The Effects of Education on Wealth Inequality over the Life Cycle

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Abstract

This study investigates the causal relationship between education and wealth accumulation. Utilizing three distinct identification strategies, the research analyzes a panel dataset from the United States, encompassing two generations, to explore the dynamics of this relationship. The empirical findings indicate that higher educational attainment, particularly at the college and postgraduate levels, leads to a significant increase in lifetime wealth. This effect varies based on an individual's life stage, their position within the wealth distribution, and the level of education attained. Subsequently, the paper develops a life-cycle heterogeneous agents model to assess the impact of educational policies on wealth accumulation. Calibrated using U.S. data, this model focuses on policies aimed at enhancing the quality and quantity of higher education. The analysis reveals that increasing the proportion of college-educated individuals could potentially reduce wealth inequality. This study contributes to the understanding of education as a relevant factor in wealth generation and distribution.

Keywords: Wealth Inequality · Returns to Education · Life Cycle

JEL Codes: D15 · D31 · E21 · I24 · I26

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1 Introduction

In recent decades, wealth concentration at the top of the distribution has been on the rise in most countries, leading to growing wealth inequality.[1] For instance, in the United States, the top 1% of households hold over 40% of the wealth, while the bottom 90% has seen little change since 1980. The accumulation of wealth at the individual level plays a critical role in protecting against negative shocks during the life cycle e.g. unemployment spells, or a source to finance future consumption, retirement, entrepreneurial investments, or human capital acquisition. However, increasing wealth inequality has resulted in a larger number of financially constrained individuals, which limits their opportunities to invest in their human capital, particularly in countries with high education fees. This creates a cycle of wealth concentration and unequal opportunities.

The relationship between human capital investments and wealth accumulation raises important questions for policymakers tasked with improving economic mobility or reducing wealth inequality through education programs. The question of this research is: Does human capital investment allow individuals to accumulate wealth? This paper aims to determine if there is a causal link between wealth and education over the life cycle or simply a positive correlation.

The classical economic literature has predominantly focused on exploring the relationship between education and labor income. Numerous studies have concluded that there exists a positive causal relationship between the two. In recent years, however, attention has shifted toward exploring net worth. Despite the growing interest, there have been only a limited number of studies due to the challenges in acquiring accurate wealth data and addressing causality issues. These studies have delved into various topics, including financial market participation, home ownership, financial literacy, and propensity to save. However, there are very few papers focusing on the impact of education on actual wealth accumulation and mainly use Scandinavian data with inconclusive results. For example, Bingley and Martinello (2017) investigates the wealth returns on education during retirement and indicates that, even if there is a positive correlation, there is no support for the effects of education on wealth over retirement in Denmark. Similarly, for Norway, Fagereng, Guiso, Holm, and Pistaferri (2020) argue that after implementing IV and twins variation analysis there is no causal wealth returns to schooling, even after obtaining positive OLS estimates. On the contrary, the research done by Girshina (2019) suggests, among other results, a causal relationship between education and wealth for the case of Sweden that affects individuals differently over the life cycle. A problem with this study is that the control for the parental economic situation is measured by parental income and not parental wealth.

Parental wealth plays an important role in shaping the future outcomes of individuals and should be considered when analyzing returns to education.[2] The analysis done by

[1] For details check Alvaredo, Chancel, Piketty, Saez, and Zucman (2018), Saez and Zucman (2016), Piketty (2014).

[2] The effects of family background on children's outcomes can be found in Blanden and Machin (2004), Chevalier, Harmon, O'Sullivan, and Walker (2013), and Atkinson and Bourguignon (2014).

Charles and Hurst (2003) confirmed a strong correlation between parent-child wealth before bequests are transmitted. Furthermore, Black, Devereux, Lundborg, and Majlesi (2015) proposed a study based on biological and non-biological relations between parent-child, suggesting that the transmission of wealth, before inheritance, from parents to children is mainly based on the environment where children develop and secondarily on the role played by genetics. The extent of the influence of parental wealth, according to Karagiannaki (2017), reaches the determination of children's higher education attainment in early adulthood. The impact of family wealth on the initial conditions provided to children should be considered in the analysis of economic returns to education due to their long-lasting and substantial effects.

To answer the main question proposed, the paper employs different empirical strategies to explore a causal relationship between education and wealth. An empirical econometric application explores this topic despite the difficulties of analyzing a potential causal relationship between wealth and education. An example of this is the fact that parental wealth affects children's human capital level but also it impacts their future economic outcomes through other channels. The results are obtained through three different empirical strategies aimed at considering different sources of endogeneity. This empirical analysis suggests that after controlling for an individual's background, especially for parental wealth, there is a causal relationship between education and wealth over the life cycle for some levels of education, with estimates that vary depending on different circumstances e.g. the life-cycle stage or the part of the wealth distribution. These results are strong only for individuals with college and postgraduate education. Some of the mechanisms driving these results are labor income, savings, and other types of financial assets. The mechanisms suggest that individuals directly benefit from education by influencing their returns to capital or indirectly via labor income.

After exploring finding a causal effect of education on wealth only for individuals with higher levels of education and understanding more the behavior of some determinants of wealth accumulation, a life cycle quantitative model is introduced. Recent research in the field of life-cycle models has sought to include features that produce enough skewness in the wealth distribution as observed in US data[3]. However, some of these models still do not replicate the high level of skewness observed in real-world wealth distribution. Idiosyncratic returns to wealth have been more recently studied to improve the fit of life-cycle models[4]. Initial research showed that idiosyncratic capital risk can produce a Pareto tail, however, the drivers of these heterogeneous returns are not well explored yet. The relationship between education and returns to wealth is also a topic of interest, with inconclusive results from the few studies in this area. Thus, it seems appropriate to include the new features of wealth inequality literature over a life cycle analysis to gain additional insights into the effects of education on wealth.

The quantitative model incorporates drivers of inequality such as initial heterogeneous levels of human capital, wealth, and heterogeneity in returns to capital and discount fac-

[3] A complete survey on wealth inequality can be found in De Nardi and Fella (2017).

[4] This is detailed in Ma, Stachurski, and Toda (2020) and Benhabib, Bisin, and Luo (2019).

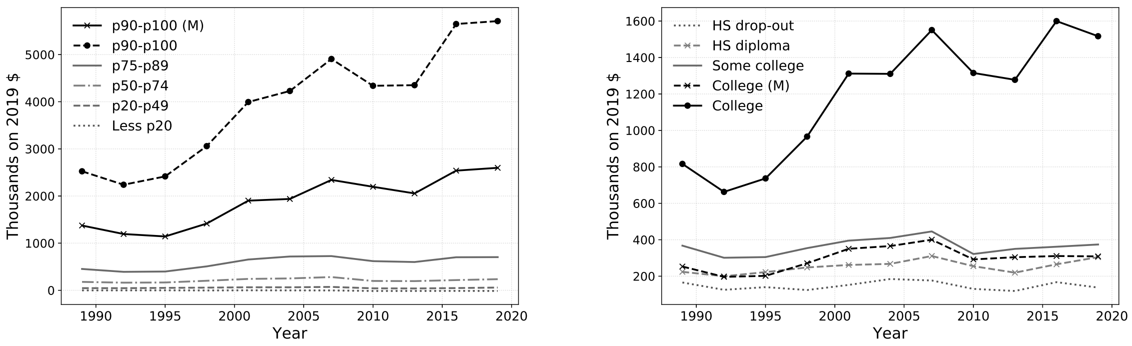
tors. The final model suggests that exogenous education's effect on idiosyncratic returns to wealth better replicates the wealth distribution and levels of inequality. After exploring the replication power of the quantitative model, some educational policies are introduced. These policies aim to find if it is possible to reduce wealth inequality or to shift wealth from the top decile of the wealth distribution to other deciles. Two separate directions are explored in the area of educational policies: quantity and quality of education. One direction represents efforts to achieve higher college access and affordability for a bigger share of the population. The second direction is to improve teacher quality, training, curriculum, instructional support, or digital access for a better-educated population. The ultimate goal is to achieve higher financial literacy, thus increasing the average rates of return for college graduates. The result of the simulations suggests that an increase in the share of individuals with a college education would reduce wealth inequality. However, having college graduates with higher rates of return to capital has the opposite effect on wealth inequality.

The remainder of the paper is organized as follows. Section 2 motivates the research. An empirical application is presented in Section 3 to explore a causal relationship between education and wealth followed by a quantitative model in Section 4 to explore potential effects of policy reforms. Finally, Section 5 presents concluding remarks and potential further research ideas.

2 Trends of Wealth Inequality

As the main objective of this research is to further understand the drivers of wealth accumulation and the differences between education groups, this subsection presents some stylized facts about these differences and their historical development. Including these figures is crucial in delineating the multi-faceted relationship between education and wealth accumulation over time and the life cycle. Economic trends in the US are analyzed in the paper by studying the evolution of net worth. Figure 1a shows the wealth distribution by percentiles from 1989 to 2019. The data reveals a widening gap between the top 10% and the rest of the distribution, with the bottom 75% experiencing wealth stagnation. Figure 1b illustrates the distribution of wealth by educational level and it also shows a big disparity between those with and without a college degree. In both panels, higher differences are found when comparing the gap between the mean and the median top 10%. This gap has also grown historically and it might suggest that education might not be the main driver of differences in wealth accumulation.

Figure 2 displays the average wealth life cycle profiles of the US in 2019 by educational level. This is integral in establishing the causal effects of education on life cycle wealth, helping to identify critical periods where education might play an important role, and understanding how wealth evolves as individuals age. It reveals substantial differences between college graduates and those with lower levels of education. Individuals with a college education have increasing levels of wealth that peak around the retirement age and then start decreasing during the later stages of life.



(a) Percentile

(b) Education Level

Figure 1: Evolution of Net Worth by Percentiles and Education
Note: Panel (a) presents the net worth by percentiles and panel (b), the average net worth by education. Source: Survey of Consumer Finances, 1989 - 2019.

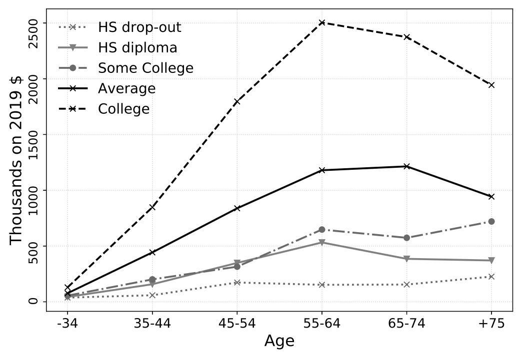


Figure 2: Average Wealth by Education and Age Cohort
Note: Panel (a) presents the average wealth and panel (b) the average income by educational level. Source: Survey of Consumer Finances, 2019.

3 Empirical Model

An important question that remains under-explored is whether the effect of higher levels of education causally increases net worth. Or it is just a simple positive correlation? This section explores these ideas by implementing different econometric models to find a causal relationship between education and net worth. Besides causality, there are other insights that this section will present that are related to the life cycle and distributional effects.

3.1 Empirical Strategy

The primary problem in this type of empirical application is the presence of unobserved variables that generate heterogeneity among individuals. Regularly in the literature on returns to education, the existence of unobservables is likely driven by factors like parental or environmental background or inherent differences in abilities. For example, higher parental levels of education or parental wealth may allow or motivate their children to

acquire the best instruction affordable in the market or to reach for a similar socioeconomic status as the parents. However, it can also increase their advantages in life even without entering the educational system.
The lack of such an ideal natural experiment setup (in which two groups, ex-ante identical, differ only in their educational level) generates the need for the development of this empirical analysis. The aim is to account for all the unobserved characteristics that might be correlated with both educational outcomes and life-cycle wealth. To achieve this, I present below three empirical strategies that aim at controlling or minimizing the effects of these unobserved characteristics in different ways.

3.1.1 Strategy 1. Control for Unobservables

This strategy aims at controlling the unobservable variables that are suspected to be affecting the estimates obtained through ordinary least squares due to endogeneity. These predetermined control variables will allow isolating the effect of educational attainment on wealth. Among these controls are found individual ability, parental background on composition, inheritance, education, and more importantly, wealth. It is necessary to highlight the importance of these variables to be measured early in life before educational decisions are made. Additionally, this analysis includes age-cohorts, year, and socio-demographic effects to cover for additional sources of variation left out from the main control variables. Strategy 1 follows the specification below:

$$W_{it} = \alpha + \beta_0 \, Educ_i + \beta_1 \, X_i + \beta_2 \, SD_{it} + \gamma_t + \upsilon_{it}, \tag{1}$$

where the indices i and t represent individuals and time respectively. W is the value of total wealth, *Educ* is the level of education obtained by the individual that is constant through the entire panel, X is a matrix of covariates that include: a measure of individual innate ability, parental wealth, and parental education of both parents in 1984. Additionally, *SD* includes some demographic control variables that include age, race, and sex of each individual, γ_t is a set of year dummy variables capturing time effects specific to year t, and lastly, υ is the error term.
After controlling for the variables considered unobservables i.e. parental background and individual abilities, the error term υ_{it} naturally can be assumed to be uncorrelated with the main independent variable which is education. However, some might insist that there are unobservables included in the error term that were not controlled and that might affect the dependent and independent variables. This is a legitimate concern that allows the introduction of alternative methods that will try to minimize the effects of these unobservable variables differently.

3.1.2 Strategy 2. Within Siblings Variation

The endogeneity problems arise by assuming that there are still characteristics in the error term that are considered unobservables. The fact that predetermined control variables of parental background and individual ability are not sufficient to solve this issue, introduces the within-siblings variation. This strategy attempts to observe the wealth outcome of two biological siblings during the same time period but after their schooling decisions were made. The idea behind the selection of two siblings is to minimize the family environment in which both grew up, develop their skills, and inherit or enjoy the same privileges regarding their parental socio-economic status. Similarly for individual ability, it is assumed that because the siblings share the family genetics, the differences with respect to other individuals with different genes are minimized.

This strategy aims to capture unobserved factors by assuming that ex-ante individuals are identical and that differences in wealth will emerge after the education period. The only control variable in this strategy is the difference in the age of the siblings as this setup does not include identical or regular twins born on the same day. As an additional consideration and to minimize the differences, siblings from the same sex and biologically related were included in this sample.

