Can Educational Policies Reduce Wealth Inequality?

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Abstract

This study examines the causal relationship between education and wealth accumulation using a panel dataset from the United States spanning two generations. Employing three distinct identification strategies, the research finds that higher educational attainment significantly increases lifetime wealth, especially at the college and postgraduate levels. This effect varies depending on an individual's life stage, wealth distribution position, and education level. Building on these findings, a life-cycle heterogeneous agents model is developed and calibrated with U.S. data, to assess the impact of educational policies on wealth accumulation and distribution. The model evaluates policies to enhance the quality of education and financial literacy and increase the quantity of higher education. The analysis reveals that increasing the proportion of college-educated individuals and fostering long-term planning substantially reduces wealth inequality. This study not only sheds light on the critical role of education in wealth generation but also provides actionable insights for policymakers striving to mitigate economic disparities through educational reforms.

Keywords: Wealth Inequality · Returns to Education · Educational Policy · College · Life Cycle

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

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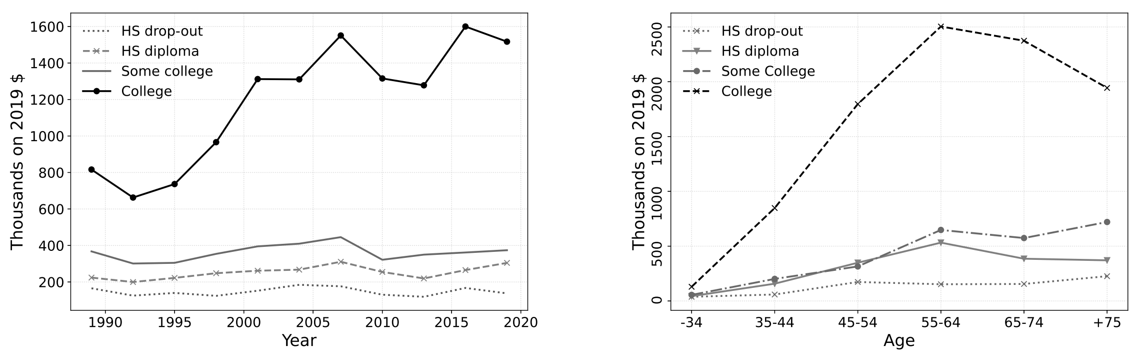
1 Introduction

In recent decades, wealth concentration at the top of the distribution has risen 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. An examination of the data reveals that educational attainment plays a pivotal role in these wealth dynamics. Analyzing wealth inequality through the perspective of education uncovers nuanced disparities that general statistics often overlook.
To illustrate this point, Figure 1a shows the distribution of wealth by educational level from 1989 to 2019, revealing a stark disparity between individuals with and without a college degree. Figure 1b presents the life cycle wealth profiles by educational level in the U.S. for 2019, highlighting that college graduates accumulate wealth in distinct patterns compared to those with lower educational achievements. However, it's important to recognize that factors e.g. inherited wealth and privilege, can obscure the effects of education on wealth. Many who benefit from educational attainment may also have significant advantages from inheritance and social connections, complicating the direct correlation between education and wealth accumulation. 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 who improve economic mobility or reduce wealth inequality through education programs. The questions of this research are: First, does human capital investment allow individuals to accumulate wealth consistently throughout

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

their life cycle? Second, can educational policies reduce wealth inequality? This paper aims to determine if there is a causal link between wealth and education and the role of educational policies in this dynamic.

