How Dose Last Generation’s Choices of Education Affect Next Generation’s Future and Education

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How dose last generation’s choices of education affect next generation’s future and education

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Name:

Signature:
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Zhili Huang

Abstract

The purpose of my paper is to investigate how can parents’ years of schooling (schooling attainment) affect children’s years of schooling and their future wage and income. In this paper, I will use both OLS estimation and IV estimation to predict results and compare the results. The result of IV estimation shows that parents’ education has positive relationship with children’s future.

I. Introduction

C. Joybell. C (2017) said that “I think that the best thing we can do for our children is to allow them to do things for themselves, allow them to be strong, allow them to experience life on their own terms, allow them to take the subway... let them be better people, let them believe more in themselves.” Parents have little influence on children’s life and future. Children must learn to walk life’s road by themselves. However, C.Joybell.C also told us. “Our parents can show us a lot of things: they can show us how we are to be and what things we ought to strive for, or they can show us how not to be and what things we ought to stray from, then you may have the kind of parents that show you all the things about you that you want to get rid of and you realize those traits aren’t yours at all but are merely your parents’ marks that have rubbed off onto you.” Parents give us guidance in our growth and lead us to a right road. The purpose of this paper is to investigate
whether parents can have influence during children's way of life and future. Parents guide children in many ways, however one of their most important mentorship moments can be to guide educational outcomes. I will focus on how parents or last generation affect their children or next generation from the part of education.

II. Literature Review

Connection between education and economics

There is a fascinating relationship between education and economics. Aristotle said,"Education is an ornament in prosperity and a refuge in adversity." Even during Aristotle’s time, it was evident that education was one of the most important investments for a person during their life. The choice of education for a person can determine the future starting point when they enter into the society. Although education is very important, some people are forced to leave early to make a living for themselves, while others continue on past graduation from university. Their decision is based on a number of factors, including parental and guardian advice. Maybe we should listen to our parents' advices. When a child faces choices of education, parents will provide advice based on their history of education. Parental schooling is the most important reference for children's schooling. Understanding parental advice is important to a child’s educational achievement, it is important to study the relationship’s interaction. How parents' choices of education affect children's choice of education and affect their future. Choice of education means schooling attainment, which refers to the highest
level of education completed. The future of a child means income or wages that they are able to earn when they enter into society. The part of literature review will study the relationship between parents' schooling attainment, children's schooling attainment and wages of their children when they step into society from different economists' views.

**Papers related to my topics**

The relationship of parents' schooling attainment and children's schooling attainment can be described as intergeneration transmission of education. Pedro and Parey (2007) investigate this relationship. They study the intergenerational effects of maternal education on children's cognitive achievement, behavioral problems, and grade repetition in the whole paper. However, due to the nature of the data, this paper focuses on the effect of maternal, but not paternal schooling. It is one of the weaknesses of the paper because they cannot compare the effects of mothers and fathers. To measure the metrics of intergenerational cognitive achievement, they use children's grades of mathematics and behavioral problems instead of children's future income and wages when they enter into the society. This is quite different from paper. In my opinion, the wages and income of next generation can represent how well the children live in the future. Children's grades and behavioral problems can only measure children's achievements during their adolescence and cannot determine their future. It seems like Pedro Carneiro, Costas Meghir and Matthias Parey's (2007) topic talks about this relationship relates to my paper a little, but this paper uses completed education (schooling attainment) to measure mothers' education, which is same to my choice of data of parents' choice of education. Before I read this paper, I am not sure which can
represent parents’ education, test scores or schooling attainment. However, this paper uses mothers' schooling attainment as maternal education. This paper says that tests in schools are various and it is hard to choose which test scores are important. Also, after-college test scores are more difficult to collect. GMAT, GRE and LSAT have different total points and it is hard to put them together to compare and analyze. Due to the difficulty of collecting data on test scores, they decide to use completed education as data of maternal education. "Completed education" is more objective and accurate than "test scores. Their result shows that maternal education has some positive effects on children's education. It gives me some indications that parents' education does have positive effects on their children. Meanwhile, this paper talks about how to deal with endogeneity. The key empirical problem they face is controlling for the endogeneity of mother’s schooling: factors that influence the mother’s decision to obtain schooling may also affect her ability to bring up children or may relate to other environmental and genetic factors relevant to child outcomes (Pdero Carnerio & Parey). They choose instrumental variables to solve the endogeneity of mothers’ schooling. The cost of education is to be used as instrumental variable. They use The variables they use to measure the costs of education include local labor market conditions, the presence of a four-year college, and college tuition at age 17, in the county where the mother resided when she was 14 years of age. To prove the validity of instrument variables, they take a falsification exercise. The results of this exercise support the validity of instrument variable and prove that instrumental variables can have better predictions. After reading
their empirical strategy, I should pay attention to the problem of endogeneity because it may make my results biased. This paper also tells me that the instruments must be correlated with mother’s schooling, but must not have an independent effect on the outcome equation except through mother’s schooling. According to this, I will choose my instrumental variables more carefully and follow the rules of their choice of instrumental variables.

I was confused about how to define variable of parents' education. It seems like that data of parental education is one variable, but it is hard to find the data can represent both mother's and father's completed education. There are two ways that can be used to define parents' education: one is to choose the highest level of completed education of the couple; the other one is to use put maternal and paternal education separately in the equation. Chevalier and Walker (2013) create a work methodology for analyzing the variables. They study the intergeneration transmission of education and investigates the extent to children's schooling attainment may be due to variations in permanent income, parental education levels and shocks to income at 16 years old. (Chevalier, Harmon, O'Sullivan, & Wallker, 2013). This paper puts maternal completed education and paternal completed education respectively in the equation and compare their effects to their children’s education. Least squares estimation reveals the results: stronger effects of maternal education than paternal because mother stay with children more. Also Benhrman and Rosenzweig also compare maternal and paternal education in their paper. They conclude that the effect of father's education is strong and large in magnitude, but
the effect of maternal education on child schooling is insignificant (Behrman & Rosenzweig, 2002). Chevalier, Harmon and Walker (2013) give some implications on my topic: increase parents' schooling attainment can increase children's schooling attainment. However, one of the dissimilarities is that this paper studies how parental education and parental income together affect children's schooling. I am not sure that whether the effects of parental education are still significant even without the effect of parents’ income. I think Chevalier, Harmon and Walker (2013) does not tell readers directly that how does parents' education affect children's schooling without the participation of parents' income.

