The Role of Family Income Shocks During Childhood and Adolescence on Children's Educational Attainment

by
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Chapter 1

Introduction

Human capital is a relatively new concept of modern society. In 1961, the economist Theodore W. Schultz (1961, p.5) was writing in his paper *Investment in Human Capital* that “the mere thought of investment in human beings is offensive to some of us”. This illustrates the novelty of this concept in human history. The concept of *Human Capital* has its roots in the work of Becker (1964) starting in 1957. He is the one who first showed the importance of human capital development through investment in schooling, on-the-job training, medical care, migration, and searching for information about prices and income. He argued that human capital investment is just like any other investment such as a bank account, providing “income and other useful outputs over long periods of time” (Becker, 1993).

Despite its modernity, the concept of human capital investment gained a lot of popularity and is now referred to as equally important as any other resource investment a country can make (World Economic Forum, 2013, p.3). In the knowledge based economies we live in, many believe that the only way to remain competitive is to have a skilled, intelligent and talented work force. As the World Economic Forum mentioned in *The Human Capital Report*, “the key for the future of any country and any institution lies in the talent, skills and capabilities of its people” (World Economic Forum, 2013, p.v). They believe in the importance of investing in human capital to such an extent that they have created a Human Capital Index, which allows for a country ranking in terms of investment in human capital. A report by the OECD agrees with the notability of human capital and says that “human capital plays an important role in economic growth" (Keeley, 2009, p.12). The World Economic Forum provides several definitions of human capital, among which one is of greater interest for this paper, that is that "human capital is the capacity of the population to drive economic growth" (World Economic Forum, 2013, p.3).

In a context of ageing populations and low fertility rates both putting pressure on public finances, knowing when and how to better invest in human capital is a crucial ally for any economy. As for the timing of investment, James J. Heckman, strongly believes that the best time to invest is as early as possible. In his paper, *Invest in early childhood development: Reduce deficits, strengthen the economy*, he advocates that the most effective way to invest is in the development of young children, especially those at risk (Heckman, 2012). Professor Heckman stipulates that this strategy holds even in times of budget crises. As for the implementation of those investments, several strategies can be applied. It is however important to know which families are the most in need. This is where this study enters the debate of knowing which set of circumstances cause the most damage in children's human capital development. More precisely, this study looks at the impact of family income shocks during childhood and adolescence on educational attainment in the United States. In other words, this research investigates whether more public policy should also focus on families experiencing a significant financial shock for the sake of protecting children from the potential consequences related to such an event, that is lower academic performance preventing the pursuance of higher studies. The study tries to find whether there exists a link between a reduction in the parents' financial ability and their children's academic outcome. As Professor Heckman puts forward in his paper, families under financial pressure have less resources to invest in their children. Moreover, the OECD paper on Human Capital argues that it is much harder for children raised in poverty to develop their skills and that they are less likely to finish high school and attend university. This is why it is interesting to know if significant reductions in household income can adversely affect children's academic performance and whether policies should be enacted to address this issue.

Chapter 2

Literature Review

2.1 Evolution of Family Income in the United States

Prior to providing an investigation of the potential link between educational attainment and movements in parents' earnings, it is helpful to have a global picture of characteristics of family income in the United States for the period of study (1968-2011). Nichols and Zimmerman (2008) found that as opposed to individual income, family income exhibited an increasing volatility pattern over their period of study, that is 1968 to 2005. Using PSID as their dataset[1], they observed that the volatility of family income rose by about a quarter over their 37 years of analysis (Nichols and Zimmerman, 2008, p.1). This result of increased volatility was also pointed out in Gottschalk and Moffitt (1994). However, they went further showing that "the widening of the earnings distribution has resulted from a rise in the instability of earnings" (Nichols and Zimmerman, 2008, p.224). Interestingly, Gosselin and Zimmerman (2008, p.25) showed that large income shocks were more likely in the 1990s and the early 2000s than in the 1970s and 1980s. Along the same line of argument, Acs, Loprest, and Nichols (2009) from *The Urban Institutes* published a paper analyzing the likelihood of experiencing a significant drop in income for families with children along with the likelihood that they recover from the shock (Acs et al., 2009, p.2). Using data from the Survey of Income Program of the 1996, 2001, and 2004 waves, they were able to study income shocks on a four-month basis, which allows for a more refined analysis. Their

[1] A description of the PSID database can be found in the methodology section.

approach was to examine the characteristics and circumstances under which families were more likely to experience income shocks. They observed that 13.6% of families live through a 50% reduction in income during a year (Acs et al., 2009, p.2). A job loss and the onset of a disability are important risk factors according to their findings. As for the recovery time, when the income shock was associated with the departure of a couple member, the recovery takes much longer (Acs et al., 2009, p.2). Lastly, they found that the level of education of the adults in the family was not significantly correlated with the occurrence of important income shocks.

In sum, the literature agrees that the volatility of family income increased during the study period of the paper, which justifies the interest in the impact of those fluctuations on the development of children's human capital. The next section discusses a paper which broached this subject while using a different methodology than the one that was used in this paper.

2.2 Impact of Fluctuations in Family Income on Education Outcomes

Elliott et al. (2012b) published a series of three papers about the potential relationship between economic instability and children's human capital. They analyzed whether there is a connection between income shocks, asset shocks, home loss and asset poverty, and education outcomes, using the Child Development Supplement and Transition to Adulthood of the Panel Survey of Income Dynamics (PSID) database, of the 1984, 1989, 1994, 1999 and 2009 waves. From their research, an interesting pattern emerged; low-income families behave following a consumption-based pattern with a very short-term perspective, as opposed to high-income families who behave according to an asset based path with a forward looking behaviour. This implies that low-income families focus on making ends meet while higher income families can concentrate on accumulating assets for long-term spending. This observation was the foundation upon which the series of papers was based. The first paper of this series discusses the *Probability of living through a period of economic instability.* They found that about 43% of children living in low-income households are experiencing a major shock during their life, which they have defined as a 50% reduction in family income. This probability goes up to 55% for minor shocks, which is a reduction in family income of 25%. Another interesting finding is that when comparing the 2005-2009 period to the 2000-2004 period, the probability that a child experiences a net worth shock[2] doubled. The second paper aims at explaining *What are the predictors of economic instability.* Change in marital status of parents or caregivers was found to be the "strongest and most consistent risk factor for a child" along with being in a family receiving Food Stamps, whose parents or caregivers experienced a job loss, and being black (Elliott et al., 2012a, p.2). Unsurprisingly, they found income to be the strongest protector against economic instability along with receiving Supplement Security Income. The last and main paper of this series investigates *The effects of economic instability on children's educational outcome.* As previously mentioned, the paper investigated whether income shocks, asset shocks, home loss and asset poverty had an impact on children's education outcomes. Those outcomes were academic performance, high school graduation, enrolment in college as well as graduation from college. Their analysis shows that children in families with low liquid assets[3] and net worth assets were more likely to underperform academically, less likely to graduate from high school, enrol in college, and if they do, less likely to graduate (Elliott, 2012, p.2). As for family income shocks, they reported that a minor income shock before the age of 11 years old was associated with higher academic performance in 2002. Furthermore, they also outlined the fact that children experiencing a 25% family income shock are 71% less likely to graduate from high school and 67% less likely when the shock is a 50% reduction. Contrastingly, they found that living through a 25% income shock was positively associated with college graduation.

Challenging the methodology of Elliott et al. (2012b), this study addresses the shortcomings of their series of papers, and expands the scope to include a longer time-series from the PSID main file along with the Child Development Supplement and Transition to

[2]Net worth shock is defined as a reduction in family wealth including "real-estate, vehicle, business assets, shares of stock in publicly held corporations, mutual funds, investment trust, checking and saving accounts, money market funds, certificates of deposit, saving bonds, treasury bills, investments in trusts, life insurance policies, minus all debts" (Elliott et al., 2012b, p.5)

[3]Liquid assets include "money in checking and or saving accounts, money market funds, certificates of deposit, government savings bonds or treasury bills" (Elliott, 2012, p.2).

Adulthood databases. The first weakness is the use of five-year increments for the income shock variables (Elliott et al., 2012b). Such increments leave a wide gap in which significant fluctuations in family income can take place. As Acs, Loprest, and Nichols (2009) mentioned in their study, about 38% of families who faced a 50% income shock recover within a year, highlighting the importance of studying the income shocks within the smallest interval possible. Also, if the reduction in income was due to loss of employment, then the five year interval leaves plenty of time to the parent or caregiver to find another position before the next wave. If the new employment is at a lower wage rate, a major shock might be treated by the researchers as a minor shock since the family income is no longer as low as before new employment is found. Another point that raises concerns is the fact that the methodology does not take into consideration increases in income in a given year that could be due to a bonus for example. This could lead researchers to believe that the family experienced a reduction in income the year following the bonus. The adjustments to the methodology implemented to address those issues are explained in the next section.

Chapter 3

Methodology

3.1 PSID Database

This study on the impact of family income shocks during childhood and adolescence on educational attainment relies on the Panel Study of Income Dynamics (PSID) database, which is believed to be the world's largest still operational household survey (Panel Study of Income Dynamics, 2014a). Established in 1968, it is a nationally representative database following 5,000 families and their descendants for a total of over 18,000 individuals. Managed by faculty at the University of Michigan, the data was collected every year up until 1997. It has been collected every two years since. The database was first constructed with two distinct samples, the Survey Research Center (SRC) and the Survey of Economic Opportunities (SEO). Created by the Survey Research Center at the University of Michigan, the SRC sample was a nationally representative sample of 2,930 households (Panel Study of Income Dynamics, 2005). The importance of the use of weights originates from the nonrepresentative sample selection on which the SEO was based. Before being merged with PSID, the SEO was run by the Census Bureau and the sample was drawn from high minority areas. For instance, the maximum earning threshold to be part of the SEO was $2,000 plus $1,000 per family member. It is therefore imperative to use weights when working with both subsamples of PSID due to the oversampled minorities caused by the unequal selection probabilities, as well as the difference in the nonresponse rates and attrition (Panel Study of Income Dynamics, 2014b).

Despite the fact that PSID has always collected some information about children of family units, the main focus was on the family unit and the adults it included. In order to provide a tool to better study the dynamics of early human capital accumulation, PSID launched the Child Development Supplement (CDS) in 1997. The objective of this new supplement was to investigate in more depth the children of the family units as well as the adults from a parent or caregiver perspective. The Child Development Supplement has three waves, one in 1997, 2002-2003 and 2007. In the first wave, 2,394 families participated, resulting in 3,563 children, aged between newborn to 12 years old, taking part in the survey (Panel Study of Income Dynamics, 2010). The 2002-2003 wave interviewed for the second time 2,021 families, for a total of 2,907 children (Panel Study of Income Dynamics, 2010). In the 2007 wave, 1,506 children aged between 10 and 19 years old were successfully re-interviewed. In 2005, in pursuance of closing another gap in the main file, PSID decided to launch an additional supplement called Transition to Adulthood (TA). Aware that the young adults were no longer leaving their parents' home as quickly as they used to a few decades ago, researchers realized that this new way of transitioning into adulthood was becoming a crucial period for human capital investment and that more data should be collected during the 18 to 28 years old period. According to PSID, less than half of individuals will start their own family before the age of 20. The Transition to Adulthood survey is seen as the bridge between the Child Development Supplement, which collected information from birth to 18 years, and the PSID main file, which collects information once economic independence is achieved. To be part of the TA survey, the individuals had to be a CDS sample member, at least 18 years old, living with his or her parents and no longer attending high school. In the 2005 wave, 745 individuals matched those criteria and were interviewed. In 2007, 1,118 individuals were interviewed. The 2009 wave interviewed 1,554 individuals, and the last wave (2011) interviewed 1,907 individuals.