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 et al. (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. By addressing various sources of endogeneity, this 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 identified key wealth determinants, a life cycle quantitative model is introduced. Recent research has focused on incorporating idiosyncratic returns to wealth to better align

[2]See Blanden and Machin (2004), Chevalier et al. (2013), and Atkinson and Bourguignon (2014) for more on family background effects.

these models with observed distribution patterns, exploring the potential of idiosyncratic capital risk to generate a Pareto tail.[3] However, the specific drivers behind these varied returns, particularly in the context of education's impact on wealth, remain underexplored. Integrating the latest insights from wealth inequality research into this life cycle analysis offers a promising avenue to deepen our understanding of how education influences wealth accumulation over time. After exploring different features driving wealth accumulation in the quantitative model and validating its replication power, some educational policies are introduced. These policies aim to find if it is possible to reduce wealth inequality or to redistribute wealth. Three directions for educational policies are explored: increase the share of college graduates, quality of education, and financial literacy. The result of the simulations suggests that an increase in long-term planning and 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.

This analysis sheds light on the multifaceted nature of wealth inequality, suggesting that a deeper understanding of the interplay between education and other determinants is essential. By exploring these dynamics, the study sets the stage for a thorough examination of how educational policies might impact wealth inequality across different segments of the population. The remainder of the paper is organized as follows. The econometric analysis is presented in Section 2 to explore a causal relationship between education and wealth. Section 3 simulates educational policies' effects on wealth inequality using a quantitative life cycle model. Finally, Section 4 presents concluding remarks and further research ideas.

2 Empirical Model

This section implements econometric models to find a causal relationship between education and wealth. 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.

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

2.0.1 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. 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:

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

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, D 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.

2.0.2 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.

2.0.3 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:

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

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:

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

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.

2.1 Data and Sample Selection

This study utilizes data from 1999 to 2019 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. 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".[4] Control variables include parental wealth and education starting from 1984 but aiming for controlling for when the FU was young, 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.

The data on compulsory schooling laws is sourced from Acemoglu and Angrist (2000). 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.

2.2 Descriptive Analysis

Table 1: Mean Wealth by Education and Cohort

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

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

Table 1 combines both educational level and age cohorts to see how the net worth of people with different education evolves over the life cycle. It is shown that the average wealth increases with educational level and as people go further in their life cycle. There is a distinctive pattern displayed for certain educational levels. For example, the mean wealth of college graduates is higher than when they have postgraduate experience. This can be explained by the earlier integration into the labor market done by college graduates compared to agents that go for a one-year postgraduate education experience. In the

[4]Table A2 reports the classification of education into categories used in the analysis.

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.[5]

2.3 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.

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.

Building upon the findings from the initial analysis, the study further investigates this relationship using an alternative empirical strategy. This approach, delineated in Table

[5] Summary statistics are presented in Table A3 and a correlation matrix in Table A4 in the Appendix.

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.

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 this 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 this 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 A1 in the appendix.

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

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.

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 the 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.

2.4 Additional Empirical Analysis

2.4.1 Parental Income vs Parental Wealth

The regression results in Table A5 in the Appendix compare the effects of different parental economic background variables on education estimates and other control variables, focusing on parental income and wealth. Parental income has a significant effect on a child's future outcomes but is not as strong as parental wealth. Following previous results, this analysis focuses on college and postgraduate-educated individuals when the head of the family unit was young. Column (A) of Table A5 includes parental income, while column (B) includes parental wealth. The estimates that account for parental wealth are more attenuated than those that use parental income.
Key comparisons show that an additional unit of parental income increases the child's future wealth by 21%, whereas an increase in parental wealth generates a 28% increase in future wealth. These findings suggest that parental wealth has a greater impact on a child's life outcomes than parental income. Including parental income or wealth helps better estimate the effect of education. The coefficient for education is lower when parental wealth is considered, indicating that only considering parental income might overestimate the effect of education on wealth.

2.4.2 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 A6 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, 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.

2.5 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) suggests 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.

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

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.