The specification of the within-siblings variation is presented as follows:

$$D.W_{jt} = \alpha + \beta_0 \, D.Educ_{jt} + \beta_1 \, D.Age_{jt} + \gamma_t * \upsilon_{jt}, \tag{2}$$

where the indices j and t represent pairs of siblings and time respectively. The letter D in front of the variables represents the difference between the value of one sibling with respect to the other sibling, considering the same order for the pairs in the subtraction. For the case of $D.W$, represents the difference in the wealth of a particular year between siblings 1 and 2. The variable $D.Age$ controls the age difference between the siblings, γ_t is the time-fixed effects, and υ is the error term of the specification.

Even if it is considered that both siblings were raised in the same parental environment, with similar genes, and enjoying the same benefits, it can still be argued that some unobserved characteristics can influence the educational choice and the individual net worth. For example, the idea that parents support their children in unequal ways regarding mentoring, company, or simply by differences in inheritances. Another possibility is that after the educational decisions take place, there might be some influence or shared knowledge from the more educated sibling to the less educated one to improve the quality of life. Additional cases can be drawn to neglect the effectiveness of this strategy. A final strategy is presented below to try to contemplate these last concerns.

3.1.3 Strategy 3. Compulsory Schooling Laws

Even though controlling for unobserved heterogeneity in the parental background and individual abilities might be sufficient to capture all the differences that can arise before the educational period takes place, it can be argued that this is not. To confirm this, the implementation of a third and final empirical strategy is proposed. It requires information regarding compulsory schooling laws in the United States. The data should include the minimum amount of years of schooling that every child must complete. The match between each individual and the corresponding number of years of compulsory schooling is done by assigning the number found in the law of the particular state of the individual at the age of 14. As the variation of compulsory education is created and enforced by the law of each state, it is considered exogenous to the individual allowing the introduction of the instrumental variables approach. The computational method used to calculate the estimates is the two-stage least squares. The first stage equation is as follows:

$$Schooling_{it} = \beta_1 \, CA_i + \epsilon_{it}, \tag{3}$$

where CA_i is the exogenous covariate of the equation of interest in the first stage. The predicted values from this regression are obtained by $Schooling_{it}$ that is included in the second stage to estimate the effect of endogenous schooling on wealth using compulsory schooling as an instrumental variable. I specify the second stage as follows:

$$W_{it} = \alpha + \beta_0 \, Schooling_{it} + \upsilon_{it}, \tag{4}$$

where $Wealth_{it}$ is the net worth of an individual and the main variable of interest. It might be argued that increases in compulsory years of schooling do not necessarily raise the levels of education but Lochner (2010) show with some formal tests that this is not the case and that it increases educational attainment over time. These laws provide insights into the externalities of human capital as they are exogenous to wealth. There is evidence supporting the validity of exogeneity in Acemoglu and Angrist (2000).

3.2 Data and Sample Selection

The data used in this analysis is obtained from the Panel Study of Income Dynamics (PSID). The PSID tracks the socioeconomic variables of a given family over time i.e., individuals and their descendants. The PSID supplements the main data set with special modules such as the wealth module implemented initially in 1984. Aside from pensions, the PSID data provide a relatively complete picture of household financial wealth. Additionally, it was designed to study economic mobility across generations therefore it tracks children of core sample respondents and includes them as members of the PSID core sample as they leave their parents' household and form their own households. This intergenerational feature of the sample makes the PSID an ideal data set for the empirical strategies I am proposing as they rely partially on the historical information of families or of initial individual characteristics. Mainly the wealth information of two linked generations.

As the empirical strategies include inter- and intra-generational family links, the analysis is split into two different samples that cover both pairs of relations. One case is a parent-child relationship and another case is a sibling relationship. I restricted both samples to individuals that are more than 30 and less than 50 years old in 1999 and that played the role of head of the family unit (FU). Only for intra-generational data, the sample is restricted to only men due to the higher availability of observations.

A relevant assumption is that the heads of the family unit by the time they are 30 years old, they already finished their education and are in the process of accumulation of wealth. In this data, every individual reports the same level of education through all the time periods. Another restriction that appears in both samples is that the relationship, parent-child, or between siblings, is biological only. In the inter-generational relationship, the children (the object of study) must be linked with the biological parents. I discard adopted children or step-children and by assuming that, I assume there will be less unobserved information. In the intra-generational relationship, the siblings must be biological siblings to minimize differences between them.

This analysis examines household wealth from two similar perspectives: total net worth excluding equity and including home equity. Net worth is measured as the total value of financial assets, non-financial assets, and primary housing, less the liabilities. I use inverse hyperbolic sine transformation to address the skewness of the two variables for net worth. The main independent variable needed in this study is the level of the human capital of a person which can be proxy by the level of educational attainment. The educational data obtained from the PSID is transformed from a continuous variable into a categorical variable. It is reported in Table 15, the new levels of education that are considered for the analysis. “Education=0” groups the individuals that years of education from 0 to 11 or report no education. “Education=1” are individuals who obtained just a high school diploma. “Education=2” are individuals with one to two years of college education, and “Education=3” for three to four years of college meaning also individuals that obtained a college degree in this sample. The last category created is “Education=4” and refers to individuals that have at least one year of postgraduate education.

Parental financial and educational information is included as control variables. The financial background of the parents is the level of parental wealth, measured by their total net worth and by the total parental family income in 1984. The parental educational background is obtained in the same way as the educational variable previously explained. It is considered the level of parental education in 1984. This is due to the fact that the main individual, the object of the study, in 1984 was in their first stage of life. Additionally, one important variable that can be extracted from the PSID is a family IQ score. Even though this type of variable can have the potential to measure incorrectly the intelligence of a person, it can be used as a proxy for the level of ability of each individual to partially have an idea of its effect. The most relevant socio-demographic characteristics of the individuals are controlled. Among these variables are included age, sex, race, and if the individuals grew up with both parents by the age of 16. It is important also to control whether the individual received an inheritance or not.[5]

Additional data regarding compulsory schooling laws were included for the last empirical strategy. This data was extracted from Acemoglu and Angrist (2000). Compulsory schooling or compulsory attendance laws are summarized as the maximum between two options. The first is the minimum years required before leaving school, taking into account age requirements. The second is the difference between the minimum dropout age and the maximum enrollment age.

[5]For more details of the variables used, check Table 14.

3.3 Descriptive Analysis

Table 1: Mean Wealth by Education and Cohort

	Education Level				
Age Cohort	**0**	**1**	**2**	**3**	**4**
30	4152.8	35925.2	61618.8	268526.7	97615.5
	(600.0)	(7500.0)	(12000.0)	(55625.0)	(38200.0)
40	15888.6	55392.5	79684.1	658240.8	239787.6
	(200.0)	(10700.0)	(17000.0)	(105000.0)	(103000.0)
50	38455.3	103747.9	115654.5	817157.1	463874.9
	(1600.0)	(13014.0)	(26750.0)	(152000.0)	(218500.0)
60	39604.4	159808.1	220448.7	831762.3	909346.1
	(3300.0)	(13000.0)	(56000.0)	(264000.0)	(360300.0)

Note: Source: Panel Study of Income Dynamics. Median value in parentheses. Data in this analysis is used with sampling weights.

Table 1 combines both educational level and age cohorts to see how the net worth of people with different skills evolves over the life cycle. In general, it is shown that the average wealth increases with educational level and as people go further in their life cycle. The value of wealth increases when individuals report higher schooling. There is a distinctive pattern displayed for certain educational levels. For example, the mean wealth of college graduates is higher than when they have postgraduate experience. This can be explained by the earlier integration into the labor market done by college graduates compared to agents that go for a one-year postgraduate education experience. In the parentheses of Table 1 are reported the median values for each educational level to check the skewness presented in the data. Similarly, the dependent variable is reported by age cohorts. The age cohorts are grouped every ten years, for example, the age cohort *30* contains individuals from 30 to 39 years old. For the dependent variable, its mean value is strictly increasing with each additional age cohort. The gap between mean and median values allows for this table to show a more insightful picture of the wealth distribution. The median is lower than the mean value due to the natural skewness of the data, but it is important to highlight that this gap increases as individuals get older.
Additional descriptive analyses are presented in the Appendix. The summary statistics of the additional control variables considered in strategy 1 are presented in Table 16 and a correlation matrix including the main variables in Table 17.

3.4 Empirical Results

3.4.1 Strategy 1. Control for Unobservables

The first table of the first strategy reports the effects of education on wealth for the average life cycle obtained using ordinary least squares. Table 2 separates in panel (1) the results of education as a continuous variable and in panel (2) by education categories.

Column (A) reports the values of education on wealth without controlling for any other characteristic. Column (B) includes the IHS transformation of inheritance, individual ability, parental presence during childhood, and parental education. Columns (C) report similar variables as the previous column, only that instead of parental education it includes parental wealth. Lastly, column (D) includes all the control variables.

Panels (1) and (2) report positive and significant estimates of education even after controlling for all these additional variables. It can be seen that the attenuation of its value is considerable, meaning that the effects of the unobservables are important to include. Interestingly the estimate of receiving inheritance still holds a big effect on wealth, together with parental wealth, with an elasticity of 12% and 31% respectively. In column (D) for both panels, the effects of individual ability, parental presence, and parental education seem to vanish after the inclusion of parental wealth. Overall it can be seen that increasing the years of education or higher educational categories increases wealth with statistically significant results.

Table 18, in the Appendix, provides a similar analysis to the one presented in Table 2. In this case, it considers the relation of education over wealth by age cohorts to study its effects over the life cycle. The results report the educational variable, without the categories, and with estimates obtained for the different unobservable variables grouped in three panels. In table 18, panel (A) reports the estimates for education on wealth when individual ability and inheritances are considered. Panel (B) controls for parental background excluding parental wealth and lastly, panel (C) includes parental wealth. In this table, the estimates for education are also significant and more importantly are increasing as individuals advance in their life cycle.

Table 3 presents the last results obtained for the first identification strategy and probably the ones that will provide a more detailed description of the effects of different categories of education over wealth across the life cycle. This table includes all the control variables used in this analysis i.e. individual ability and parental education, presence, and wealth. So far, additional control variables like age, sex, and race were not mentioned for brevity even though they are included in the majority of the results presented. The tables presented so far, including Table 3 use as dependent variable wealth excluding home equity but the results still hold in the same way when home equity is included as it is reported in Table 22 on the Appendix.

The results obtained from the control variables have the same impact as presented previously. However, two variables are important to mention, inheritance and parental wealth. According to Table 3, inheritance is only statistically significant in the forties and fifties. This is because the average value of inheritances is higher at that particular age. The most relevant variable is parental wealth, as it dramatically increases the wealth of individuals at every stage of life.

The estimates reported for education in this table are detailed by education categories and stage of life. The results are compared to the first category described which is "Education=0" which stands for high school drop-outs. The estimates for "Education=1" or individuals with high school degrees are positive and statistically significant which is

Table 2: OLS Regression: Effects of Education on Wealth

(1) Education on Wealth				
	(A)	**(B)**	**(C)**	**(D)**
Education	3758.61***	2041.74***	2033.08***	1771.06***
	(319.08)	(368.16)	(341.87)	(368.72)
Inheritance		0.13***	0.12***	0.12***
		(0.02)	(0.02)	(0.02)
P.Education W.		1157.74*		652.35
		(556.25)		(544.39)
P.Education H.		923.04*		600.09
		(462.47)		(443.42)
P.Wealth 1984			0.35***	0.31***
			(0.05)	(0.05)
Adjusted R^2	0.22	0.34	0.36	0.37
(2) Educational Levels on Wealth				
	(A)	**(B)**	**(C)**	**(D)**
Education=1	8017.76***	5352.63***	4735.15***	4685.59***
	(1255.16)	(1132.33)	(1157.98)	(1120.62)
Education=2	11044.20***	7004.54***	6376.06***	6034.59***
	(1357.91)	(1327.07)	(1327.58)	(1314.27)
Education=3	21980.45***	13300.10***	12697.63***	11655.58***
	(2006.25)	(2069.07)	(2024.16)	(2092.44)
Education=4	24606.72***	12328.92***	12552.36***	10594.28***
	(2374.42)	(2584.69)	(2392.12)	(2499.44)
Inheritance		0.13***	0.12***	0.12***
		(0.02)	(0.02)	(0.02)
P.Education W.		1235.41*		729.04
		(577.79)		(559.55)
P.Education H.		952.19*		631.19
		(468.06)		(447.86)
P.Wealth 1984			0.35***	0.31***
			(0.05)	(0.05)
Adjusted R^2	0.22	0.34	0.36	0.37
Observations	7500	6700	6700	6700
Cohort Effects	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes
Socio-Dem. Effects	No	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-demographic effects include the variables: age, sex, race, parents, and ability. The constant term is omitted for brevity.

higher at the first stages of life and decreases in late adulthood until reaching a negative and non-significant estimate. The results for ”Education=2” provide a non-significant estimate during the first age cohort and with additional significant and positive values in the rest of the life cycle, suggesting that individuals might get wealth benefits from acquiring just a few years of a college education. The remaining estimates of Table 3 are positive and increasing with levels of education. Interestingly, the differences found previously between individuals who finished college and those who have some postgraduate education, are clarified in this table. Panel (2) of Table 2 indicated that higher estimates were obtained from ”Education=4” when compared to ”Education=3” and it was mentioned that could be the late integration to the labor market an explanation for it. In this last Table 3, the same pattern is found but only during the first two age cohorts, meaning that having just a college education will provide higher wealth than postgraduate education but during early adulthood. The last two estimates for the cohort of 50 and 60 years of age show that the estimates are higher for the postgraduate level, suggesting that in the last stages of life, the highest level of education will generate the highest estimates.

Table 3: OLS Regression: Effects of Education Levels on Wealth by Cohort

Dependent Variable: Wealth				
	Age Cohort			
	30	**40**	**50**	**60**
Education=1	5681.47**	6186.18***	5060.96*	−1461.37
	(2153.47)	(1766.79)	(2235.27)	(3879.33)
Education=2	3581.85	7388.11**	7191.85**	2025.48
	(2954.18)	(2372.16)	(2665.32)	(4171.00)
Education=3	16550.04***	14082.21***	15459.77***	9705.70*
	(3951.75)	(2594.89)	(3273.93)	(4618.48)
Education=4	13478.86*	11584.72**	14656.99***	13322.22**
	(5514.62)	(3535.60)	(3713.56)	(4416.22)
Inheritance	0.33	0.44**	0.28+	0.29
	(0.33)	(0.15)	(0.16)	(0.21)
P.Education W.	98.81	486.26	580.74	676.82
	(796.10)	(761.83)	(758.82)	(993.37)
P.Education H.	−339.53	821.41	963.65+	1273.33
	(776.11)	(545.81)	(583.91)	(851.07)
P.Wealth 1984	0.20*	0.19**	0.29***	0.39**
	(0.08)	(0.06)	(0.07)	(0.12)
Observations	303	633	619	304
Adjusted R^2	0.24	0.37	0.35	0.42
Year Effects	Yes	Yes	Yes	Yes
Socio-Dem. Effects	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Sociodemographic effects include the variables: age, sex, and race, and the constant term is omitted for brevity. More details of the variables are in the Appendix.

