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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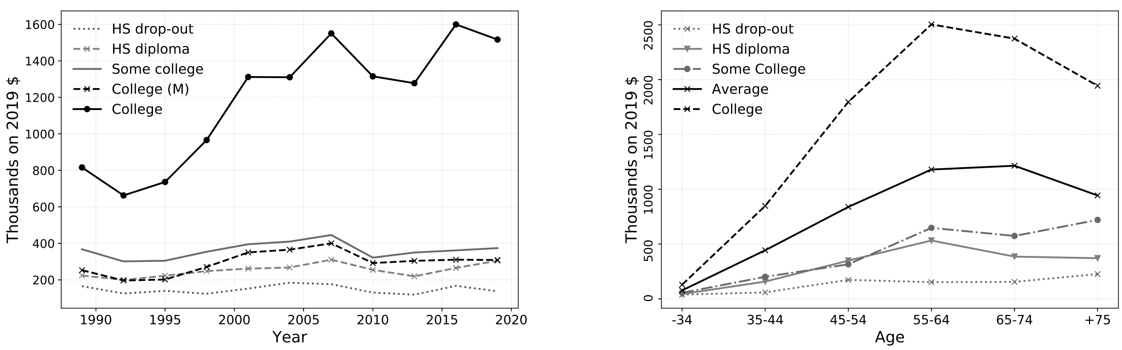
1 Introduction

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. Such disparities in wealth distribution have sparked a broad discussion on the mechanisms of wealth accumulation and the barriers to economic mobility faced by the majority. A deeper dive into the data reveals that educational attainment is a key factor in these wealth dynamics. Viewing wealth inequality through the lens of education reveals distinct disparities that broad statistics alone don't capture. To elucidate this point, Figure 1a illustrates the distribution of wealth by educational level from 1989 to 2019. This evidence highlights a stark disparity between individuals with and without a college degree. Notably, the gap between the mean and the median within the top 10% has also expanded over time, suggesting that the mechanisms of wealth accumulation may diverge significantly based on educational attainment. Similarly, Figure 1b presents the life cycle wealth profiles by educational level in the U.S. for 2019. It becomes evident that college graduates accumulate wealth in patterns distinctly different from those with lower educational achievements, with peaks around retirement age followed by a decrease in later stages. These differences underscore the importance of examining how education influences wealth accumulation across the life cycle, providing a critical backdrop for the ensuing discussion on the causal impacts of education on wealth.



(a) Education Level

(b) Life Cycle Profile

Figure 1: Evolution of Net Worth by Education
Note: Panel (a) presents the net worth by education level and (b) the life cycle profile of net worth by education level in 2019. Source: Survey of Consumer Finances, 1989 - 2019.

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 questions of this research are: First, does human capital investment allow individuals to accumulate wealth? Is this effect

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

consistent throughout the life cycle? Second, can educational policies reduce wealth inequality? This paper aims to determine if there is a causal link between wealth and education over the life cycle or simply a positive correlation.

Traditional economic studies have mainly focused on the link between education and labor income, consistently finding a positive causal relationship. Recently, the focus has shifted to the effects of education on net worth. However, research in this area is sparse, primarily due to difficulties in obtaining accurate wealth data and addressing causality. The existing studies, which often rely on Scandinavian data, have explored aspects like financial market participation, home ownership, financial literacy, and saving behaviors, but direct evidence of education's impact on wealth accumulation remains limited and inconclusive. For instance, Bingley and Martinello (2017) found no evidence that education influences wealth during retirement in Denmark, despite observing a positive correlation. Similarly, in Norway, Fagereng, Guiso, Holm, and Pistaferri (2020) found no causal returns to schooling on wealth, even with positive OLS estimates, after using IV and twins variation analysis. Conversely, Girshina (2019) suggests a causal link between education and wealth in Sweden, with effects varying across the life cycle. However, this study's limitation lies in its measurement of parental economic background through income rather than wealth.

Parental wealth significantly influences children's future outcomes, including their educational achievements and economic returns.[2] Research by Charles and Hurst (2003) has shown a strong link between the wealth of parents and their children before inheritances are passed on. Additionally, Black, Devereux, Lundborg, and Majlesi (2015) found that wealth transmission is largely influenced by the children's developmental environment and, to a lesser extent, genetics. Karagiannaki (2017) further indicates that parental wealth is a critical factor in children's access to higher education in early adulthood. Therefore, the role of family wealth is crucial in understanding the economic returns of education, given its significant and enduring impact.

This paper investigates the causal link between education and wealth using multiple empirical strategies, despite the challenges inherent in establishing causality in this context. Key among these challenges is the influence of parental background, especially parental wealth, not only on children's human capital but also on their broader economic outcomes. By addressing various sources of endogeneity, our analysis reveals a causal relationship between education and wealth across the life cycle, particularly for individuals with college and postgraduate education. These relationships, however, vary by life-cycle stage and wealth distribution segment. The findings underscore the role of labor income, productivity, and financial literacy and behavior as mechanisms through which education impacts wealth. Essentially, education enhances individuals' ability to generate wealth, both through direct effects on capital returns and indirectly through increased labor income.

Having established a causal effect of higher education levels on wealth accumulation and

[2]See Blanden and Machin (2004), Chevalier, Harmon, O'Sullivan, and Walker (2013), and Atkinson and Bourguignon (2014) for more on family background effects.

identified key wealth determinants, we introduce a life cycle quantitative model. This model addresses the need for greater skewness in wealth distribution, as seen in U.S. data—a feature that previous models have struggled to fully replicate.[3] Recent efforts have focused on idiosyncratic returns to wealth to better align these models with observed distribution patterns, exploring the potential of idiosyncratic capital risk to generate a Pareto tail.[4] Yet, the specific drivers behind these varied returns, especially in the context of education's impact on wealth, remain underexplored. Incorporating the latest insights from wealth inequality research into our life cycle analysis offers a promising avenue to deepen our understanding of how education influences wealth accumulation over time.

The quantitative model incorporates drivers of inequality such as initial heterogeneous levels of human capital, wealth, and heterogeneity in returns to capital and discount factors. 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 Empirical Model

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]For an overview of wealth inequality, see De Nardi and Fella (2017).

[4]Idiosyncratic returns and their implications are discussed in Ma, Stachurski, and Toda (2020) and Benhabib, Bisin, and Luo (2019).

2.1 Empirical Strategy

A major challenge in analyzing the returns to education is accounting for unobserved variables that contribute to individual differences. Such variables often include factors like parental education, wealth, and inherent abilities. For instance, children from wealthier families or those with higher parental education levels might have better access to quality education or inherent advantages that predispose them to higher socioeconomic status, irrespective of their educational achievements.
The absence of a perfect natural experiment—where two groups, otherwise identical, only differ in their education level—necessitates the development of an empirical approach to control for these unobserved factors. This is critical for accurately isolating the impact of education on life-cycle wealth. To address this, I propose three empirical strategies designed to mitigate the influence of unobserved characteristics on the study's outcomes.

2.1.1 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:

$$\mathrm{W}_{it} = \beta_0 + \beta_1\,\mathrm{Educ}_i + \beta_2\,\mathrm{X}_i + \beta_3\,\mathrm{SD}_{it} + \gamma_t + \upsilon_{it}, \tag{1}$$

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.

2.1.2 Strategy 2. Within Siblings Variation

Endogeneity issues emerge from the presence of unobservable characteristics in the error term, not fully accounted for by control variables related to parental background and individual ability. To address this, we use a within-siblings variation strategy, comparing the wealth outcomes of two biological siblings who have made their schooling decisions. This approach assumes siblings, sharing a similar family environment and genetics, have minimized differences in socioeconomic status and inherent abilities. However, differences in wealth are expected to manifest post-education. This strategy is formalized as:

$$\mathrm{D.W}_{jt} = \alpha_0 + \alpha_1\,\mathrm{D.Educ}_{jt} + \alpha_2\,\mathrm{D.Age}_{jt} + \gamma_t + \upsilon_{jt}, \tag{2}$$

Here, $D.W_{jt}$ represents the wealth difference between siblings at time t, with $D.Educ_{jt}$ and $D.Age_{jt}$ accounting for differences in education and age, respectively. γ_t captures time-fixed effects, and υ_{jt} is the error term. Despite the shared upbringing and genetic similarities, it's recognized that unobserved factors, such as differential parental support or knowledge transfer between siblings, could still influence education choices and net worth. These potential influences highlight the complexity of isolating the effect of education on wealth, leading to the development of an additional strategy to address these nuances.