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

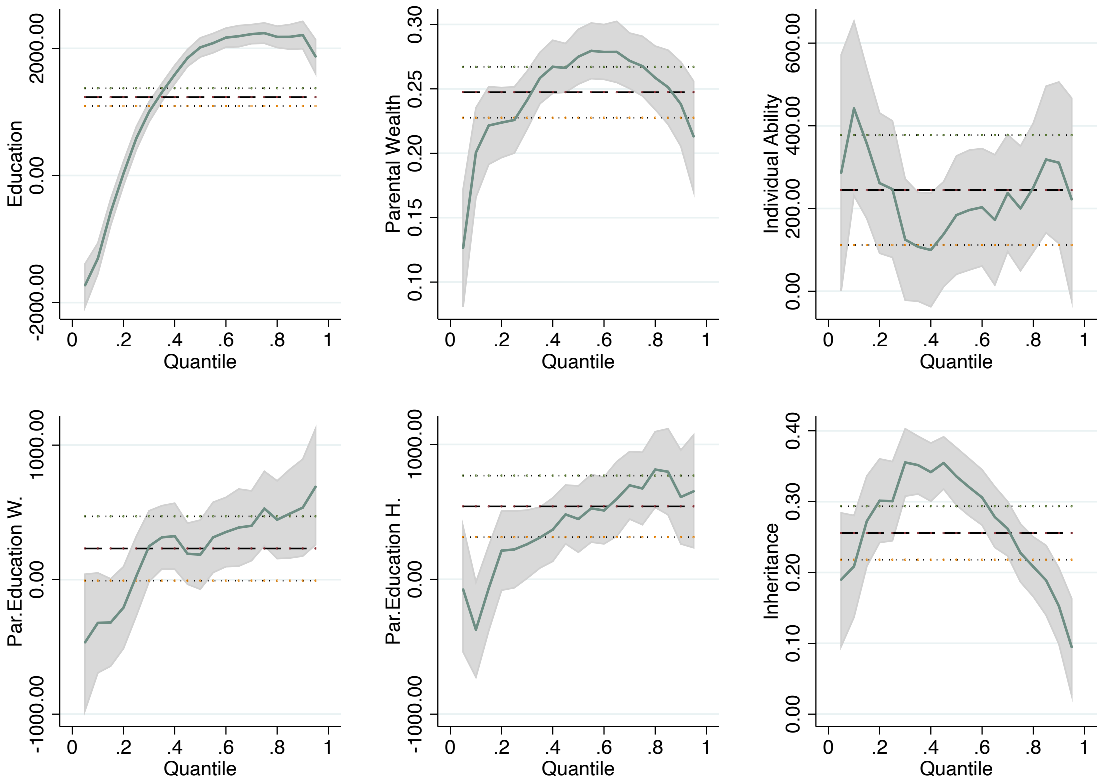


Figure 2: Education per Quantile of Wealth

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.

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 A12 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 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

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.

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, 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.

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.

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 et al. (2004) not only on average but throughout the life cycle (Loaiza, 2021) 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 A13 and A14 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 quan-

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.

titative partial equilibrium life cycle model aims to explore potential scenarios for educational reforms. The standard Income Fluctuation Problem is extended, by including exogenous connections between education and wealth, to create counterfactual scenarios to test these policies.

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, they 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:

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

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 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.

[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).

[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).

3.1 Household Recursive Problem

In this model, a t-year-old agent chooses consumption c_t and asset holdings a_{t+1} for the next period. The state variables for an agent are the level of human capital h_t, market resources m_t, and discount factor β_t. The optimal decision rules are functions for consumption, $c(h_t, m_t, \beta_t)$, and next-period asset holdings, $a(h_t, m_t, \beta_t)$, that together solve the dynamic programming problem described below. The household's assets at the end of the period, a_t, are generated from the cash-on-hand m_t (all market resources) minus their consumption c_t, expressed as $a_t = m_t - c_t$. Given this structure, human capital h_t and market resources m_t start with strictly positive values, $(h_t, m_t) \in (0, \infty)$. For simplicity, it is assumed that agents cannot borrow against their future income, implying that they cannot die in debt, conditioned by $c_T \leq m_T$.