3.4.2 Strategy 2. Within Siblings Variation

This is an alternative strategy that tries to control for unobservable characteristics of individuals that were not considered or captured previously. The within-sibling variation relies on data about biological siblings between 30 and 50 years of age in 1999 to minimize the effect of genetic factors and parental background. Two people from different families will tend to have a more diverse background than if these two people are biologically related and grow up under similar circumstances. The results of this strategy are provided in the table 4. Column (A) reports the education of the siblings as a continuous variable. This strategy assumes that the only difference between siblings is provided by the acquired education and after controlling for age, it can be seen that there is a positive

Table 4: Within-Siblings Regression: Effects of Education on Wealth

	(A)	(B)		(C)	(D)	
	Avg	Age Cohort		Avg	Age Cohort	
		30	50		30	50
D.Education	1944.89***	2397.34***	1723.10**			
	(323.40)	(483.83)	(551.14)			
D.Education=1				-2898.00^{+}	-728.51	-980.28
				(1693.67)	(2014.35)	(3573.89)
D.Education=2				85.66	4988.93*	1088.35
				(1885.92)	(2382.51)	(3778.94)
D.Education=3				5606.35**	10091.61***	4388.77
				(2119.67)	(2771.20)	(4139.71)
D.Education=4				6476.99**	6935.46^{+}	6478.61
				(2391.28)	(3840.01)	(4385.75)
D.Age	389.69*	448.59	163.73	390.85*	382.62	262.27
	(179.95)	(279.29)	(206.41)	(180.86)	(318.49)	(315.67)
Observations	3050	991	1337	3050	991	1337
Adjusted R^2	0.017	0.026	0.004	0.018	0.028	-0.001
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Effects	Yes	No	No	Yes	No	No

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The constant term is omitted for brevity.

and significant effect of an additional year of education on wealth. The variable Age in this regression is also positive and significant and tries to control for the differences that might appear from the age difference between brothers.

The effect found in column (A) is also found in column (B) when the results are divided to include two different stages of the life cycle. The age cohorts in strategy 2 are merged from 4 groups into 2, due to the low amount of observations in the sample that reach 305 pairs of brothers per time period. The first cohort shown as *30* contains pairs of siblings within the age range from 30 to 49 years old and the second cohort shown as *50* contains ages between 50 to 70. It seems that due to the bigger range of age in each cohort (unlike in the previous strategy that was just 10 years difference between cohorts) the effects of education over wealth seem bigger and more significant during early adulthood than the ones obtained in late adulthood. Both results for education per cohort are shown as positive and significant confirming the results obtained in the previous strategy. The variable for age is not significant due to the life cycle inherent structure of the results.

The results of columns (C) and (D) of table 4 now divide the educational variable into separate levels of education and try to find consistency with the results from the previous strategy. The lowest educational level of this data is taken as a base for comparison i.e. high school drop-outs. Column (C) reports some significant estimates but not for every educational category. Positive and significant results are only found for individuals with college or postgraduate education. Interestingly, the estimates for lower levels of education do not show statistical relevance. Similar effects can be found in column (D) when the effects of education on wealth are separated by age group. During early adulthood, even lower levels of education show significant estimates, including only individuals with two years of a college education. However, during late adulthood, this significance disappears and remains only for postgraduate education. The differences from columns (C) and (D) show the importance of analyzing these effects over the life cycle and not only for the average. A wider variety of levels of education seem to have higher significance with a positive effect on individuals during their early stages of life.

The results obtained in the last two columns of Table 4 can be explained by the fact that it seems very difficult to accumulate wealth solely out of education at the end of the working life cycle. In the data, there are apparent differences in wealth concentration at 50 years of age, but suggesting that these differences might arise from education seems to not be the case.

The causal effect of education on wealth at late stages in life is not yet confirmed but it is for early adulthood as shown in the last two columns of the table. In general, the results for both age cohorts are also confirmed as long as education is considered as an average of all education levels as in column (B). This gives the idea that additional years of education indeed will increase wealth even suggesting that will happen at every stage of life. The reality is that a causal effect can only be confirmed for the highest levels of education. These results do not confirm the ones found in the previous strategy. The estimates show a low significance in obtaining a cause-effect conclusion for late adulthood when education is separated into categories. However, they show some interesting causal results for educational effects on wealth during the early stages of life.

The results presented in Table 23 of the Appendix section, show that the results have the same characteristics when home equity is included in the measures of wealth. The inconclusive results of this second identification strategy can be caused by the relatively small sample of strategy 2 and the high level of specificity that is required between education categories and age cohorts. An additional strategy is required to have more certainty about this possible causal relation.

3.4.3 Strategy 3. Compulsory Schooling Laws

This last identification strategy relies on the exogenous variation of compulsory schooling laws from every state of the U.S., for that reason additional data is required to construct the instrumental variables analysis that aims to assess how changes in the minimum amount of years of education required per state will influence education and hence future wealth. In table 5 the results are divided into two panels, the top panel reports the results for instrumental variables (IV) regression that considers education as a continuous variable, and the bottom panel only individuals with a college education.

In this analysis, the educational variable is divided into categories but the results are presented only for college graduates because are the only ones that present significant results. Additionally in the table, within each panel, it is reported in the first column the average life cycle results and the last four columns report the life cycle estimates by cohorts.

The estimates of education in table 5 are calculated by the two stages least squares with

Table 5: Instrumental Variables Regression: Effects of Education on Wealth

Dependent variable: Wealth					
	Avg	Age Cohort			
		30	40	50	60
(a) Avg. Education					
Education	8453.09***	15639.28	17055.14***	14192.43***	18975.93***
	(2905.97)	(9918.25)	(4861.26)	(4047.57)	(5569.79)
	First Stage				
Comp. Education	0.07	0.03	0.05***	0.05***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
R^2	0.21	−0.34	−0.40	0.05	−0.11
F-stat.	15.55	2.05	2.62	2.41	3.85
(b) College					
College	51647.00***	32089.82	75823.42*	60910.21**	99468.65*
	(24560.25)	(17380.81)	(29529.94)	(22538.23)	(49256.96)
	First Stage				
Comp. Education	0.12***	0.015***	0.011***	0.012***	0.015***
	(0.002)	(0.007)	(0.005)	(0.005)	(0.007)
R^2	0.11	0.02	−1.62	−0.60	−2.17
F-stat.	14.25	2.82	1.40	1.43	1.35
Cohort Effects	Yes	No	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes	Yes
Observations	7320	318	691	675	347

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The instrument is the years of compulsory schooling by state. More details of the variables are in the Appendix.

the first stage including the data of the compulsory schooling laws as an independent variable. The data of this analysis add the exogenous variation of minimum compulsory school attendance into the original sample used in the first strategy. This sample considers males from 30 to 50 years old in 1999 from every state in the U.S., allowing for heterogeneity in the educational background affected by compulsory schooling laws.

The first stage of the instrumental variable analysis uses as an independent variable the new data of minimum years of education by geographical states to analyze its impact on the education reported by the PSID. The results obtained from the first stage suggest that compulsory education will have a positive and significant effect on education. meaning that the higher the requirements by law for minimum education will transform into higher education reported during adulthood. These estimates will be used as an endogenously generated independent variable for the second stage to see whether compulsory education serving as an instrument will influence wealth, which is the final dependent variable of the analysis. The results show clear support for the causal relationship between education and wealth. For a clear comparison, the estimates of the basic OLS regression in column (A) of table 2 can be considered. These results suggest that the average life cycle estimate for education will increase wealth with strong significant results.

The remaining part of the panel (a) of the table 5 details the life cycle results and suggests that positive and significant estimates are found for the last 3 age cohorts, including individuals ages between 40 and 70. However, the estimates for the initial age cohort are

positive but not statistically significant meaning that education does have not a causal impact on wealth at an early age. These results do not necessarily contradict the ones obtained from strategy 2 as this separates the age cohorts into smaller groups.
The previous strategy aggregates individuals between 30 to 49 years old for the initial age cohort and this strategy from 30 to 39 years old. The life cycle estimates obtained from the instrumental variable analysis provide additional insights about the initial level of wealth during the earliest stage of adulthood. The lack of a causal effect in this stage might be attributed potentially to the payment of student loans, resulting in initial low saving rates.
The bottom part of the table 5 reports the results obtained only for college graduates. As it was explained previously, the remaining educational levels are not included because the estimates are non-significant, including individuals with some experience in postgraduate education. The results for the college level are similar to the ones obtained in the previous panel. The marginal increase is larger for the college level compared to the average education but the significance is similar, meaning that during early adulthood, the estimates of education on wealth are not robust. In general, these results support the positive life cycle effects of education but only for individuals with higher educational attainment.
Additional results are presented in the Appendix for the same two main independent variables with the difference that additional controls are included. These control variables are parental income and wealth in 1984 and are presented in table 19 and 20 respectively. The inclusion of these variables is to cover the possibility of violations to the exclusion restriction to provide robustness to the main results.
The exclusion restriction might be affected for example when more years of compulsory schooling are implemented in a State, there is a chance that young individuals would be stopped from starting their ventures in the labor market, delaying labor earnings. This will keep their parents as the primary providers of resources, thus the inclusion of parental income or wealth would correct this issue. Under both controls, these results surely provide a more credible F-statistic and provide a more robust conclusion mainly about the wealth returns of higher educated individuals.

3.5 Additional Empirical Analysis

3.5.1 Parental Income vs Parental Wealth

This is an extension of the first identification strategy. The idea of Table 6 is to obtain estimates of the effects of education on wealth after controlling for individual ability and parental background but with the latter including either parental income or parental wealth in 1984. The two regression results aim to compare the different effects of parental economic background over the education estimates and the other control variables. The importance of this analysis appears because parental income is supposed to have a relevant effect on the child's future outcomes but not as strong as the effect of parental wealth.
Column (A) of Table 6 reports the results including parental income in 1984 and column

Table 6: Parental Income and Wealth

	(A)	**(B)**
Education	1943.29***	1771.06***
	(370.56)	(368.72)
Inheritance	0.13***	0.12***
	(0.02)	(0.02)
P.Education W.	890.90	652.35
	(575.14)	(544.39)
P.Education H.	777.13+	600.09
	(460.03)	(443.42)
P.Income 1984	0.23**	
	(0.08)	
P.Wealth 1984		0.31***
		(0.05)
Observations	6700	6700
Adjusted R^2	0.35	0.37
Year · Cohort · SD	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-Demographics (SD) includes the variables: age, sex and race. Additionally, parents and individual ability. The constant term is omitted for brevity.

(B) parental wealth in the same year. The results of column (B) are identical as in Table 2. When comparing both effects of education over wealth, it can be seen that the estimates that include parental wealth as a control variable, are more attenuated than the other that uses parental income. Additionally, the elasticity from an inheritance is 1% higher when parental income is considered. The same effect is found for the remaining control variables. Even when observing the estimates of the education of the father, both columns report positive estimates but column (A) is the only one reporting significant results.

The most important results to compare are the estimates for parental income or parental wealth over the accumulated wealth of the individual, and as expected, an additional unit of income of the parents increases the future wealth of the child by 23% but an increase in parental wealth generates a 31% wealth in the future for the child. These results are important as they suggest that parental wealth has a bigger impact on the life outcomes of the children than parental income. The importance of including either parental income or wealth is to better estimate the effect of education. It can be seen that the coefficient for education is lower when parental wealth is considered. Only considering parental income might overestimate the effect of education on wealth of a person.

3.5.2 Quantile Regression

This analysis is introduced after the causality relationship has been explored. It is done with the same data, and covariates, and under a similar specification as the first strategy.

Table 7: Quantile Regression: Effects of Education on Wealth

	(A) Quantile of Wealth Distribution					
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education	1108.01***	2147.39***	2811.90***	2786.20***	2176.59***	4236.05***
	(243.77)	(172.22)	(176.77)	(186.35)	(191.75)	(727.42)
Inheritance	0.26**	0.25***	0.26***	0.16***	0.08***	0.03
	(0.08)	(0.05)	(0.02)	(0.02)	(0.01)	(0.16)
P.Wealth 1984	0.21***	0.31***	0.29***	0.27***	0.16***	0.27***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)
P.Education W.	1217.00***	555.45	−46.37	170.78	1207.05***	2517.01*
	(265.72)	(342.68)	(247.22)	(273.95)	(331.10)	(1226.95)
P.Education H.	−419.77	377.36	831.86***	663.70***	582.89***	−2815.08***
	(274.06)	(280.09)	(205.37)	(194.12)	(162.88)	(499.51)
Observations	6687	6687	6687	6687	6687	6687
	(B) Quantiles of Wealth Distribution by Age Cohort					
	Age Cohort: 40			**Age Cohort: 60**		
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education	2531.89***	3643.12***	4817.50**	3402.74**	4867.06***	2093.78
	(709.61)	(781.99)	(1612.25)	(1266.67)	(1231.15)	(1986.99)
Inheritance	0.56***	0.70**	0.01	0.76+	0.26	−0.38+
	(0.12)	(0.23)	(0.53)	(0.40)	(0.27)	(0.23)
P.Wealth 1984	0.18*	0.19**	−0.01	0.43**	0.41**	0.47*
	(0.08)	(0.07)	(0.14)	(0.14)	(0.13)	(0.18)
P.Education W.	298.89	1230.57*	2664.44+	725.53	708.07	1139.23
	(1148.30)	(579.18)	(1415.64)	(1845.15)	(896.06)	(1953.61)
P.Education H.	112.87	604.97	597.80	2072.88**	2014.13*	836.21
	(815.06)	(568.08)	(809.13)	(651.26)	(779.67)	(908.17)
Observations	633	633	633	304	304	304

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-demographic effects include the variables: age, sex, and race. Additionally, parents and individual ability. The constant term is omitted for brevity. More details of the variables are in the Appendix.