2.1.3 Strategy 3. Compulsory Schooling Laws

While controlling for unobserved heterogeneity in parental background and individual abilities is crucial, it may not capture all pre-educational differences. To address this, a third empirical strategy leverages information on compulsory schooling laws across U.S. states. This strategy utilizes the minimum required schooling years, matched to individuals based on the laws in their state when they were 14 years old. Since these laws vary by state and are considered exogenous, they serve as the basis for an instrumental variables approach, allowing us to isolate the effect of education on wealth more cleanly. The analysis employs a two-stage least squares method, with the first stage predicting schooling based on compulsory education laws:

$$\mathrm{Schooling}_{it} = \beta_1\,\mathrm{CA}_i + \epsilon_{it}, \tag{3}$$

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:

$$\mathrm{W}_{it} = \alpha + \beta_0\,\mathrm{Schooling}_{it} + \upsilon_{it}, \tag{4}$$

Here, W_{it} indicates an individual's net worth. This approach assumes that compulsory schooling laws, as external factors, indeed affect educational attainment—a premise supported by Lochner (2010), who confirm that these laws significantly increase education levels. Moreover, the validity of these laws as exogenous instruments, separate from wealth, is backed by evidence in Acemoglu and Angrist (2000), highlighting their role in identifying the effects of education on wealth.

2.2 Data and Sample Selection

This study utilizes data from the Panel Study of Income Dynamics (PSID), which captures the socioeconomic variables of families and their descendants over time, including comprehensive household financial wealth data from the wealth module initiated in 1984. Designed to facilitate the study of economic mobility across generations, the PSID uniquely tracks children as they form their households, making it suitable for the proposed empirical strategies that examine inter- and intra-generational wealth dynamics. The analysis employs two distinct samples to investigate parent-child and sibling relationships, focusing on individuals aged 30 or older who were heads of their family units (FUs). For intra-generational comparisons, the sample is limited to men due to higher data availability. It is assumed, for both samples, that by age 30, individuals have completed their education and begun accumulating wealth, consistently reporting the same level of education across different survey periods.

Both samples exclusively consider biological relationships to minimize unobserved heterogeneity. Household wealth is analyzed through two lenses: total net worth excluding and including home equity, using the inverse hyperbolic sine transformation to address distribution skewness. Education is treated as a categorical variable, segmented into five levels based on the number of years of education completed, ranging from high school drop-outs, “Education=0”, to postgraduate studies, “Education=4”[5]. Control variables include parental wealth and education from 1984, leveraging the PSID’s detailed data to account for the financial and educational background of the parents. A family IQ score from the PSID is used as a proxy for individual ability, alongside key socio-demographic characteristics such as age, sex, race, family structure by age 16, and inheritance receipt. For the final empirical strategy, data on compulsory schooling laws, sourced from Acemoglu and Angrist (2000), supplement the analysis. These laws provide an exogenous variation in educational attainment, essential for the instrumental variable approach, summarized as the higher of the minimum schooling years required or the difference between dropout and enrollment age requirements.

2.3 Descriptive Analysis

Table 1 combines both educational level and age cohorts to see how the net worth of people with different education 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

[5] Table 14 reports the classification of education that are considered for the 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.

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 15 and a correlation matrix including the main variables in Table 16.

2.4 Empirical Results

The empirical findings, as detailed in Table 2, shed light on the nuanced relationship between education and wealth across the life cycle, analyzed through ordinary least squares regression. This analysis is divided into two distinct panels: Panel (A) examines the impact of education as a continuous variable on wealth, while Panel (B) delves into the effects based on categorized educational levels.
Across both panels, education emerges as a significant predictor of wealth, underscoring its important role in wealth accumulation. Specifically, the continuous measure of education in Panel (A) reveals that, on average, education correlates with an increase in wealth, with significance levels intensifying across different age cohorts. Notably, this effect escalates dramatically for individuals in their 60s, where education increases in wealth more

than in previous age groups. Panel (B) further dissects these findings by categorizing education into discrete levels. The results underscore a progressive increase in wealth with higher education levels. For instance, individuals with a high school diploma (Education=1) see a wealth increment, which significantly amplifies for those with one to two years of college education (Education=2). This trend continues, with postgraduate education (Education=4) showcasing the most substantial wealth gains, especially pronounced in the later life stages.

Table 2: OLS Regression: Effects of Education on Wealth

(A) Education on Wealth Over the Life Cycle					
	Avg	**Cohort**			
		30	**40**	**50**	**60**
Education	422.18**	516.37***	1376.98***	1782.41***	2866.07***
	(142.31)	(151.44)	(156.36)	(177.29)	(249.54)
Inheritance	0.15***	0.73***	0.52***	0.50***	0.50***
	(0.02)	(0.08)	(0.06)	(0.05)	(0.07)
Parental Wealth	0.28***	0.24***	0.22***	0.22***	0.15***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Par.Education W.	336.87	180.95	554.87*	−185.27	−60.97
	(255.58)	(221.35)	(250.06)	(318.47)	(430.86)
Par.Education H.	559.40*	−46.19	733.53**	1394.33***	1264.36**
	(266.38)	(211.34)	(232.74)	(269.64)	(393.37)
Observations	20558	7028	6436	4825	1920
Adjusted R^2	0.26	0.16	0.23	0.28	0.37
(B) Education Categories on Wealth Over the Life Cycle					
	Avg	**Cohort**			
		30	**40**	**50**	**60**
Education=1	1220.52*	1832.99**	4196.66***	5523.55***	2089.51
	(611.31)	(629.30)	(649.82)	(867.19)	(1393.96)
Education=2	2429.58***	1903.49**	5569.92***	6265.32***	8461.72***
	(677.35)	(697.32)	(768.53)	(966.68)	(1564.55)
Education=3	2439.55**	5044.87***	10598.11***	10108.45***	10385.52***
	(783.29)	(791.38)	(866.67)	(1089.23)	(1685.97)
Education=4	2606.89**	1007.09	7252.09***	13484.91***	17702.61***
	(988.58)	(1135.31)	(1132.53)	(1258.68)	(1697.00)
Inheritance	0.15***	0.76***	0.51***	0.50***	0.53***
	(0.02)	(0.08)	(0.06)	(0.05)	(0.07)
Parental Wealth	0.28***	0.24***	0.22***	0.21***	0.16***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Par.Education W.	362.50	258.52	641.68**	−175.27	−149.77
	(254.99)	(220.33)	(247.48)	(316.91)	(435.19)
Par.Education H.	597.69*	−13.73	807.43***	1463.31***	1206.75**
	(266.59)	(209.87)	(232.48)	(274.07)	(399.40)
Observations	20558	7028	6436	4825	1920
Adjusted R^2	0.26	0.16	0.23	0.28	0.37

Note: Source: PSID. 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. Year, 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 wealth. Panel (B) reports the effects of education categories on wealth. The constant term is included but not reported for brevity.

Inheritance and parental wealth consistently contribute positively across all models and life stages, highlighting the intertwined nature of wealth accumulation with familial economic backgrounds. Interestingly, the coefficients for parental education's wealth effects vary, indicating a complex relationship between parental education and offspring wealth, which merits further exploration. The adjusted R-square values across different cohorts suggest that the models explain a significant portion of the variance in wealth, particularly in the older age groups, indicating that the impact of education on wealth becomes more pronounced as individuals age.