During the full-time working stage, from age 20 to 64 (period $t = 1$ to $t = 44$), agents consume, work, and save assets, using their exogenously obtained human capital in the labor market. In this stage, the state variables are presented as a state vector $\bar{z}_t = (h_t, m_t, \beta_t)$. The value function for this period, subject to the previously detailed constraints, 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.

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

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

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

During retirement, from age 65 to 90, agents consume, receive their pension, save assets, and face survival probabilities, introducing the risk of death. Consequently, individuals derive utility from leaving bequests to the next generation. The value function for this stage is given by:

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

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

Different steps are implemented to obtain the model's parameters: first, some parameters are set to values from the literature. Second, some parameters are obtained using the PSID, and third, the remaining parameters are internally calibrated using real data moments.[9]

[9] The summary of the parameters is presented in Table 9

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. The value of the majority of 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 et al. (1999), and Gourinchas and Parker (2002), who estimated it using consumption data. The one-period survival probabilities s_t are obtained from Bell et al. (1992).

The labor income process is based on Carroll et al. (2015), Carroll et al. (1992), and DeBacker et al. (2013). The labor income process includes: the income growth factor is set to $G = 1.03$ 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 $\mu = 0.15$ with probability $\mu = 0.07$. The pension benefit of individuals during retirement is a fraction $\kappa = 0.70$ 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 had been estimated for uncertain income processes.

The average rate of return to capital is set to 1.04%. The mean value is obtained from Ma et al. (2020) and set to $\bar{u}_r = 0.0238$ and the value of $\bar{w}_r = 0.215$, to match the average rates of return. The average discount factor β is set to 0.96 by setting the parameters $\bar{u}_\beta = 0.91$ and $\bar{w}_\beta = 0.004$. The details of the discretization process are detailed in section B.1 in the Appendix.

Using the PSID data, I obtained the probabilities of receiving an inheritance in five-year intervals. These probabilities were used to generate random inheritances for individuals in the model, ensuring that the average inheritance received by age in the model matched the empirical data. Additionally, a parameter determining that the 97% of the population that does not receive any inheritance was included. The model's fit to the real data is detailed in section B.3 in the Appendix.

The initial asset distribution is generated from a Weibull distribution with a mean value of $\mu_m = 0.27955$, obtained from the PSID data. A zero fraction parameter, set at 0.33, was included to reflect the proportion of the population with no initial assets. The initial distribution of human capital was generated using a lognormal distribution with parameters obtained from the initial distribution of wages. The parameters $\mu_p = 0.23425$ and $\sigma_p = 0.21865$ were obtained from the PSID data.

The last set of parameters to be calibrated are the bequest parameters, θ_1 and θ_2. These parameters are calibrated to replicate the bequest-to-wealth ratio observed of 1.18, accounting for inter-vivo transfers and college expenditures (De Nardi & Yang, 2016). Through the calibration process, the values $\theta_1 = 9.30$ and $\theta_2 = 11.37$ result in a bequest-to-wealth ratio of 1.16 produced by the model. This calibration ensures that the model accurately reflects the proportion of wealth that is bequeathed, aligning it closely with empirical observations.

Table 9: Summary of Parameters

Parameter	Description	Value
Preferences		
γ	Risk aversion coefficient	1.5
$\bar{u}_\beta$	Stationary mean discount factor	0.91
$\bar{w}_\beta$	Standard deviation discount factor	0.004
θ_1	Bequest strength	9.30
θ_2	Bequest as luxury good	11.37
Labor Income		
G	Growth income factor	1.03
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	0.70
Capital Income		
$\bar{u}_r$	Mean persistence constant	0.0238
$\bar{w}_r$	Volatility constant	0.215
Initial Conditions		
μ_h	Mean of initial human capital h_p	0.466
σ^2_h	Variance of initial human capital h_p	0.213
μ_a	Mean of initial assets a_p	1.266

3.3 Calibration Results

Having established the foundational parameters of the model, the next step is to observe the model's outcome to see if that reflects key aspects of real-world wealth distribution. The calibration targets are derived from comparisons with 2019 U.S. data, sourced from the Survey of Consumer Finances. These targets include metrics such as the average Gini coefficient and the percentage of wealth held by various percentile groups within the wealth distribution. By aligning the model with these targets, the aim is to ensure that it accurately reflects the distributional patterns observed in real-world data.