Similar to Chevalier and Walker's paper, Chevalier (2004) also talks about the intergenerational educational transmission. This paper identifies the effect of parental education on their offspring's schooling attainment using a discontinuity in the parental educational attainment (Chevalier, Parental Education and Children's Education: A Natural Experiment, 2004). While this paper did not try to find a relationship between other variables, just parental education and children’s education. Chevalier (2004) only talks about how last generation's education affects their children. It is closer to my topic. However, he uses data from UK; I will study American parents and children. Usually the correlation between generations has two possible channels: causal\(^1\) and nature\(^2\) (Chevalier, Parental Education and Children's Education: A Natural Experiment, 2004).

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\(^1\) Causal means parents’ education can generate an effect on children's education.

\(^2\) Nature means children's education has no relationship with parents’ education.
This paper and agree with the causal correlation between generations. They find that a positive effect of both parents' education on their children’s schooling achievements when focusing on natural3 parents only. One of interesting points of this paper is that they study not only on the natural parents but also on step parents. They find that step parents have no or negative effect on children's education. I will also focus on natural parents and children only. As I mention in the previous part, I will not only study intergenerational transmission of education. I will also want to examine how parents' education affects next generation's income or wages. Chevalier (2004) gives me answer that the children's income and wages are substantial with the effects of parental education. Meanwhile, Arnaud Chevalier talks about policies in this paper. Sometimes children's schooling attainment is not only affected by their parents' schooling attainment. The policies of education have effects on children's education. Lots of countries have policies of compulsory schooling, which ensures children graduate with a minimum education. However, while this many mandate a certain level of education, it creates other problems. Cameron and Heckman (1998) for the US and Chevalier and Lanot (2002) for the UK show that the effect of financial constraints on educational choice is less important than the effect of family background (mainly parental education). The effect of policies is controversial in different papers. Chevalier and Walker (2013) give a result that policies are beneficial to children's education in the future. Chevalier (2004) states the result after regression: the 4 to 8 percentage points

3 Natural parent’s children and parents means generically related parents and children.
increase in post-compulsory education is equivalent to an average increase of 0.1 to 0.2 years of education for the whole population (Chevalier, Parental Education and Children's Education: A Natural Experiment, 2004). It means that the effect of policy does exist because it has positive coefficient number, but is small, which is only 0.1 to 0.2 increases. Besides the effect of policy, Pedro Carneiro, Costas Meghir and Matthias Parey (2007), Chevalier (2004) and Cameron and Heckman (1998) talk about genetic effects in the study of intergenerational transmission of education. Children inherit similar gene from their parents. In this way, some children decide to leave school early because they do not inherit good intelligence and are not good at studying. Their schooling attainment may not be affected from their parents' schooling attainment. Both Bruce Sacerdote (2002) and Erik Plug (2003) compare adopted and natural children. They find that genetics account for about 50% of the correlation in education between generations but that after accounting for genetics, the causal effects of parental education remains highly significant.

Blezil and Henson (2003) talks about how parents’ education affects children’s wages with great detail when compared to the other literature discussed. They study both intergenerational transmission of education and children's income. They investigate the relative importance of family background variables (especially parents' education) and individual specific abilities in explaining cross-sectional differences in schooling attainments and wages (Belzil & Hansen, 2003). In this paper, the individual differences in wages are mostly explained by abilities. Only 27% of the explained variation in
wages is accounted for by parents' background variables (Belzil & Hansen, 2003). This paper set up two models to study the relationship between parental education and last generation's income. The first model is built to how last generation's schooling attainment affects next generation's schooling attainment without considering the effect of endogeneity. They achieve the result only by OLS estimation. The second model study the same equation but they use an instrumental variable to run the result by Two-Least Square. They consider the effect of endogeneity in the second model. It gives me references and hints to build models in my paper. I can run both OLS estimation and Two-Least Square. Then I can compare the two different results and take the most accurate one for my final result. Meanwhile, it talks about ability. When we talk about topics related to education, we must connect them to the idea of ability. In the theory of labor economics, different people have different rates of return to schooling (or wages) due to their abilities. Higher ability-persons will choose to go to school more because they have more returns to additional schooling. Because ability is unobserved, we usually measure the impact of ability by relating it to rate of return to schooling. In other words, the wage differential between two persons incorporates the impact of both education and ability (Belzil & Hansen, 2003). Given ability, household background variables (especially parents’ education) account for 68% of the schooling attainments. When the effects of parents’ education variables on ability are also taken into account, the percentage raises to 85%. However, individual differences in wages are mostly explained by abilities. Only 27% of the explained variation in wages is accounted for
by parents’ education as opposed to 73% by unobserved abilities (independent to parents ‘education). When ability is correlated with parents’ education, ability endowments explain as much as 81% of individual wages (Belzil & Hansen, 2003). In general, ability bias is one of the most important limitations that cause the result biased.