3.2 Data Selection

To find whether there exists a link between a family income shock during childhood and adolescence on educational attainment, the analysis was conducted in two steps. The first analysis was conducted using the PSID main dataset. The subsample used includes 3,200 individuals, born between 1968 and 1986, who responded to the 2011 wave, and who had a complete time-series of family income. This subset of the main PSID dataset was chosen in order to properly construct the income shock variables, which requires data on total family income during the entire life of the individual. The upper threshold of 1986 was selected to allow in the dataset only individuals with completed education, assuming a general time period for completion. This way, in 2011, when the survey was administered, those individuals were aged between 24 and 43 years old, depending on when the questionnaire went out during the year. The second step of the study was conducted on the Child Development Supplement and Transition to Adulthood databases. The analyses conducted on the CDS dataset in 2002 included 2,240 children. The analyses on the Transition into Adulthood dataset included 722, 544 and 1,450 individuals in 2007, 2009 and 2011 respectively. It is also important to note that some immigrant families were dropped from the study altogether because they were first introduced in the PSID database in the late 1990's, which means that data on total family income was not reported for the entire life of the children. It sums to 301 individuals part of immigrant families not included in the study.

3.3 Description of the Variables Used

In order to study the role of income shocks on children's educational outcomes, several variables were used.

Total Family Income

Total family income was the sum of taxable income of Head[4] and Wife[5], transfer income of Head and Wife, taxable income of other family unit members, transfer income of other family unit members and Social Security income. All values of the total family income time series were adjusted for inflation with the 2009 price level using the consumer price index obtained from the St-Louis Federal Reserve.

[4] See Appendix A.
[5] See Appendix A.

Average Family Income

Average family income was calculated by summing all family members' income from the year of birth either until the year a particular analysis was conducted or until 18 years old and then dividing by the appropriate number of years.

Income Shock

The objective of this variable is to indicate whether a child was part of a family that experienced an income shock. In order to do so, a comparison between the realized total family income and expected total family income was done. This approach ensures, for example, that no income shock is recorded following a bonus in a given year since each realized total family income is compared to the expected total family income. The advantage of this method is the focus it gives to the study. It emphasizes income shocks that are below the potential income based on the characteristics of the Head[6,7]. An alternative approach is described in Appendix B.

The expected total family income was estimated using the linear dynamic panel estimator of Blundell and Bond. Linear dynamic panel specification model regress the dependent variable on a set of explanatory variables as well as the lag of itself. This creates a problem as the lagged dependent variable is correlated with the unobservable panel effect. Blundell and Bond (1998) proposed a method for solving this issue, which involves using moment conditions in which "lagged differences are used as instruments for the level equation in addition to the moment conditions of lagged levels as instruments for the differenced equation" (Blundell and Bond, 1998). The explanatory variables included in this model were age of the Head, gender of the Head, employment status of the Head, family size, family composition, education level of the Head, and region at the time of interview. See Table C.1 and Table C.2 for regression outputs for the PSID as well as CDS and TA datasets respectively.

[6]PSID started collecting all the information on the Wife or "Wife" only in 1985. Including it starting in 1985 was creating a structural break in the analysis. This is why the information of the Wife or "Wife" is not included in the model's predicted total family income.

[7]This way, when a family earns a lot more than the expected income in $year_t$ but much less in $year_{t+1}$, if the earnings in $year_{t+1}$ remain above the expected income, the reduction in income will not be recorded as a family income shock. This particular household is expected to be able to maintain investment in their children's human capital in this situation.

Once the fitted values for all families were obtained, several binary variables were generated as follow:

Minor Shock

A minor shock was considered to be a difference of at least 25% but less than 35% between the realized and expected total family income.

Moderate Shock

A moderate shock was considered to be a difference of at least 35% but less than 50% between the realized and expected total family income.

Major Shock

A major shock was considered to be a difference of 50% or more between the realized and expected total family income.

Once those family income shock binary variables were obtained, another binary variable was created to indicate whether an individual ever faced a certain kind of family income shock before the age of 18. The 18 years old threshold is important because the objective is to know whether a family income shock during childhood and adolescence has an impact on educational attainment. Another variable indicating whether the individual experienced a shock before a certain threshold, e.g. before 2002, was also created.

Moreover, the analysis was also performed with another version of the family income shock, that is whether the children experienced a shock before and/or after 10 years old. Since the last year of elementary school is generally completed during the 10th year of a child's life (Path2usa, 2014), it seems to be an appropriate threshold between childhood and adolescence[8].

Lastly, it was interesting to combine the experience of an income shock with the fact of being in a low-income, average-income or high-income family when a given shock took place. In other words, a categorical variable was created to indicate in which of

[8] The variable *ever experienced a family income shock at or before the age of 10 years old* is inclusive of the 10th year unlike the variable *ever experienced a family income shock after the age of 10 years old.*

the nine possible combinations individuals were[9]. The thresholds of the three income categories were created using the quartiles. Each year, the data was used to calculate the three quartile thresholds as Table B.1 illustrates. Those thresholds were then used to categorize the families into three groups. The bottom 25% of the sampled families were included in the low-income class, the middle 50% were included in the average-income, and the upper 25% were categorized as high-income.

In order to quantify educational attainments of children, four measures were used at different stages of children's lives.

Academic Achievement

The Child Development Supplement reports the score of the Woodcock-Johnson Revised (WJ-R) tests of achievement. Those tests are:

> "designed to provide a normative score that shows the CDS target child's reading and match abilities in comparison to national average for the child's age. The normed scores are constructed based on the child's raw score on the test (essentially the number of correct items completed) and the child's age to the nearest month. Raw scores are charted on normative tables based on the child's age and what percentile the child falls into."(Panel Study of Income Dynamics, 2014a)

The variable academic achievements is the weighted average of the percentile rank of all tests completed. The tests included Applied Problems, Calculation, Letter-Words and Passage Comprehension.

High School Graduation

High school graduation was generated by a dummy variable being equal to 1 if the variables asking the year of graduation was not equal to 0, otherwise the dummy was equal to 0.

[9]The complete list of possibilities is: 1) experienced a minor family income shock while being in a low-income family, 2) experienced a minor family income shock while being in an average-income family, 3) experienced a minor family income shock while being in a high-income family, 4) experienced a moderate family income shock while being in a low-income family, 5) experienced a moderate family income shock while being in an average-income family, 6) experienced a moderate family income shock while being in a high-income family, 7) experienced a major family income shock while being in a low-income family, 8) experienced a major family income shock while being in an average-income family, 9) experienced a major family income shock while being in a high-income family.

Enrolled in College

Whether children were ever enrolled in college was obtained through only one question asking directly for that information. The Transition into Adulthood also made the distinction between being enrolled in a 2-year, 4-year or graduate college program.

Control Variables

Many variables were used in order to control for specific characteristics of each child.

Logarithm of Average Total Family Income

The logarithm of the average total family income was taken in order to capture the average income of the family in the regression analysis and to address the skewness of the distribution.

Change in Employment Status of the Head

This variable indicates whether the Head of the family went from employed to unemployed at some point during the life of the child.

Ever Received Supplemental Security Income

This variable was created from a variable asking the amount of Supplemental Security income received in a specific year. Whenever the answer was greater than 0, the binary variable ever received SSI was set to 1.

Ever Received Food Stamps

This variable was created using a variable asking about the amount received in Food Stamps. Whenever this variable was greater than 0 the binary variable ever received Food Stamps was set to 1.

Education of Head

This variable was generated from a variable asking the highest level of education of the Head. It was divided into five categories: less than high school, high school, some college, bachelor degree and graduate school.

Region

This variable represented the region where the children's family was living at the time of the interview. The states were assigned by PSID to regions as follows:

Northeast

Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, Vermont.

North Central

Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, Wisconsin.

South

Alabama, Arkansas, Delaware, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, Washington DC, West Virginia.

West

Arizona, California, Colorado, Idaho, Montana, Nevada, New Mexico, Oregon, Utah, Washington, Wyoming.

Change in Marital Status

This binary variable equals 1 whenever the Head changed marital status during the child's life.

Sample Weights

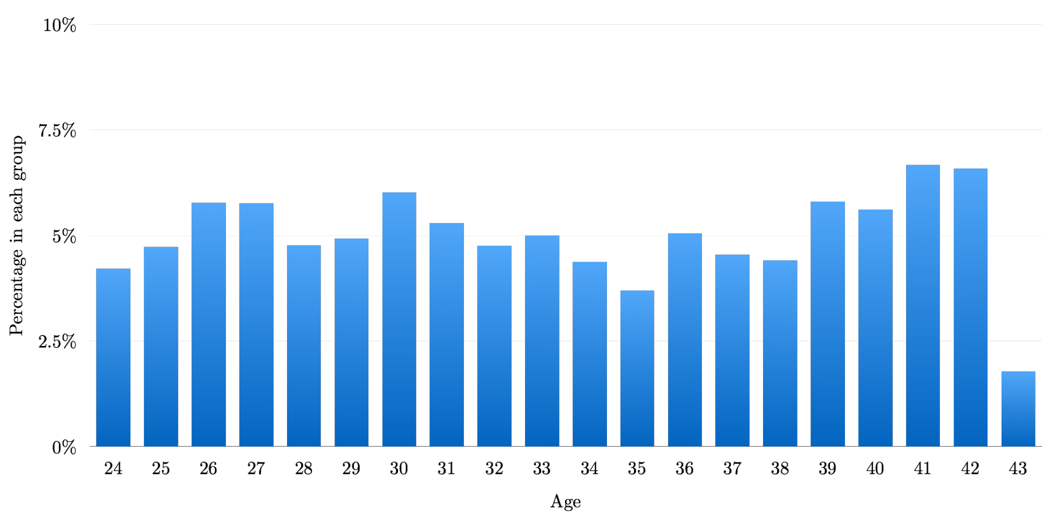
As mentioned previously, in order to obtain a sample representative of the american population using the combination of the SRC and the SEO samples, the use of sample weights is necessary because of the unequal selection probability. Not using the sample weights and assuming simple random sampling would lead to an underestimation of the variance of the survey estimates as explained by Heeringa et al. (2011, p.3) in a technical paper on sampling error estimation specifically for the PSID database. One way to address this issue is to use the Taylor Series Linearization method. This method deals with complex sampling designs with unequal clusters, which is exactly the case of PSID. A cluster is, according to The Statistics Glossary (2014), a subgroup of the entire population from which a random sample will be drawn. The consequence of having such a sample design is that the estimates will not be a linear function of the data. This is how Taylor Series Linearization comes into play, by linearizing the relationship. In this particular study, the individual weights provided by PSID have been used for the analysis conducted on the PSID main file, the child weights from the Child Development Supplement were used for the analysis on academic achievement on the Woodcock-Johnson test, and the Transition to Adulthood sample individual weights were used for the analysis on the high school graduation, college enrolment, whether enrolled in a 2-year, 4-year or graduate program, and finally on the highest grade achieved.

3.4 Summary Statistics

3.4.1 Demographics

First in terms in race, in 2011 about 73% of the individuals were white, 14% were black, 2% were american indian or Alaska native, 2% asian and native Hawaiian pacific islander. Furthermore, there was about 50% male and 50% female. Figure 3.1 illustrates the age distribution of the cohort in 2011. All ages seem to have around 5% which makes the age distribution relatively even.

