, suggesting returns of over seventeen percent. The OLS estimate being smaller than the instrumental variables estimate is an interesting feature. A common explanation for the OLS bias is the following: the unobserved variable is ability or motivation. People with higher ability and motivation also tend to be the ones who obtain more education. By not accounting for the correlation between ability and schooling, one mistakenly attributes the returns to ability as returns to education. Therefore, the estimated returns to education are biased upwards.

However, Card (1995b) examines a set of returns to education papers whose results are not consistent with this explanation. The paper finds that many studies that use instrumental variables obtain higher estimates of the returns to education with IV than they obtain with OLS. Card argues that the instrumental variable estimates are not estimates of the returns to education, rather they are estimates of the average marginal return to an extra year of education. Individuals buy education up to the point where marginal benefit equals marginal costs. The marginal returns to education are decreasing in the quantity of education and students from poorer families have higher marginal costs. Therefore, students from poorer families end their education earlier, but have a higher marginal return to education than those students who end their education later. As a result, Card argues that the OLS estimates understate the returns to education.

However, there are other possible reasons for Card's results. Payne and Siow (1998) show that IV estimates larger than OLS estimates can be caused an omitted factor input into the wage equation. If education and the other input are substitutes then IV estimates should be larger than OLS estimates. Furthermore, the IV estimate provides a lower bound on the true returns to education.

Another possible reason for Card's result, as mentioned before, the instruments could be poor. In other words, the instruments are not highly correlated with years of schooling. Thus, the estimates are imprecise and biased. Along these lines a feature to consider is the first stage F-stat. This is the statistic used to test the whether all the coefficients of the instruments are zero in the first stage regression. The F-stats of 2 to 4 imply that one rejects the hypothesis that all of the coefficients are zero. However, this does not imply using these instruments will not cause bias from poor correlation. The results from Bound et al. (1995) indicate that using three instruments with a first stage F-stat of 4 implies that the IV estimates have nine percent of the bias of the OLS estimate. Furthermore, asymptotic standard errors are probably too small. In order to observe the magnitude of this problem I also calculated the standard errors by bootstrapping. I find that the asymptotic standard errors on **Education** in the first four columns of Tables 6A and 6B are underestimated by 0.02.

The last two columns of Tables 6A and 6B contain estimates of the returns to schooling when I use family background variables along with the quarter of birth dummies as instruments. Including the extra instruments reduces the asymptotic standard errors by more than half. Furthermore, the bootstrapped standard errors and the asymptotic standard errors differ by only a few thousandths. These estimates of the returns to education are also all larger than their OLS counterparts. However, the point estimates of the returns to education are smaller than the ones suggested by using just quarter of birth as an instrument. Also, both the returns to skill and the coefficient on family income are larger when one uses the family background variables as instruments. Also, the black-white wage gap declines. It is statistically insignificant when conditioning on family income and AFQT.

Tables 7A and 7B[14], also contain Instrumental Variable estimates. In this case, the instruments are proximity to two and four-year colleges and quarter of birth. The results in these tables are similar to those in Tables 6A and 6B. The IV estimates of the returns to schooling are larger than the OLS estimates. However, with the extra proximity instruments included the estimates decline from the IV estimates of Tables 6A and 6B. None of the family background variables have a statistically significant effect on wages with the exception of family income. Again, the asymptotic standard errors of the returns to education estimate are about 0.02 smaller than the bootstrapped standard errors for the first four columns, whereas the difference of the final two columns is only a few thousandths.

In Tables 7A and 7B extra instruments were included in order to get more precise estimates. However, as pointed out earlier adding extra instruments that are more poorly correlated with education might do more harm than good. Thus in Table 8, I present returns to education estimates using only **Momedu** and **Dadedu** as instruments. When one does not control for either AFQT or family income the returns to education are 12.3 percent which is larger than OLS estimates. The upward bias in these IV estimates could be caused by not cotrolling for AFQT. If one does not control for AFQT then parntal education is correlated with the unobserved ability term. However, when one controls for AFQT and family income there is a sharp decline in the estimates of the returns to education to 0.5 percent. Furthermore, the large first stage F-stats and the fact that I am only using two instruments imply that there is little bias in these estimates.[15]

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[14]I estimated the regressions in the first columns of Tables 7A and 7B with the observations that are missing family background information. The returns to education estimates is about 7.3 percent when one does not control for AFQT and they decrease to 2.8 percent if one does control for AFQT. Both these estimates have standard errors that are larger than the size of the estimate.