Blanden, Havemen, Smeeding and Kathryn (2013) also mention income and education. They find that those countries with higher demand in income tend to have a strong link between education levels across generations. Income weighs heavy on determining the correlation of effect of parent’s schooling on children's schooling. This paper is different than other papers because they build a cross-national research to examine the relationships underlying estimates of relative intergenerational mobility in the United States and Great Britain. I focus on the part that they talk about US. In the United States, primarily because of the higher returns to education and skills, the pathway through offspring education is relatively more important than it is in Great Britain (Bladen, Havemen, Smeeding, & Kathryn, 2013). It gives us a hint: British people may have lower return to education. According to the Blanden and Kathryn’s paper, the difference of rate of return to schooling is due to the capital put in education and constrains in labor markets. United States allocates more than double in education than Great Britain. Meanwhile, there are less constrains in US labor market than in British labor market. Because of the rigid labor market of Britain, there will be less wage differences for different people. It implies us that nations with fewer constrains and hence large and growing earnings and income inequality, are likely to have higher
rates of return on human capital investments (higher rates of return to schooling). The cross-national data can lead me to consider the intergenerational transmission of education with the effect of market.

When the above papers focus on estimating the causal link between the education of parents and their children, Holmlund, Lindahl and Plug (2008) focus on the methods. The find that intergenerational mobility of education provides evidence that is far from conclusive. They give some explanations as to why intergenerational education connection is inconclusive. First is that these studies rely on different data sources, gathered in different countries at different times. Second, these studies use different identification strategies. Three identification strategies that are currently in use rely on: identical twins; adoptees; and instrumental variables. These identification strategies are used to solve endogeneity of independent variables. Lots of the above papers use twin parents and compare natural children and adoptees. To deal with the endogeneity, most papers that relate to education will choose to take methods of instrumental variables. Therefore, Holmlund, Lindahl and Plug (2008) apply each of these three strategies to one particular Swedish data set. They want to explain the disparate evidence in the recent literature, learn more about the quality of each identification procedure, and get at better perspective about intergenerational effects of education. They conclude that all three strategies produce lower causal estimates than the corresponding OLS estimates, which means that the intergenerational transmission of human capital is much lower when ability bias is taken into account. Ability bias is one of the
commonest problems in economics of education. It tells us that if there are unobserved ability differences in the population, earning differentials across workers do not estimate the returns to schooling only. They think that when we also consider ability bias into the paper, the effects of intergenerational mobility of education is much lower and can be ignored. Like the previous paper “Structural Estimates of the intergenerational Education Correlation” concludes that only 27% of wage differentials can be explained by family backgrounds (especially education) and the other 73% is explained by unobserved ability (Holmlund, Lindahl, & Plug, 2010). Finally, they conclude that income is a mechanism linking parent’s and children’s schooling, that can partly explain the diverging results across methods. This paper also says something on the policy implications. Referring to Swedish policies, their findings indicate that the intergenerational schooling associations are largely driven by inherited abilities and child-rearing talents (Holmlund, Lindahl, & Plug, 2010).

**Inspirations of these papers**

The above papers are very suitable for my topics. I can receive different ideas and opinions from these papers. Pedro (2007) and Parey (2007) use maternal data to study how mothers' education affect children's development and achievements. It's good for them to use mothers' schooling attainment to measure mothers 'education. However, it is unreasonable to use children's scores of mathematics as children's development. Different children are good at different classes. You cannot determine a child's development only by his or her grades of mathematics. If Pedro and Parey (2007) wants to use test scores to represent children's development, I suggest them to use SAT scores,
which include mathematics, writing and reading. Chevalier (2004) pays attention to the income and parental education together, because Holmlund, Lindahl and Plug mentions that income is a mechanism linking parent's and children's schooling, that can partly explain the diverging results of different literatures. It is better to put income in the study of intergenerational mobility of education. However, I cannot understand why they choose children at 16 years old. Most 16-year-old children study in high school at this time. If they choose children at this age it is hard to see their future path of education. We cannot know the completed education from the data of 16-year-old children. Chevalier (2004) mentions that 16-year-old children are facing whether to continue to go to high school or leave school. Government is targeting at reducing students who leave school early. I think it will become more and more usual for 16-year-old-student to stay at school instead of entering into society. Belzil and Hansen (2003) do not only study the importance of family background variables (especially education) but also study the effect how these family background variables affect children's wage differences in labor market. The models and methods are perfect for me to learn about. However, they do not mention the problems of endogeniety. I think it will cause bias to their results. Holmlund and Plug (2010) study why the causal link between the education of parents and their children provide evidence that is far from conclusive. It is the only paper that notices this problem. They think that the diverging results of different papers are due to the identification strategies, which rely on adoptees, identical twins and instrumental variables. It is reasonable for them to apply each method on
their data and then give this conclusion. However, they use data from Sweden. One country cannot represent all the other countries. I think they can only draw their conclusion in Sweden. I will have reservations for the perspectives of Holmlund and Plug’s paper.

After reading these literatures, I find directions for my paper. I will choose to use schooling attainment as the data of education. I will use both parents' data and compare their effects. Also I will notice the problems of endogeneity. Although instrumental variables are rejected by Holmlund and Plug (2010). They are used in other papers and solve the problem of endogeneity. I will try instrumental variables in my paper and apply them in the data from USA. When I do my research, I should pay attention to the problems of ability bias.

III. Analytical Framework

My theory of economics is based on mincer-earning equation. In labor economics and education economics, we usually use Mincer-Earning equation as our theoretical model to study the relationship between education and future. Mincer earnings function is a single-equation model that explains earnings as a function of schooling and experience, named after Jacob Mincer. Mincer showed that the human capital model generates an age-earnings profile (Borjas, 2010). I collected data from Panel Study of Income Dynamics (PSID). PSID is a reliable source of data, which is a nationally representative sample of over 18,000 individuals living in 5,000 families in the United States. Over 3,000 peer-reviewed
publications have been based on the PSID. I use data in 2011 for my paper because it is the latest data in PSID. The sort of my data is cross-sectional.