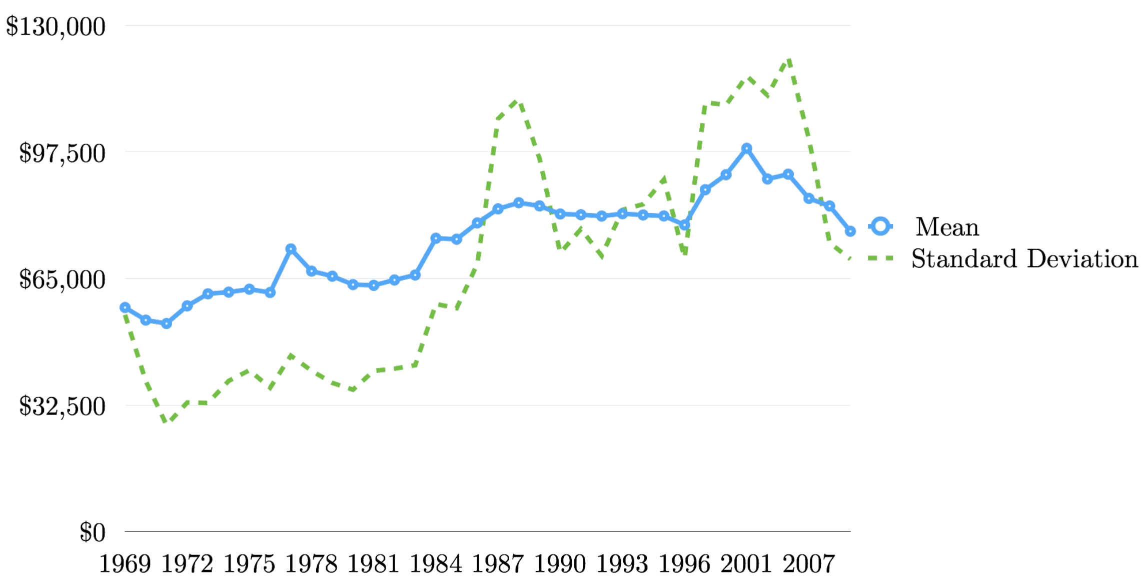
Figure 3.1: Percentage of Individuals in Each Age Category of the 2011 Cohort using the PSID Dataset



3.4.2 Total Family Income

Since total family income is central to this analysis, it is interesting to look more into it. Figure 3.2 provides information about the mean and standard deviation of total family income over the period of study (1968-2011) of individuals who participated in the 2011 wave. The mean consistently increased over the period of analysis, starting from about $57,000 in 1968 to about $77,000 in 2011, both expressed in 2009 dollars. This is equivalent to a growth of about 1.67% per year. The late 80's brought a significant increase in total family income volatility. In line with income, it is interesting to know that about 40% of individuals in the study lived in a family unit that received Food Stamps at some point during the child's life. In 2011, about 15% of the surveyed families benefited from that program. This contrasts with the fact that only about 8% of individuals lived in families who received Supplemental Security Income.

Figure 3.2: Means and Standard Errors of Total Family Income for the Study Period (1968-2011) using the PSID Dataset



3.4.3 Outcome Variables

This study is constructed in such a way that the longitudinal information provided by PSID on family demographics is exploited and then inputted in a cross-sectional analysis of outcomes. The first outcome looked at was the highest grade achieved in 2011 of those born between 1968 and 1986. As Table 3.1 shows, in 2011, the year in which the analysis was conducted, about 10% had less than high school as their highest level of educational attainment, 27% had high school, 26% had some college, 22% had a Bachelor's degree, and 14% had some or completed graduate school.

Table 3.1: Distribution of Highest Level of Completed Education in 2011 using the PSID Dataset

Highest level of completed education in 2011	**Percentage**
Less than high school	10%
High school	27%
Some college	26%
Bachelor degree	22%
Graduate degree	14%

The second outcome analyzed was academic achievement in 2002. Before attempting to explain why a kid would do better than the others, it interesting to know how the sample is doing in representing the normalized distribution of the grades when the tests were initially conducted. In 2002, the percentile rank distribution is as shown in Table 3.2, about 38% of children were below the 50^{th} percentile rank threshold on average for all tests completed, about 28% were between the 50^{th} and the 75^{th} percentile rank threshold on average for all tests completed and approximately 19% were between the 75^{th} and the 90^{th} percentile rank threshold and 14% were above the 90^{th} percentile rank threshold. Clearly, the sample is slightly off but it is still offering a great deal of information about the distribution of the grades.

The third outcome analyzed in this study is high school graduation in 2007. In 2007, the youngest was 9 years old and the oldest was 23 years old. Children aged 18 to 23 years old are hence used for this analysis. This leaves enough room for some children who might have encountered some difficulties leading to postponing graduation. The outcome variable

Table 3.2: Percentile Rank on Average for All Tests Completed Using the CDS Dataset

Percentile rank	**Percentage of Children**
Below the 50^{th}	38%
Between the 50^{th} and the 75^{th}	28%
Between 75^{th} and the 90^{th}	19%
Above the 90^{th}	14%

asked whether they have graduated from high school in or before 2007. From the 40% of young adults who could have graduated before or in 2007 because they were at least 18 years old, about 87% graduated.

The fourth outcome in terms of educational attainment analyzed is whether the children from the 1997 CDS wave enrolled in college and if so if they were enrolled in a 2-year, 4-year or graduate program in 2009. Interestingly, about 61% of those aged 18 years old or more were enrolled in college in 2009. Of those enrolled in college, about 28% were seeking a 2-year program, 56% were seeking a 4-year program and 14% were seeking graduate school. The remaining individuals enrolled in college were not seeking a degree, they were just taking courses.

Lastly, the study looked once more at the highest grade achieved but with the data from the Child Development Supplement and Transition to Adulthood databases. The gain from conducting this additional analysis is that it allows for a different sample group to be analysed. Young adults that are still in the Transition to Adulthood were still living with their parents, which could potentially be a sign of more human capital investment than their counterpart in the PSID main file who have acquired their independence. The youngest in 2011 was 14 years old and the oldest was 27 years old. The results are expressed in Table 3.3.

Table 3.3: Highest Level of Completed Education by Young Adults in 2011 Using the TA Dataset

Highest level of completed education	**Percentage**
Less than high school	0.6%
High school	23%
Some college	52%
Bachelor degree	4%
Graduate degree	14%

3.4.4 Shock Variables

The objective of this study is, as previously mentioned, to find whether there is a link between family income shocks during childhood and adolescence on educational attainment. To attain this objective, income shock variables had to be defined. The next section explains those variables and analyzes the likelihood of going through a financial shock during the period of study (1968-2011).

The first income shock looked at was a 25% difference between realized and expected total family income. The same procedure was used for moderate and major income shocks. Table 3.4 illustrates the total percentage of individuals who experienced at least once a total family income shock during their childhood or adolescence.

Table 3.4: Percentage of Individuals who Experienced a Total Family Income Shock at Least Once During Childhood or Adolescence Using the PSID Dataset

Magnitude of the income shock	**Percentage**
Minor income shock (-25%)	49%
Moderate income shock (-35%)	47%
Major income shock (-50%)	44%

For the entire period (1968-2011), about 49% of individuals have lived through a family income shock of at least 25%. Approximately 47% experienced a moderate reduction of income of 35% and 44% faced a reduction in income of at least 50%.

As for the sample from Child Development Supplement and Transition to Adulthood, it seems like more respondents reported having lived through all shocks during their life, as Table 3.5 illustrates.

Table 3.5: Percentage of Individuals who Experienced a Total Family Income Shock at Least Once During Childhood or Adolescence Using the CDS and TA Datasets

Magnitude of the income shock	**Percentage**
Minor income shock (-25%)	50%
Moderate income shock (-35%)	56%
Major income shock (-50%)	59%

Figure 3.3: Percentage of Individuals who Experienced a Total Family Income Shock per Year Over the Study Period (1968-2011) Using PSID Dataset

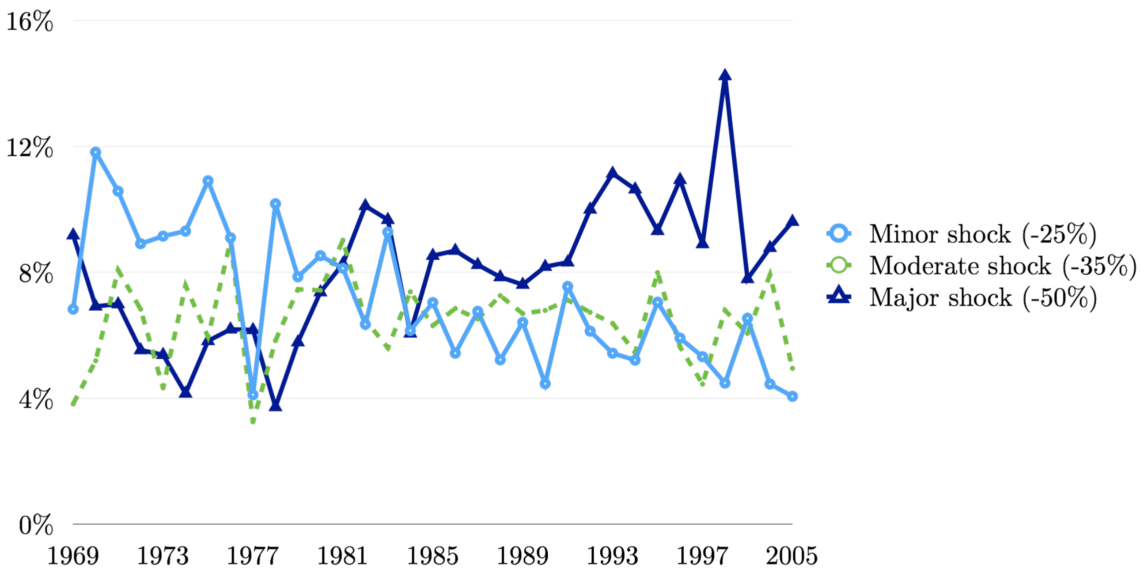


Figure 3.3[10] illustrates the percentage of children and adolescents who experienced a total family income shock per year over the study period by type of shock. There is clearly a downward trend in the probability of experiencing a minor income shock during the period of interest. As for the probability of experiencing a moderate shock, it seems like there is an oscillation around a long-term average. The probability of experiencing a major shock seems to increase over time. Before the beginning of the 80's, the likelihood of experiencing a minor shock was slightly higher than the one of experiencing a major shock. However, the situation reversed quite rapidly after this point.

Breaking down those probabilities by income allows for a better understanding of which income class is more prone to the three main levels of income shocks. The thresholds of the three classes were created using the quartiles. Each year, the data was used to calculate the three quartile thresholds as Table B.1 illustrates. Those thresholds were then used to categorize the families into three groups. The bottom 25% of the sampled families were included in the low-income class, the middle 50% were included in the average-income, and the upper 25% were categorized as high-income. Figure 3.4 illustrates the probability of

[10]Each year, the percentage of children experiencing an income shock was calculated only out of the total number of children born that year, not over the whole sample size. This allows a more accurate measure of the probability of experiencing an income shock.

experiencing a minor family income shock given that the families were categorized as low, average or high-income. Figure 3.5 illustrates the probability of experiencing a moderate family income shock given that the families were categorized as low, average or high-income. Figure 3.6 illustrates the probability of experiencing a major family income shock given that the families were categorized as low, average or high-income. The most striking feature of those graphs is that low-income families were more likely to be affected by all three types of income shocks, especially major shocks. The percentage of low-income families who faced a major income shock fluctuated around 30% throughout the analyzed period. Average-income families were more prone to minor income shocks than any other types of shocks. The common element among the three graphs is definitely the fact that high-income families barely experience any type of income shocks during the period of interest. A reason for this result is the fact that the model predicting expected family income tends to underestimate the actual family income for families in the fourth quartile. Since the coefficients in the model are calculated with the whole sample of families, they give the average impact of a given variable on the dependent variable, which is in this case total family income. However, when applying those coefficients to richer families, the model systematically underestimates the expected income. This could be because family income of richer families is more dependent on the previous year's income than on gender, region, etc. This is why when finding the predicted income, applying a coefficient of 0.58 to income almost consistently underestimates the potential household income. For less affluent families, education of the Head, gender, region could be more significant factors. This is clearly a drawback of using this methodology. However, the associated advantage is that it focuses on income shocks of families for which an income shock can have a much deeper impact on their ability to invest in their children's human capital. In other words, for families in the fourth quartile of the income distribution, an income shock will have an impact but probably not as major as it would have in a families in the first quartile of the income distribution.