This analysis underscores the critical importance of educational attainment in wealth accumulation over the life cycle. It also highlights the significant role of inheritance and parental wealth, suggesting that economic advantages are compounded across generations. The findings advocate for policies that promote educational attainment as a means to foster economic mobility and reduce wealth disparities.

Building upon the findings from our initial analysis, the study further investigates this relationship using an alternative empirical strategy. This approach, delineated in Table 3, employs within-sibling variation to control for unobservable individual characteristics that the previous model may not have fully captured. By focusing on differences between siblings, this strategy aims to isolate the effect of education by minimizing genetic and familial background influences, assuming siblings differ primarily in their educational attainment.

The results, categorized by education level and reported in Table 3, underscore a consistently positive and significant effect of education on wealth across all categories when compared to the baseline (i.e., individuals without a high school diploma). The variable 'Age' is also included to adjust for potential disparities arising from age differences between siblings, further refining our analysis.

Table 3: Within Variation Regression: Effects of Education on Wealth

	Avg	**Cohort**			
		30	**40**	**50**	**60**
D.Highschool	2774.54***	1830.78***	1956.65***	4326.30***	7237.41***
	(395.97)	(546.25)	(540.83)	(672.83)	(1752.25)
D.Some College	4026.92***	2703.14***	3580.97***	5810.34***	8654.81***
	(453.50)	(608.57)	(617.89)	(775.10)	(2091.42)
D.College	7780.61***	1636.41^{+}	7941.77***	11026.27***	22559.15***
	(732.46)	(957.20)	(1016.52)	(1415.25)	(3032.05)
D.Postgraduate	4081.46***	$-$2029.47^{+}	6337.08***	6666.97***	15819.36***
	(888.46)	(1178.16)	(1236.68)	(1713.20)	(3595.53)
Observations	15111	4688	5646	3890	967
Adjusted R^2	0.01	0.04	0.04	0.03	0.07

Note: Source: PSID. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Time, socio-demographic, and cohort effects are included but not reported for brevity. Socio-demographics include the difference of age between siblings. The constant term is included but not reported for brevity.

A detailed examination of life stage-specific impacts reveals that education's positive influence on wealth persists across all cohorts, reinforcing the premise that higher education levels correlate with increased wealth accumulation at every life stage. Notably, the results for college and postgraduate education indicate substantial wealth gains, particularly in later life stages, suggesting a strong causal relationship between higher education and wealth accumulation for these groups.

While these findings align with the previous strategy in indicating education's role in wealth enhancement, the within-sibling variation method introduces nuanced insights into the education-wealth nexus. Specifically, it reveals that the causal effects of education on wealth are most pronounced at higher education levels. However, the variation in significance across different life stages and educational categories suggests that the pathway from education to wealth may be influenced by factors beyond those captured by our model, including the timing and nature of education received.

Transitioning from exploring the direct and within-sibling variation effects of education on wealth, we delve into the third and final identification strategy. This strategy leverages the exogenous variation provided by compulsory schooling laws across U.S. states to discern how mandated education minimums impact long-term wealth accumulation. The core of this analysis lies in determining the extent to which variations in state-level educational policies contribute to differences in educational attainment and subsequent wealth. A representation of the heterogeneity in the compulsory attendance by each state is presented in figure 5 in the appendix.

Table 4: I.V. Regression: Effects of Education on Wealth

(a) Avg. Education					
	Avg	**Cohort**			
		30	**40**	**50**	**60**
Education	6155.57**	3977.16*	6171.54***	7609.57***	11040.17***
	(2189.31)	(1964.08)	(1246.49)	(1437.43)	(2826.96)
F-statistic	38.58	17.02	51.70	53.82	21.98
Observations	10281.00	1389.00	3912.00	3681.00	1243.00
(b) College Education					
	Avg	**Cohort**			
		30	**40**	**50**	**60**
College	48225.00^{+}	44545.21	39592.40***	61499.81***	71930.67**
	(26147.80)	(30959.81)	(9109.58)	(15707.51)	(27347.92)
F-statistic	22.21	8.59	39.84	29.44	9.97
Observations	10281.00	1389.00	3912.00	3681.00	1243.00
(c) Postgraduate Education					
	Avg	**Cohort**			
		30	**40**	**50**	**60**
Postgraduate	75971.12	39170.62^{+}	97973.17**	100234.87**	1192573.86
	(56081.63)	(22383.26)	(37598.58)	(34781.66)	(6269276.76)
F-statistic	15.45	12.71	14.32	15.95	0.05
Observations	10281.00	1389.00	3912.00	3681.00	1243.00

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. Year and cohorts effects are included. Parental wealth is included but not reported for brevity.

This analytical approach is predicated on two-stage least squares regression, with the initial stage incorporating compulsory schooling laws as instrumental variables. This method aims to capture the nuanced impact of legislated education requirements on reported educational levels within the PSID data set. While the details of the first-stage results are omitted for brevity, they essentially confirm that higher schooling requirements positively correlate with higher reported education in adulthood.
Table 4 reports the findings from this instrumental variable (I.V.) regression, highlighting the influence of education—categorized into average, college, and postgraduate levels—on wealth across different life stages. The primary column delineates the average life cycle effects, while subsequent columns disaggregate these effects by specific age cohorts.
The I.V. regression outcomes affirm a robust causal relationship between education and wealth, particularly notable in the 'Education' category within the average column and throughout the later life cohorts. These findings are compared against the basic OLS regression results, underscoring a significant wealth increment associated with education across the life cycle. Notably, the early adulthood cohort (age 30) displays positive but non-significant estimates, suggesting the influence of education on wealth might not manifest strongly until later stages, possibly due to factors like student loan repayments or early career development.
Further dissecting these effects, Panels (b) and (c) of Table 4 exclusively examine the wealth impact for individuals with college and postgraduate education. These detailed insights reveal a larger marginal wealth increase for college-educated individuals than the general education average, though early adulthood estimates remain less robust. This nuanced perspective reinforces the notion that higher educational attainment—particularly at the college and postgraduate levels—plays a significant role in wealth accumulation throughout the life cycle, albeit with varied significance across different stages.
Incorporating parental wealth into the analysis addresses potential concerns regarding the exclusion restriction. This inclusion helps mitigate bias that could arise from shifts in compulsory schooling potentially delaying young individuals' entry into the labor market and prolonging financial dependence on parents. The robust F-statistics provided lend further credibility to the instrumental variables used in this analysis. Overall, the results from this comprehensive strategy not only complement the insights gained from our earlier analyses but also provide a deeper understanding of the dynamic effects of education on wealth, especially highlighting the significant benefits accrued from higher levels of educational attainment over time.

2.5 Additional Empirical Analysis

2.5.1 Parental Income vs Parental Wealth

The regression results presented in table 17 in the Appendix, aim to compare the effects of different parental economic background variables over the education estimates and the other control variables. These variables are parental income and wealth. Parental income has a relevant effect on the child's future outcomes but is not as strong as the

effect of parental wealth. Following the results previously obtained, the effects of parental economic background when the head of the family unit was young, will focus only on college and postgraduate-educated individuals. Column (A) of table 17 reports the results including parental income and column (B) parental wealth. 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.
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 21% but an increase in parental wealth generates a 28% 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 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.