IV. Methodology

Variables in OLS estimation

Besides the original variables from the mincer-earning equation, I add mothers’ years of schooling, fathers’ years of schooling and gender to the equation. So my final regression model is the following one.

\[
\ln w = \beta_0 + \beta_1 s + \beta_2 t + \beta_3 t^2 + \beta_4 fedu + \beta_5 medu + \beta_6 F + \beta_7 F \times s + \text{error}
\]

\(s\) represents the years of schooling of next generation and \(t\) represents the working experience of next generation. \(w\) represents the wage rate of next generation. \(fedu\) represents the years of schooling of father and \(medu\) represents the years of schooling of mother. \(F\) is a dummy variable, which represents gender. When \(F\) equals to 1, it represents female; when \(F\) equals to 0, it represents male.

Chevalier, Harmon, O’Sullivan and Wallker(2013) also use dummy variable to distinguish and compare the difference of son’s return to schooling and daughter’s return to schooling. \(F \times s\) is the product of years of schooling of next generation and gender. I put \(F \times s\) here because it is critical to discover the difference between female and male’s rate of return to schooling. Dummy variable \(F\) alone cannot show the difference. The coefficient on schooling \(\beta_1\) estimates the percent increase in earnings resulting from one additional year of schooling and is typically
interpreted as the rate of return to schooling. In this way, the coefficients on schooling of fathers and mothers $\beta_4$ and $\beta_5$ estimate the percentage increase in earnings of next generation due to the one additional year of fathers’ or mothers’ schooling. The coefficient on experience and experience squared estimate the rate of growth in earnings resulting from one additional year of labor market experience and are typically interpreted as measuring the impact of on-the-job training on earnings. If the worker did not invest in on-the-job training, the coefficients of the experience variables would be zero because there would be no reason for real earnings to increase with labor market experience. The coefficient of $F$ and $F^*s$ is special. If $f$ equals to 0, the equation will become

$$\ln w = \beta_0 + \beta_1 s + \beta_2 t + \beta_3 t^2 + \beta_4 f edu + \beta_5 medu$$

If $f$ equals to 1, the equation will become

$$\ln w = (\beta_0 + \beta_6) + (\beta_1 + \beta_7)s + \beta_2 t + \beta_3 t^2 + \beta_4 f edu + \beta_5 medu$$

From the above two equations, we can see that we cannot get the accurate gender difference of rate of return to schooling. Then we add $Fs$ to the equation. When $F$ equals to zero, the coefficient on $s$ estimates the rate of returning for male. When $F$ equals to 1, $s+F^*s$ represent the rate of return to schooling for female. It gives us a hint: if $Fs$ is bigger than zero, it means that female has lower rate of return to schooling than male. I think the relationship between parents’ education and children’s rate of return to schooling is positive because they are important parts
of our growth.

**Results of OLS Estimation (first regression)**

After collecting data and selecting the theoretical model, I regress all my variable and get my results (see table 1).

The results of OLS estimation (see table 1) give us a shocked result. The coefficient of fathers' years of schooling is positive, which means that father's years of schooling have positive relationship with children's rate of return to schooling. It gives us a hint that father will have positive effect on children's future, but the effect is tiny according to small number of coefficient on fathers' years of schooling. However, the coefficient of mothers' years of schooling is negative. It means that mothers will have negative effect on children's future. It is not a good result. Lots of mothers raise their children by themselves and they are necessary parts during the growth of children. The result implies that if children want to achieve a better future and life, they should get rid of their mothers according to the negative number of coefficient on mothers' years of schooling. I compare my result to the related literatures and found that they have quite different results from mine. Pedro and Parey (2007) prove that one year of additional mother's education increases mathematics standardized scores by 5% of a standard deviation at ages 7 and 8 according to the OLS results. Although the results also show that the effects of mother's education tend to be smaller at ages 12-14, at least they tells people that mothers' education do have positive effect on children's outcomes (Pedro Carnerio & Parey, 2007). Pedro and Parey (2007) use data in
2006, which is quite close to the time of my data. Chevalier, Harmon, O'Sullivan & Wallker (2013) have a little different result: Least squares estimation reveals conventional results - stronger effects of maternal education than paternal, and stronger effects on sons than daughters. Their results show that both parents should have positive effect on children’s education and future. Holmlund, Lindahl, and Plug (2010) also concludes that there is positive intergenerational transmission of education. Parents' education is important to children's education and life, but fathers will cause more and mothers cause smaller (Holmlund, Lindahl, & Plug, 2010). Chevalier, Harmon, O'Sullivan, and Wallker (2013) reveal that conventional results - stronger effects of maternal education than paternal, and stronger effects on sons than daughters. It is one of the literatures that divide next generation into two groups: male and female. I also add gender to my equation. The coefficient on F* is 0.027. As I mentioned in the previous part, if F* is bigger than zero, it means that the female has higher rate of return to income than male. From the view of whole equation, it means that the effect of education of parents will be stronger on daughters than sons. The rate of return for son is 0.146, which one more year of schooling will increase 14.6 percent more of his wage; the rate of return for daughter is 0.173 and it means that an additional year of schooling will increase daughter's wage 17.3 percent more. Daughter’s rate of return to schooling is 2.7 percent more than son’s. It is different with Chevalier, Harmon, O'Sullivan, and Wallker's results. Their results show that son has higher
rate of return than daughter. Although some articles have different results for the degree of effect of parents’ education on their children, they all reveal that both parents’ education have positive relationship with children’s education and future. All these literatures are from 2004 to 2013 and they have good references for my results. So far I can conclude that my result is bias. I can make sure that the source of my data is reliable because it is from PSID, which is recognized by The National Science Foundation as one of the 60 most significant advances funded by NSF in its 60-year history. My theoretical model-mincer-earning equation provides a reasonably accurate description of schooling-earning profiles not only in the United States, but also in the labor markets of many other counties and is the most widely-used equation for solving labor and education problems. In this way, there must be something wrong with my methodology. I checked all my literatures and found that all the papers were strive for a problem called "endogeneity." I totally ignored "endogeneity when I started to run my regression. I think it is the biggest element that caused my result biased. I can get very fair and unbiased result by solving the problem of "endogeneity."