The quantile regression follows

$$Q_q(W_{it}) = \alpha_q + \beta_{0q}\, Educ_i + \beta_{1q}\, X_i + \beta_{2q}\, SD_{it} + \upsilon_{itq} \tag{5}$$

where the equation (5) is jointly estimated for the 10th, 25th, 50th, 75th, 95th, and 99th percentiles of the distribution of the wealth. The quantile regression, in contrast to the OLS regression of equation (1), aims to explore the non-linear effects of education on wealth accumulation to see if education affects specific parts of the distribution differently. This regression also provides results by age cohorts to observe effects at different stages of life and by educational categories. Table 7 provides the results for the quantile regression with two panels (A) and (B), with the former reporting the effects of the average education across life and the latter reporting the results by two age cohorts, 40 and 60. These two age cohorts intend to provide more details of the effects of education on wealth during stages in life that previously showed a causal relation, hence excluding the age cohort from 30-49.

The results reported in panel (A) suggest that the estimates for education are statisti-

cally significant and show a positive effect over wealth for every percentile. However, these results argue that the estimates cannot be considered constant, as was previously mentioned in the Table 2 column (F). These estimates would change depending on the part of the distribution of wealth that is referring to. The values reported start with lower estimates that grow as higher percentiles are considered with a peak before the 0.75 quantile. These estimates obtained from the quantile regression can be appreciated more clearly in the figure 3, which additionally reports the OLS results with a dashed line and confidence intervals with a dotted line.
The results for all the independent variables show non-linearities across the distribution with some interesting insights about parental wealth and inheritances. These variables present also a concave shape that increases and peaks around the middle of the distribution lowering their estimates for people at the top of the distribution, suggesting that for them, parental monetary conditions will increase their wealth but with not as strong an impact as for middle-class people. The results of parental educational background indicate that at the bottom tail of the distribution, more educated parents have lower effects on wealth than the top part of the distribution and this might occur due to the trade-off that parents have to make between acquiring more education or integrating to the labor market to solve short term economic problems.

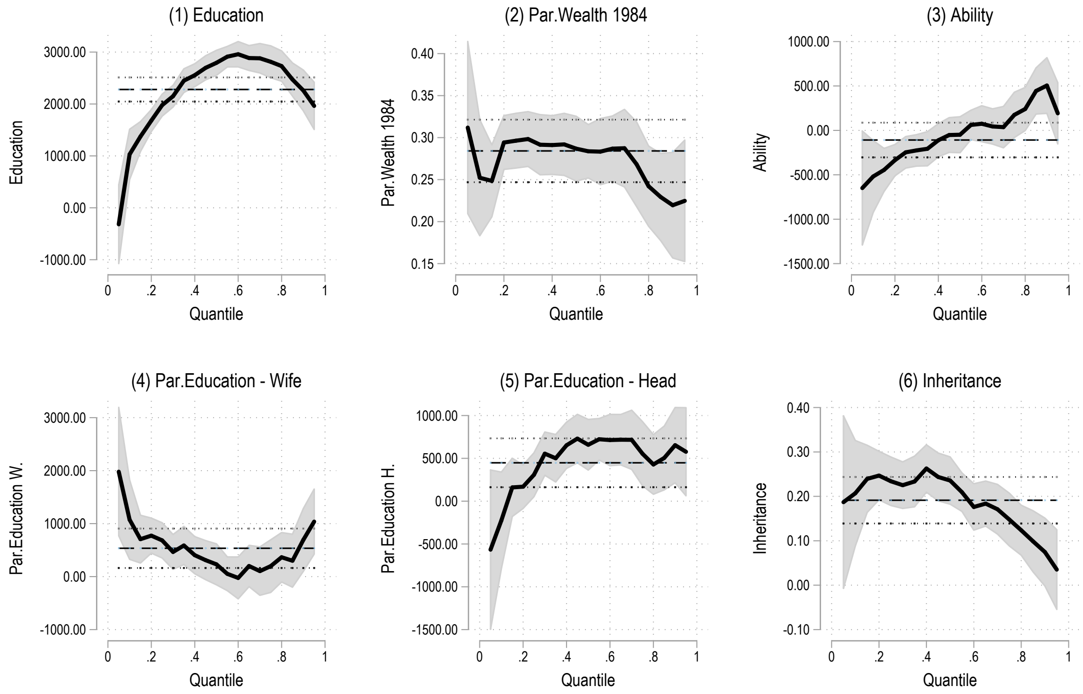


Figure 3: Education per Quantile of Wealth

Note: The graph shows the results of the quantile regression for some variables on household wealth including home equity. Each panel has the estimates from the OLS regression with a black dashed line and confidence intervals. The solid lines are the estimates from the quantile regression with confidence intervals at 95%. The results are heteroscedasticity robust and sample-weighted. Source: Panel Study of Income Dynamics.

Panel (B) of Table 7 shows the quantile results for two different age cohorts, 40 and 60, for three parts of the distribution to understand better the non-linear behavior of the estimates at different stages in life. The main independent variable, education, for both age cohorts, shows positive and statistically significant results that increase with each quantile. This suggests that there are more benefits from education to people at the top of the distribution. From this first row of panel (B), the only exception is the top 0.95 percentile of the last age cohort which reports a lower estimate than the previous quantile. This might be attributed to that, at later stages in life, the educational impact of wealth diminishes allowing other factors to be more important at the moment of accumulating wealth.

In the Appendix, table 21 reports results by separating the main independent variable, education, into categories. High school drop-outs (”Education=0”) are used for comparison to the remaining categories. The results show that for individuals that belong to the percentile 0.10, it is, in fact, counterproductive to not complete years of college education or postgraduate education regarding wealth outcomes. This means for example that individuals with postgraduate education at this decile will not have statistically significant results and even if significant, it would be lower than for college. The only positive and statistically significant results obtained at this particular decile are from people finishing college education.

For the other parts of the distribution in panel (A), additional years of education increase wealth when compared to being a high school dropout. The patterns found before suggesting lower returns due to the late start of labor income, as in the first identification strategy, can also be found here for the different quantiles. The educational category that obtains higher estimates is for people finishing college education and from that group, people from the 0.99 percentile have the highest results. Similar results of the quantile analysis are found also for the wealth-dependent variable that includes home equity. The results are detailed in the Appendix in Table 25 and Figure 7.

The last panel of this table, reports different parts of the wealth distribution at different educational levels for two different age groups. As it is expected, similar behavior can be found in these results. Estimates vary by age, education level, and part of the wealth distribution. Interestingly, for individuals with a high school diploma, the estimates of education are higher for cohort 40 than for cohort 50 for the same part of the wealth distribution. On the contrary, for individuals with higher levels of education, the older they get, the higher the estimates of education they are for the majority of the distribution. As explained before, the same nonlinear effect can be found in education in the top part of the wealth distribution.

3.6 Mechanisms of Transmission

To further understand the effects of education on wealth, it is important to consider the mechanisms that are driving the previous results. It is common in the literature to find that the main effects of education on wealth are through earnings. However, it can be argued that there are other ways that these effects might be transmitted. As it was mentioned before, after controlling for parental wealth and parental income in Table 6, the initial conditions of individuals do not explain the entire differences in individual wealth. Although they benefit greatly from high initial resources and later on inheritances, education still plays a significant role in generating wealth.

Table 8: Labor Income and Savings

Dependent variable: Wealth			
	(A)	**(B)**	**(C)**
Education	1771.06***	1656.15***	1220.87***
	(368.72)	(367.22)	(282.12)
Inheritance	0.12***	0.13***	0.07***
	(0.02)	(0.02)	(0.02)
P.Wealth 1984	0.31***	0.31***	0.25***
	(0.05)	(0.05)	(0.04)
P.Education W.	652.35	634.36	389.49
	(544.39)	(545.44)	(440.87)
P.Education H.	600.09	590.00	375.21
	(443.42)	(440.96)	(350.82)
Labor Income		0.08**	
		(0.03)	
Savings			0.66***
			(0.03)
Observations	6700	6700	6700
Adjusted R^2	0.37	0.37	0.53
Year·Cohort·SD	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-Demographics (SD) includes the variables: age, sex and race. Additionally, parents and individual ability. The constant term is omitted for brevity.

The first way to explain these dynamics is by following the direction of Card (1999) related to the effects of education on labor earnings. Individuals with higher educational attainment tend to have higher labor earnings, and as a consequence, they might accumulate more wealth. The results regarding this mechanism are presented in column (B) of Table 8. It can be appreciated that the estimates of labor income are positive and statistically significant, suggesting that this might be a possible mechanism that explains the effect of education on wealth.

In the same table, a second possibility to explain the results is explored. It arises from the idea that higher educated individuals have higher savings. Regardless of the different motivations to save throughout life, it seems that as educational attainment increases also savings increase. A positive link between education and savings is examined by Dynan, Skinner, and Zeldes (2004), allowing this channel of transmission to be considered. This idea might be confirmed by the positive and significant results provided by the coefficient for savings obtained in column (C) of Table 8. This suggests mechanisms driven by education generate higher savings and, thus higher wealth.

Table 9: Annuities, Stocks and Other Assets

Dependent variable: Wealth			
	(A)	**(B)**	**(C)**
Education	1110.31***	1493.71***	1645.99***
	(289.06)	(304.91)	(342.34)
Inheritance	0.11***	0.11***	0.11***
	(0.02)	(0.02)	(0.02)
P.Wealth 1984	0.24***	0.27***	0.29***
	(0.04)	(0.04)	(0.05)
P.Education W.	622.13	473.24	518.80
	(414.38)	(449.20)	(522.42)
P.Education H.	41.01	230.92	666.38
	(345.53)	(368.88)	(415.01)
Annuity/IRA	0.53***		
	(0.02)		
Stocks		0.41***	
		(0.02)	
Other Assets			0.42***
			(0.03)
Observations	6700	6700	6700
Adjusted R^2	0.56	0.48	0.42
Year·Cohort·SD	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-Demographics (SD) includes the variables: age, sex and race. Additionally, parents and individual ability. The constant term is omitted for brevity.

Table 9 explores three different assets that might explain the transmission of education on wealth. The first one is through annuities and retirement accounts with results presented in column (A). In general, the idea is that highly educated individuals will participate more in annuities and individual retirement accounts (IRA). This was examined by Bingley and Martinello (2017) who found that individuals with higher levels of education will increase the value of pension annuity claims. The positive and significant estimates obtained from the regression analysis suggest that this might be a possible mechanism. The dynamics could drive highly educated individuals to invest in retirement accounts, thus wealth during retirement would not suffer directly, for example, from negative medical expenses.

The second is through directly held stocks. This emerges from individuals with higher educational attainment tend to increase their probability of owning stocks Campbell (2006), higher return and participation in risky assets Ehrlich, Hamlen Jr, and Yin (2008) and higher stock market participation Bertaut (1998). The results of this mechanism are reported in column (B) with positive and highly significant results. The possible channel of transmission would be that higher levels of education, increase participation and returns from stocks, increasing wealth. The third is through the investment in other assets. This includes bonds, rights in a trust or estate, cash value in a life insurance policy, or a valuable collection for investment purposes. In a similar manner as for

stocks, the results reported in column (C) suggest a mechanism where individuals with higher educational attainment, increase these investments, thus increasing wealth.
A final idea that is highly considered in this research is that education directly affects wealth. McKay (2013) suggest that individuals with high education might be better equipped to learn, search, and assess risk and the trade-offs of choosing good investments.

4 Quantitative Model

After exploring the effects of education on net worth and discovering that only a strong case for causality can be made for college and postgraduate-educated individuals, a quantitative life cycle model aims to explore potential scenarios for educational reforms.
A partial equilibrium model considered the baseline model, a variation of the standard Income Fluctuation Problem, explores different features aiming at replicating the wealth distribution. After additional extensions, The model will account for heterogeneous capital income risk and exogenous effects of education on wealth.
This economy is populated by unitary individuals who live at most T periods but they also face a positive probability of death π_t starting from retirement at every period. In the first time period, agents exogenously acquire the human capital that will affect their working life and retirement. When agents enter the model at age 20, start their working stage, where they use human capital, consume, and save. Finally, the agents retire at age 65 when they no longer work and only receive interest from accumulated assets, pensions, and utility from consumption.
Preferences of individuals are identical over consumption c_t. These preferences are time separable, with an idiosyncratic stochastic discount factor β_t and survival probabilities s_t at each time t. Additionally, individuals derive utility from leaving a bequest to the next generation.

$$E_0 \left[\sum_{t=0}^{T} \left(\prod_{i=0}^{t} \beta_i \right) s_t \, u(c_t) + (1 - s_t) \, \theta(b_t) \right] \tag{6}$$

Here, s_t is the probability of surviving to period t and $(1 - s_t)$ is the probability of not surviving to period t, leaving a bequest b_t. The period utility function from consumption $u(c_t)$ is of the constant relative risk aversion class, where $\gamma > 1$ is the coefficient of relative risk aversion.