2.5.2 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 empirical strategy. 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. The quantile regressions results using education as a continuous variable are presented in table 18 in the Appendix. The most interesting result from this regression is that for individuals in the 10th percentile of wealth distribution, more education reduces their wealth. The results for the control variables are similar to the ones provided in table 5.
The results obtained in table 5 show positive and statistically significant coefficients for the education categories not only for the average but also over the life cycle. The clear results show that for college graduates there is no effect and for postgraduate educated individuals, there is a negative effect of education on wealth when these individuals belong to the 10th percentile of the wealth distribution. The effects of education for the higher percentiles, increase until a peak point between the 50th and 75th percentile when later, the coefficients start reducing their value. Similar non-linear effects can also be seen for variables such as inheritance and parental wealth. These results might suggest that even though these variables contribute to wealth accumulation for the majority of individuals,

Table 5: Quantile Regression: Effects of Education on Wealth

	(A) Quantiles of Wealth Distribution					
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education=1	2233.98***	906.30*	3472.00***	4739.12***	3829.28**	7582.75***
	(557.24)	(430.68)	(486.34)	(559.06)	(1212.89)	(879.15)
Education=2	431.57	1336.53*	5652.41***	7088.34***	6250.97***	8841.04***
	(593.41)	(576.08)	(546.04)	(623.92)	(1174.98)	(1084.64)
Education=3	850.80	5178.97***	10924.69***	12501.78***	10550.40***	14881.19***
	(924.38)	(731.30)	(590.12)	(606.71)	(1204.03)	(1629.12)
Education=4	−6113.21***	5677.32***	14522.20***	14932.71***	11275.85***	12084.83***
	(1232.35)	(1203.41)	(728.57)	(650.08)	(1170.62)	(1143.66)
Inheritance	0.24**	0.41***	0.35***	0.21***	0.08***	0.05
	(0.08)	(0.05)	(0.02)	(0.02)	(0.02)	(0.04)
Parental Wealth	0.17***	0.23***	0.28***	0.27***	0.20***	0.03
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)
Par.Education W.	−578.55*	−231.43	65.83	370.51*	600.39**	597.81*
	(272.33)	(243.60)	(180.54)	(163.43)	(184.11)	(257.43)
Par.Education H.	148.74	511.95*	818.90***	1019.43***	956.25***	669.48+
	(211.55)	(223.49)	(179.60)	(158.33)	(181.14)	(394.27)
Observations	20556	20556	20556	20556	20556	20556

	(B) Quantiles of Wealth Distribution by Age Cohort					
	Cohort: 40			**Cohort: 60**		
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education=1	3288.23***	2976.58***	4647.41**	4422.23***	2063.75	−1332.98+
	(428.65)	(551.23)	(1699.36)	(1080.78)	(1311.62)	(764.11)
Education=2	3939.58***	4930.85***	8209.59***	7379.38***	10804.34***	2450.88*
	(628.42)	(651.10)	(1767.93)	(1161.26)	(1977.45)	(1109.39)
Education=3	7845.91***	11137.99***	12725.15***	12094.71***	12963.23***	7232.86***
	(704.80)	(774.17)	(1810.63)	(1452.85)	(1613.91)	(1006.09)
Education=4	4110.27*	10966.64***	12692.98***	22372.68***	20440.86***	7044.63***
	(1824.02)	(938.93)	(1852.72)	(1108.08)	(2081.58)	(903.51)
Inheritance	0.68***	0.67***	0.15***	0.83***	0.42***	0.24***
	(0.10)	(0.05)	(0.04)	(0.06)	(0.08)	(0.07)
Parental Wealth	0.21***	0.27***	0.13***	0.09**	0.15**	0.19***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.05)	(0.03)
Par.Education W.	521.23	1132.62***	1217.21***	−285.19	−665.31	644.67***
	(335.24)	(284.05)	(264.12)	(387.05)	(704.62)	(173.10)
Par.Education H.	213.19	796.12***	761.68*	823.28**	2227.46**	1607.47***
	(289.33)	(215.47)	(316.21)	(317.64)	(686.82)	(229.53)
Observations	6436	6436	6436	1920	1920	1920

Note: Source: PSID. 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. Panel (B) reports effects of education on different quantiles of the distribution of wealth by age cohorts. Constant term is included but not reported for brevity.

there are other more important influential factors for the ones on top of the wealth distribution. These estimates obtained from the quantile regression can be appreciated more clearly in the figure 2, which additionally reports the OLS results with a dashed line and confidence intervals with a dotted line. The non-linear effects are seen for education, inheritance, and parental wealth.

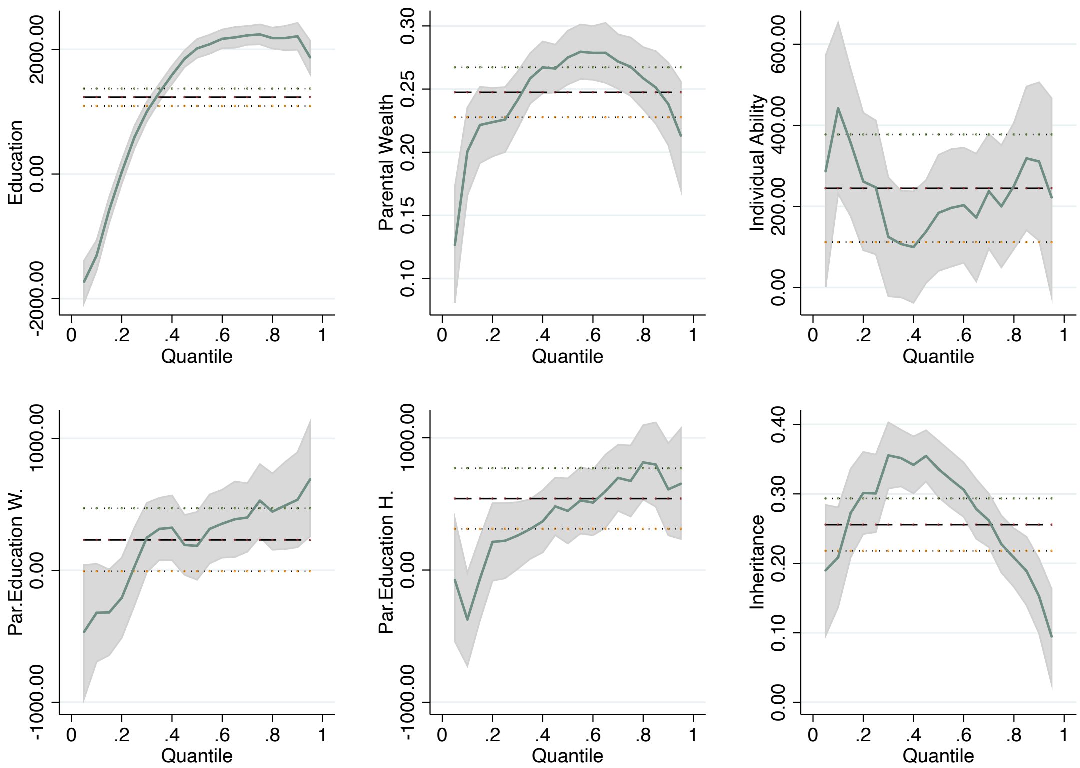


Figure 2: Education per Quantile of Wealth

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.

2.6 Mechanisms of Transmission

To further understand the effects of education on wealth, it is important to consider the mechanisms that are driving the main results. It is common in the literature to find the income effects relevant, however, it can be argued that there are other ways that these effects might be transmitted. In this subsection, I argue that increased productivity, financial literacy, and better financial behavior, are suitable candidates to explain the positive effects of education on wealth found for the highest levels of education. The last two mechanisms might allow individuals to perceive the idea 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. However, here it argued that this is done via financial literacy and financial behavior.

The first mechanism presented in table 6 is productivity and it is described as the individual's ability to generate income through labor or capital. The way this mechanism works would be that education enhances skills and knowledge, which can increase an individual's productivity in the workforce Gintis (1971). This increased productivity is often rewarded with higher labor income Card (1999), bonuses, and opportunities for investment income, such as rent.

Table 6: wealth's Regression Mechanisms: Productivity Effect

Dependent Variable: Wealth			
	(A)	**(B)**	**(C)**
Education=1	1027.58^{+}	1207.42*	1253.42*
	(600.53)	(609.71)	(607.00)
Education=2	2126.64**	2414.61***	2469.98***
	(673.69)	(675.49)	(672.13)
Education=3	1771.38*	2372.60**	2464.87**
	(782.51)	(781.74)	(777.57)
Education=4	1523.49	2457.52*	2581.73**
	(989.47)	(983.72)	(981.38)
Labor Income	0.15***		
	(0.02)		
Bonuses		0.23***	
		(0.04)	
Rent			0.30***
			(0.04)
Adjusted R^2	0.28	0.26	0.27
Observations	20558	20558	20558

Note: Source: PSID. 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. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

The variables included in this mechanism are income obtained from labor, work bonuses, and rents. In this case, labor income is directly tied to productivity at work, however, this variable can also be considered as measuring the known income effect. This means that if individuals obtain more income, this would allow them to accumulate higher wealth over time. In this analysis, bonuses are the main measure of labor productivity as they are often awarded for exceptional performance or productivity at work. Lastly, the rent obtained reflects income from property investments, which can be considered a form of capital productivity. The results suggest that these variables serve as a good mechanism as they increase the value of wealth while attenuating the effect of the highest educational categories. Even though their effects are different, the three variables show significant results. Similar results are presented in table 24 for wealth that includes home equity in the Appendix.