[15] Bound et al. (1995) report that IV estimates have 0.00 bias relative to the OLS estimates when the first stage F-stats are larger than 10 and two instruments are used.

Moreover, the asymptotic and bootstrapped standard errors of the returns to education only differ by a few thousandths.

The results in Table 8 are not exclusive to the NLSY. I estimated the parameters of similar wage equations using the data from National Longitudinal Survey: Class of 1972 (NLS72). Using OLS, the NLS72 estimates of the returns to education range from 6.5 to 7.6 percent. Using Instrumental Variables and not controlling for skill or family income, the returns to education estimate is 11.7 percent. The returns to education estimate drops to 5.8 percent if one controls for both family income and skill. This estimate has a standard error of 0.038. Therefore, one cannot reject the hypothesis that the rate of return is zero if one controls for family income and skill, just as in the NLSY.

Thus, from these results one can see two very different pictures of the role of AFQT score, education and family income in determining wages. If one believes that family background variables are inappropriate instruments and relies on quarter of birth and proximity to a college as instruments then one sees large returns to education. Furthermore, there is little role for AFQT and family income in determining wages beyond their influence on education. However, these results are likely to be biased due to the poor correlation between the instruments and education. Alternatively, if one believes that the family background variables are appropriate then the returns to education are small. Wages are determined by AFQT score and family income.

This leads one to question the appropriateness of family background variables as instruments. In order to answer this question, I regressed the residuals from each of the regressions in Tables 6A, 6B, 7A, 7B and 8 on the exogenous variables and instrument of each regression. The number of observations multiplied by the R^2 from these regressions are distributed P^2 with degrees of freedom equal to the number of overidentifying restrictions under the null hypothesis that the instruments are valid. One cannot reject the validity of any of the instruments in the above regressions at a 5 percent significance level. The test statistic is reported as nR^2 in Tables 6A, 6B, 7A, 7B and 8. Furthermore, the test statistic is approximately zero when one uses only **Momedu** and **Dadedu** as instruments. However, since the parent's education variables are so highly correlated the tests have little power.

Finally, a note should be made on how to interpret the result that the returns to education estimate is close to zero. It is unlikely that education has no effect on earnings. However, the object of interest might be wrong. Instead of focusing on the returns to an extra year of education, one should focus on the returns to increased quality of education. It is quite possible that the results are being driven by AFQT score and family income being better proxies for education quality than years of education.

VI. Relationship to Previous Literature

The results of the previous section are consistent with those of the previous returns to education studies. Card (1995b) reviews a portion of this literature and finds that when variables such as quarter of birth or proximity to a local college are used as instruments then OLS estimates are smaller than the IV estimates. For example, using nearby college in county of residence in 1966 as an instrument using the NLS Young Men Survey, Card (1995a) finds that the OLS estimate is 0.073 (0.004) and the IV estimate is 0.132 (0.049).[16] Similarly, Angrist and Krueger (1991) using the males born from 1930-1939 surveyed in the 1980 census and using year*quarter of birth and state*quarter of birth as instruments finds that the OLS estimate is 0.0628 (0.0003) and the IV

[16] Standard errors in parentheses. Other covariates: region in 1966, SMSA in 1996, race, in South in 1976, family structure at age 14, father's and mother's education, quadratic in experience (treated as endogenous).

estimate is 0.0811 (0.0109).[17] Using similar instruments I found comparable results. My OLS estimate is approximately eight percent and using the similar instruments my IV estimates are approximately twelve to seventeen percent. As pointed out earlier a possible reason for the IV estimates being larger than the OLS estimates is that the instruments are poorly correlated with education and the resulting IV estimates are biased. Using more highly correlated instruments I find that the returns to schooling are close to zero if one controls for AFQT and family income. However, if one does not control for either AFQT or family the OLS estimate is eight percent and the IV estimate is twelve percent. If one controls for family income only the OLS and IV results are similar. This last result is in line with results from the sibling literature.