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{7}$$

The utility derived from bequests follows De Nardi (2004)

$$\theta(b) = \theta_1 \left(1 + \frac{b}{\theta_2} \right)^{1-\gamma} \tag{8}$$

where θ_1 is the strength of the bequest motive and θ_2 determines the extent of it being a

luxury good.
The initial conditions refer to human capital and assets and differ from agent to agent. It will be provided every period of their working stage of life (from age 20 to 65) to the productive sector. Agents start their life with a level of human capital $h_c \geq 0$ inherited from their parents. Second, the initial level of assets refers to the monetary resources that agents obtained in their first period. These resources can be seen as a regular use of parental wealth. This intergenerational transfer is assumed to be received at the beginning of their life cycle, even though they are often received later in life. In the baseline model, this level of assets is identical for all households but later on, it differs. Both initial conditions follow a log-normal distribution. The model abstracts from complicated family dynamics and strategic interactions between parents and children and assumes an exogenous intergenerational transmission of human and monetary capital.
The labor income of individuals, y_t, consists of two idiosyncratic components h_t and ξ_t and it is given by the following equation:

$$y_t = h_t \, \xi_t \tag{9}$$

where h_t is a permanent component and ξ_t is a transitory shock. At $t = 1$, human capital $h_t = h_c$ as agents start the model by using the human capital exogenously inherited from the previous generation.

$$\xi_{t+1} = \begin{cases} \mu & \text{pr } \pi \\ \phi_{t+1}/(1-\pi) & \text{pr } (1-\pi) \end{cases} \tag{10}$$

During all the working stages, labor income is obtained by the equation 9. The transitory shock ξ_t, presented in equation 10, gives a small probability π that income will be μ, i.e. temporary unemployment or unemployment insurance. Additionally, ϕ is presented as a mean-one IID random variable that satisfy $\mathrm{E}_t[\phi_{t+n}] = 1 \;\; \forall \, n \geq 1$ and $\phi \in [\underline{\phi}, \bar{\phi}]$.

$$h_t = G \; \psi_t \; h_{t-1}, \tag{11}$$

Equation 11 can be seen as the permanent income part of the process and consists of its previous value, a parameter G_t that represents a permanent income growth factor and a mean-one IID permanent shock ψ_t that satisfies $\mathrm{E}_t[\psi_{t+n}] = 1 \;\; \forall \, n \geq 1$ and $\psi \in [\underline{\psi}, \bar{\psi}]$. The distribution of the shocks follows:

$$\log \; \psi_{t+n} \sim N \; (-\sigma_\psi^2/2, \sigma_\psi^2)$$
$$\log \; \phi_{t+n} \sim N \; (-\sigma_\phi^2/2, \sigma_\phi^2)$$

Labor income shocks are independent across agents.[6] This implies that there is no uncertainty over the aggregate labor endowment even though there is uncertainty at the

[6] A more complex earning process is provided in De Nardi, Fella, and Paz-Pardo (2020) with a better fit for consumption inequality, but it shows similar results for wealth inequality as a standard process.

individual level. During retirement, there is no uncertainty from permanent or transitory shocks. Individuals receive an income or pension that is determined by a fixed retirement replacement rate κ obtained from the income of the period before retirement.
It is common in the literature to take the interest rate as fixed but in this model, the gross return on assets R_t will be state-dependent.[7] This means that there are idiosyncratic rates of return to capital following:

$$\log R_t = \bar{u}_r + \eta_t^r \; \bar{w}_r \tag{12}$$

where $\bar{u}_r$ and $\bar{w}_r$ are constants, R is a time-invariant non-negative function, and η is an IID standard normal innovation process.[8]
The introduction of discount factors provides additional heterogeneity for individuals in a similar fashion as capital income but with constant values for $\bar{u}_\beta$ as the stationary mean and $\bar{w}_\beta$ as the standard deviation and an IID standard normal innovation process.

$$\log \beta_t = \bar{u}_\beta + \eta_t^\beta \; \bar{w}_\beta \tag{13}$$

The main assumption in this set-up regarding heterogeneous capital risk and discount factors is based on the idea that when R and β were constants, it was required to have $\beta R < 1$ to ensure stability and existence but now that they are stochastic, it is required to fulfill a more general condition:

$$F_{\beta R} := \lim_{n \to T} \left(E \prod_{t=1}^{n} \beta_t \; R_t \right)^{1/n} < 1 \tag{14}$$

The value $F_{\beta R}$ in equation (14) can be thought of as the long run (geometric) average gross rate of return discounted to present value to ensure existence and stability.

4.1 Household Recursive Problem

The model described in the previous subsection considers that, during each period, a t-year-old agent chooses consumption c and asset holdings a for the next period. For the given conditions, the state variables for an agent are h_t, m_t, and β_t which are the level of human capital, market resources, and discount factors respectively. The optimal decision rules are functions for consumption, $c(h_t, m_t, \beta_t)$ and the next period asset holding $a(h_t, m_t, \beta_t)$, that together solve the dynamic programming problem described below.
The household expects assets at the end of the period, a_t, generated from the cash-on-hand m_t (all market resources) minus their in-the-period consumption c_t. This is expressed by $a_t = m_t - c_t$

[7] For more intuition and theoretical properties on capital income risk and heterogeneous discount factors check Ma et al. (2020).

[8] It is possible to improve the model by introducing mean persistence and time-varying volatility to the return on assets highlighted by Fagereng, Guiso, Malacrino, and Pistaferri (2016) and Fagereng, Guiso, Malacrino, and Pistaferri (2020).

Given this structure, human capital h_t and market resources m_t start with strictly positive values, $(h_t, m_t) \in (0, \infty)$. In this model for simplicity is assumed that agents cannot borrow from their future income. This implies that each agent is restricted to not dying in debt. This is conditioned by $c_T \leq m_T$

The first part of the life cycle, when agents are in their full-time working stage, is described below. From period $t = 1$ until $t = 44$ (from 20 to 64 years of age), agents just consume, work and save assets. They will use in the labor market the human capital exogenously obtained. In this stage, the state variables are discount factors, labor, and capital income that for readability are presented as a state vector $\bar{z}_t = (h_t, m_t, \beta_t)$. The value function of this period subject to the constraints previously detailed is given by

$$v(\bar{z}_t) = \max_{c_t} \left\{ u(c_t) \ + \ \beta_t s_t E_t \left[v_{t+1}(\bar{z}_{t+1}) \right] + (1 - s_t)\theta(a_t) \right\} \tag{15}$$

s.t.

$$a_t = m_t - c_t \tag{16a}$$

$$y_{t+1} = (\psi_{t+1} \ G \ h_t) \ \xi_{t+1} \tag{16b}$$

$$m_{t+1} = R_{t+1} \ a_t + \ y_{t+1} \tag{16c}$$

The next stage in this model is retirement, from 65 to 90 years of age. In this stage agents consume, receive their pension, and save assets. Additionally, the survival probabilities for individuals are not 1 anymore, facing a risk of death. This also means that individuals start deriving utility from leaving bequests to the next generation.

$$v(\bar{z}_t) = \max_{c_t} \left\{ u(c_t) \ + \ \beta_t s_t E_t \left[v_{t+1}(\bar{z}_{t+1}) \right] \ + \ (1 - s_t)\theta(a_t) \right\} \tag{17}$$

s.t.

$$a_t = m_t - c_t \tag{18a}$$

$$m_{t+1} = R_{t+1} \ a_t + \ p_{t+1} \tag{18b}$$

As demonstrated by Carroll (2006), a method to facilitate the solution of these models is to rearrange the problem to reduce its amount of state variables. In this case, these variables are h and m and the transformation to a ratio form can be achieved by the bold letter $\mathbf{m} = m/h$, reducing the number of states variables to one. The same definitions of variables can be done for $\mathbf{c} = c/h$, $\boldsymbol{\beta} = \beta/h$ and $\mathbf{a} = a/h$. Additionally, by defining $v_t(\mathbf{m}_t, \boldsymbol{\beta}_t) = v(h_t, m_t, \beta_t)/h_t^{1-\gamma}$ and if the ratio transformation is applied to the previous Bellman equation

$$v(\bar{z}_t) = \max_{c_t} \left\{ \frac{(\mathbf{c}_t h_t)^{1-\gamma}}{1-\gamma} + \beta_t E_t v_{t+1}(\bar{z}_{t+1}) \right\} \tag{19a}$$

$$\frac{v(\bar{z}_t)}{h_t^{1-\gamma}} = \max_{c_t} \left\{ \frac{(\mathbf{c}_t h_t)^{1-\gamma}}{(1-\gamma)h_t^{1-\gamma}} + \beta_t E_t \frac{v_{t+1}(\bar{z}_{t+1})}{h_t^{1-\gamma}} \right\} \tag{19b}$$

$$v_t(\bar{\mathbf{z}}) = \max_{c_t} \Big\{ \frac{\mathbf{c}_t^{1-\gamma}}{1-\gamma} + \beta_t E_t \Big[\frac{v_{t+1}(\bar{z}_{t+1})}{h_t^{1-\gamma}} \frac{h_{t+1}^{1-\gamma}}{h_{t+1}^{1-\gamma}} \Big] \Big\} \tag{19c}$$

where $\bar{\mathbf{z}} = (\mathbf{m}, \boldsymbol{\beta})$ is the new vector of state variables. Lastly, by including the transformed budget constraints, the final bellman equation that has to be solved is presented by:

$$v_t(\bar{\mathbf{z}}) = \max_{c_t} \Big\{ u(\mathbf{c}_t) + \beta_t E_t \Big[(G\psi_{t+1})^{1-\gamma} v_{t+1}(\bar{\mathbf{z}}_{t+1}) \Big] \Big\} \tag{20}$$

s.t.

$$\mathbf{m}_{t+1} = \frac{R_{t+1}}{G\psi_{t+1}} (\mathbf{m}_t - \mathbf{c}_t) + \xi_{t+1} \tag{21}$$

This trick allows this basic dynamic problem, which due to the three idiosyncratic shocks can be computationally costly, to be solved faster because it has just two-state variables. The development of the first-order conditions with respect to consumption, $\mathbf{c}_t$, grants the opportunity to get to the Euler equation afterward.

4.2 Solution Method and Calibration

An alternative solution to the value function iteration is the endogenous grid method (EGM) proposed by Carroll (2006). The convergence of the algorithm depends on the condition in equation (14). The process of discretization of $\beta_{t+1}, R_{t+1}, \psi_{t+1}$ and ξ_{t+1} is done by a standard Gauss-Hermite quadrature transforming the shocks into β^i, R^i, ψ^i and ξ^i respectively, with 8 quadrature points and weights π_β^i, π_R^i, π_ψ^i and π_ξ^i also associated. This method simplifies the root-finding process done by the time iteration, reduces the computational time, and increases accuracy and efficiency even during its implementation on more complex models. The main idea of EGM is to start with the assets $\mathbf{a}_t$ accumulated at the end of each period, to analytically calculate the optimal policy rule, i.e., consumption $\mathbf{c}_t$, to provide as output market resources $\mathbf{m}_t$ at the beginning of the same period endogenously. The algorithm for solving the finite dynamic programming household problem with uncertain labor and capital income follows:

Algorithm:

1. Construct a grid on assets
   $a \in \Gamma_a \equiv \{a_1, a_2, a_3, ..., a_j\}$.

2. For each $a_i \in \Gamma_a$, while taking into account labor, capital income and discount factor shocks, find consumption c_i using the Euler equation

$$\mathbf{c}_i = \mathrm{E}_t \left[\beta_t R_t \Big(G\psi_{t+1} \mathbf{c}_{t+1}^* \Big(\frac{R_{t+1}}{\psi_{t+1}} \mathbf{a}_i + \xi_{t+1} \Big) \Big)^{-\rho} \right]^{-\frac{1}{\rho}} \tag{22}$$

3. After obtaining the pairs $\{a_i, c_i\}$, find the endogenous state m_i

$$\mathbf{a}_i = \mathbf{m}_i - \mathbf{c}_i \;\Leftrightarrow\; \mathbf{m}_i = \mathbf{a}_i + \mathbf{c}_i \tag{23}$$

4. Then repeat for each period the same procedure.

As this model is based on the U.S., the parameters will try to be in line with what had been previously estimated and with values that will be extracted from related estimates in the empirical literature. The total number of households simulated in the model is $n = 100,000$, starting with a working stage from age 20 until retirement at 65 years of age. The length of each time period is one year, and the maximum age at which agents exit the model is 90, a total of 70 time periods.
For household preferences, the constant discount factor β is set to 0.96 to match the capital-GDP ratio of 3. When the household faces heterogeneous discount factors, the parameters are set to $\bar{u}_\beta = 0.96$ and $\bar{w}_\beta = 0.006$, with the mean value trying to match the same capital-GDP ratio. The coefficient of relative risk aversion γ at 1.5, from Attanasio, Banks, Meghir, and Weber (1999), and Gourinchas and Parker (2002), who estimate it from consumption data. This value is in the commonly used range (1-5) in the literature. The labor income process is based on Carroll, Slacalek, and Tokuoka (2015), Carroll, Hall, and Zeldes (1992), and DeBacker, Heim, Panousi, Ramnath, and Vidangos (2013). The income growth factor is set to $G = 1.02$ which is the annual average GDP per capita growth rate for the U.S. between 1947 and 2014. The unemployment insurance replacement rate is found between 0.30 and 0.15 but in this paper, it is set to $\mu = 0.15$. For the permanent and transitory shock, the variances are set to an annual value of $\sigma_\psi^2 = 0.01$ and $\sigma_\phi^2 = 0.01$ respectively to match what had been estimated for uncertain income processes. The pension benefit of individuals during retirement is a fraction κ of their permanent income at retirement. For the capital income process, the parameters are obtained from Ma et al. (2020) and set to $\bar{u}_r = 0.0281$ and $\bar{w}_r = 0.0393$ which are the stationary mean reduced values estimated originally from AR(1) models using data on Norwegian financial returns over 1993–2003.
The parameters for the initial log-normal distribution of assets are obtained by trying to match the real data values of the wealth Gini coefficient of individuals that are less than 35 years of age and the parent-child wealth elasticity at the same age. This elasticity is used based on the previous assumption that the initial level of assets comes from an inheritance or parental wealth. The elasticity of parent-child wealth is obtained from Charles and Hurst (2003). For this reason, the log-normal distribution sets a mean $\mu_a = 1.266$ and variance $\sigma_a^2 = 1.896$. The parameters of the initial distribution of human capital are found in Table 2 of Huggett, Ventura, and Yaron (2011) and allow individuals to be separated into 2 different education groups. The share of agents per group is obtained from the Survey of Consumer Finances of 2019, i.e. individuals with a college education constitute 36% of the total population, and non-college educated 64%.

4.3 Quantitative Results

This subsection shows the evolution of results for each of the different experiments up to the main theoretical model calibrated for the United States. This subsection aims to know what are the features that can be included in a life-cycle model that can reproduce

Table 10: U.S. Calibration of Parameters

Parameter	Description	Value
Preferences		
γ	Risk aversion coefficient	1.5
β	Discount factor	0.96
$\bar{u}_{\beta}$	Stationary mean discount factor	0.96
$\bar{w}_{\beta}$	Standard deviation discount factor	0.006
θ_1	Bequest strength	9.5
θ_2	Bequest as luxury good	11.6
Labor Income		
G	Growth income factor	1.02
σ^2_{ψ}	Variance log Permanent shock	0.01
σ^2_{ϕ}	Variance log transitory shock	0.01
π	Probability of zero income shock	0.07
μ	Unemployment insurance payment	0.15
κ	Retirement replacement rate	0.90
Capital Income		
R	Return factor (constant)	1.04
$\bar{u}_r$	Mean persistence constant	0.0281
$\bar{w}_r$	Volatility constant	0.0393
Initial Conditions		
μ_h	Mean of initial distribution h_p	0.466
σ^2_h	Variance of initial distribution h_p	0.213
μ_a	Mean of initial distribution a_p	1.266
σ^2_a	Variance of initial distribution a_p	3.595

the degree of wealth inequality evident in the microdata. The summary of the results is presented in table 11 which reports the percentage of the wealth accumulated at different sections of the wealth distribution. These results can be compared to the 2019 U.S. data reported in the first row of the table. After the initial presentation of a baseline life cycle model, additional features are included to bring a more realistic behavior.