Now that some crucial characteristics of the variables used in the analysis have been discussed, the next step is to try to find whether there is a link between family income shocks during childhood on educational attainment.

Figure 3.4: Percentage of Individuals who Experienced a Minor Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset

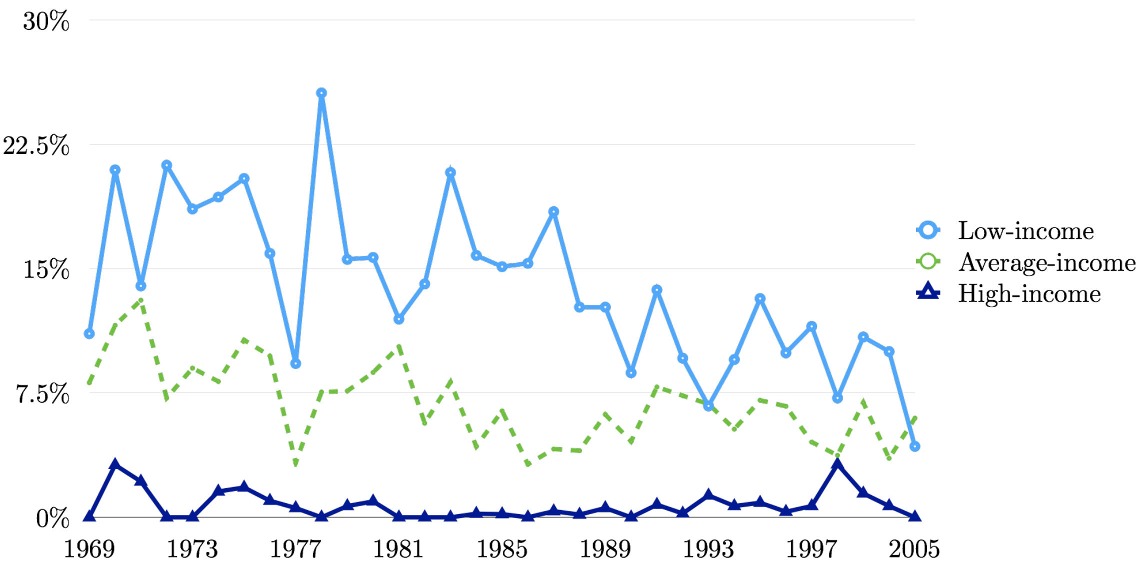


Figure 3.5: Percentage of Individuals who Experienced a Moderate Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset

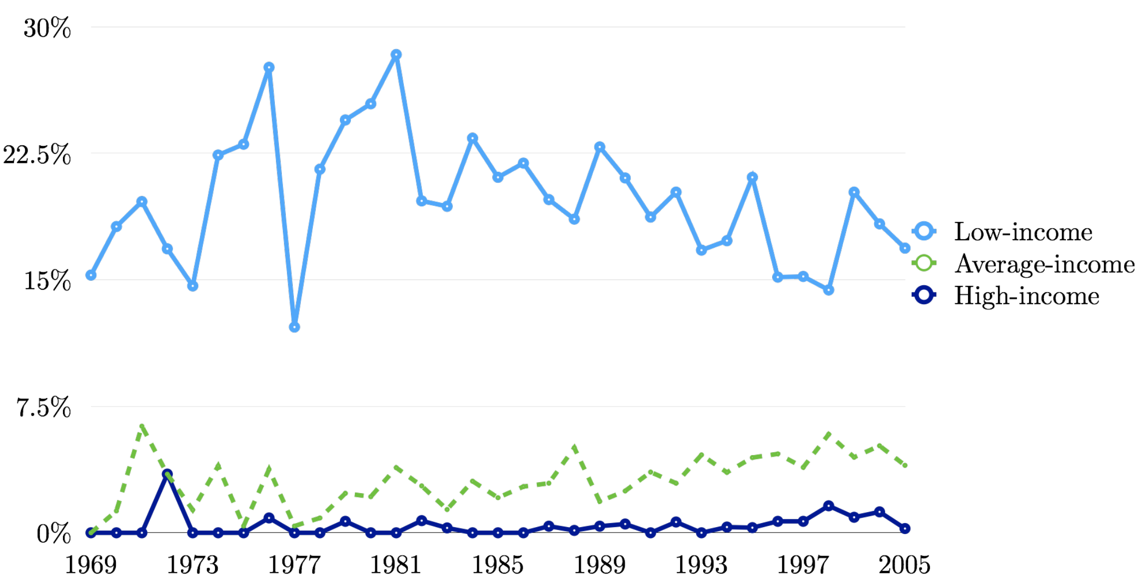
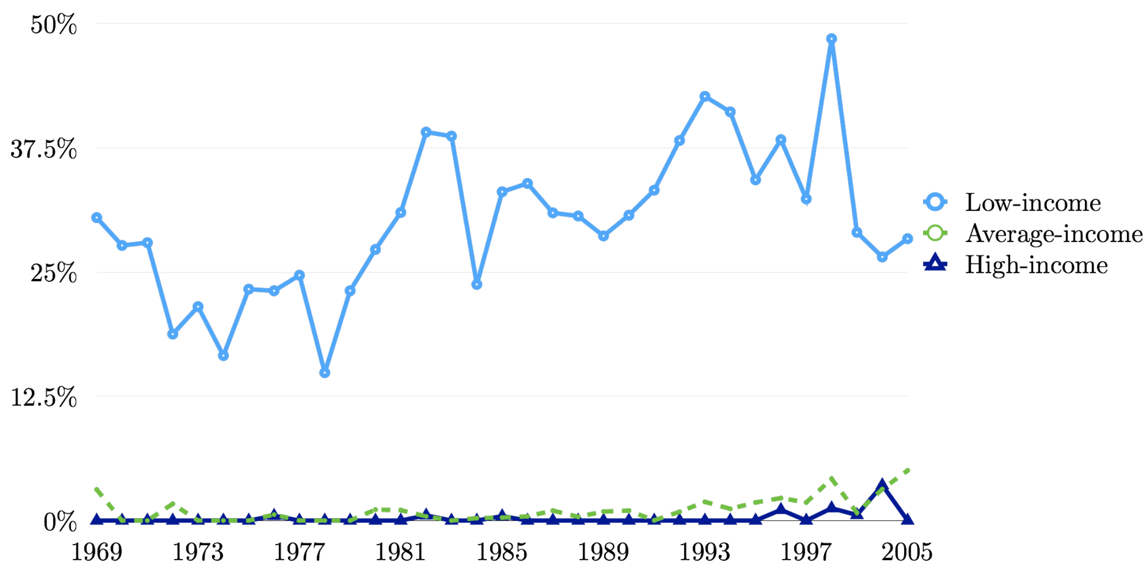


Figure 3.6: Percentage of Individuals who Experienced a Major Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset



Chapter 4

Econometric

The objective of this study is to find whether there is a link between experiencing a family income shock during childhood and adolescence and educational attainment. This section will attempt to do so in two steps. The first part will exploit the PSID main dataset on a subsample of 3,200 individuals, born between 1968 and 1986, who responded to the 2011 wave, and who had a complete time-series of total family income. The question this sample will help understand is if there exists a link between the highest grade achieved by an individual and whether or not he or she experienced a family income shock during childhood and adolescence. The strength of this analysis is most certainly the large number of years included in the main file (1968 to 2011) as well as the number of individuals it includes. The drawback however, is the narrow set of questions asked about education. Despite this significant inconvenience, it is possible to extract interesting information by combining the knowledge obtained in this analysis with the second step of this study, which is on the Child Development Supplement and Transition to Adulthood databases. The gain of adding this second step is that the CDS and TA databases offer several measures of educational attainment such as academic performances, whether graduated high school, whether enrolled in college, and if so, in what kind of program, and the highest grade achieved. The downside is that it has a limited scope in terms of time-series and a much smaller sample size. The fact that both the analysis conducted on the PSID database as well as on the CDS and the TA datasets have an educational attainment measure in common, *highest grade achieved*, makes it possible to compare the results obtained in both parts.

This allows for a corroboration of the results.

4.1 Description of the Models Used

Most regression analyses in this study rely on logistic regression to find whether there exists a link between educational attainment and experiencing family income shocks during their childhood and adolescence. A logistic regression is used when the dependent variable is a binary variable. Preliminary to analyzing the results, it is crucial to clearly grasp the concept of odds ratios. The odds ratios of a logistic regression represent the ratio of the odds of success over the odds of failure of a given binary variable. Here, success is seen as the outcome variable being equal to one.

$$\text{odds ratio} = \frac{\left[\frac{\text{probability of success for binary variable} = 1}{\text{probability of failure for binary variable} = 1}\right]}{\left[\frac{\text{probability of success for binary variable} = 0}{\text{probability of failure for binary variable} = 0}\right]} \tag{4.1}$$

$$\text{odds ratio} = \frac{\text{odds of binary variable} = 1}{\text{odds of binary variable} = 0} \tag{4.2}$$

It can now easily be understood that if an odds ratio is greater than 1 and it is statistically significant, there exists a positive relationship between the binary variable and the outcome variable. To the contrary, if the odds ratio is less than one and statistically significant there exists a negative relationship between the binary variable and the outcome variable. It is also important to note that when the odds ratio is equal to 1, it means that there is no significant relationship. Hence, if the number 1 is included in the 95% interval of the odds ratio, the odds ratio is not statistically significant at 5% significance level. This is easy to understand since the odds ratio is the exponential of the beta coefficient, thus if the β is equal to 0, the odds ratio will be equal to 1.

Furthermore, ordered logistic regressions will be used when the dependent variable has multiple ordered categories, such as *highest grade achieved*. This variable has five ordered categories: less than high school, high school degree, only some college, undergraduate degree and graduate degree. Clearly, there exists a hierarchy among those levels of education which justifies the choice of ordered logistic regression as an analysis tool. The particularity of estimating an ordered logistic is the assumption that there exists a continuous preference for school underlying the discrete choice of educational level. As explained in Greene (2011, p.825), the observed year of schooling represents a censored version of the underlying preference for school. As opposed to a multinomial logistic regression, an ordered logistic accounts for the ranking of outcomes. However, a drawback of using this method is the proportional odds assumption of ordered logistic regression, which assumes a constant relationship between going from one outcome to the other. Finally, some analyses will be conducted using ordinary least squares.

4.2 Highest Grade Achieved using the PSID Dataset

Table 4.1 reports the odds ratios and the standard errors of the variables having a significant impact on the highest grade achieved by individuals. The most important result of this study is the fact that when experiencing a major income shock, that is a negative difference of 50% between the realized family income and the expected family income, the odds of attaining a higher level of education are only 0.8 times those of individuals who did not experience a major shock during their childhood and adolescence. Another important result is the significant impact of average family income. The study found that an increase of 1% in the average family income increases the odds of achieving a higher level of education by about 1.2 times. Being a female also has a positive relationship with the attainment of higher grades, it increases the odds by 1.9 times. Interestingly, living in a family that receives Food Stamps during childhood or adolescence reduces the odds of pursuing further studies to 0.7 of those of children or teenagers who lived in a family that never received Food Stamps. Lastly, Head's level of education is the variable that matters the most in terms of increasing the odds of going longer to school. When the Head's level of education is high school, the odds of attaining a higher grade is 3.7 times higher than if the Head's education was less than high school. In the case in which the Head's level of education is some college, the odds increase by 30.9 times. As for Head's level of education being an undergraduate degree, the odds increase by 302.6 times. Finally, when the Head has a graduate degree the odds of attaining a higher level of education is 6,204 times the odds of those with a Head's level of education being less than high school.