The sibling literature estimates the returns to education by considering brothers. The unobservables in the earnings equation that are correlated with education are assumed to be family specific. Thus differencing the outcomes of brothers gets rid of the endogeneity problem. The returns to education can be estimated by regressing differenced earnings on differenced education. However, differencing exacerbates problems of measurement error. Thus, researchers instrument for differenced education. Ashenfelter and Zimmerman (1997) using a matched brother sample from the NLS original cohort finds the OLS estimate and the differenced then instrumented estimate of the returns to schooling are very similar. On the other hand, in a study of identical twins Ashenfelter and Krueger (1994) finds the differenced an instrumented estimates to be much larger than the OLS estimates. However, Ashenfelter and Rouse (1998) using a larger sample of identical twins finds results similar to Ashenfelter and Zimmerman (1997). A problem with these studies is the assumption that all of the unobserved differences that affect education are family

[17] Standard errors in parentheses. Other covariates: race, central city, married, age, age-squared, state of residence, state of birth.

specific. Grililches (1979) points out this problems and shows the correlation in IQ scores across siblings is 0.5. Thus, even though children in the same family have similar abilities, these abilities are not the same. If a variable such as AFQT is not family specific there is still an omitted variable problem. In my results not accounting for AFQT implied that OLS results were similar to IV results. Including AFQT score caused a sharp decline in my estimate of the returns to education.

VII. Conclusion

The goal of this paper is to examine how much of the correlation in earnings across generations can be explained by skill and education. Estimating the returns to education leads to two very different answers to this question. If one believes that family background variables are valid instruments for education, then one sees that the returns to schooling are small. Furthermore, there are high returns to skill and a portion of the intergenerational income mobility coefficient is left unexplained.

On the other hand, if one believes that family background variables are invalid instruments for years of education and relies on instruments such as quarter of birth and proximity to a local college then one sees high returns to education, on the order of ten to seventeen percent. Furthermore, there are low returns to skill and most of the intergenerational mobility coefficient is explained by schooling.

However, the small correlations between quarter of birth, proximity to a local college and education makes one question the validity of these instruments. The estimates from these instruments are imprecise and possibly biased. Furthermore, one cannot reject the validity of the family background variables as instruments. Thus, the most plausible answer seems to be that the returns to education are small, and that excluding family income and skill as determinants of wage overstates the returns to education. There are high returns to skill and much still needs to be explained about the channel that distributes parents wealth to children. One possibility is that years of education might be the wrong object of interest. One should focus on the returns to increased quality of education. It is quite possible that the results are being driven by skill and family income being better proxies for education quality than years of education.

Table 1
Variable Definitions

Variable	Definition
Wage	The 1995 wage of the individual measured in 1992 dollars.
Family Income	The income of the respondent's family in 1979 measured in 1992 dollars.
AFQT	The AFQT test score of the respondent. It is used as the measure of skill of the respondent.
Education	The number of years of schooling the respondent had completed by May 1994.
Age	The age of the respondent in 1995.
White	An indicator of whether the respondent is white.
South	An indicator of whether the respondent lived in the South in 1994.
SMSA	An indicator of whether the respondent lived in an SMSA in 1994.
NE79	An indicator of whether the respondent lived in the Northeast Region in 1979.
NC79	An indicator of whether the respondent lived in the North Central Region in 1979.
S79	An indicator of whether the respondent lived in the South Region in 1979.
W79	An indicator of whether the respondent lived in the West Region in 1979.
SMSA79	An indicator of whether the respondent lived in an SMSA in 1979.
Dadedu	The highest grade completed by the respondent's father.
Momedu	The highest grade completed by the respondent's mother.
Dadhouse	Indicator of whether there is a father (or stepfather) present in the respondent's household and in 1979.

Table 1 Continued
Variable Definitions

Momhouse	Indicator of whether there is a mother (or stepmother) present in the respondent's household and in 1979.
Quarter I	Indicator of whether the respondent was born in the first quarter of the year.
Quarter II	Indicator of whether the respondent was born in the second quarter of the year.
Quarter III	Indicator of whether the respondent was born in the third quarter of the year.
4year	Indicator of whether there is a 4 year college in the respondent's 1979 county of residence.
2year	Indicator of whether there is a 2 year college in the respondent's 1979 county of residence.