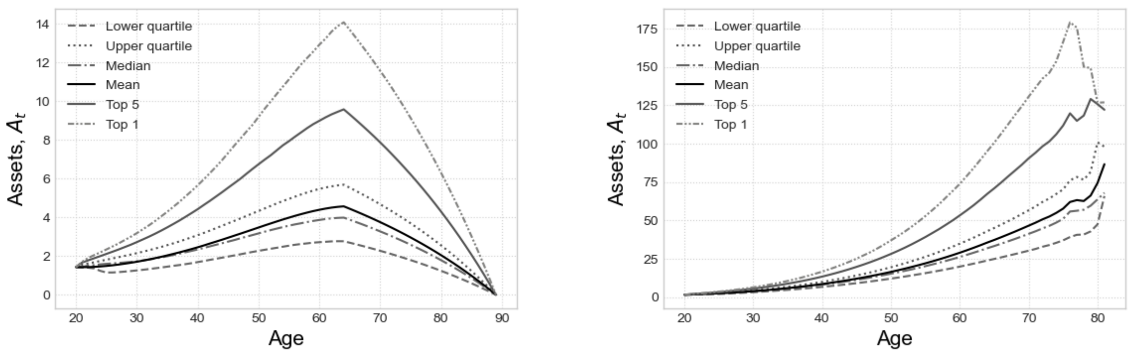
Table 11: Main Calibration Target: Wealth Distribution

	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
U.S. Data 2019	0.82	37.4	65.4	76.7	87.5	96.4	99.7	0.2
Baseline								
Equal h_o - Equal m_o	0.39	4.8	16.9	28.1	45.3	68.8	84.6	15.3
Equal h_o - Equal m_o - IGL	0.49	5.8	20.1	33.1	52.1	76.6	90.2	9.7
Experiment 1								
Unequal m_o - Unequal h_o	0.62	24.3	36.9	47.9	63.9	83.8	94.3	5.6
Experiment 2								
Unequal m_o - capital risk	0.67	30.8	46.1	56.8	70.3	85.6	94.0	5.9
Experiment 3								
Unequal m_o - capital risk - β	0.68	25.9	44.9	57.1	71.5	86.7	94.6	5.3

Note: Author's calculations. Source for U.S. Data: Survey of Consumer Finances, 2019.

4.3.1 Baseline

The baseline model is based on the Income Fluctuation Problem and keeps equal initial human capital and assets for all individuals. The only uncertainty shown in the baseline model is the labor income. The purpose of this initial model is to see how much wealth inequality can be generated from a framework with equal initial conditions.
As expected the results of the baseline model of Table 11 indicate a poor capability to replicate the wealth distribution observed in the U.S. Data. This results in a 4.8% accumulation of wealth in the top 1%, compared to the 37.4% observed in the data, and a 14.1 percentage point increase in the bottom 40% of the wealth distribution. The model also produces a low level of wealth inequality, with an average Gini coefficient of 0.39. This is a level of wealth inequality very low compared to the one found in the data.
The next step in the model is to include intergenerational links (IGL). The inclusion of voluntary bequests has been proven to contribute to the increase of wealth concentration at the top of the distribution (De Nardi, 2004). Additionally, the inclusion of inheritances might reduce wealth inequality (Elinder, Erixson, & Waldenström, 2018).
These two additional features provide an additional level of realism to the model. Its results can be observed in the second row of Table 11. As expected the distribution of wealth shifted from the bottom 40% to the remaining parts of the distribution even generating higher levels of inequality shown by a Gini coefficient of 0.49.
The asset's life cycle profile per percentiles is shown in Figure 4. There are clear differences in the accumulation of wealth in these profiles from the baseline model 4a to the model with intergenerational links 4b.



(a) Assets

(b) Assets with IGL

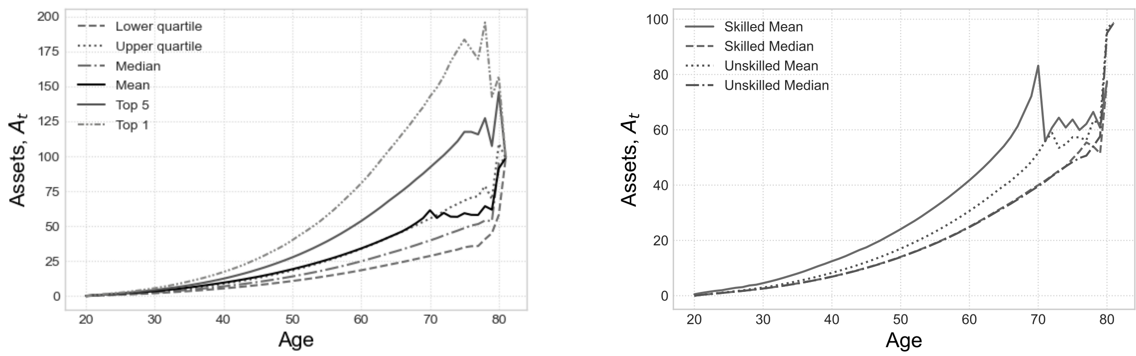
Figure 4: Baseline Life-Cycle Profile
Note: Baseline model is presented in panel (a) and the model with the inclusion of intergenerational links (IGL) in panel (b). The life cycle profiles for assets report lower and upper quartile, mean, median, top 5%, and top 1% of the distribution.

4.3.2 Unequal Initial Conditions

This new experiment will explore the effects of initial conditions based on the previous model with intergenerational links. It will add unequal initial conditions for human capital and assets. There are important effects on the life cycle development across people emerging from unequal initial conditions. As it is highlighted by Huggett et al. (2011), these variations are more relevant for lifetime wealth and income inequality than labor income shocks during working life.

The results, as seen in row 3 of Table 11, revealed an improvement in the fit from the previous model compared to the real U.S. data. These results show a higher concentration of assets, while the bottom 40% held a share of wealth closer to the real data. This fit could be attributed to the interaction between initial conditions in human capital and assets; individuals with higher human capital tend to accumulate more wealth, which is then passed on through generations, accounting for the observed differences in asset concentration.

A similar accumulation of assets can be observed in the life cycle profiles presented in figure 5. The profiles are presented now by percentiles 5a and by education level 5b. In this case, education is classified as college or skilled workers and non-college or unskilled individuals. In both cases, we can see how the gap in the profiles between the top of the wealth distribution and the skilled workers is compared to others.



(a) Assets

(b) Assets by Ed.

Figure 5: Experiment 1.3: Life-Cycle Profiles with Both Unequal Conditions
Note: Simulation 3 of experiment 1 plots the distribution of assets, (5a), and reports lower and upper quartile, mean, median, top 5% and top 1% of the distribution. Panel (5b) plots the average assets by educational level.

4.3.3 Heterogeneous Rates of Return to Capital

The second experiment introduces idiosyncratic capital income risk into the life-cycle model. This additional uncertainty can be seen at every time period by every agent. The previous model showed that initial conditions are essential to consider because they provide higher levels of wealth concentration. This second experiment includes unequal initial conditions, intergenerational links, and idiosyncratic labor income but now also adds idiosyncratic capital income.

The results of this experiment in the fourth row of table 11 show that when compared to the baseline model and the SCF data, the results still do not generate the same levels of wealth accumulation at the top of the distribution. Nevertheless, the replication power of this model is better than previous versions. The top 40% of the wealth distribution now is closer to the real values of the distribution. However, the bottom 40% generate a higher share of wealth than in the real data. Additionally, the general level of wealth inequality improved by 5 points with a Gini coefficient now at 0.67.

4.3.4 Heterogeneous Discount Factors

This final experiment aims to understand how wealth distribution is affected by the incorporation of idiosyncratic discount factors. The results are presented in the final row of Table 11 and show a decrease in the share of wealth held by the top 10% compared to the previous simulation. However, this higher level of accumulation of wealth at the top of the wealth distribution, allowed the bottom 90% to be closer to the real U.S. data. This also includes the share of wealth held by the bottom 40% that now is 5.3%. Additionally, the Gini coefficient went from 0.67 to 0.68, which is closer to the real data. Overall the power of the last simulation to replicate the U.S. data values appears to be higher than in the previous experiments. In general, the problem with the idiosyncratic discount factors presented in this simulation is that they reduce the concentration at the top of the distribution.

4.3.5 Exogenous Effects of Education

In the previous section, it was shown that education has a causal effect only on college graduates. Also, it was discussed some of the potential mechanisms by which education affects wealth. As discussed before and as commonly mentioned in the literature, a significant part of the impact of education on wealth comes through its effect on labor income. However, there is also evidence suggesting that education can influence rates of capital returns as well, either directly or indirectly. For example, literature related to returns to education suggests that it increases the probability of owning stocks (Campbell (2006) and Bertaut and Starr-McCluer (2000)), also increases risk-taking in financial markets (Black, Devereux, Lundborg, & Majlesi, 2018), higher returns and participation in risky assets (Ehrlich, Hamlen, & Yin, 2008), the value of pension annuity claims (Bingley & Martinello, 2017), and stock market participation (Bertaut, 1998). Additionally, it has also been associated with a lower stock market entry cost (Cooper & Zhu, 2016). Additional ideas can be suggested to allow education to influence rates of returns such as risk management, entrepreneurial ventures, networks, and access to capital.

The aim now is to include these direct and indirect effects of education on wealth in the model and see how the wealth distribution is affected. The indirect effect of education on wealth is via labor income. It is done by affecting the permanent component of the labor income process. This can be done through a higher income growth factor or higher mean of the permanent income shock for college than for non-college graduates. To recreate the causal effect of education on wealth via returns to capital, without adding endogenous decisions on portfolio choices, the link is included exogenously only to individuals with

higher education. This means that while keeping the heterogeneous rates of return to capital, its mean value will be higher for college than for non-college graduates.
To test these mechanisms, a model from table 11 is selected. This model includes idiosyncratic rates of return to capital as it shows the closest share of wealth for the top 1% of the wealth distribution. Even though the last model including idiosyncratic discount factors does a good job replicating the wealth distribution, an important objective of this paper is to focus on the redistribution from the top 1% to other parts of the wealth distribution. The results of the inclusion of the direct and indirect effects of education on wealth on the model selected are presented in table 12

Table 12: Main Calibration Target: Wealth Distribution

	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
U.S. Data 2019	0.82	37.4	65.4	76.7	87.5	96.4	99.7	0.2
Model	0.67	30.8	46.1	56.8	70.3	85.6	94.0	5.9
Model + Direct Effects	0.69	31.7	47.4	58.2	71.6	86.4	94.4	5.5
Model + Direct & Indirect Effects	0.70	32.0	48.3	59.3	72.6	87.2	94.8	5.1

Source for U.S. Data: Survey of Consumer Finances, 2019. Note: The model selected is presented in subsection 4.3.3 and it includes idiosyncratic rates of return to capital.

From this table, it can be appreciated, in the second row, that the inclusion of direct effects improves the fit of the model compared to the model selected. However, the model that includes the direct and indirect effects does an even better job of replicating the U.S. wealth distribution. These models not only increase the share of wealth for the top 1% but also to the bottom 40% of the wealth distribution. Additionally, in general, the average Gini coefficient is closer to the real data. This model, including the direct and indirect effects of education on wealth, will be used for the counterfactual simulations.

4.4 Counterfactual Simulations

After exploring different features that might be able to replicate the wealth distribution and the various forms of wealth inequality and finding a suitable model, this subsection exploits this and sees whether policies can be simulated. The main idea is to gain insights into whether it is possible to reduce wealth inequality with educational policies. The redistribution objective is to tackle inequality of opportunity and not inequality of outcomes. This is done by redistributing from the bottom of the wealth distribution and not necessarily by imposing a tax on the people at the top. This direction of redistribution with educational policies is proven effective for income distribution. For example, Keller (2010) showed that expenditures in education per student, enrollment rates, and public expenditures in education significantly improve the income distribution with an equalizing effect.
The educational policies studied in this paper relate to the quantity and quality of college education. These policies are based on the idea that education causally increases the

wealth of individuals with a college education. The main educational policy that will be explored here investigates whether an increase in the share of the population with a college degree would indeed reduce wealth inequality. This can be understood as several policies aiming at reducing the prices or costs of university entrance. This should not be discussed only from the financial costs but also other barriers stopping people from obtaining a college education. However, this paper does not deal with the reason for these barriers. The focus is on addressing higher college access and affordability for a bigger share of the population.

The second type of educational policy investigated is to improve teacher quality, training, curriculum, instructional support, or digital access for a better-educated population. This second direction aims at increasing the effect that education has on rates of return to wealth. This relates to the literature previously discussed on returns to education and mainly on financial literacy.

The model selected includes idiosyncratic rates of return to capital and direct and indirect effects of education on wealth. The first policy in this model is included by exogenously increasing the level of college-educated individuals. The second policy exogenously increases the average direct effect of education on wealth for college graduates. The results of these simulations are presented in table 13.

Table 13: Simulation Results: Wealth Distribution

	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
Model	0.67	30.8	46.1	56.8	70.3	85.6	94.0	5.9
Model + Direct Effects	0.69	31.7	47.4	58.2	71.6	86.4	94.4	5.5
Model + Direct & Indirect Effects	0.70	32.0	48.3	59.3	72.6	87.2	94.8	5.1
S1: ↑ College Share	0.69	31.3	47.4	58.3	71.7	86.5	94.5	5.5
S2: ↑ Avg. Rates of Return	0.70	32.7	49.0	59.8	72.9	87.2	94.8	5.1
S3: ↑ Both	0.70	32.2	48.9	59.9	73.2	87.4	94.9	5.0

Source for U.S. Data: Survey of Consumer Finances, 2019.