Table 10: Main Calibration Target: Wealth Distribution

	Avg.	**Percentage Wealth in the Top**						**Bottom**
	Gini	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	0.66	16.4	38.2	52.5	69.3	86.6	95.0	5.0

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

The results in Table 10 demonstrate that the model, incorporating idiosyncratic rates of return to capital, heterogeneous discount factors, intergenerational links, and idiosyncratic labor income, achieves a reasonable approximation of the wealth distribution. The model captures key aspects of wealth accumulation, particularly at the extremes of the wealth distribution, and produces a Gini coefficient that, while lower than the real data, indicates a significant degree of wealth inequality. However, this is not the final model.

The current results serve as a foundation that will be further refined by incorporating the role of education affecting wealth accumulation. These enhancements are expected to improve the model's alignment with real-world data, particularly in capturing the nuanced impacts of educational attainment on wealth distribution and inequality.

3.3.1 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 in the life cycle model, individuals within the model are classified into 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. To classify individuals as 'College' or 'Non-College', the probability of college attendance was calculated using logistic regression parameters detailed in subsection B.2 in the Appendix. This methodological approach has been validated by ensuring that the model's classification closely aligns with the real distribution, which shows that 34% of individuals have and 66% do not have a college education.

Assigning individuals into college and non-college categories holds significance only if these distinctions manifest in observable differences. As discussed in section 2, there are 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, and have effects on financial asset participation (Loaiza, 2021). 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 et al., 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. In this model, the indirect effect of education on wealth is via labor income. It is done by increasing the labor income process, specifically, the average permanent income ψ for college graduates is 6.5% higher than for non-college individuals. The direct effects aim to recreate the causal effect of education on wealth via rates of returns to capital for college graduates. This is done exogenously to not add more computational difficulty by adding endogenous decisions on portfolio choices. 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. The average rates of return to capital for college graduates go from 1.04 to 1.12. 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	0.66	16.4	38.2	52.5	69.3	86.6	95.0	5.0
Model + Direct Effects	0.82	35.1	62.2	74.4	85.5	94.4	98.1	1.9
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0

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

From the results presented in Table 11, it is evident that the inclusion of direct effects of education on wealth significantly improves the fit of the model, as seen in the second row. This model aligns more closely with the U.S. wealth distribution compared to the base model. When both direct and indirect effects are included, the model further enhances its alignment with real-world data, particularly in replicating the wealth distribution among the top 1% and the bottom 40% of the population. The average Gini coefficient also becomes closer to the actual data, indicating a better overall representation of wealth inequality.

3.3.2 Model Validation

The model, incorporating intergenerational links, different idiosyncratic shocks, and both indirect and direct effects of education on wealth, aims to capture disparities in wealth accumulation between college and non-college individuals over their life cycle. Validating the model's performance against empirical data is crucial to ensure its robustness. Table 12 presents the validation outcomes, comparing key metrics derived from the model with corresponding values from U.S. data obtained from the PSID for 2019. These metrics capture the trend of wealth inequality across different life stages and education levels.

Table 12: Validation: Wealth Gini Coefficient

	U.S. Data	**Model**
Age		
Early Adulthood (20–39 y.o.)	0.82	0.60
Mid Adulthood (40-59 y.o.)	0.81	0.71
Late Adulthood (60-79 y.o.)	0.79	0.79
Education		
College	0.81	0.81
Non-College	0.80	0.66

Source for U.S. Data: Panel Study of Income Dynamics, 2019.