Table 2
Summary Statistics

Variable	Observations With No Missing Family Background Variables			Observations With 1 or More Missing Family Background Variables		
	# obs	Mean	Standard Deviation	# obs	Mean	Standard Deviation
Wage	881	13.48	9.01	467	12.06	8.40
Ln(**Wage**)	881	2.42	0.61	467	2.29	0.64
Family Income	881	43505.92	27389.81	225	27672.75	22750.56
Ln(**Family Income**)	881	10.47	0.69	221	9.95	0.80
AFQT	881	0.00	0.94	467	-0.35	0.97
Education	881	13.36	2.42	467	12.87	2.31
Age	881	32.95	1.04	467	32.90	1.03
White	881	0.72	0.45	467	0.55	0.50
South	881	0.37	0.48	465	0.47	0.50
SMSA	881	0.78	0.41	467	0.78	0.41
NE79	881	0.19	0.39	467	0.19	0.39
NC79	881	0.34	0.47	467	0.25	0.44
S79	881	0.34	0.48	467	0.45	0.49
W79	881	0.12	0.33	467	0.09	0.29
SMSA79	875	0.68	0.47	466	0.63	0.48
Dadedu	881	11.63	3.32	297	11.90	3.43
Momedu	881	11.68	2.38	391	11.38	2.58
Dadhouse	881	0.88	0.33	357	0.80	0.40
Momhouse	881	0.97	0.18	430	0.95	0.22
Quarter I	881	0.23	0.42	467	0.20	0.40
Quarter II	881	0.26	0.44	467	0.24	0.43
Quarter III	881	0.28	0.45	467	0.32	0.47
4year	858	0.74	0.44	451	0.70	0.46
2year	858	0.88	0.33	451	0.87	0.34

Table 3
Variance/Covariance and Correlation Matrix:
Possible Instruments, ln(Wage), Education and ln(Family Income)

	ln(Wage)	**Education**	**Momedu**	**Dadedu**	**4year**	**Quarter I**	**ln(Family Income)**
ln(Wage)	0.37	0.39*	0.26*	0.27*	0.04	0.06	0.34*
Education	0.57	5.85	0.43*	0.42*	0.03	0.09*	0.31*
Momedu	0.37	2.46	5.65	0.62*	0.15*	-0.01	0.40*
Dadedu	0.54	3.33	4.88	11.05	0.12*	-0.03	0.41*
4year	0.01	0.03	0.15	0.18	0.19	-0.02	0.12*
Quarter I	0.02	0.09	-0.01	-0.05	0.00	0.18	-0.01
ln(Family Income)	0.14	0.51	0.65	0.94	0.04	0.00	0.48

Note: Variance/Covariance Matrix is the diagonal and lower triangle portion of the matrix. The Correlation Matrix is the upper triangle. * estimate of correlation coefficient is significant at a .01 level (one-tailed test).

Table 4
Log Wage Regressions

White	0.3174*	0.2570*	0.0643	-0.0093	0.1443*
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)
Age	0.0422*	0.0316	0.0380*	0.0311	0.0299
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
AFQT			0.2818*	0.2482*	
			(0.02)	(0.02)	
AFQT^2			-0.0072	-0.0035	
			(0.02)	(0.02)	
Education		0.0921*			
		(0.01)			
ln(Family Income)				0.1550*	0.2572*
				(0.03)	(0.03)
R^2	0.0589	0.1912	0.2154	0.2381	0.1277

Note: Number of observations =881. (standard errors in parentheses) *estimate is significant at .05 level.

Table 5A
Log Wage Regressions
Estimation Technique: OLS

Education	0.087**	0.088**	0.081**	0.080**	0.075**
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
Age	0.032*	0.031*	0.031*	0.030*	0.025
	(0.018)	(0.018)	(0.018)	(0.018)	(0.017)
White	0.265**	0.253**	0.237**	0.220**	0.166**
	(0.043)	(0.044)	(0.045)	(0.047)	(0.048)
South	-0.021	0.097	0.101	0.105	0.096
	(0.040)	(0.068)	(0.068)	(0.068)	(0.067)
SMSA	0.155**	0.127**	0.121**	0.121**	0.114**
	(0.046)	(0.051)	(0.051)	(0.051)	(0.051)
Momedu			0.012	0.011	0.031
			(0.010)	(0.010)	(0.046)
Dadedu			0.006	0.006	0.003
			(0.007)	(0.008)	(0.010)
Momhouse				0.105	0.095
				(0.105)	(0.104)
Dadhouse				0.071	-0.047
				(0.059)	(0.064)
ln(**Family Income**)					0.156**
					(0.036)
Region79	No	Yes	Yes	Yes	Yes
R^2	0.203	0.209	0.212	0.214	0.231
obs	881	875	875	875	875

Note: Region79 = Yes implies **NE79, NC79, W79** and **SMSA79** have been included in the estimation.
(standard errors in parentheses) * estimate significant at 10% level . ** estimate is significant at 5% level.