IV estimation

**Endogenous Variable**

Endogenous variable is a factor in a causal model or causal system whose value is determined by the states of other variables in the system; contrasted with an exogenous variable. Since the endogenous variable is related to another equation in the whole system and appears not only in the equation that we investigate but
also appears in both equations, the changes in another equation will cause the change for the endogenous variable and cause a different result for the equation we want to investigate. In other words, endogenous is jointly determined and could be another factor beyond our control. Obviously, the endogenous variable in my equation is mothers' years of schooling. The coefficient on other independent variable is normal. Only the coefficient of mothers' years of schooling is quite different from all the related literatures. I will focus on solving the endogeneity of mothers' years of education. Pedro and Parey (2007) also noticed the endogeneity of mothers' years of schooling in their paper. They believe that factors that influence the mother's decision to obtain schooling may also affect her ability to bring up children or may relate to other environmental and genetic factors relevant to child outcomes (Pedro Carnerio & Parey, 2007). The endogeneity will cause a quite different result. Chevalier, Harmon, O'Sullivan, and Walker (2013) found that the education effects remain significant even when household income is included. However, after solving the problem of endogeniety, they found that the strong effects of parental education become insignificant and permanent income matters much more. Belzil and Hansen found that the percentage of rate of return to schooling increase to 85 percent after controlling for the endogeneity (Belzil & Hansen, 2003). Chevalier (2004) noticed the endogeneity of parental education leads to estimates of mother's effect on the decision to remain in post-compulsory education that are twice as large. In almost all the models he presented, Chevalier
reject the endogeneity of parental education.

Instrumental Variable

To solve the problem of endogeneity, I will use "instrumental variable" to fix this problem. In statistics, econometrics, epidemiology and related disciplines, the method of instrumental variables (IV) is used to estimate causal relationships when controlled experiments are not feasible. So far eighty percent of papers in the literature review use instrumental variable to delete the endogeniety. A good instrumental variable should be a good proxy for the endogenous variable and uncorrelated with the error term. It is hard to find a perfect instrumental variable. I can infer a good instrumental variable from related literatures’ choices of instrumental variable. Chevalier (2004) uses local employment as an instrumental variable. The other paper also uses the grades of parents and unemployment of labor market. However, I think it is too hard to find the data of these variables. Pedro and Parey (2007) use cost of education as their instrumental variable. These variables have previously been used as instruments for schooling by Card (1993), Kane and Rouse (1993), Currie and Moretti (2003), Cameron and Taber (2004), and Carneiro, Heckman, and Vytlacil (2006), among others. I think it is a perfect instrumental variable for me now and I can find it in PSID. After find the instrumental variable, we will do Two-Stage Least Squares estimation. Two-stage Least Squares (2SLS) is a method of systematically creating instrumental variables to replace the endogenous variables where they appear as explanatory variables in simultaneous equations systems. First, I will run an OLS on the reduced-form
equations for each of the endogenous variable and get yhat for the endogenous variable. Second, I will substitute the reduced form yhat for the orginal endogenous variable that appear on the right side and then run OLS.

**IV Estimation(second regression)**

The endogenous variable I choose is school-related expense, which is not only tuition but also cost of other things in school. The year of data is also in 2011. First, I need to run OLS on my reduced-form equation. However, it is hard to find another identified equation in the whole systems. I make a short-cut for my reduced-form equation. I will run OLS on my endogenous equation (mothers’ years of schooling), instrumental variable (school expense) and other exogenous variables in my mincer-earning equation. The equation is like the following one.

\[
medu = \alpha_0 + \alpha_1 \text{schooling expense} + \alpha_2 \text{exprience}
\]

After regression, I will predict yhat for this equation. Yhat will become my instruments to substitute the endogenous problems in my mincer-earning equation. The purpose stage one is not to generate meaningful reduced-form estimated equations but rather to generate use meaningful instrumrnts (yhat) to use as substitutes for endogenous variables in the second stage. In the second step, I substitute yhat for the endogenous variables (mothers’ years chooling) and I got the following results (see table 2).

In this equation, we use yhat to infer the coefficient of mothers’ years of schooling. So the coefficient on yhat represents the relationship between mothers’ years of schooling and rate of return to schooling. I am glad to see that the
coefficient finally become positive after solving the problem of endogeneity. The coefficient on schooling indicates that an additional year of schooling for male will increase 14 percent of wage rate. We plus the coefficient of schooling and F*s and get the result that female will get 16.8 percent of rate of return to schooling if they have an additional year of schooling. Female will get higher rate of return to schooling and they will be affect by their parents' education more. The coefficient on the father's years of schooling reveals that an additional year of father's schooling will increase children's wage 0.7 percent. The coefficient on mothers' years of schooling indicates that children can achieve 41.6 percent more of wages if mother's education increases one more year. After regression, I make a vif test (see table 3) and hypothesis test. The result of hypothesis test is equal to zero.