Table 4.1: Odds Ratios and Standard Errors of Income Shock Variables and Control Variables Having a Significant Impact on the Highest Grade Achieved by Individuals in 2011 using the PSID Dataset

Control Variable	**Odds Ratio**	**Standard Error**
Minor Income Shock (-25%)	0.982	0.082
Moderate Income Shock (-35%)	1.125	0.109
Major Income Shock (-50%)	0.783***	0.061
Log of Average Family Income	1.196**	0.104
Race		
Others	1.737**	0.413
Gender		
Female	1.929***	0.167
Ever Received Food Stamps	0.729**	0.096
Head Education		
High School	3.659***	0.853
Some College	30.886***	9.033
Undergraduate	302.649 ***	103.251
Graduate School	6,204.047***	2,614.950

*p<0.1, **p<0.05, ***p<0.01

Other control variables are: Change in Employment Status of Head,

Race, Ever Received SSI, Region and Family Size.

See Table D.1 for the complete regression output.

An interesting extension is to combine the experience of an income shock with the fact of being in a low-income, average-income or high-income family when a given shock took place. As mentioned before, the thresholds of the three income categories were created using the quartiles. Each year, the data was used to calculate the three quartile thresholds as Table B.1 illustrates. Those thresholds were then used to categorize the families into three groups. The bottom 25% of the sampled families were included in the low-income class, the middle 50% were included in the average-income, and the upper 25% were categorized as high-income. Table 4.2 reports that experiencing a minor income shock while living in a low-income family reduces the odds of attaining a higher level of education to about half the odds of those who did not experience such an event. The same holds for experiencing a moderate shock and major shock, each reducing the odds to about 0.8 and 0.6 times respectively. As before, higher average family income has a positive impact on achieving higher grades, increasing the odds about 1.2 times. When differentiating for the income category, race becomes an important factor. Being of an other race than white without being black increases the odds to 1.7 times those of a white individual. Being a female increases the odds of higher grade attainment by almost two times. Living in a family that received Food Stamps while being a child or an adolescent reduces the odds to about 0.7 times. As in the previous regression, Head's education level is very crucial in the odds of reaching higher grade levels. Having a Head with a high school degree, some college, an undergraduate degree, or a graduate degree increases the odds of achieving higher grades by about 3.5, 28.9, 286.6 and 5,816.5 times respectively, compared to an individuals with a Head having less than high school as educational level.

Table 4.2: Odds Ratios and Standard Errors of Income Shock Variables and Control Variables Having a Significant Impact on the Highest Grade Achieved by Individuals in 2011 by Income Categories using the PSID Dataset

Control Variable	**Odds Ratio**	**Standard Error**
Minor Income Shock - High Income	16.521	28.591
Minor Income Shock - Average Income	0.749	0.193
Minor Income Shock - Low Income	0.573***	0.095
Moderate Income Shock - High Income	6.187	7.172
Moderate Income Shock - Average Income	0.920	0.123
Moderate Income Shock - Low Income	0.798*	0.098
Major Income Shock - High Income	0.301	0.387
Major Income Shock - Average Income	0.761	0.188
Major Income Shock - Low Income	0.635***	0.087
Log of Average Family Income	1.209**	0.107
Race		
Others	1.715**	0.388
Gender		
Female	1.927***	0.165
Ever Received Food Stamps	0.732**	0.088
Head Education		
High School	3.467***	0.787
Some College	28.918***	8.087
Undergraduate	286.580***	94.756
Graduate School	5,816.503***	2,393.271

*p<0.1, **p<0.05, ***p<0.01

Other control variables are: Change in Employment Status of Head,

Race, Ever Received SSI, Region and Family Size.

See Table D.2 for the complete regression output.

Distinguishing for when the income shock took place in the life of individuals is another insightful extension. Looking at Table 4.3, it is immediately obvious that splitting the income shocks by age group eliminates statistical significance in most cases. A major income shock before the age of 10 is the only exception. It is significant at a 5% significance level and reduces the odds by 0.8 times. As for the other control variables, they preserve their significance as well as magnitude of impact.

Table 4.3: Odds Ratios and Standard Errors of Income Shock Variables and Control Variables Having a Significant Impact on the Highest Grade Achieved by Individuals in 2011 by Age Group using the PSID Dataset

Control Variable	**Odds Ratio**	**Standard Error**
Minor Income Shock - Before the Age of 10	1.044	0.096
Minor Income Shock - After the Age of 10	0.982	0.110
Moderate Income Shock - Before the Age of 10	1.070	0.080
Moderate Income Shock - After the Age of 10	0.981	0.100
Major Income Shock - Before the Age of 10	0.814**	0.072
Major Income Shock - After the Age of 10	0.879	0.085
Race		
Others	1.728**	0.406
Gender		
Female	1.941***	0.163
Ever Received Food Stamps	0.731**	0.0998
Head Education		
High School	3.648***	0.842
Some College	31.094***	9.137
Undergraduate	307.441***	105.710
Graduate School	6,262.359***	2,665.930

*p<0.1, **p<0.05, ***p<0.01

Other control variables are: Change in Employment Status of Head,

Race, Ever Received SSI, Region and Family Size.

See Table D.3 for the complete regression output.

4.3 Child Development Supplement and Transition to Adulthood Analysis

4.3.1 Academic Achievement

The very first educational achievement the study looks at during the life of the 1997 cohort is the performance on the Woodcock-Johnson (WJ-R) tests in 2002. By that time, children were between 5 and 18 years old. Looking at the three income shock variables in Table D.4, experiencing a total family income shock does not seem to matter in the test results. More generally, an important determinant of academic performance is average family income. A 1% increase in average total family income increases test score averages by slightly more than 5%. Race is also a significant determinant according to this result. On average, a white child gets about 15% more on test score averages than a black child, keeping the rest constant. Also, being of an other race increases the average test score by 10%. Consistent with the other findings, when a child grows up in a family having received Supplemental Security Income (SSI), he or she is likely to score about 9% less than those who did not receive any SSI on average. The same is true for Food Stamps, where the difference is about 4% on average. Family size also seems to have a signifiant negative impact of about 1.1%. Children living in the west part of the United States tend to score on average about 4% less than children living in the Northeast part of the country. Another major determinant of average test scores is the educational level of the Head. All are statistically significant at 1% except high school which is statistically significant at 5%; the more the head is educated, the higher kids tend to score on average on their tests. Having a Head with a high school education increases the average test score by about 4.6% more than children having a Head with less than high school as their educational level. Children having a Head with some college, undergraduate or graduate as education level score on average 9.7%, 13.1% and 15.8% higher respectively. The place of residence also influences test scores. An interesting question one can ask is if the age at which the shock occurs matters in determining the impact on educational attainment of those shocks. Could the same shock affect the child differently depending on the age? Table D.5 shows that when the shock happens after the age of 10[11] years old, a minor shock has a significant (at 1% significance level) negative impact of about 8.7% on the test scores on average. The previous regression analysis with no distinction between the ages at which the shock occurred showed no significant effect of minor income shocks on test score averages. This indicates that teenagers are more affected than young children by minor shocks to total family income. When looking at other types of shocks, they seem not to affect performance on average. In sum, in addition to average family income, race, gender, whether the family received SSI and Food Stamps, family size, and Head's education, minor income shocks after the age of 10 years old have an impact on kids academic performance.

4.3.2 High School Graduation

The next step in understanding the impact that family income shocks have on educational attainment is high school graduation. In 2007, children from the cohort were aged between 10 and 24 years old. The logistic regressions were run on only the teenagers in age of graduating from high school, that is on those aged 18 years old and more. For young adults of 18 years old and older, about 86% graduated high school in or before 2007. With that in mind, a better understanding of the determinants of high school graduation can be achieved by looking at Table D.6. Interestingly, experiencing a minor income shock has a negative impact on high school graduation. The odds are 0.3 times those of individuals who did not experience such a shock, at 5% significance level. Facing a major income shock also reduces the odds to 0.3 times but this impact is statistically significant at 10%. What really seems to influence high school graduation negatively are a job loss of the Wife or "Wife" and family size. Conversely, average family income, being of an other race than black and the Head's educational level have a positive impact. The results truly convey the impression that the more the Head is educated the more likely teenagers are to graduate from high school, keeping the rest constant. More precisely, if a teenager has a Head with a high school degree, he or she is about 7.5 times more likely to graduate from college than someone who has a family Head with less than high school. The same holds for higher

[11] 10 years old was chosen as it is the beginning of middle school and for most children the end of childhood. Another threshold could have been chosen.

levels of education, where the increase in odds is 4.4 times greater for some college and 16.3 times for an undergraduate degree, all significant at 1% significance level. As for graduate degree, it had to be dropped from the regression as it was a perfect predictor of high school graduation in or before 2007. Lastly, the bigger the family, the less likely teenagers are to graduate high school on average. When distinguishing for whether the shock occurred during childhood or adolescence, the story does not change much except that the effect of minor and major income shocks is only observed after the age of 10 years old. Experiencing a minor income shock after the age of 10 years old reduces the odds of graduating high school to 0.24 times of those who did not experience a shock, and experiencing a major income shock after the age of 10 years old reduces the odds of graduating high school to 0.28 times of those who did not experience a shock. Overall, teenagers seem more affected by income shocks than children.

4.3.3 Enrolled in College

The next logical step is to look at whether family income shocks have a significant impact on college enrolment in 2009. The independent variable in this analysis is coming from a question asking whether they were enrolled in a college program at the time of the interview. Table D.8 illustrates the results of a logistic regression. Without distinguishing for the age at which the family income shock happened, none of the income shocks matter. Having received Food Stamps during their life is statistically significant, and has a negative relationship with being enrolled in college. Interestingly, Head's level of education is not as important as it was for the other academic achievement outcomes. As done above, it is interesting to look at the same logistics regression but to distinguish between living through a family income shock before and after the age 10. Table D.9 shows that a minor family income shock before the age of 10 years old has a negative impact on the probability of being enrolled in college at the 5% significance level. More precisely, experiencing a minor total family income shock before starting middle school makes the odds of being enrolled in college in 2009 0.5 times those of a teenager who did not experience a similar shock. Surprisingly, the logarithm of average family income has no influence on going to college, which is slightly counterintuitive. Looking at the odds of being enrolled in a 2-year, 4-year or graduate program once enrolled in college reveals that, as showed in Table D.10, moderate total family income shocks are now positively affecting the choice of program. This result is surprising but not too concerning since the increase in odds is significant only at 10%. Average family income along with Head's level of education have positive relationships with the dependent variable. For Head education, statistical significance is only observed for undergraduate and graduate school. Hence, the higher the average family income and the more educated the Head is, the more likely teenagers are to choose a 4-year program to the 2-year, or to choose a graduate program to the 4-year. When distinguishing by age, the moderate income shock is no longer significant but minor income shock before 10 years old now has a negative impact on the choice of program at 10% significance level.

4.3.4 Highest Grade Achieved

The last outcome variable to be analyzed from the Child Development Supplement and the Transition to Adulthood supplement is the highest grade achieved in 2011 by the cohort. Table D.12 shows the results of an ordered logistic regression. The same explanatory variables as in previous model were used, which are the log of the average family income, whether the Head or the Wife experienced a job loss before 2011, race of the child, gender, whether the family ever received SSI or Food Stamps before 2011, region, family size, Head's education level, and whether the family went through a change in marital status. The dependent variable was the highest grade achieved by the young adults of the cohort in 2011. The dependent variable *highest grade achieved* was divided in six categories: less than high school diploma, General Education Degree or high school diploma, some college, an associate's degree, a Bachelor's degree and a Master's degree. The oldest young adults in 2011 were 27 years old and there were very few of them. This leaves little time to complete a PhD, and this is probably why nobody indicated that they had completed a PhD. When the three kinds of shocks are not divided by the age at which the shock occurred, moderate and major shocks have an impact on the highest grade achieved. Unexpectedly, experiencing a moderate shock during childhood or adolescence increases the odds of achieving a higher educational level by about 1.3 times and experiencing a major shock during childhood or adolescence increases the odds of achieving a higher educational level by about 1.8 times.