Table 5B
Log Wage Regressions Controlling for AFQT
Estimation Technique: OLS

Education	0.047**	0.049**	0.048**	0.047**	0.045**
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Age	0.034**	0.033*	0.032*	0.032*	0.028
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
White	0.127**	0.124**	0.124**	0.103**	0.064
	(0.047)	(0.047)	(0.047)	(0.049)	(0.050)
South	0.001	0.079	0.080	0.085	0.078
	(0.039)	(0.066)	(0.066)	(0.067)	(0.066)
SMSA	0.132**	0.102**	0.102**	0.102**	0.097*
	(0.045)	(0.050)	(0.050)	(0.050)	(0.050)
Momedu			0.003	0.002	-0.004
			(0.010)	(0.010)	(0.010)
Dadedu			0.000	0.000	-0.004
			(0.007)	(0.007)	(0.007)
Momhouse				0.124	0.114
				(0.103)	(0.102)
Dadhouse				0.084	-0.018
				(0.058)	(0.063)
ln(**Family Income**)					0.132**
					(0.035)
AFQT	0.183**	0.178**	0.176**	0.177**	0.168**
	(0.028)	(0.028)	(0.029)	(0.029)	(0.029)
AFQT^2	-0.028	-0.027	-0.026	-0.029	-0.023
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Region79	No	Yes	Yes	Yes	Yes
R^2	0.245	0.248	0.248	0.251	0.263
obs	881	875	875	875	875

Note: Region79 = Yes implies **NE79, NC79, W79** and **SMSA79** have been included in the estimation.
(standard errors in parentheses) * estimate significant at 10% level. ** estimate is significant at 5% level.

Table 6A
Log Wage Regressions
Quarter of Birth as an Instrument for Education

Education	0.151*	0.172**	0.142*	0.157**	0.126**	0.099**
	(0.082)	(0.082)	(0.080)	(0.078)	(0.017)	(0.020)
Age	0.025	0.019	0.026	0.020	0.028	0.024
	(0.021)	(0.021)	(0.019)	(0.019)	(0.018)	(0.018)
White	0.224**	0.168**	0.224**	0.181**	0.240**	0.168**
	(0.069)	(0.050)	(0.048)	(0.051)	(0.045)	(0.050)
South	-0.006	0.006	-0.017	-0.010	-0.012	-0.004
	(0.046)	(0.044)	(0.042)	(0.043)	(0.040)	(0.039)
SMSA	0.094	0.061	0.113*	0.090	0.118**	0.116**
	(0.093)	(0.079)	(0.061)	(0.058)	(0.049)	(0.047)
Momedu			-0.006	-0.017	Inst	Inst
			(0.024)	(0.022)		
Dadedu			-0.003	-0.010	Inst	Inst
			(0.015)	(0.014)		
Momhouse			0.023	0.000	Inst	Inst
			(0.132)	(0.131)		
Dadhouse			0.067	-0.029	Inst	Inst
			(0.062)	(0.069)		
ln(**Family Income**)		0.063		0.121**		0.137**
		(0.089)		(0.054)		(0.036)
nR^2	3.612	3.876	3.700	4.317	5.374	6.255
Partial R^2	0.0096	0.0107	0.0124	0.0131	0.1822	0.1352
First Stage F-STAT	2.84	3.16	3.64	3.87	31.97	23.58
obs	881	881	881	881	881	881

Note: Instruments are **Quarter I, Quarter II , Quarter III** and variables marked Inst. nR^2 is the test statistic for the overidentification test. Partial R^2 is the amount of variation of **Education** explained by the instruments controlling for the variation explained by other exogenous variables. The First Stage F-STAT is the test statistic for the coefficients on instruments equaling 0 in the first stage regression.
(standard errors in parentheses) * estimate significant at 10% level. ** estimate is significant at 5% level.