IV estimation (second regression)

From the results of IV estimation, we can see that both mother and father's education will cause positive effect on children's future. Before we solve for the problem of endogeneity, we get the result that the coefficient of mothers' years of schooling is negative. It is not a feasible result. Although we fix the problem of endogeneity, the result is as reasonable as the other related literatures' results. The difference of coefficient on mother's education and father's education is so big. It indicates that fathers nearly have no impact on children's education and future. Mother take the major responsibility of children's education. However, in our real life, fathers and mothers both take responsibility of their children's education.
Chevalier, Harmon, O'Sullivan and Wallker (2013) reveals that difference between the coefficient of mothers' year of schooling and fathers' years of schooling is only 4 percent. However, the difference in my regression model is nearly 40 percent. I do not think it is very reasonable. I looked the results of vif test and hittest test. All the independent variables in my equation have values of vif are less than 5. However, p-value in my equation is less than 5 percent, which means I should reject it. I think now it is one of the reason that my result is a little biased. Meanwhile, I think that some exogenous variables in my equation may also be endogenous. Anyway, I prove that parents have positive effect on children's education and future. I will continue to solve the rest of my problems in my equation.

**Final regression (third regression)**

The result of my first OLS estimation is biased and the coefficient on mother's years of schooling is negative. I found the root of the problem is the endogeneity of mother's years of schooling. I use an instrumental variable to fix the problem of mother's years of schooling and get a positive coefficient on mother's years of schooling. However, the result of my IV estimation (second regression) is still biased. We can see that the difference between the coefficients on mother's years of schooling and father's years of schooling is huge. The coefficient on father's years of schooling is only 0.007. It is a very small number and means that fathers nearly have on effect on children's education and future. We all know that a child should be raised by mother and father together. Both parents have significant
effect son children's education. Although in some single parent families, only mother or father takes the main responsibility of children's education. I checked the data from PSID and found that single parent families are only small part among the whole population. Most families are not single parent families. So the coefficient on father's years of schooling is biased and I need to fix it. In my third regression, I plan to solve the problem of variable of father mainly.

**Endogeneity of Father's Years of Schooling**

In my first OLS estimation, I only noticed the endogeneity of mother's years of schooling. The property of father's years of schooling should be similar to mother's years of schooling. I should solve the endogeneity of father's years of schooling too. Then I can make sure the accurateness of my result. Similar to the ways of solving the endogeneity of mother’s years of schooling, I will use Two-Stage Least Square in my equation. Before this, I need to choose an instrumental variable. The instrumental variable for father's years of schooling is still school expense. In my IV estimation, I did not separate the mother's school expense and father's expense from the total school expense. I notice that it may affect my final result. I collect the data of mother's school expense and father's school expense respectively in PSID in this regression. In my first step, I will regress mothers' years of schooling, mothers' school expense and the other exogenous variables in my equation.

\[
medu = \alpha_0 + \alpha_1 \text{mother's schooling expense} + \alpha_2 \text{experience}
\]

(1)

Then I will predict yhat1 for this equation. In my second step, I regress father's
years of schooling, father's school expense and the other exogenous variables in my equation.

\[ f_{edu} = \alpha_0 + \alpha_1 \text{father's schooling expense} + \alpha_2 \text{experience} \]

(2)

Then I will predict \( y_{hat2} \) for this equation. The third step is to replace \( y_{hat1} \) and \( y_{hat2} \) for mother's years of schooling and father's years of schooling in my equation.

\[ \ln w = \alpha_0 + \alpha_1 s + \alpha_2 t + \alpha_3 t^2 + \alpha_4 y_{hat1} + \alpha_5 y_{hat2} + \alpha_6 F + \alpha_7 F \times s \]

(3)

Equation (3) is my final regression equation. I think I will achieve the most accurate result from this equation.

**Dealing with Data**

All the data in PSID is primitive and I never manage the sources of these data. Before I run my final regression, I need to make a progress for my data. In my first regression (OLS estimation) and second regression (IV estimation), I download data directly from the website of Panel Study of Income Dynamics (PSID). These data are very important and useful for my regression. However, they are first-hand data and there must be something unsuitable for my result. PSID collect data by making survey for all American families. when I check these data in excel, I find that some have very huge numbers, such as 999999, 999 and 99. These numbers are strange and unreasonable. For example, a person's years of schooling cannot be 99. I read the instructions of PSID and get the answer. Some people may miss
their survey or refuse to answer survey. The interviewer put the number like "99," "999" and "9999" as the responding of the survey. In this way, I eliminate those numbers in my data and can get a more accurate result. The PSID gathers data describing the circumstances of the family as a whole as well as data about particular individuals in the family. In PSID, there are different kinds of data, because the interviewees may be wives, husbands, and parents. Some data is only related to one person (such as wives of husbands). Some data combines the answers of a whole family. While some information is collected about all individuals in the family, the greatest level of detail is ascertained for the primary adult(s) heading the family. The data of wages, schooling of next generation and experience use the information of the head of family. However, the data of my instrumental variable (school expense) is consisted of a whole family. I categorize these data into groups of mothers, groups of father and groups of children. Then I delete the groups of children and keep the groups of mothers and groups of fathers.

The last problem of my data is pairing. Although the name of data in PSID website is like "completed education of head", "completed education of mothers" and "completed education of mother, I cannot make sure that they have relationship with each other. I need to make pairs for these children and parents. Then I can know these parents affect their own children in education and future life. It is a huge work to make pairs of these data. I find the data of "relation to the head" in PSID website and then check the code number of last generation and next
generation. If they have same code numbers, they are real households. The original number of my observation is 20,000. After pairing, there are only 8000 observations. My data becomes more precise.

Tests for my data

After dealing with the details of my data in PSID, I start to regress my final regression equation. Table 4 shows my final results. Also, I do VIF test again. Table 5 shows the result of VIF test of the data that I reorganized. At first, I do VIF test for each of my variable appearing in the equation. However, I find that multicolinearity is based on liner function. There are two variables (quadric of experience and F*s) are not the composition of liner function. So I change my equation in linear version and only test variables of F, experience, schooling of last generation, mother's years of schooling and father's years of schooling (see table 5). All my variables have small values, which is less than 5. I also test Park’s test heteroscedasticity of my data. The p-value is zero and is less than 5 percent. The heteroscedasticity is a problem and I robust it for my regression. The table 7 shows the robust standard errors.