Higher average family income increases those same odds by about 2 times and being a female by 1.6 times the odds of a male. Living in a family composed of more people reduces the odds of achieving a higher level of education to 0.7 times the odds of a young adult with a one unit smaller family. Head education level odds ratios were all statistically significant at 1% significance level. Interestingly, of all the possible levels of education the Head can have, the one that has the greatest impact on the highest grade achieved of the children is having a bachelor degree, the odds ratio being equal to about 95.3 times. Looking now at the same ordered logistic regression but with a distinction of the age at which the family income shock occurred, Table D.13 shows that all the counterintuitive results found in the previous regression are no longer statistically significant. The rest of the variables have the same impact as before the age differentiation.

Chapter 5

Conclusion

With human capital playing such an important role in the shaping of economic growth throughout the world, and particularly in countries plagued by ageing populations and low fertility rates, this research sought to identify which families were most in need of public assistance when struck by a family income shock, which could potentially jeopardize their ability to invest in the human capital of their children. It was found that, despite a relatively high percentage of individuals who experienced a total family income shock at least once during their childhood and adolescence, there is no clear and obvious link between experiencing a family income shock and educational attainment.

Using the PSID dataset, an unambiguous negative relationship between highest grade achieved and major family income shocks was identified. Differentiating by income class, a very interesting finding emerged; minor, moderate and major income shocks were all reducing the likelihood of achieving a higher grade, but only for low-income families. For average and high-income families, experiencing an income shock did not translate into lower levels of education. This result did not carry through when analyzing the relationship between highest grade achieved and family income shocks using the CDS and TA datasets. Academic achievement on the WJ-R tests was adversely affected by moderate family income shocks before 10 years old. The probability of graduating high school was lowered by minor and major family income shocks. Furthermore, when distinguishing by age, the effects were only observed for shocks after 10 years old. The probability of being enrolled in college was reduced only by minor family income shocks occurring before 10 years old. As for the probability of choosing a more demanding program among a 2-year, 4-year or graduate program, the findings with and without age differentiation are inconsistent with one another. In the more general case, a moderate income shock is weakly positively associated with the choice of a more demanding program. However, when differentiating by age group, experiencing a minor income shock before the age of 10 is weakly negatively associated with the choice of a more demanding program.

Overall, findings about the profound impact of all types of family income shocks on the highest grade achieved by individuals living in low-income families provides support for changes in public policy targeted toward those families. However, the fact that no clear pattern was found in the CDS and TA datasets justifies the need for further investigation before proceeding with public policy reforms. Further research could look more into the reasons for a job loss, for example, the onset of a disability. Other areas that merit supplementary research include whether the family income shock led to a depletion of asset and the different impact depending on the time span before income recovers.

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Appendices

Appendix A

Definitions

Head of the family unit

"The Head of the family unit must be at least 16 years old and the person with the most financial responsibility for the Family Unit. If this person is female and she has a husband in the Family Unit, then he is designated as Head. If she has a boyfriend with whom she has been living for at least one year, then he is Head. However, if the husband or boyfriend is incapacitated and unable to fulfill the functions of Head, then the Family Unit will have a female Head" (Panel Study of Income Dynamics, 2014c).

Wife of the family unit

A Wife or a "Wife" that is "an opposite sex romantic partner who has moved into a family unit less than 1 year prior to the interview is labeled as boyfriend or girlfriend in that first wave that he or she appears in the study. If the cohabiter has moved in at least one year before the interview, the couple will be coded as Head and "Wife". In the next wave, if the boyfriend or girlfriend is still living in the family unit and the couple is still unmarried, they are recoded as Head and "Wife" (That is, a male head will remain head but his girlfriend will be labeled "Wife" or a Female Head will become "Wife" while her boyfriend will become Head). If the couple is married, then the girlfriend will be labeled as Wife" (Panel Study of Income Dynamics, 2014c).

Appendix B

Income Shock Definition - Alternative Approach

Obviously, several definitions of a total family income shock could have been used to conduct this study. One other possibility could have been to use a similar method to the one used by Elliott et al. (2012b), which is described below.

Minor Shocks

A minor shock was considered to be a diminution of at least 25% in total family income but less than 35% from one year to another.

Moderate Shocks

A moderate shock was considered to be a diminution of at least 35% in total family income but less than 50% from one year to another.

Major Shocks

A major shock was considered to be a diminution of at least 50% in total family income from one year to another.

Essentially, if total family income in $year_t$ was between 25% to 35% lower than in $year_{t-1}$ the binary variable minor shock was set to 1. The same procedure was used for moderate and major income shocks. This is, as said before, similar to Elliott et al. (2012b) but with yearly data as opposed to 5 year increments. Clearly, using a different methodology yields different results. The next section will discuss the descriptive part of the total family income shocks that this alternative method would generate.

Looking at Figure B.1, the upward trend in the probability of experiencing an income shock regardless of the type of shock is undeniable. This is in line with the results found by Elliott et al. (2012b, p.2) that there is a significant increase around the late 90's and that the probability keeps on growing all the way through the Great Recession. A very interesting phenomenon is that before the late 80's, the three kinds of shocks were equally likely to occur. However, afterward, major income shocks started to become more and more likely to occur and the probability of experiencing a major shock became almost twice the likelihood of experiencing a moderate or minor shock. Breaking down those probabilities by income class allows a better understanding of which income class is more prone to the three main levels of income shocks. The thresholds of the three classes were created using the quartiles. Each year, the data was used to calculate the three quartile thresholds. Those thresholds were then used to categorize the families into three groups. The bottom 25% of the sampled families were included in the low-income class, the middle 50% were included in the average-income, and the upper 25% were categorized as high-income. Figure B.2 illustrates the probability of experiencing a minor family income shock given that the families were categorized as low, average or high-income. Figure B.3 illustrates the probability of experiencing a moderate family income shock given that the families were categorized as low, average or high-income. Figure B.4 illustrates the probability of experiencing a major family income shock given that the families were categorized as low, average or high-income. The common element among the three graphs is definitely the fact that before the mid-80's, families with an average-income were more likely to experience income shocks. Afterward, families with a high-income were more likely to experience an income shock. Also, as Gosselin and Zimmerman (2008) found in their own analysis, larger income shocks were more likely in the 1990s and the early 2000s than in the 1970s and 1980s.

Figure B.1: Percentage of Individuals who Experienced a Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset

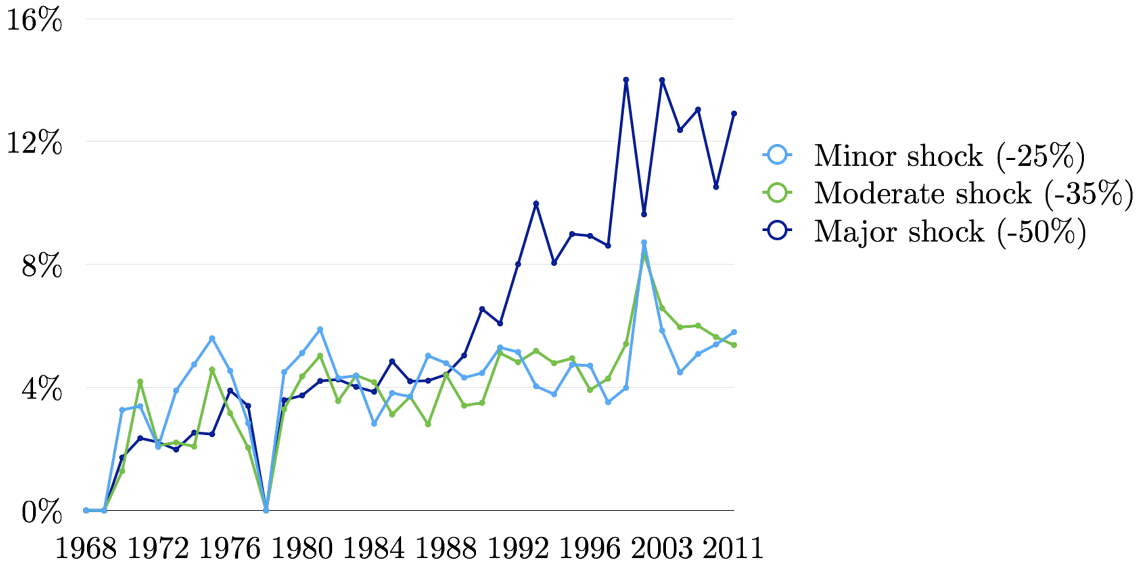

Figure B.2: Percentage of Individuals who Experienced a Minor Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset

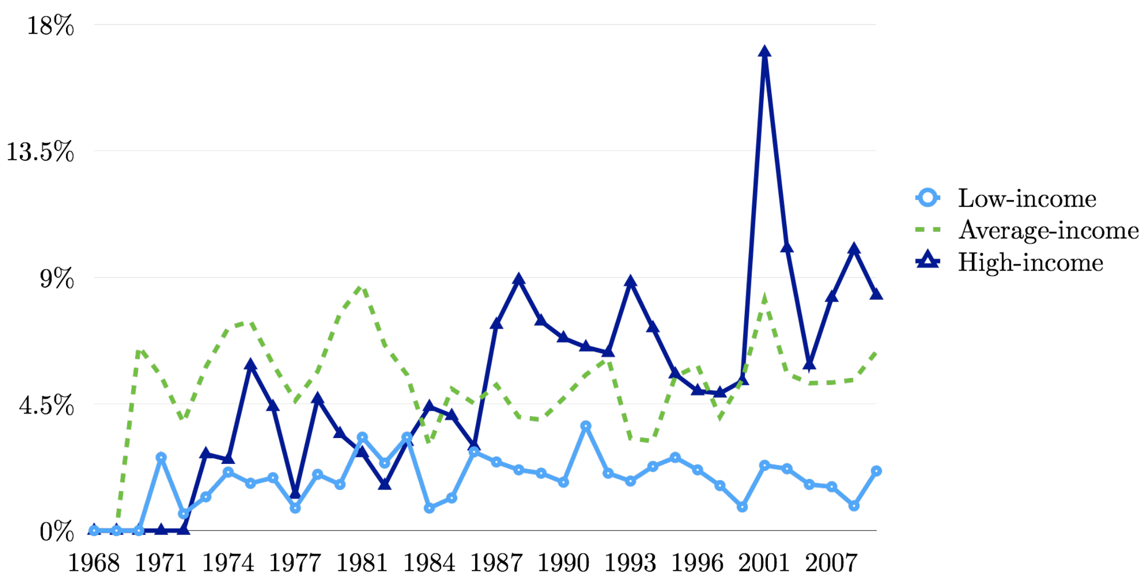

Figure B.3: Percentage of Individuals who Experienced a Moderate Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset

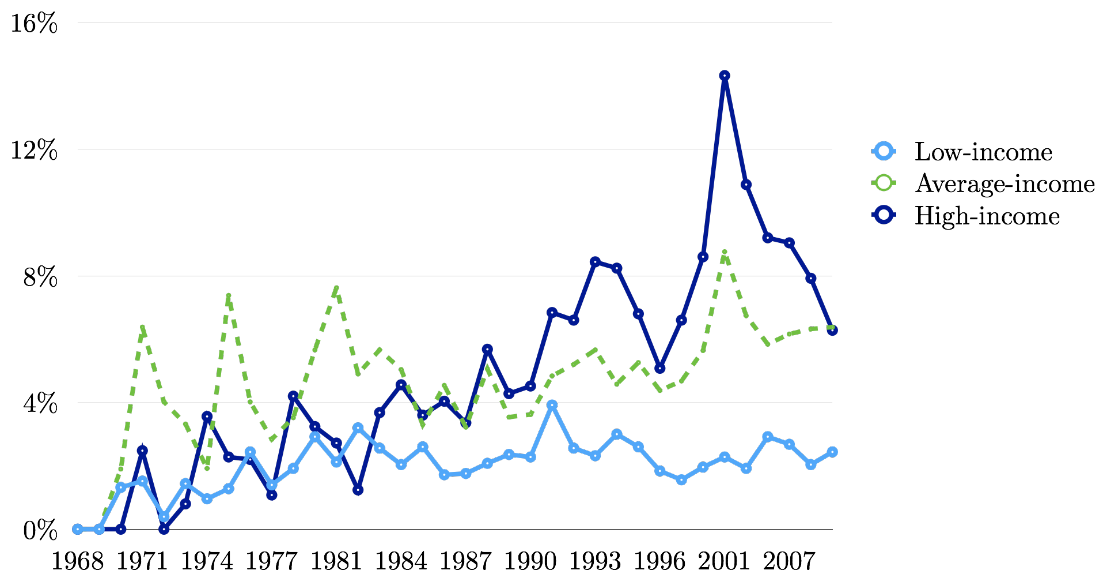

Figure B.4: Percentage of Individuals who Experienced a Major Total Family Income Shock per Year Over the Study Period (1968-2011) Using the PSID Dataset

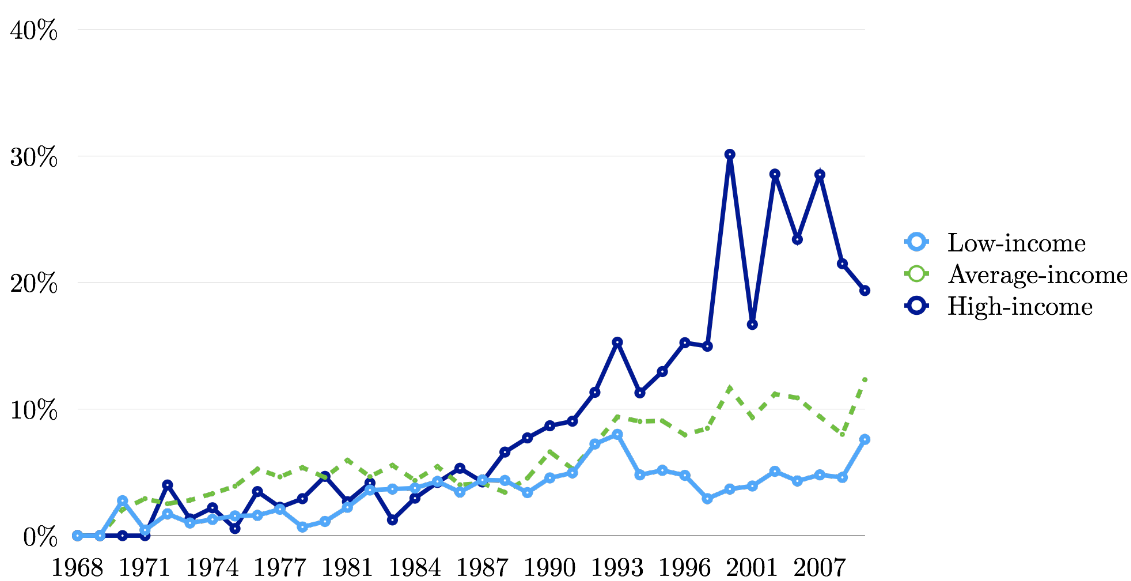

Table B.1: Thresholds of the Total Family Income Quartiles by Year in 2009 Dollars Using the PSID Dataset

Years	**First Quartile Threshold**	**Second Quartile Threshold**	**Third Quartile Threshold**
1969	35,382$	50,588$	63,835$
1970	35,917$	49,731$	63,380$
1971	36,531$	50,598$	66,758$
1972	41,043$	54,413$	69,773$
1973	41,071$	56,378$	75,000$
1974	41,277$	56,126$	71,964$
1975	41,989$	55,822$	71,357$
1976	39,971$	55,665$	72,758$
1977	48,494$	64,801$	87,785$
1978	43,970$	59,362$	81,873$
1979	42,863$	59,827$	80,606$
1980	40,237$	57,273$	78,100$
1981	37,751$	58,008$	77,155$
1982	38,481$	59,525$	80,256$
1983	36,994$	59,874$	85,082$
1984	40,262$	68,150$	94,997$
1985	42,055$	68,310$	94,934$
1986	43,207$	66,963$	99,987$
1987	42,142$	70,804$	102,877$
1988	42,632$	71,703$	102,498$
1989	42,140$	70,954$	101,672$
1990	41,049$	68,962$	103,296$
1991	39,381$	66,850$	101,604$
1992	38,353$	65,533$	107,454$
1993	34,414$	65,927$	105,285$
1994	34,735$	64,121$	104,993$
1995	34,263$	63,764$	102,345$
1996	35,562$	62,234$	100,722$
1997	38,641$	65,608$	108,579$
1999	39,410$	69,612$	114,368$
2001	41,113$	74,651$	118,483$
2003	37,391$	67,509$	113,545$
2005	36,346$	68,205$	112,445$
2007	34,054$	64,278$	105,019$
2009	37,864$	66,261$	105,623$
2011	33,551$	61,402$	101,434$

All numbers are in 2009 dollars

Appendix C

Predicted Family Income - Blundell and Bond Regression Results

Table C.1: *Blundell and Bond* Regression Results of Total Family Income on the Head's Characteristics using the PSID Dataset

	β	SE
Total Family Income$_{t-1}$	0.586***	(0.008)
Age of Head	92.217**	(42.278)
Gender		
Female	−3189.956***	(887.299)
Employment Status of Head	3129.613***	(488.716)
Head Education		
High school	925.380	(1061.987)
Some College	2285.960	(1588.684)
Undergraduate	14368.601***	(2821.996)
Graduate	16177.190***	(4376.727)
Region		
North Central	−6724.364*	(3684.920)
South	−12401.440***	(3178.291)
West	−6554.911*	(3809.403)
Alaska/Hawaii	−3114.470	(7624.842)
Foreign Country	−10800.073**	(4646.022)
Family Size	2169.560***	(200.784)
Family Composition	−1148.560***	(113.161)
Constant	16082.856***	(3479.741)
Observations	111095	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is white.

Table C.2: *Blundell and Bond* Regression Results of Total Family Income on the Head's Characteristics using the CDS and TA Datasets

	β	SE
Total Family Income$_{t-1}$	0.382***	(0.010)
Age of Head	736.711***	(61.423)
Gender		
Female	−14797.672***	(1062.852)
Head Education		
High school	5393.609***	(1235.675)
Some College	8539.632***	(1767.873)
Undergraduate	24442.089***	(3213.175)
Graduate	27153.695***	(5008.683)
Region		
North Central	−13399.468**	(5446.879)
South	−14669.888***	(4874.680)
West	−11943.112**	(5793.912)
Alaska/Hawaii	−12914.699	(8950.069)
Foreign Country	−18226.750***	(6760.980)
Employment Status of Head	3191.551***	(557.189)
Family Size	2562.219***	(256.466)
Family Composition	−808.823***	(164.287)
Constant	6811.849	(5413.439)
Observations	63439	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast and the base case for Education of Head is less than high school.

Appendix D

Educational Attainment - Regression Results

Table D.1: Odds Ratios of Ordered Logistic Results of Highest Level of Education on Control Variables in 2011 using the PSID Dataset

	Odds Ratio	SE
Minor Income Shock	0.982	(0.082)
Moderate Income Shock	1.125	(0.109)
Major Income Shock	0.783***	(0.061)
Log of Average Family Income	1.196**	(0.104)
Change in Employment Status of Head	1.090	(0.107)
Race		
Black	0.819	(0.104)
Others	1.737**	(0.413)
Gender		
Female	1.928***	(0.157)
Ever Received SSI	0.886	(0.087)
Ever Received Food Stamps	0.729**	(0.096)
Region		
North Central	0.976	(0.106)
South	1.005	(0.101)
West	0.913	(0.124)
Family Size	0.989	(0.025)
Head Education		
High School	3.659***	(0.853)
Some College	30.886***	(9.033)
Undergraduate	302.649***	(103.251)
Graduate School	6204.047***	(2614.950)
Observations	2824	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: he base case for Region is Northeast and the base case for Education of Head is less than high school.

Table D.2: Odds Ratios of Ordered Logistic Results of Highest Level of Education on Control Variables in 2011 by Family Income Categories using the PSID Dataset

	Odds Ratio	SE
Minor Income Shock - High Income	16.521	(28.591)
Minor Income Shock - Average Income	0.749	(0.193)
Minor Income Shock - Low Income	0.573***	(0.095)
Moderate Income Shock - High Income	6.187	(7.172)
Moderate Income Shock - Average Income	0.920	(0.123)
Moderate Income Shock - Low Income	0.798*	(0.098)
Major Income Shock - High Income	0.301	(0.387)
Major Income Shock - Average Income	0.761	(0.188)
Major Income Shock - Low Income	0.635***	(0.087)
Log of Average Family Income	1.209**	(0.107)
Change in Employment Status of Head	1.090	(0.102)
Race		
Black	0.824	(0.104)
Others	1.715**	(0.388)
Gender		
Female	1.927***	(0.165)
Ever Received SSI	0.907	(0.091)
Ever Received Food Stamps	0.732**	(0.088)
Region		
North Central	1.000	(0.111)
South	1.025	(0.097)
West	0.939	(0.125)
Family Size	0.971	(0.024)
Head Education		
High School	3.467***	(0.787)
Some College	28.918***	(8.087)
Undergraduate	286.580***	(94.756)
Graduate School	5816.503***	(2393.271)
Observations	2824	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is white.

Table D.3: Odds Ratios of Ordered Logistic Results of Highest Level of Education on Control Variables in 2011 by Age Group using the PSID Dataset

	Odds Ratio	SE
Minor Income Shock - Before the Age of 10	1.044	(0.096)
Minor Income Shock - After the Age of 10	0.982	(0.110)
Moderate Income Shock - Before the Age of 10	1.070	(0.080)
Moderate Income Shock - After the Age of 10	0.981	(0.100)
Major Income Shock - Before the Age of 10	0.814**	(0.072)
Major Income Shock - After the Age of 10	0.879	(0.085)
Log of Average Family Income	1.158	(0.102)
Change in Employment Status of Head	1.088	(0.106)
Race		
Black	0.833	(0.105)
Others	1.728**	(0.406)
Gender		
Female	1.941***	(0.163)
Ever Received SSI	0.898	(0.090)
Ever Received Food Stamps	0.731**	(0.098)
Region		
North Central	0.967	(0.103)
South	0.992	(0.101)
West	0.904	(0.120)
Family Size	0.993	(0.025)
Head Education		
High School	3.648***	(0.842)
Some College	31.094***	(9.137)
Undergraduate	307.441***	(105.710)
Graduate School	6262.359***	(2665.930)
Observations	2824	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is white.