Table 6B
Log Wage Regressions Controlling for AFQT
Quarter of Birth as an Instrument for Education

Education	0.113	0.126	0.108	0.116	0.090**	0.049
	(0.094)	(0.094)	(0.091)	(0.090)	(0.039)	(0.042)
Age	0.028	0.023	0.028	0.023	0.030*	0.028
	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)	(0.017)
White	0.183**	0.147	0.158*	0.133	0.163**	0.067
	(0.092)	(0.110)	(0.095)	(0.100)	(0.057)	(0.064)
South	-0.001	0.006	-0.009	-0.001	0.000	0.010
	(0.040)	(0.040)	(0.042)	(0.042)	(0.039)	(0.039)
SMSA	0.113**	0.096*	0.121**	0.105**	0.119**	0.114**
	(0.053)	(0.051)	(0.048)	(0.047)	(0.046)	(0.045)
Momedu			-0.005	-0.013	Inst	Inst
			(0.016)	(0.015)		
Dadedu			-0.002	-0.007	Inst	Inst
			(0.009)	(0.009)		
Momhouse			0.060	0.045	Inst	Inst
			(0.125)	(0.124)		
Dadhouse			0.084	-0.012	Inst	Inst
			(0.060)	(0.065)		
ln(**Family Income**)		0.098**		0.123**		0.128**
		(0.048)		(0.041)		(0.034)
AFQT	0.064	0.021	0.083	0.057	0.105	0.153**
	(0.171)	(0.165)	(0.144)	(0.142)	(0.073)	(0.073)
AFQT^2	-0.053	(0.055)	-0.053	-0.051	-0.044*	-0.026
	(0.041)	(0.042)	(0.039)	(0.034)	(0.025)	(0.026)
nR^2	3.876	4.581	3.700	4.581	6.784	7.048
Partial R^2	0.0117	0.0119	0.0131	0.0133	0.0519	0.0433
First Stage F-STAT	3.45	3.50	3.86	3.92	8.89	7.30
obs	881	881	881	881	881	881

Note: Instruments are **Quarter I, Quarter II , Quarter III** and variables marked Inst. nR^2 is the test statistic for the overidentification test. Partial R^2 is the amount of variation of **Education** explained by the instruments controlling for the variation explained by other exogenous variables. The First Stage F-STAT is the test statistic for the coefficients on instruments equaling 0 in the first stage regression.
(standard errors in parentheses) * estimate significant at 10% level. ** estimate is significant at 5% level.

Table 7A
Log Wage Regressions
Quarter of Birth and Proximity to a Local College as Instruments for Education

Education	0.126*	0.146**	0.115*	0.140**	0.128**	0.104**
	(0.072)	(0.069)	(0.067)	(0.063)	(0.018)	(0.021)
Age	0.025	0.018	0.025	0.018	0.024	0.021
	(0.020)	(0.019)	(0.019)	(0.019)	(0.018)	(0.018)
White	0.255**	0.184**	0.244**	0.196**	0.253**	0.185**
	(0.068)	(0.049)	(0.048)	(0.049)	(0.046)	(0.047)
South	-0.014	-0.001	-0.015	-0.007	-0.013	-0.005
	(0.043)	(0.042)	(0.041)	(0.042)	(0.040)	(0.040)
SMSA	0.119	0.082	0.125**	0.095**	0.117**	0.113**
	(0.084)	(0.070)	(0.058)	(0.055)	(0.049)	(0.048)
Momedu			0.003	-0.012	Inst	Inst
			(0.021)	(0.018)		
Dadedu			0.003	-0.006	Inst	Inst
			(0.013)	(0.012)		
Momhouse			0.045	0.012	Inst	Inst
			(0.123)	(0.121)		
Dadhouse			0.048	-0.054	Inst	Inst
			(0.062)	(0.067)		
ln(**Family Income**)		0.085		0.126**		0.127**
		(0.077)		(0.048)		(0.036)
nR^2	5.062	5.491	5.062	5.749	5.663	7.636
Partial R^2	0.0118	0.0138	0.0159	0.0185	0.1816	0.1369
First Stage F-STAT	2.07	2.51	2.94	3.48	23.32	17.05
obs	858	858	858	858	858	858

Note: Instruments are Quarter I, Quarter II, Quarter III, 4year, 2year and variables marked Inst. nR^2 is the test statistic for the overidentification test. Partial R^2 is the amount of variation of **Education** explained by the instruments controlling for the variation explained by other exogenous variables. The First Stage F-STAT is the test statistic for the coefficients on instruments equaling 0 in the first stage regression. (standard errors in parentheses) * estimate significant at 10% level. ** estimate is significant at 5% level.