Final results (third regression)

The results of my final regression is much better than the previous two regressions. The coefficient on father's years of schooling is much larger than the previous results. An additional year of father's years of schooling will increase children's rate of return to schooling 31.7 percent. The coefficient on mother's years of schooling is 0.519, which means that one more year of schooling of mother
will increase their wage 51.9 percent. Both coefficient on mother's years of schooling and father's years of schooling are positive. The results show that parents have positive effect on children's education and wages. The numbers of coefficient on parents' years of schooling are all very big. It shows that parents are very important for children's education. The difference between coefficients on parents' years of schooling is not as large as the results of second regression (IV estimation), but the coefficient on fathers' years of schooling is still lower than that on mothers' years of schooling. The coefficient on "s" (schooling) is 0.136, which means that the rate of return for male or sons is 0.136. An additional year of schooling for sons will increase his wage 13.6 percent. The coefficient on "F*s" is 0.0317, which means that female have higher wage return to schooling than male. The total rate of return for female is 0.13917 ("F*s" +"s") and tells people that female or daughters can achieve 13.917 percent more wages if they go to school one more year. The R-square of second regression (IV estimation) is 40.6 percent. After dealing with the problem of endogeneity and data, the R-square increases to 41.6 percent. Although the R increased, the number is still very small. Only 40.6 percent of result can be explained by my independent variables. Chevalier, Harmon, O’ Sullivan and Walker (2013) talk have similar problem. Only 41.6 percent of result can be explained by the variables they used in the equation. They thought the rest of percentage of result should be explained by ability bias. Blezil and Henson (2003) also mentions that the individual differences in wages are mostly
explained by abilities.

**Ability Bias**

Ability bias is a very common problem in labor economics and education economics. The rate of return to education plays a key role in much of labor economics. In my paper, my dependent variable $\ln w$ (logarithm of wage rate) is referred to the rate of return to schooling. Estimates of the return to schooling are central to discussions of the usefulness of education for development policy, for fighting poverty and for limiting race-related wage differentials (Lang, 1993). However, as economists began to estimate the impact of schooling on wages, they recognized that different abilities of people will make the result of rate of return to schooling biased. In labor economics, economists think that each worker faces a different wage-schooling locus-which, in turn, implies that each worker has a different marginal rate of return schedule. It is often assumed that higher ability levels shift the marginal rate of return schedule to the right (means higher wages), so that the earnings gain resulting from an additional year of schooling outweighs the increase in forgone earnings (Borjas, 2010). In other words, more able persons get relatively more from an extra year of schooling. More able persons are encouraged to go to school more because they can earn more money from an additional year of schooling. The conclusion of "more schooling is better" is not suitable for less able persons. Instead, an additional year of schooling wastes less able persons’ money because they cannot increase their earnings by going to school one more year. For those less able persons, entering to society early can
enable them to make more money. So ability bias is a critical part in determining
the rate of return to schooling. In most economists' views, ability bias appears as
an omitted variable in the mincer-earning equation. It seems that we just need to
put the variable of abilities of different people in my equation and then we can fix
this problem. However, the most difficult part of dealing with ability bias is how to
define ability bias. Ability of a person is a very abstract idea. It is hard to find the
information to express what specific idea of ability. For most people who tried to
solve this problem, they will use test scores to define abilities of different people.
I think it is very controversial. First, test scores are various and we cannot choose
which test scores to represent a person's ability. Should we choose SAT scores, GPA
or highest test scores in colleges or universities? Second, some people are just
good at studying and they can master the skills to achieve high test scores or GPA.
Some people who are not good at studying but have high abilities. Nobel prize
winners Yoshinori Ohsumi's grade was not well in his high school. His biology
teacher told him that he was not suitable to study Biology in the future due to his
performance in Biology exam. However, with his own efforts, he finally won Nobel
Prize in Biology. For a more accurate result, I still put variable of test scores in my
equation and want see how different result it is. I choose the overall GPA in high
school to define ability. Table 6 shows the result of my regression.

\[
\ln w = \alpha_0 + \alpha_1 s + \alpha_2 t + \alpha_3 t^2 + \alpha_4 \text{hat1} + \alpha_5 \text{hat2} + \alpha_6 F + \alpha_7 F \times s + \alpha_8 \text{gpa}
\]
When I put the variable of GPA in my equation, I found the unexpected results. The coefficients on yhat2 (father's years of schooling) and yhat1 (mother's years of schooling) are both negative. The coefficient on GPA is only 0.0009. It is a very small number and it has little effect on the rate of return to schooling. I also checked the R-square and I found it does not change a lot. The R-square of my final regression is 40.6 and the R-square of this regression is 40.779. There is no huge difference between these two results. In this way, I plan to give up adding the independent variable of GPA in my equation because it causes some strange results and does not improve R-square. I will only take the results of my final regression.

V. Policy Implication

My results of my final regression (table 4) show that both parents have positive effect on children's education and future. This intergenerational relationship of education encourages parents to receive more education and therefore your children will be beneficial from parents' education. We need to raise the schooling of each parent when they are in youth. A policy implication is that intergenerational transmission is important for understanding long term policy effectiveness. This is important because many programs are struggling to improve outcomes for poor children. Policy makers may not see the improvement of raising schooling very quickly, because it is cross-generational and we need to wait for a
period of time to see the effect of policy of increasing schooling of parents. Pedro, Meghir, Parey and Matthias (2007) also mentions the importance of timing because policies related to education really need a period of time to prove the effectiveness. However, programs which manage to increase parents’ schooling are likely to be important not only for parents now but also for their future children, and should be designed and judged with this in mind. In America, much money is spent on the educational system. If better educated parents are better in providing an environment that improves the success of children in school because of their education, improving the educational achievement of one generation has long term consequences; the educational achievement of future generations would then improve as well. Having said this, my findings indicate that the intergenerational schooling associations are largely driven by both mother’s education and father’s education. Since the impact of parental schooling on child schooling is large, we believe that educational expenses in United States that aim to improve the school outcomes of children may be beneficial not only within generations but also across generations.