The second mechanism analyzed relates to financial literacy. It refers to the knowledge and understanding that enables an individual to make informed and effective decisions with all of their financial resources. For example, investments in stocks, annuities, and other assets suggest a higher level of financial literacy, as these decisions require an understanding of complex financial products and markets. Higher levels of education are associated with increased financial literacy Zhou, Yang, and Gan (2023), enabling individuals to make more informed decisions about investments, and financial products, which can lead to greater wealth accumulation.

Table 7: Wealth's Regression Mechanisms: Financial Literacy

	Dependent Variable: Wealth			
	(A)	**(B)**	**(C)**	**(D)**
Education=1	1371.04*	1591.78**	1050.28+	1224.15*
	(571.21)	(531.46)	(567.45)	(608.22)
Education=2	2223.07***	2346.42***	2184.52***	2430.21***
	(624.32)	(591.13)	(643.66)	(674.83)
Education=3	1726.54*	1563.35*	2251.57**	2452.27**
	(730.65)	(684.46)	(749.00)	(780.23)
Education=4	1360.07	364.85	2051.26*	2583.78**
	(913.79)	(866.00)	(945.17)	(984.42)
Stocks	0.48***			
	(0.01)			
Annuity/IRA		0.57***		
		(0.01)		
Other Assets			0.51***	
			(0.02)	
Interest				0.09***
				(0.02)
Adjusted R^2	0.38	0.45	0.32	0.27
Observations	20558	20558	20558	20558

Note: Source: PSID. 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. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

Table 7 explores the three different types of assets that might explain the transmission of education on wealth. The first one is through directly held stocks. Individuals with higher educational attainment tend to increase their probability of owning stocks Campbell (2006), and higher stock market participation Bertaut (1998). The results of this mechanism are reported in column A with positive and significant results.

The second is through annuities and retirement accounts with positive and statistically significant results presented in column (B). 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 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 third variable of table 7 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,

Table 8: Wealth's Regression Mechanisms: Financial Behavior

Dependent Variable: Wealth		
	(A)	**(B)**
Education=1	1277.80*	949.33
	(508.51)	(613.50)
Education=2	1828.73**	2062.60**
	(571.34)	(690.39)
Education=3	1323.68*	2044.10*
	(658.18)	(794.41)
Education=4	382.32	2084.18*
	(874.28)	(995.52)
Savings	0.78***	
	(0.02)	
Money Problem		−4768.88***
		(576.23)
Adjusted R^2	0.46	0.28
Observations	18057	19929

Note: Source: PSID. 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. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

increase these investments, thus increasing wealth. However, when comparing the coefficients of education, it can be seen that the indirect effect of education via other assets is smaller than for the previous assets presented. The last variation of good financial literacy is done through income from interest. The main idea is that education would lead to higher returns and participation in risky assets Ehrlich, Hamlen Jr, and Yin (2008), leading to higher wealth accumulation. The results report a positive and significant effect of income from interests.

The last mechanism trying to explain the main results is financial behavior which encompasses how individuals manage their finances, in this particular case, via saving, and whether individuals can pay their bills when due. A positive link between education and savings is examined by Dynan, Skinner, and Zeldes (2004) not only on average but throughout the life cycle **?** allowing this channel of transmission to be considered. This mechanism suggests that education generates higher savings and effective financial management, thus higher wealth. The results presented in table 8 confirm this intuition with significant results presented in column (A). The second variable, money problem, indicates whether a person has money problems paying bills when due and reflects responsible financial management skills. The intuition of this variable is that if individuals have more money problems or bad financial behavior, it would decrease their wealth. The results presented in column (B) of table 8 report negative and statistically significant effects of money problems on wealth. Similar results for the two mechanisms are presented in tables 25 and 26 for wealth with home equity in the Appendix.

3 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 partial equilibrium life cycle model aims to explore potential scenarios for educational reforms. A variation of the standard Income Fluctuation Problem is considered as the baseline and 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 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. Human capital 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 is assumed to be received at the beginning

of their life cycle. 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 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

[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.

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

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.

3.1 Household Recursive Problem

The model 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 $a_t = m_t - c_t$. 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, it 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

[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).

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.

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

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

3.2 Calibration

To obtain the model's parameters, two steps are implemented: first, some parameters are set to values from the literature. Second, the remaining parameters are estimated: inheritances, initial levels of education and wealth, and the probability of being highly educated. For the first step, the value of the parameters will be extracted from related estimates in the empirical literature. For household preferences, the coefficient of relative risk aversion γ at 1.5, from Attanasio, Banks, Meghir, and Weber (1999), and Gourinchas and Parker (2002), who estimated it from consumption data. The one-period survival probabilities s_t are obtained from Bell, Wade, and Goss (1992). The constant discount factor β is set to 0.96. 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 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 $\mu = 0.15$. The pension benefit of individuals during retirement is a fraction $\kappa = 0.90$ of their permanent income at retirement. For the permanent and transitory shock, the variances are set to an annual value of $\sigma^2_\psi = 0.01$ and $\sigma^2_\phi = 0.01$ respectively to match what

Table 9: 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

had been estimated for uncertain income processes. 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%. 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 period is one year, and the maximum age at which agents exit the model is 90, a total of 70 time periods.

3.3 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 the degree of wealth inequality evident in the microdata. The summary of the results is presented in table 10 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 10: 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.

3.3.1 Baseline

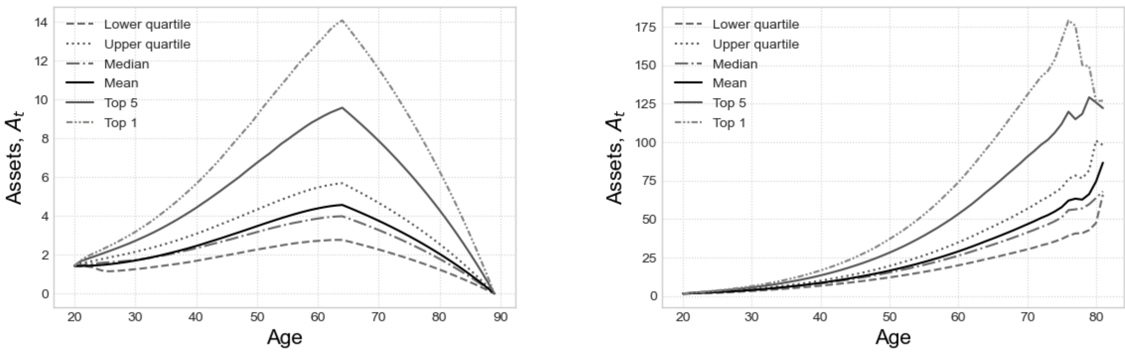
The baseline model is based on the Income Fluctuation Problem and keeps equal initial human capital and assets for all individuals. The only uncertainty shown in the baseline model is the labor income. The purpose of this initial model is to see how much wealth inequality can be generated from a framework with equal initial conditions.

As expected the results of the baseline model of Table 10 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 10. 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 3. There are clear differences in the accumulation of wealth in these profiles from the baseline model 3a to the model with intergenerational links 3b.