Table 7B
Log Wage Regressions Controlling for AFQT
Quarter of Birth and Proximity to a Local College as Instruments for Education

Education	0.084	0.097	0.075	0.094	0.091**	0.054
	(0.085)	(0.085)	(0.083)	(0.081)	(0.040)	(0.044)
Age	0.028	0.022	0.028	0.022	0.027	0.025
	(0.019)	(0.019)	(0.019)	(0.019)	(0.018)	(0.017)
White	0.172**	0.131	0.148*	0.130	0.177**	0.090
	(0.081)	(0.096)	(0.085)	(0.088)	(0.056)	(0.064)
South	-0.001	0.006	-0.003	0.003	0.000	0.009
	(0.040)	(0.040)	(0.041)	(0.041)	(0.039)	(0.039)
SMSA	0.123**	0.104**	0.127**	0.107**	0.121**	0.114**
	(0.052)	(0.050)	(0.048)	(0.048)	(0.047)	(0.046)
Momedu			0.000	-0.009	Inst	Inst
			(0.015)	(0.014)		
Dadedu			0.001	-0.005	Inst	Inst
			(0.008)	(0.008)		
Momhouse			0.080	0.058	Inst	Inst
			(0.120)	(0.118)		
Dadhouse			0.070	-0.018	Inst	Inst
			(0.061)	(0.063)		
ln(**Family Income**)		0.103**		0.124**		0.120**
		(0.046)		(0.040)		(0.035)
AFQT	0.119	0.076	0.136	0.092	0.107	0.148*
	(0.153)	(0.146)	(0.132)	(0.128)	(0.075)	(0.077)
AFQT^2	-0.041	-0.044	-0.040	-0.042	-0.044	-0.027
	(0.040)	(0.040)	(0.038)	(0.038)	(0.026)	(0.027)
nR^2	5.062	5.834	4.805	5.749	6.521	7.722
Partial R^2	0.0139	0.0141	0.0150	0.0193	0.0519	0.0435
First Stage F-STAT	2.43	2.50	2.67	2.82	6.44	5.24
obs	858	858	858	858	858	858

Note: Instruments are **Quarter I, Quarter II, Quarter III, 4year, 2year** and variables marked Inst. nR^2 is the test statistic for the overidentification test. Partial R^2 is the amount of variation of **Education** explained by the instruments controlling for the variation explained by other exogenous variables. The First Stage F-STAT is the test statistic for the coefficients on instruments equaling 0 in the first stage regression. (standard errors in parentheses) * estimate significant at 10% level. ** estimate is significant at 5% level.

Table 8
Log Wage Regressions
Parent's Education Variables Instrument for Education

Education	0.123**	0.088**	0.069	0.005
	(0.018)	(0.021)	(0.045)	(0.053)
Age	0.027	0.025	0.031*	0.031*
	(0.018)	(0.017)	(0.017)	(0.018)
White	0.226**	0.173**	0.123**	0.025
	(0.047)	(0.047)	(0.060)	(0.072)
South	-0.016	-0.002	-0.004	0.014
	(0.041)	(0.040)	(0.039)	(0.039)
SMSA	0.123**	0.119**	0.128**	0.120**
	(0.049)	(0.047)	(0.046)	(0.046)
Momhouse	0.041	0.064	0.090	0.127
	(0.108)	(0.106)	(0.101)	(0.110)
Dadhouse	0.070	-0.042	0.091	-0.012
	(0.059)	(0.065)	(0.058)	(0.063)
ln**(Family Income)**		0.156**		0.148**
		(0.041)		(0.040)
AFQT			0.145*	0.229**
			(0.085)	(0.093)
AFQT^2			-0.039	-0.010
			(0.026)	(0.029)
nR^2	0	0	0	0
Partial R^2	0.1657	0.0979	0.0342	0.0233
First Stage F-STAT	101.23	67.07	22.01	16.26
obs	881	881	881	881

Note: Instruments are **Momedu** and **Dadedu**. nR^2 is the test statistic for the overidentification test. Partial R^2 is the amount of variation of **Education** explained by the instruments controlling for the variation explained by other exogenous variables. The First Stage F-STAT is the test statistic for the coefficients on instruments equaling 0 in the first stage regression. (standard errors in parentheses) * estimate significant at 10% level. ** estimate is significant at 5% level.

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