The results obtained by 13 suggest that increasing the share of college-educated individuals will decrease the wealth accumulation at the top of the wealth distribution and increase the share held by the bottom. The simulation results of the first educational policy reduce the Gini coefficient. The second policy simulated has the opposite effect. While keeping the share of college graduates constant, but increasing their average rates of return to capital, the wealth inequality increases. The last simulation includes a combination of both policies. The effect of the second policy crowds off the effect of the first one, leading to an increase in wealth inequality as well.

5 Conclusions

It can be argued that one of the consequences of a more unequal accumulation of wealth is that more individuals will have less capacity to afford investment opportunities, including higher education investments, affecting their future life outcomes. This leaves individuals wondering whether the effort of investing in education is still worth it. This research examines the effects of education on wealth accumulation, namely wealth returns to education. The question proposed in this research is if there is a causal relationship between education and wealth accumulation and if this causality applies to all education levels and throughout the life cycle.

The first part of this research is done by developing an econometric analysis with different empirical strategies. The results indicate that overall, there is a causal relationship between education and wealth even after controlling for parental wealth. These results are explored in detail and show that under certain conditions, the causal status is difficult to sustain. For example, when the analysis is separated by age cohorts, the education estimates show inconsistent results when individuals are in their early adulthood. But besides the results from the first age cohort, a causal relation for the remaining life cycle is supported by the three identification strategies implemented in the analysis. A strong causal relationship can be found for college or postgraduate education but not for lower levels of education. Additional results obtained from a quantile regression, show that these estimates depend importantly on the part of the wealth distribution that the agent belongs to.

After finding that there is a causal effect of education on wealth for college and postgraduate-educated individuals, this research focuses on the simulation of educational policies that aim at reducing the level of wealth inequality in the economy. This is done by developing a life cycle quantitative model with heterogeneous agents. The initial objective of the quantitative model is to explore different features that might replicate the desired right skewness found in the U.S. wealth distribution. This is done by the inclusion of unequal initial conditions, intergenerational links, idiosyncratic labor income, and additionally by including idiosyncratic rates of returns to capital. Later, the selected model adds direct and indirect mechanisms that transmit educational effects on wealth. The second part of the quantitative model is to explore educational policies and to provide counterfactual simulations. These educational policies aim at increasing the share of individuals in college and the quality of their education to reduce wealth inequality. The results obtained by the counterfactual simulations suggest that an increase in the share of college graduates decreases the share of wealth held at the top of the distribution and increases the one held by the bottom 40%.

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6 Appendix

6.1 Description of the Variables used in the Empirical Analysis

Table 14: Description of Variables

Variable	Description
Wealth	Total value of financial assets, non-financial assets, less the value of liabilities (mortgage and land contracts, family mortgage debt, education debt owed for personal and government loans, and other debt), and excluding the value of home equity.
Wealth Eq.	Total value of financial assets, non-financial assets, and primary housing, less the value of liabilities, including the value of home equity.
Education	Highest year of education completed. Education is classified into 5 categories (detailed in subsection 3.3).
Par.Wealth 1984	Parental net worth reported in 1984.
Par.Education W.	Highest year of education completed by the mother up to 1984.
Par.Education H.	Highest year of education completed by the father up to 1984.
Par.Income 1984	Total parental income reported in 1984.
Ability	IQ score tests as a proxy for ability with results that range from zero to thirteen.
Parents	Reports as “1” if the individual lived with both parents until 16 years old and “0” otherwise.
Inheritance	Value of inheritance received by the individual.
Age	Current age of each individual in a particular year.
Race	*Race* is reported as ”1” if White and ”0” for others.
Sex	*Sex* is reported as ”1” for males and ”0” for females.
CA	Compulsory assistance or schooling laws are the minimum years of education that an individual had as law in a respective state when 14 years of age.

Table 15: Classification of the Educational Variable

Category	Level	Year	Pct.
Education=0	High school D.O.	0-11	15.1
Education=1	High school	12	32.7
Education=2	College	13-14	20.2
Education=3	College	15-16	20.4
Education=4	Post-graduate	17	11.6
Education	Total		100

Source: Panel Study of Income Dynamics Data

Table 16: Summary Statistics

Summary Statistics					
	Obs.	Mean	St.D.	Min	Max
Age	7486	50.97	8.44	30	70
Sex	7486	0.76	0.42	0	1
Race	7486	0.83	0.38	0	1
Parents	7486	0.81	0.39	0	1
Ability	7486	9.76	2.08	0	13

Note: Source: Panel Study of Income Dynamics. Significance levels are denoted as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data in this analysis is used with sampling weights.

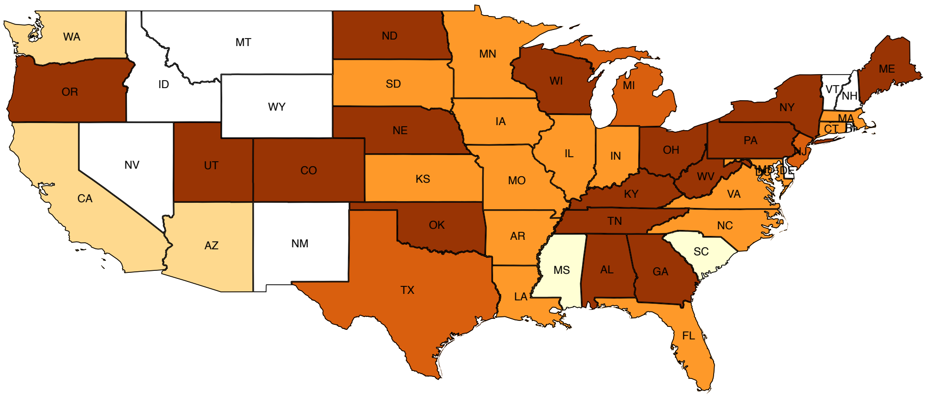
Table 17: Correlation Matrix

Correlation Matrix			
	Wealth	Wealth Eq.	Education
Wealth	1		
Wealth Eq.	0.90***	1	
Education	0.46***	0.47***	1
Ability	0.28***	0.28***	0.36***
Par.Wealth 1984	0.46***	0.49***	0.44***
Par.Education W.	0.32***	0.31***	0.42***
Par.Education H.	0.35***	0.34***	0.50***
Inheritance	0.17***	0.16***	0.12***

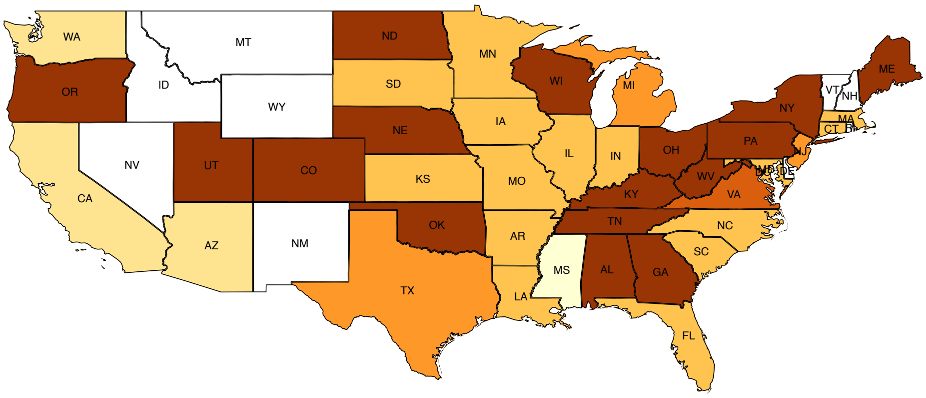
Note: Source: Panel Study of Income Dynamics. Significance levels are denoted as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data in this analysis is used with sampling weights.

6.2 U.S. Compulsory Schooling Laws

(a) 1965



(b) 1972



(c) 1978

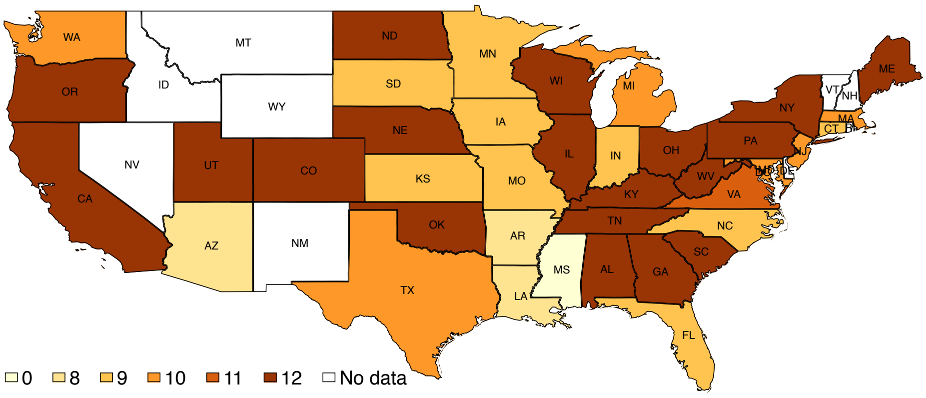


Figure 6: Evolution of Compulsory Education Laws
Note: The compulsory years of education in the U.S. by state in 1965, 1972 and 1978.

6.3 Additional Empirical Results

Table 18: OLS Regression: Effects of Education on Wealth by Cohort

	Age Cohort			
	30	**40**	**50**	**60**
	(1) Control for Ability			
Education	4576.74***	4553.59***	5771.56***	6257.57***
	(864.65)	(685.48)	(720.01)	(959.16)
Inheritance	0.54	0.54***	0.59***	0.67**
	(0.34)	(0.14)	(0.13)	(0.22)
Ability	173.35	31.43	−29.54	702.20
	(489.86)	(354.67)	(402.60)	(496.93)
Observations	317	693	682	350
Adjusted R^2	0.20	0.33	0.29	0.33
	(2) Control for Parental Background			
Education	4703.44***	3405.63***	4432.12***	5111.57***
	(1092.80)	(783.04)	(863.05)	(963.37)
Inheritance	0.52	0.49***	0.42**	0.51*
	(0.33)	(0.15)	(0.15)	(0.22)
Parents	−172.68	2405.27	3902.37	12202.36***
	(2691.19)	(1825.46)	(2126.99)	(3033.93)
Par.Education W.	343.64	583.72	879.02	921.52
	(841.45)	(722.90)	(753.43)	(1052.52)
Par.Education H.	−247.38	978.67	1115.73	1695.18*
	(785.96)	(538.32)	(581.83)	(841.53)
Observations	303	639	624	310
Adjusted R^2	0.19	0.34	0.31	0.39
	(3) Control for both			
Education	4266.93***	3134.77***	4132.97***	4585.04***
	(1174.87)	(827.33)	(909.09)	(1015.87)
Inheritance	0.39	0.46**	0.27	0.32
	(0.36)	(0.15)	(0.16)	(0.20)
Parents	−1567.02	1124.83	1796.07	9834.09**
	(2658.18)	(1796.63)	(2069.59)	(3119.02)
Par.Wealth 1984	0.19*	0.20**	0.29***	0.38**
	(0.09)	(0.06)	(0.07)	(0.12)
Ability	7.26	−374.66	−535.72	467.38
	(589.14)	(392.47)	(428.40)	(576.75)
Par.Education W.	121.21	313.78	512.00	724.44
	(855.40)	(744.34)	(741.79)	(992.23)
Par.Education H.	−479.46	836.46	950.80	1276.46
	(825.96)	(549.63)	(577.62)	(854.09)
Observations	303	633	619	304
Adjusted R^2	0.21	0.35	0.34	0.42
Year Effects	Yes	Yes	Yes	Yes
Socio-Dem. Eff.	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-Demographics effects include the variables: age, sex and race and the constant term is omitted for brevity. More details of the variables are in the Appendix.

Table 19: IV Regression: Effects of Education on Wealth with Parental Income

Dependent variable: Wealth					
	Avg	**Age Cohort**			
		30	**40**	**50**	**60**
(a) Avg. Education					
Education	7589.32**	18770.46	20370.18*	12807.49*	14762.59*
	(4066.83)	(16983.29)	(8649.05)	(5429.62)	(6350.10)
Par.Income 1984	0.09	−0.48	−0.50	0.18	0.26
	(0.44)	(1.05)	(0.59)	(0.38)	(0.48)
	First Stage				
Comp. Education	0.05	0.02	0.03***	0.04***	0.06***
	(0.009)	(0.02)	(0.01)	(0.01)	(0.02)
R^2	0.22	−0.75	−0.80	0.13	0.18
F-stat.	21.92	3.71	4.58	8.96	13.97
(b) College					
College	35345.68	29131.94	62476.16*	45032.25*	55041.14+
	(21568.10)	(19276.19)	(27102.97)	(21356.01)	(29738.24)
Par.Income 1984	0.47	0.29	0.11	0.43	0.71
	(0.28)	(0.27)	(0.34)	(0.30)	(0.39)
	First Stage				
Comp. Education	0.011***	0.015***	0.011***	0.012***	0.015**
	(0.002)	(0.007)	(0.005)	(0.005)	(0.007)
R^2	0.15	0.06	−0.88	−0.09	−0.29
F-stat.	20.01	6.94	4.38	7.16	8.86
Observations	6660	301	630	615	303
Cohort Effects	Yes	No	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The instrument is the years of compulsory schooling by state. More details of the variables are in the Appendix.

Table 20: IV Regression: Effects of Education on Wealth with Parental Wealth

Dependent variable: Wealth					
	Avg	Age Cohort			
		30	40	50	60
(a) Avg. Education					
Education	5586.68	18631.75	18653.46*	8913.47	12652.17*
	(3769.71)	(27536.38)	(9355.85)	(5294.47)	(5676.00)
Par.Wealth 1984	0.32	−0.14	−0.12	0.39*	0.36
	(0.25)	(0.87)	(0.35)	(0.20)	(0.24)
	First Stage				
Comp. Education	0.05***	0.01	0.03***	0.04***	0.06***
	(0.001)	(0.02)	(0.01)	(0.01)	(0.02)
R^2	0.28	−0.77	−0.59	0.31	0.29
F-stat.	31.88	4.87	6.40	16.48	21.32
(b) College					
College	25228.72	21481.81	55153.79*	30501.18	48999.06+
	(18773.87)	(21414.28)	(27371.56)	(19114.13)	(27347.15)
Par.Wealth 1984	0.49***	0.28	0.18	0.49***	0.55**
	(0.14)	(0.17)	(0.20)	(0.15)	(0.20)
	First Stage				
Comp. Education	0.011***	0.012+	0.010**	0.011**	0.015**
	(0.002)	(0.007)	(0.005)	(0.005)	(0.007)
R^2	0.23	0.19	−0.56	0.24	−0.10
F-stat.	29.13	10.70	6.53	14.81	13.78
Observations	6660	301	630	615	303
Cohort Effects	Yes	No	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The instrument is the years of compulsory schooling by state. More details of the variables are in the Appendix.