VI. Conclusion

Summary of my regression

I run three regressions in this paper. I use the original data from PSID to run my first regression (table 1). The result is very not expected and the coefficient on mother’s years of schooling is negative. When I run my second regression (table
2), I solve the problem of endogeneity of mother's years of schooling and I get the positive coefficient on mothers's years of schooling. However, I find that there is a huge difference between the numbers of coefficient of parents' years of schooling. In my third regression (table 4), I deal with the endogeneities of both mother's years of schooling and father’s years of schooling. At the same time, I reorganize my data from PSID and delete some useless data. The results of the third regression are the most accurate one because I finish dealing with all the possible problems of my data and equations. The results show that parents have very positive effect on children's education and future. If parents accept more education, children will also accept more education and earn more money when they enter into society. The coefficient of mother's years of schooling is larger than that of father's years of schooling. It implies that mother will have more effects on children's education. Chevalier, Harmon, O'Sullivan & Wallker(2013) have the result as mind. They also find that maternal education has larger effect on children's education than paternal education. It is true that mother will spend more on children's education than father. Survey from Foundation for Children Development give us a conclusion: mothers will spend two to three hours more in a day accompanying their children than fathers (Hernandez & Napierala, 2008). Since mothers spend more time with their children than fathers, they have more chance to educate their children and give instructions for their children. In this case, mothers apparently affect their children more. However, it does not mean
that paternal education is useless. Both parents are critical for the children's education and growth, but maternal education will contribute more. The R-square is very low. Chevalier, Harmon, O'Sullivan, and Wallker's results reveal that son's education will be affected more by parent's education, but I got the opposite result. I find that female will achieve wages than male if they go to school one more year under the effect of parents' education. My results mean that the rise of female. If both female and male accept same education, female will earn more than male. In nowadays society, although the world is still dominated mainly by male. We can still see that female's position is becoming more and more important. However, there is still a big problem for results. My independent variable can account for 40.6 percent of my results. According to Chevalier, Harmon, O’ Sullivan and Walker (2013), the rest of results should be explained by ability bias.

**Limitations of my result**

Although I took action to fix the problem of ability bias, the result is not very well. I used GPA to define ability bias in my equation but I think it is biased and I give up this method. I will only keep the result of final regression. It is the only result that can explain my answers to my research question. Chevalier, Harmon, O’ Sullivan and Walker (2013) do not take action to fix the ability bias. Both my paper and their paper think that it is hard to add a specific variable of ability in the equation. I think my result is biased because of the limitations of ability bias. Maybe in the future, economists can fix the problem of ability bias very perfect. We need more research and find out very perfect variable to define different abilities
of people. Meanwhile, the R-square is not always close to zero in both my paper and the other papers in my literature review. We cannot determine that the rest part of my result, that is cannot be explained by the independent variables in the equations, is totally due to ability bias. There must be some other hidden variables and it needs further study in education economics. So the future steps for those people who study education economics are might focus on finding out hidden variables behind mincer-earning equation.

**My contribution**

Holmud, Lindal and Plug (2010) use data in 2009. Their paper is the latest one in my part of literature review. However, I use data in 2011 from PSID and it means my result represents the latest trend of relationship between parents’ years of schooling and children's future. I use data from PSID, which covers all American families’ information. Pedro and Parey (2007), Plug (2003), and Chevalier, Harmon, O’ Sullivan and Walker (2013) only study one or few states in America. So my paper has a bigger picture of the relationship between the parents’ education and children’s future. Although Chevalier (2004) also talks about the whole America, he compares data in UK and information in USA. My paper only focuses on America and talks more specifically about American education than Chevalier (2004)'s paper. Lots of paper uses panel data to study the effect of parents' education. Pedro and Parey (2007) uses a panel which follows 12,686 young men and women, aged between 15 and 22 years old in the first survey year of 1979. Surveys are conducted annually from 1979 until 1994, and every two years from 1994 onwards. They use
data up to 2002. My data is cross-sectional since there is data for parents' education in PSID. Panel data needs accumulate years of data from the adolescences to adults. Pedro and Parey (2007) observe mothers over a number of years. It is convenient for those only focus on one parent's education. We all know that it is easy to track one's information from her graduation until marriage. However, it is hard to track both parents' information together from their adolescences to becoming fathers and mothers. So I think PSID will be a good choice to include both parents' information. Since it is family-level data, we can extract all information we want, such as children's information. mother's information and father's information. It is more accurate and reliable. As I mentioned in the part of results, many papers get a result that sons will be affected by parents' education. I think it is one of my contribution that prove female will earn more money than male after they graduation. 

Cheavlier (2004), Holmund, Lindal and Plug (2010) and Pedro and Parey (2007) only study how parents' education affects children' education or grades. The rate of return schooling represents the impact of last generation's income with the effect of schooling. It is a combination which connects education and children's income together. I uses rate of return to schooling in my equation and then I study the effect both children's education and future, which is referred to income.
VII. List of graphs

First Regression

<table>
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<tr>
<td>fathers' schooling</td>
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<td>F*S</td>
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Table 1 (OLS estimation)
Second Regression

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<td>fathers' years of schooling</td>
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<td>F*s</td>
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Table 2 (IV estimation)

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## Final regression

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<td>$F^*s$</td>
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## Table 4

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Table 5

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Regression with GPA

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Table 6

<table>
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<tr>
<td>F*S</td>
<td>0.0144</td>
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Table 7
References


Lang, K. (1993). Ability Bias, Discount Rate And the Return to Schooling. *Economics Department of Boston University, 28.*