Table D.4: OLS Regression Results of Academic Achievement of Children on Control Variables in 2002 using the CDS Dataset

	β	SE
Minor Income Shock	1.638	(1.323)
Moderate Income Shock	−0.199	(1.640)
Major Income Shock	−2.347	(1.643)
Log of Average Family Income	5.123***	(1.468)
Change in Employment Status of Head	−1.908	(1.313)
Race		
White	15.024***	(3.100)
Others	10.245**	(4.533)
Gender		
Female	0.227	(1.309)
Change in Employment Status of Wife	0.163	(1.407)
Ever Received SSI	−9.748***	(2.698)
Ever Received Food Stamps	−3.947*	(2.156)
Region		
North Central	−2.665	(2.497)
South	2.727	(2.397)
West	−4.722*	(2.740)
Family Size	−1.073*	(0.584)
Head Education		
High School	4.643**	(1.776)
Some College	9.673***	(2.278)
Undergraduate	13.098***	(2.361)
Graduate School	15.863***	(2.986)
Change in Marital Status	−1.726	(2.122)
Constant	−8.815	(15.677)
Observations	2240	

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.5: OLS Regression Results of Academic Achievement of Children on Control Variables in 2002 by Age Group using the CDS Dataset

	β	SE
Minor Income Shock - Before 10 yrs old	1.910	(1.304)
Minor Income Shock - After 10 yrs old	−0.608	(2.668)
Moderate Income Shock - Before 10 yrs old	1.548	(1.682)
Moderate Income Shock - After 10 yrs old	−8.736***	(1.821)
Major Income Shock - Before 10 yrs old	−1.747	(1.613)
Major Income Shock - After 10 yrs old	−1.469	(2.124)
Log of Average Family Income	4.907***	(1.515)
Change in Employment Status of Head	−1.431	(1.411)
Race		
White	15.066***	(3.180)
Others	10.477**	(4.911)
Gender		
Female	0.376	(1.283)
Change in Employment Status of Wife	0.544	(1.345)
Ever Received SSI	−9.709***	(2.760)
Ever Received Food Stamps	−3.630	(2.165)
Region		
North Central	−2.928	(2.553)
South	2.422	(2.445)
West	−5.120*	(2.867)
Family Size	−1.172*	(0.595)
Head Education		
High School	4.984***	(1.712)
Some College	10.029***	(2.262)
Undergraduate	13.380***	(2.321)
Graduate School	16.134***	(2.978)
Change in Marital Status	−2.313	(2.074)
Constant	−6.674	(16.243)
Observations	2240	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.6: Odds Ratios of Logistic Results of Probability of Graduating High School on Control Variables in 2007 using the TA Dataset

	Odds Ratio	SE
Minor Income Shock	0.329**	(0.179)
Moderate Income Shock	0.915	(0.554)
Major Income Shock	0.333*	(0.198)
Log of Average Family Income	4.702***	(2.350)
Change in Employment Status of Head	0.659	(0.242)
Race		
White	4.157	(4.422)
Others	4.737*	(4.313)
Gender		
Female	1.046	(0.330)
Change in Employment Status of Wife	0.447*	(0.208)
Ever Received SSI	1.105	(0.730)
Ever Received Food Stamps	1.398	(0.672)
Region		
North Central	1.092	(0.499)
South	1.939	(0.850)
West	0.723	(0.375)
Family Size	0.823*	(0.079)
Head Education		
High School	7.543***	(3.002)
Some College	4.356***	(1.686)
Undergraduate	16.290***	(14.780)
Change in Marital Status	1.031	(0.434)
Observations	722	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.7: Odds Ratios of Logistic Results of Probability of Graduating High School on Control Variables in 2007 by Age Group using the TA Dataset

	Odds Ratio	SE
Minor Income Shock - Before 10 yrs old	0.576	(0.302)
Minor Income Shock - After 10 yrs old	0.239***	(0.094)
Moderate Income Shock - Before 10 yrs old	1.428	(0.787)
Moderate Income Shock - After 10 yrs old	0.577	(0.281)
Major Income Shock - Before 10 yrs old	1.206	(0.718)
Major Income Shock - After 10 yrs old	0.277**	(0.140)
Log of Average Family Income	4.149***	(2.097)
Change in Employment Status of Head	0.728	(0.261)
Race		
White	3.771	(3.823)
Others	5.256	(5.790)
Gender		
Female	1.048	(0.346)
Change in Employment Status of Wife	0.436*	(0.211)
Ever Received SSI	1.116	(0.726)
Ever Received Food Stamps	1.538	(0.742)
Region		
North Central	1.167	(0.490)
South	2.107*	(0.892)
West	0.794	(0.382)
Family Size	0.826**	(0.070)
Head Education		
High School	7.580***	(3.094)
Some College	4.847***	(1.779)
Undergraduate	20.033***	(15.438)
Change in Marital Status	0.956	(0.365)
Observations	722	

* p < 0.1, ** p < 0.05, *** p < 0.01. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.8: Odds Ratios of Logistic Results of Probability of Being Enrolled in College on Control Variables in 2009 using the TA Dataset

	Odds Ratio	SE
Minor Income Shock	0.706	(0.263)
Moderate Income Shock	1.219	(0.545)
Major Income Shock	1.219	(0.311)
Log of Average Family Income	0.715	(0.185)
Change in Employment Status of Head	0.848	(0.225)
Race		
White	1.048	(0.544)
Others	1.372	(0.683)
Gender		
Female	0.865	(0.231)
Change in Employment Status of Wife	0.639*	(0.167)
Ever Received SSI	0.505	(0.420)
Ever Received Food Stamps	0.570*	(0.166)
Region		
North Central	0.846	(0.237)
South	0.809	(0.207)
West	0.860	(0.300)
Family Size	1.112	(0.116)
Head Education		
High School	1.533	(1.174)
Some College	2.508	(1.816)
Undergraduate	1.747	(1.297)
Graduate School	4.140	(3.564)
Change in Marital Status	0.901	(0.266)
Observations	544	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black

Table D.9: Odds Ratios of Logistic Results of Probability of Being Enrolled in College on Control Variables in 2009 by Age Group using the TA Dataset

	Odds Ratio	SE
Minor Income Shock - Before 10 yrs old	0.488**	(0.160)
Minor Income Shock - After 10 yrs old	1.184	(0.352)
Moderate Income Shock - Before 10 yrs old	0.874	(0.333)
Moderate Income Shock - After 10 yrs old	1.075	(0.288)
Major Income Shock - Before 10 yrs old	1.441	(0.402)
Major Income Shock - After 10 yrs old	0.864	(0.270)
Log of Average Family Income	0.681	(0.176)
Change in Employment Status of Head	0.832	(0.229)
Race		
White	1.480	(0.794)
Others	1.480	(0.944)
Gender		
Female	0.866	(0.235)
Change in Employment Status of Wife	0.713	(0.185)
Ever Received SSI	0.486	(0.410)
Ever Received Food Stamps	0.496**	(0.135)
Region		
North Central	0.797	(0.215)
South	0.783	(0.193)
West	0.800	(0.274)
Family Size	1.146	(0.110)
Head Education		
High School	1.408	(1.182)
Some College	2.361	(1.962)
Undergraduate	1.612	(1.329)
Graduate School	3.402	(3.135)
Change in Marital Status	0.935	(0.284)
Observations	544	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.10: Odds Ratios of Ordered Logistic Results of Probability of Being Enrolled in a 2-year, 4-year or Graduate degree on Control Variables in 2009 using the TA Dataset

	Odds Ratio	SE
Minor Income Shock	0.742	(0.147)
Moderate Income Shock	1.456*	(0.322)
Major Income Shock	0.920	(0.185)
Log of Average Family Income	1.369*	(0.230)
Change in Employment Status of Head	0.732	(0.137)
Race		
White	0.786	(0.291)
Others	0.610	(0.278)
Gender		
Female	0.996	(0.135)
Change in Employment Status of Wife	0.825	(0.139)
Ever Received SSI	0.849	(0.494)
Ever Received Food Stamps	0.768	(0.191)
Region		
North Central	1.104	(0.315)
South	1.233	(0.284)
West	0.922	(0.310)
Family Size	0.868*	(0.060)
Head Education		
High School	1.247	(0.460)
Some College	1.583	(0.617)
Undergraduate	5.889***	(2.182)
Graduate School	9.882***	(3.575)
Change in Marital Status	0.732	(0.138)
Observations	1014	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.11: Odds Ratios of Ordered Logistic Results of Probability of Being Enrolled in a 2-year, 4-year or Graduate degree on Control Variables in 2009 by Age Group using the TA Dataset

	Odds Ratio	SE
Minor Income Shock - Before 10 yrs old	0.736*	(0.133)
Minor Income Shock - After 10 yrs old	0.766	(0.140)
Moderate Income Shock - Before 10 yrs old	1.381	(0.309)
Moderate Income Shock - After 10 yrs old	1.066	(0.191)
Major Income Shock - Before 10 yrs old	1.096	(0.206)
Major Income Shock - After 10 yrs old	0.897	(0.141)
Log of Average Family Income	1.340	(0.241)
Change in Employment Status of Head	0.716*	(0.132)
Race		
White	0.845	(0.341)
Others	0.622	(0.300)
Gender		
Female	1.001	(0.136)
Change in Employment Status of Wife	0.822	(0.131)
Ever Received SSI	0.845	(0.494)
Ever Received Food Stamps	0.747	(0.187)
Region		
North Central	1.123	(0.320)
South	1.251	(0.277)
West	0.949	(0.310)
Family Size	0.867**	(0.059)
Head Education		
High School	1.194	(0.440)
Some College	1.554	(0.636)
Undergraduate	5.774***	(2.220)
Graduate School	9.565***	(3.788)
Change in Marital Status	0.728	(0.139)
Observations	1014	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.12: Odds Ratios of Ordered Logistic Results of Highest Level of Education on the Control Variables in 2011 using the TA Dataset

	Odds Ratio	SE
Minor Income Shock	1.091	(0.197)
Moderate Income Shock	1.335*	(0.215)
Major Income Shock	1.752**	(0.481)
Log of Average Family Income	2.016***	(0.350)
Change in Employment Status of Head	0.876	(0.159)
Race		
White	0.531*	(0.180)
Others	0.586	(0.283)
Gender		
Female	1.574***	(0.219)
Change in Employment Status of Wife	0.957	(0.154)
Ever Received SSI	0.706	(0.182)
Ever Received Food Stamps	0.957	(0.186)
Region		
North Central	0.880	(0.181)
South	1.076	(0.249)
West	0.923	(0.278)
Family Size	0.718***	(0.047)
Head Education		
High School	3.261***	(0.887)
Some College	12.283***	(3.604)
Undergraduate	95.315***	(33.252)
Graduate School	18.685***	(5.818)
Change in Marital Status	0.781	(0.153)
Observations	1450	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.

Table D.13: Odds Ratios of Ordered Logistic Results of Highest Level of Education on Control Variables in 2011 by Age Group using the TA Dataset

	Odds Ratio	SE
Minor Income Shock - Before 10 yrs old	1.039	(0.196)
Minor Income Shock - After 10 yrs old	1.239	(0.180)
Moderate Income Shock - Before 10 yrs old	1.344	(0.271)
Moderate Income Shock - After 10 yrs old	0.964	(0.190)
Major Income Shock - Before 10 yrs old	1.116	(0.222)
Major Income Shock - After 10 yrs old	1.416	(0.386)
Log of Average Family Income	2.011***	(0.369)
Change in Employment Status of Head	0.884	(0.158)
Race		
White	0.609	(0.225)
Others	0.669	(0.360)
Gender		
Female	1.568***	(0.215)
Change in Employment Status of Wife	0.983	(0.159)
Ever Received SSI	0.709	(0.182)
Ever Received Food Stamps	0.946	(0.176)
Region		
North Central	0.864	(0.174)
South	1.082	(0.258)
West	0.923	(0.277)
Family Size	0.718***	(0.047)
Head Education		
High School	3.260***	(0.836)
Some College	12.191***	(3.451)
Undergraduate	91.405***	(28.878)
Graduate School	18.379***	(5.448)
Change in Marital Status	0.783	(0.168)
Observations	1450	

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in parentheses.

Note: The base case for Region is Northeast, the base case for Education of Head is less than high school, and the base case for race is black.