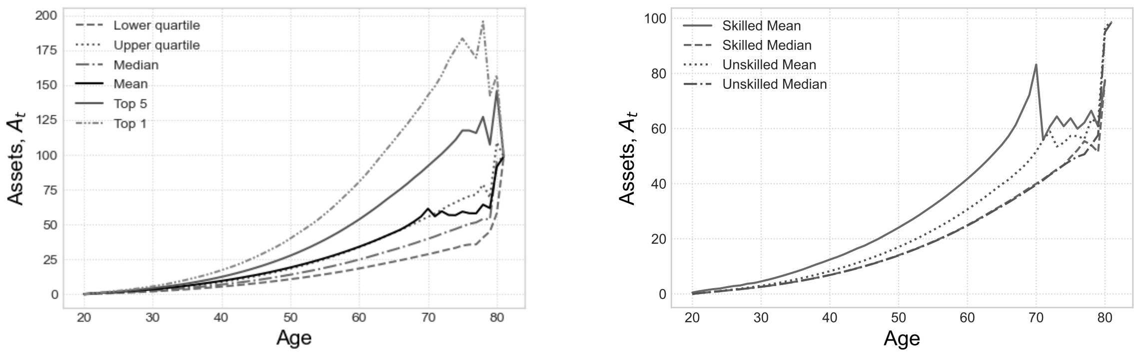


(a) Assets (b) Assets with IGL

Figure 3: 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.

3.3.2 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 10, 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 4. The profiles are presented now by percentiles 4a and by education level 4b. 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 4: Experiment 1.3: Life-Cycle Profiles with Both Unequal Conditions
Note: Simulation 3 of experiment 1 plots the distribution of assets, (4a), and reports lower and upper quartile, mean, median, top 5% and top 1% of the distribution. Panel (4b) plots the average assets by educational level.

3.3.3 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 10 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.

3.3.4 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 10 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.

3.3.5 Exogenous Effects of Education

Section 2 showed that education has a causal effect on wealth accumulation for individuals with college and postgraduate education. To include this empirical result into the life cycle model, individuals are classified in two categories: college and non-college. This decision is made exogenously in the first period of their life and depends on the level of human capital and wealth they have. It utilizes a logistic function to translate these background values into probabilities, which are then used to make classifications. These classifications will be adjusted later for different hypothetical scenarios by altering the logistic function's parameters. By aggregating the result of this classification, the shares of individuals with and without college education are obtained. These shares are then compared to empirical data for validation.

Section 2 also discussed some of the potential mechanisms by which education affects wealth. As is 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 10 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 11

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
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 3.3.3 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.

3.4 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 12.

Table 12: 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 12 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.

4 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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5 Appendix

5.1 Description of the Variables used in the Empirical Analysis

Table 13: 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 2.3).
Par. Wealth	Parental net worth reported when the child was young.
Par.Education W.	Highest year of education completed by the mother.
Par.Education H.	Highest year of education completed by the father.
Par. Income	Total parental income reported when the child was young.
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 14: 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 15: 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.

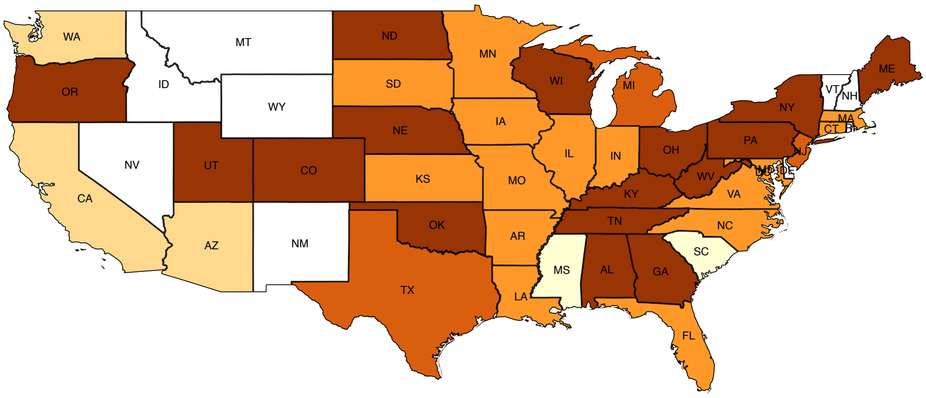
Table 16: Correlation Matrix

	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 c	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***

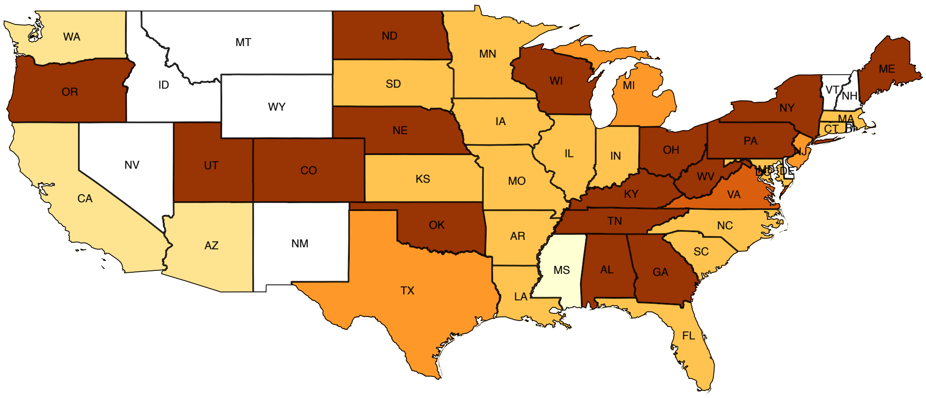
Note: Source: Panel Study of Income Dynamics. Significance levels are denoted as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data in this analysis is used with sampling weights.

5.2 U.S. Compulsory Schooling Laws

(a) 1965



(b) 1972



(c) 1978

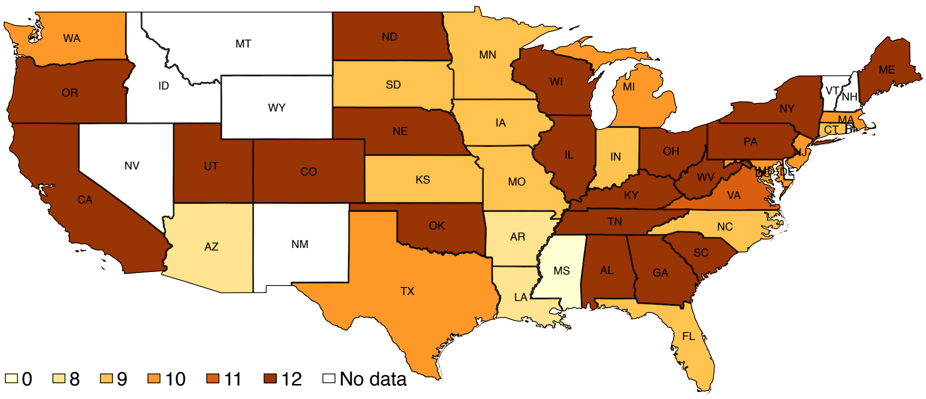


Figure 5: Evolution of Compulsory Education Laws
Note: The compulsory years of education in the U.S. by state in 1965, 1972 and 1978.