Table 21: Quantile of Wealth Distribution by Education Levels

(a) Quantile of Wealth Distribution						
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education=1	−332.74	61.90	2250.02**	7223.37***	7951.50***	7909.95**
	(600.91)	(563.96)	(858.62)	(1035.20)	(1862.18)	(2508.73)
Education=2	−1204.50	1779.23+	5660.95***	8500.54***	8466.37***	5333.40+
	(966.86)	(983.02)	(1195.00)	(951.38)	(1816.73)	(3001.77)
Education=3	4792.42***	9141.30***	14194.64***	16848.72***	16506.18***	31782.29***
	(1141.50)	(1126.55)	(1066.60)	(1018.94)	(2026.74)	(2651.60)
Education=4	3746.23	11687.06***	15210.41***	16212.33***	11938.17***	12125.88***
	(2352.00)	(1398.98)	(1276.42)	(1143.66)	(1914.10)	(3030.18)
Inheritance	0.25***	0.27***	0.27***	0.15***	0.07**	−0.01
	(0.07)	(0.05)	(0.02)	(0.01)	(0.02)	(0.09)
Par.Wealth 1984	0.24***	0.31***	0.28***	0.27***	0.18***	0.29***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)
Par.Education W.	1072.89***	525.36	51.30	328.32	1747.39***	1880.50***
	(295.45)	(346.81)	(257.77)	(291.19)	(345.44)	(378.19)
Par.Education H.	−224.37	344.34	839.93***	926.36***	566.63***	−730.43*
	(167.27)	(277.17)	(219.43)	(187.35)	(163.85)	(369.56)
Observations	6687	6687	6687	6687	6687	6687
(b) Quantiles of Wealth Distribution by Cohort						
	Cohort: 40			**Cohort: 50**		
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education=1	5298.21**	4737.26**	12616.44***	2236.87	3803.62+	9546.99**
	(1687.89)	(1678.28)	(3348.07)	(1525.51)	(2093.95)	(3085.48)
Education=2	3569.02	9162.29**	11362.67***	5849.87**	9702.83***	2186.23
	(2191.63)	(2853.70)	(3011.49)	(2229.27)	(2257.38)	(3122.00)
Education=3	9464.80**	14491.74***	21987.37+	9650.04**	17074.02***	16510.95+
	(3077.60)	(2976.34)	(11567.77)	(3418.77)	(3213.98)	(8698.88)
Education=4	8713.26*	12404.03***	18032.24*	10571.73***	18755.04***	11542.73*
	(4115.85)	(2829.24)	(7273.29)	(2872.89)	(3414.96)	(5830.80)
Inheritance	0.59**	0.61**	0.00	0.28	0.31*	0.19
	(0.19)	(0.19)	(0.83)	(0.17)	(0.14)	(0.31)
Par.Wealth 1984	0.18*	0.19**	0.18	0.33***	0.27***	0.12
	(0.08)	(0.06)	(0.13)	(0.08)	(0.07)	(0.10)
Par.Education W.	385.18	985.98*	2577.29	1847.42	187.26	2473.56+
	(1120.67)	(425.53)	(1835.02)	(1127.84)	(780.04)	(1357.52)
Par.Education H.	200.71	954.59+	1432.51	840.52	427.40	1700.38
	(798.13)	(520.32)	(1581.18)	(882.66)	(694.12)	(1077.59)
Observations	633	633	633	619	619	619
Soc. Dem. Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Effects	Yes	Yes	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-Demographics effects include the variables: age, sex and race. The constant term is omitted for brevity. More details of the variables are in the Appendix.

Online Appendix

Extra Empirical Results: Wealth including Home Equity

Table 22: OLS Regression: Effects of Education Levels on Wealth Eq. by Cohort

Dependent Variable: Wealth Eq.				
	Age Cohort			
	30	**40**	**50**	**60**
(1) Education on Wealth				
Education	5628.26***	3554.62***	4560.04***	4336.89***
	(1216.51)	(919.71)	(893.60)	(1064.44)
Inheritance	0.53	0.42**	0.29+	0.32+
	(0.35)	(0.14)	(0.16)	(0.19)
Par.Wealth 1984	0.16+	0.25***	0.30***	0.47**
	(0.09)	(0.07)	(0.07)	(0.15)
Ability	−188.10	−72.80	−373.99	83.79
	(636.53)	(436.35)	(428.76)	(632.91)
Par.Education W.	509.00	597.87	280.49	26.92
	(963.11)	(757.79)	(754.60)	(1011.72)
Par.Education H.	−1023.24	572.20	541.89	1179.49
	(859.91)	(557.67)	(554.84)	(820.69)
Adjusted R^2	0.25	0.36	0.37	0.37
(2) Educational Levels on Wealth				
Education=1	8430.59***	8819.70***	7925.35**	1618.79
	(2493.45)	(2179.06)	(2513.89)	(4534.29)
Education=2	6995.60+	10881.66***	10795.79***	6477.23
	(3709.38)	(2765.41)	(3026.91)	(4758.60)
Education=3	21265.30***	16234.18***	16546.78***	11031.25*
	(3979.67)	(2923.89)	(3478.63)	(5161.37)
Education=4	19085.35**	14589.96***	19138.42***	15402.50**
	(5793.09)	(3959.36)	(3711.48)	(4813.66)
Inheritance	0.49	0.42**	0.30+	0.31
	(0.34)	(0.14)	(0.16)	(0.19)
Par.Wealth 1984	0.16+	0.24***	0.30***	0.48**
	(0.09)	(0.07)	(0.07)	(0.15)
Ability	33.08	−106.46	−389.59	103.10
	(677.86)	(454.54)	(443.60)	(649.59)
Par.Education W.	471.30	800.03	351.92	26.19
	(890.00)	(784.64)	(769.01)	(996.84)
Par.Education H.	−835.27	593.33	576.14	1175.34
	(806.00)	(555.83)	(559.55)	(814.65)
Observations	301	632	617	303
Adjusted R^2	0.28	0.37	0.37	0.37
Year Effects	Yes	Yes	Yes	Yes
Socio-Dem. Effects	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Data in this analysis is used with sampling weights. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-Demographics effects include the variables: age, sex and race and the constant term is omitted for brevity. More details of the variables are in the Appendix.

Table 23: Within-Siblings Regression: Effects of Education on Wealth Eq.

	(A)	**(B)**		**(C)**	**(D)**	
	Avg	**Age Cohort**		**Avg**	**Age Cohort**	
		30	**50**		**30**	**50**
Education	1688.54***	2437.92***	1308.77*			
	(355.31)	(543.06)	(595.88)			
D.Education=1				−2107.87	1124.08	186.31
				(1861.70)	(2261.09)	(3860.77)
D.Education=2				911.30	5149.44+	2675.00
				(2073.03)	(2674.35)	(4082.28)
D.Education=3				4833.17*	11980.40***	1673.03
				(2329.98)	(3110.65)	(4472.01)
D.Education=4				6177.26*	8473.53*	6717.69
				(2628.53)	(4310.39)	(4737.80)
Observations	3050	991	1337	3050	991	1337
Adjusted R^2	0.018	0.036	0.003	0.017	0.038	−0.000
Soc.Dem.&Year FXs	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Effects	Yes	No	No	Yes	No	No

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Socio-demographics (Soc.Dem.) effects (FXs) include the difference in age between siblings. The section (A) reports education as a continuous variable and by cohort. Section (B) reports education by levels of education and by cohort. The constant term is omitted for brevity.

Table 24: IV Regression: Effects of Education on Wealth Eq.

	Dependent variable: Wealth				
	Avg	**Age Cohort**			
		30	**40**	**50**	**60**
	(a) Avg. Education				
Education	6986.77***	17150.81	15327.87***	12460.09**	15283.47**
	(2814.00)	(9745.06)	(4573.65)	(4010.49)	(5058.33)
	First Stage				
Comp. Education	0.07***	0.04	0.05***	0.06***	0.07***
	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
R^2	0.22	−0.23	−0.09	0.14	0.05
F-stat.	28.75	2.27	2.90	2.56	3.26
	(b) College				
College	42432.38**	36320.83	68111.76*	52088.10*	80108.57
	(23324.55)	(18565.56)	(27739.77)	(21199.11)	(42508.63)
	First Stage				
Comp. Education	0.012***	0.017***	0.011***	0.013***	0.013***
	(0.002)	(0.007)	(0.005)	(0.005)	(0.007)
R^2	0.10	0.00	−1.03	−0.37	−1.43
F-stat.	26.99	2.81	1.56	1.60	1.27
Observations	7,320	316	690	673	346
Cohort Effects	Yes	No	No	No	No
Year Effects	Yes	Yes	Yes	Yes	Yes
Instrument	Yes	Yes	Yes	Yes	Yes

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The instrument is the years of compulsory schooling by state. More details of the variables in the Appendix.

Table 25: Quantile Regression: Wealth Eq.

	(A) Quantiles of Wealth Eq. Distribution					
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education	1890.72***	3100.40***	2712.94***	2456.66***	1895.65***	3961.61***
	(288.31)	(224.27)	(160.97)	(122.23)	(179.45)	(763.66)
Inheritance	0.27***	0.22***	0.18***	0.12***	0.05*	0.03
	(0.05)	(0.02)	(0.01)	(0.01)	(0.02)	(0.10)
Par.Wealth 1984	0.34***	0.42***	0.29***	0.24***	0.15***	0.19***
	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.05)
Ability	−348.06**	68.39	−56.32	−295.93*	−617.59***	203.91
	(127.13)	(206.32)	(169.34)	(132.92)	(169.13)	(254.78)
Par.Education W.	268.37	234.80	124.02	382.93*	1329.54***	2530.18+
	(323.67)	(297.42)	(250.59)	(192.96)	(241.33)	(1297.84)
Par.Education H.	−231.67	157.84	605.63***	561.46***	547.51***	−2718.90***
	(379.56)	(267.37)	(183.14)	(122.57)	(165.20)	(822.67)
Observations	6687	6687	6687	6687	6687	6687
	(B) Quantiles of Wealth Eq. Distribution by Cohort					
	Cohort: 40			**Cohort: 60**		
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education	4433.25***	4515.10***	4310.84***	4444.26***	4822.42***	1541.06
	(835.71)	(816.21)	(1111.59)	(898.71)	(1045.77)	(1856.74)
Inheritance	0.42	0.49***	0.07	0.57*	0.13	−0.34
	(0.35)	(0.08)	(0.23)	(0.28)	(0.13)	(0.62)
Par.Wealth 1984	0.30***	0.23**	0.04	0.69***	0.41***	0.37+
	(0.08)	(0.07)	(0.08)	(0.08)	(0.11)	(0.20)
Ability	−57.44	−335.56	−1668.57***	1375.72**	688.56	1109.92
	(460.59)	(454.88)	(401.35)	(529.88)	(799.45)	(1102.98)
Par.Education W.	1197.48+	758.78	1633.07*	−1458.07	232.45	1731.07
	(613.11)	(732.95)	(755.90)	(1211.35)	(1069.24)	(1376.45)
par.Education H.	310.18	755.03	715.23	1449.77+	1094.83+	727.79
	(660.16)	(542.65)	(703.01)	(769.70)	(560.37)	(1006.60)
Observations	632	632	632	303	303	303

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are heteroskedastic robust. The data uses sampling weights. Time, socio-demographic and cohort effects are included in the panel (A) and (B). Socio-demographic variables include age, sex and race of individuals. Panel (A) reports the effects of education on different quantiles of the distribution of wealth including home equity. Panel (B) reports the effects of education on different quantiles of the distribution of wealth including equity by age cohorts. The constant term is omitted for brevity.

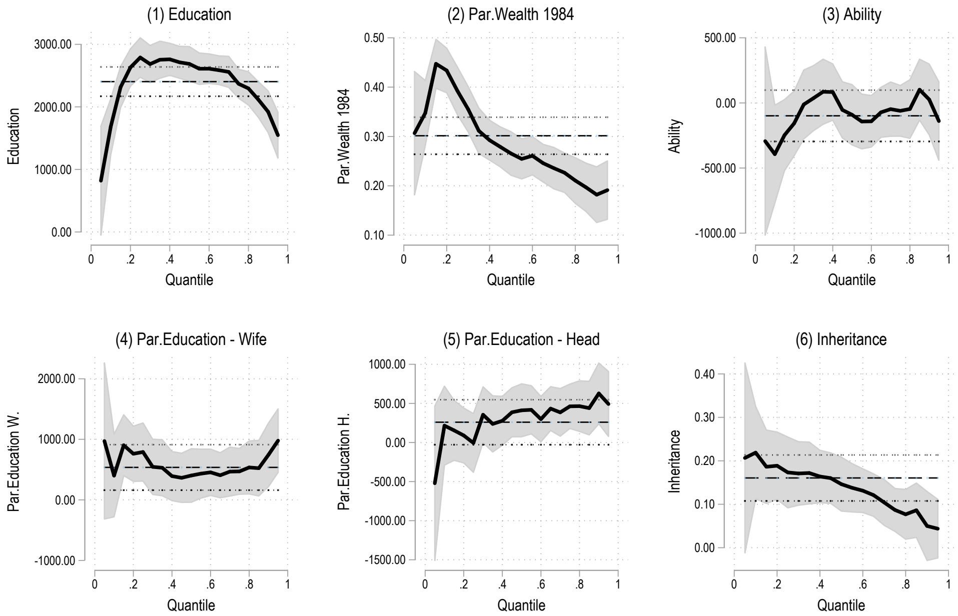


Figure 7: Education per Quantile of Wealth Eq.

Note: The graph shows the estimated results of the quantile regression for some variables on household wealth including home equity. Each panel has the estimates from the OLS regression with a black dashed line and confidence intervals. The solid lines are the estimates from the quantile regression with confidence intervals at 95%. The results are heteroscedasticity robust and sample weighted. Source: Panel Study of Income Dynamics.