5.3 Additional Empirical Results: Parental Income

Table 17: Parental Income and Wealth

Dependent Variable: Wealth		
	(A)	**(B)**
Education=1	1211.87*	1220.52*
	(616.73)	(611.31)
Education=2	2350.31***	2429.58***
	(678.62)	(677.35)
Education=3	2492.54**	2439.55**
	(781.36)	(783.29)
Education=4	2751.91**	2606.89**
	(1005.75)	(988.58)
Inheritance	0.16***	0.15***
	(0.02)	(0.02)
Par.Education W.	571.10*	362.50
	(251.78)	(254.99)
Par.Education H.	910.48***	597.69*
	(269.70)	(266.59)
Parental Income	0.21***	
	(0.04)	
Parental Wealth		0.28***
		(0.02)
Adjusted R^2	0.24	0.26
Observations	20461	20558

Note: Source: PSID. 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. Time, socio-demographics, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

5.4 Additional Empirical Results: Quantile Regression

Table 18: Quantile Regression: Effects of Education on Wealth

(A) Quantiles of Wealth Distribution						
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education	−657.04***	1116.44***	2323.32***	2270.86***	1764.80***	1867.29***
	(154.11)	(131.65)	(103.91)	(100.52)	(131.62)	(241.95)
Inheritance	0.24*	0.42***	0.33***	0.23***	0.09***	0.03
	(0.10)	(0.07)	(0.02)	(0.01)	(0.02)	(0.02)
Parental Wealth	0.17***	0.22***	0.27***	0.26***	0.21***	0.03
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.04)
Par.Education W.	−658.05*	−298.20	77.43	369.58*	407.04+	−46.70
	(284.97)	(250.24)	(183.49)	(156.12)	(212.56)	(424.08)
Par.Education H.	74.52	446.77*	752.33***	926.12***	912.30***	698.71+
	(234.20)	(223.46)	(178.09)	(151.41)	(195.84)	(414.98)
Observations	20556	20556	20556	20556	20556	20556
(B) Quantiles of Wealth Distribution by Age Cohort						
		Cohort: 40			**Cohort: 60**	
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education	914.89***	1970.52***	2051.52***	3518.82***	3756.80***	1561.26***
	(135.95)	(136.69)	(214.05)	(236.95)	(258.18)	(139.84)
Inheritance	0.64***	0.63***	0.19*	0.80***	0.40***	0.38***
	(0.08)	(0.02)	(0.08)	(0.06)	(0.07)	(0.07)
Parental Wealth	0.22***	0.27***	0.15***	0.06*	0.10*	0.15***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)
Par.Education W.	168.20	1055.00***	1353.59***	212.13	−935.72	430.84*
	(299.25)	(276.72)	(334.43)	(339.46)	(631.51)	(204.00)
Par.Education H.	140.83	728.71**	545.98	5.95	2403.39***	1881.97***
	(255.82)	(226.59)	(347.90)	(253.38)	(646.90)	(140.32)
Observations	6436	6436	6436	1920	1920	1920

Note: Source: PSID. 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. Panel (B) reports effects of education on different quantiles of the distribution of wealth by age cohorts. Constant term is included but not reported for brevity.

5.5 Additional Empirical Results: Wealth including Home Eq.

Table 19: OLS Regression: Effects of Education on Wealth Eq.

(A) Education on Wealth Eq. Over the Life Cycle					
	Avg	Cohort			
		30	40	50	60
Education	476.90**	901.03***	1575.66***	1735.75***	2432.72***
	(159.51)	(157.41)	(166.20)	(179.89)	(257.47)
inheritance	0.12***	0.76***	0.52***	0.45***	0.39***
	(0.02)	(0.08)	(0.06)	(0.05)	(0.06)
Parental Wealth	0.29***	0.27***	0.26***	0.23***	0.20***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Par.Education W.	368.26	112.53	152.95	−138.86	224.33
	(267.42)	(237.56)	(264.61)	(323.10)	(423.82)
Par.Education H.	713.67**	−166.28	603.43*	1370.22***	1365.84***
	(271.98)	(225.65)	(245.56)	(274.40)	(378.02)
Observations	20558	7028	6436	4825	1920
Adjusted R^2	0.29	0.18	0.23	0.28	0.36

(B) Education Categories on Wealth Eq. Over the Life Cycle					
	Avg	Cohort			
		30	40	50	60
Education=1	2062.37**	2881.70***	5662.70***	7053.99***	5483.54***
	(741.49)	(722.36)	(752.65)	(983.32)	(1512.25)
Education=2	3320.32***	3971.31***	7381.58***	9529.15***	11283.67***
	(812.40)	(784.44)	(877.38)	(1071.25)	(1654.55)
Education=3	2986.74**	7834.79***	11988.29***	11631.05***	11246.22***
	(910.27)	(852.16)	(945.82)	(1157.99)	(1849.08)
Education=4	3400.48**	3525.22**	9796.29***	14556.03***	18051.71***
	(1079.76)	(1202.61)	(1252.43)	(1330.31)	(1791.15)
Inheritance	0.12***	0.79***	0.51***	0.44***	0.43***
	(0.02)	(0.08)	(0.06)	(0.05)	(0.06)
Parental Wealth	0.29***	0.27***	0.25***	0.22***	0.19***
	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Par.Education W.	404.07	196.83	259.76	−87.60	112.77
	(266.44)	(236.15)	(262.05)	(322.57)	(428.95)
Par.Education H.	767.08**	−135.23	688.70**	1461.90***	1371.54***
	(271.66)	(223.40)	(246.15)	(279.57)	(382.48)
Observations	20558	7028	6436	4825	1920
Adjusted R^2	0.29	0.19	0.23	0.28	0.36

Note: Source: PSID. 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. Year, 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 wealth. Panel (B) reports effects of education categories on wealth. Constant term is included but not reported for brevity.

Table 20: Within Variation Regression: Effects of Education on Wealth Eq.

	Avg	Cohort			
		30	**40**	**50**	**60**
D.Highschool	5180.01***	3057.01***	2870.73***	9197.81***	14289.43***
	(472.92)	(645.87)	(667.43)	(853.50)	(2195.64)
D.Some College	6136.76***	3520.96***	4710.34***	9086.89***	16606.90***
	(530.93)	(706.72)	(755.59)	(947.18)	(2599.84)
D.College	9938.91***	4284.55***	9123.87***	14363.56***	26293.76***
	(813.75)	(1082.73)	(1184.74)	(1586.65)	(3583.42)
D.Postgraduate	7553.34***	−68.56	9298.66***	10803.63***	25156.73***
	(972.49)	(1313.92)	(1436.40)	(1854.10)	(4008.21)
Observations	15111	4688	5646	3890	967
Adjusted R^2	0.02	0.05	0.03	0.03	0.07

Note: Source: PSID. Standard errors in parentheses. Significance levels are denoted as follows: $^+$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Time, socio-demographic, and cohort effects are included but not reported for brevity. Socio-demographics include the difference of age between siblings. The constant term is included but not reported for brevity.

Table 21: I.V. Regression: Effects of Education on Wealth Eq.

(a) Avg. Education

	Avg	Cohort			
		30	**40**	**50**	**60**
Education	5214.97*	4298.75*	5970.03***	6070.50***	7220.21**
	(2153.51)	(2046.20)	(1276.97)	(1346.67)	(2351.84)
F-statistic	59.40	24.35	56.43	59.89	29.19
Observations	10281.00	1389.00	3912.00	3681.00	1243.00

(b) College Education

	Avg	Cohort			
		30	**40**	**50**	**60**
College	41083.30+	48147.04	38299.61***	49061.23***	47042.29*
	(24338.53)	(32544.40)	(9347.43)	(13972.40)	(20651.74)
F-statistic	38.04	12.07	43.34	36.34	16.07
Observations	10281.00	1389.00	3912.00	3681.00	1243.00

(c) Postgraduate Education

	Avg	Cohort			
		30	**40**	**50**	**60**
Postgraduate	64866.24	42337.88+	94774.11*	79961.97**	779937.13
	(49720.29)	(23911.07)	(36811.03)	(29276.04)	(4094872.82)
F-statistic	28.80	17.29	17.11	21.99	0.11
Observations	10281.00	1389.00	3912.00	3681.00	1243.00

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. Year and cohorts effects are included. Parental wealth is included but not reported for brevity.

Table 22: Quantile Regression: Effects of Education on Wealth Eq.

(A) Quantiles of Wealth Eq. Distribution						
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education	−167.23	1940.67***	2239.15***	1913.80***	1533.83***	1856.79***
	(181.08)	(150.05)	(102.88)	(87.19)	(132.46)	(223.40)
Inheritance	0.29***	0.30***	0.23***	0.15***	0.08***	0.03+
	(0.09)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Parental Wealth	0.22***	0.30***	0.30***	0.27***	0.18***	0.03
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)
Par.Education W.	−1335.29***	−95.58	377.10*	258.75+	539.25**	308.83
	(196.67)	(286.18)	(185.11)	(146.30)	(192.57)	(447.40)
Par.Education H.	178.35	644.84**	596.77***	799.54***	622.77***	378.08
	(297.49)	(240.88)	(165.36)	(144.49)	(188.48)	(484.51)
Observations	20556	20556	20556	20556	20556	20556

(B) Quantiles of Wealth Eq. Distribution by Age Cohort						
	Cohort: 40			**Cohort: 60**		
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education	1852.65***	2478.70***	1256.52***	2500.15***	2898.93***	2101.86***
	(219.76)	(151.22)	(120.60)	(223.02)	(217.32)	(170.42)
Inheritance	0.73***	0.54***	0.11*	0.64***	0.23***	0.48***
	(0.12)	(0.02)	(0.05)	(0.07)	(0.04)	(0.13)
Parental Wealth	0.34***	0.34***	0.13***	0.17***	0.26***	0.16***
	(0.03)	(0.02)	(0.02)	(0.03)	(0.04)	(0.03)
Par.Education W.	−344.12	964.18***	812.12***	47.35	593.37	279.40
	(320.54)	(249.18)	(133.81)	(324.78)	(422.55)	(243.48)
Par.Education H.	673.13*	8.68	552.47**	1039.85***	1274.72***	1386.56***
	(314.31)	(228.78)	(209.31)	(269.01)	(353.80)	(284.02)
Observations	6436	6436	6436	1920	1920	1920

Note: Source: PSID. 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. Panel (B) reports effects of education on different quantiles of the distribution of wealth by age cohorts. Constant term is included but not reported for brevity.

Table 23: Quantile Regression: Effects of Education on Wealth Eq.

	(A) Quantiles of Wealth Eq. Distribution					
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Education=1	2131.75***	2775.01***	6230.38***	4936.36***	4216.07***	7641.05***
	(368.36)	(642.88)	(702.31)	(793.98)	(802.08)	(968.96)
Education=2	3254.44***	6195.79***	8762.64***	8291.40***	6474.96***	7978.07***
	(581.49)	(692.72)	(752.52)	(841.49)	(918.88)	(1663.60)
Education=3	3235.12***	10101.19***	13166.38***	11218.82***	9414.03***	14035.97***
	(972.01)	(837.33)	(758.48)	(817.41)	(915.63)	(1605.56)
Education=4	−4304.51**	10750.37***	15770.30***	13925.89***	10683.51***	11531.81***
	(1514.47)	(1240.54)	(818.07)	(875.11)	(834.75)	(1094.73)
Inheritance	0.28**	0.31***	0.22***	0.15***	0.09***	0.03
	(0.09)	(0.02)	(0.02)	(0.02)	(0.02)	(0.08)
Parental Wealth	0.22***	0.30***	0.29***	0.27***	0.17***	0.04
	(0.02)	(0.02)	(0.01)	(0.01)	(0.02)	(0.03)
Par.Education W.	−1138.68***	9.05	545.70**	210.04	606.15***	585.69
	(177.46)	(291.11)	(181.82)	(147.05)	(173.98)	(397.13)
Par.Education H.	132.06	671.93**	657.91***	940.19***	684.00***	548.27
	(218.55)	(243.60)	(168.82)	(140.16)	(186.31)	(405.92)
Observations	20556	20556	20556	20556	20556	20556

	(B) Quantiles of Wealth Eq. Distribution by Age Cohort					
	Cohort: 40			**Cohort: 60**		
	0.25	**0.50**	**0.95**	**0.25**	**0.50**	**0.95**
Education=1	4819.51***	6803.47***	8569.74***	3711.13	6512.26***	−2586.65*
	(585.39)	(989.76)	(1362.75)	(3041.18)	(1034.40)	(1195.71)
Education=2	6439.31***	10206.93***	9673.67***	8024.00*	13234.05***	3989.41***
	(736.61)	(1099.56)	(1313.99)	(3131.52)	(1428.89)	(746.63)
Education=3	13125.38***	15443.11***	13622.44***	8975.96**	14945.21***	5441.49
	(1124.07)	(1029.90)	(1373.37)	(3247.68)	(1548.77)	(3463.22)
Education=4	7625.88**	16011.21***	13243.71***	16081.91***	20854.86***	6329.41***
	(2807.78)	(1170.21)	(1334.34)	(2961.07)	(1775.84)	(1024.07)
Inheritance	0.70***	0.54***	0.12**	0.55***	0.30***	0.36+
	(0.05)	(0.03)	(0.04)	(0.06)	(0.06)	(0.19)
Parental Wealth	0.33***	0.32***	0.13***	0.18***	0.27***	0.23***
	(0.03)	(0.02)	(0.02)	(0.05)	(0.04)	(0.03)
Par.Education W.	−341.41	1097.30***	853.82***	−443.39	602.33	701.36*
	(311.64)	(269.72)	(217.83)	(383.10)	(608.39)	(318.52)
Par.Education H.	659.36*	331.14	703.17***	1470.99***	696.35	1804.45***
	(325.36)	(251.27)	(174.06)	(400.03)	(594.11)	(252.54)
Observations	6436	6436	6436	1920	1920	1920

Note: Source: PSID. 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. Panel (B) reports effects of education on different quantiles of the distribution of wealth by age cohorts. Constant term is included but not reported for brevity.

Table 24: wealth's Regression Mechanisms: Productivity Effect

Dependent Variable: Wealth Eq.			
	(A)	**(B)**	**(C)**
Education=1	1903.34**	2053.13**	2095.13**
	(728.65)	(739.84)	(737.75)
Education=2	3062.58***	3310.81***	3362.41***
	(803.05)	(810.54)	(807.71)
Education=3	2374.06**	2934.63**	3023.21***
	(902.91)	(908.89)	(905.08)
Education=4	2343.49*	3274.82**	3401.14**
	(1076.92)	(1076.58)	(1073.57)
Labor Income	0.16***		
	(0.02)		
Bonuses		0.20***	
		(0.04)	
Rent			0.22***
			(0.04)
Adjusted R^2	0.31	0.29	0.29
Observations	20558	20558	20558

Note: Source: PSID. 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. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

Table 25: Wealth's Regression Mechanisms: Financial Literacy

	Dependent Variable: Wealth Eq.			
	(A)	**(B)**	**(C)**	**(D)**
Education=1	2199.43**	2455.67***	1953.27**	2073.33**
	(708.53)	(680.28)	(720.53)	(738.45)
Education=2	3205.31***	3446.90***	3162.64***	3332.60***
	(767.65)	(745.58)	(794.80)	(809.53)
Education=3	2567.11**	2694.43**	2890.18**	3015.72***
	(868.36)	(837.09)	(888.73)	(906.99)
Education=4	2620.84*	2163.36*	3030.49**	3400.97**
	(1020.07)	(994.73)	(1048.73)	(1075.62)
Stocks	0.35***			
	(0.01)			
Annuity/IRA		0.40***		
		(0.01)		
Other Assets			0.38***	
			(0.02)	
Interest				0.07***
				(0.01)
Adjusted R^2	0.36	0.40	0.33	0.29
Observations	20558	20558	20558	20558

Note: Source: PSID. 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. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

Table 26: Wealth's Regression Mechanisms: Financial Behavior

Dependent Variable: Wealth Eq.		
	(A)	**(B)**
Education=1	2290.04***	1694.38*
	(639.95)	(741.87)
Education=2	3075.20***	2769.95***
	(711.41)	(823.71)
Education=3	2451.19**	2337.67*
	(787.15)	(921.31)
Education=4	2062.79*	2713.32*
	(970.08)	(1088.62)
Savings	0.61***	
	(0.02)	
Money Problem		−5284.08***
		(620.54)
Adjusted R^2	0.43	0.31
Observations	18057	19929

Note: Source: PSID. 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. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

5.6 Life Cycle Model: Solution Method

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

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

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

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

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.

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 β_{t+1}, R_{t+1}, ψ_{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^i_β, π^i_R, π^i_ψ and π^i_ξ 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.