In early adulthood (20–39 y.o.), the model's Gini coefficient is 0.60, compared to the U.S. data value of 0.82, indicating the model predicts less inequality than observed. By mid-adulthood (40-59 y.o.), the model's Gini coefficient is 0.71, closer to but still lower than the real data value of 0.81. In late adulthood (60-79 y.o.), the model accurately replicates the level of wealth inequality, matching the U.S. data Gini coefficient of 0.79. The model also captures disparities within each education category, perfectly matching the wealth inequality for college-educated individuals with a Gini coefficient of 0.81. For non-college individuals, the model shows a Gini coefficient of 0.66, lower than the observed 0.80, suggesting the model underestimates inequality within this group.

The model's accuracy among college-educated individuals is particularly beneficial given the future policies analyzed in this study, which focus on improving education quality and increasing the share of college graduates. These features ensure that the model can provide reliable insights into the effects of such policies on wealth distribution and inequality. While the model's underestimation of inequality in early and mid-adulthood and among non-college individuals suggests areas for improvement, these discrepancies do not fundamentally undermine the model's usefulness. The primary focus of the policies is on the broader impacts of educational attainment and quality, and the model's strong performance in capturing the key trends and disparities within the relevant groups ensures its effectiveness for this purpose.

3.4 Policy Simulations

This subsection explores the impact of educational policies on wealth distribution and inequality using the selected model for counterfactual simulations. The chosen model, used as a baseline, incorporates education's direct and indirect effects on wealth accumulation. The aim is to investigate whether educational policies can effectively reduce wealth inequality, particularly by targeting the initial opportunities rather than focusing solely on economic outcomes. This direction of redistribution through educational policies has proven effective in improving income distribution. For example, Keller (2010) demonstrated that expenditures in education per student, enrollment rates, and public expenditures in education significantly enhance income distribution with an equalizing effect. Three main types of educational policies are examined: improving education quality, increasing the population's share with a college degree, and enhancing long-term planning. The first policy aims to address barriers to higher education access and affordability, thereby increasing the proportion of individuals attaining higher education. The second and third policies seek to enhance the returns to education, particularly for college graduates, by improving educational quality and their financial literacy.

3.4.1 S1: Improving the Quality of Education

To examine the effects of improving the quality of education on wealth accumulation and inequality, this policy focuses on enhancing the returns to education for college graduates by increasing their average rates of return on capital investments. The theoretical foundation for this policy is based on the idea that better quality education equips individuals with superior skills and knowledge, enabling them to make more informed and effective investment decisions, thereby increasing their rates of return on capital investments.

Better quality can be achieved, for example, by improving teacher quality, curriculum modernization, and creating skill-based programs or digital access. This concept is supported by existing literature on the returns to education and financial literacy, as well as previous research indicating that higher educational attainment leads to greater involvement with financial assets and improved financial behaviors (Loaiza, 2021). The modeling approach involves exogenously increasing the average rates of return to capital for college graduates.

The simulation results, presented in Table 13, indicate that a 5% increase in the average rates of return to capital for college graduates significantly affects wealth distribution. Specifically, the simulation shows an increase of approximately 7% in the wealth Gini coefficient, indicating a rise in overall wealth inequality. This increase in inequality is primarily driven by the changes in wealth distribution at the extremes: the wealth held by the top 1% of the wealth distribution increases by about 33%, highlighting a concentration of wealth among the wealthiest individuals. Conversely, the wealth of the bottom 40% of the distribution decreases by around 70%, exacerbating the economic disparity between the wealthiest and the poorest individuals. These shifts in wealth distribution underscore the mechanisms through which increased returns to capital for college graduates can amplify wealth inequality.

Table 13: Simulation Results: Quality of Education

	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S1: ↑ Avg. Rates of Return	0.93	49.7	81.9	92.2	97.1	99.0	99.7	0.3

Source: Author's calculations.

Further simulations were conducted and the results are presented in table B3 in section B.5 in the Appendix. The results indicate that improving the quality of education (S1) tends to increase wealth inequality across all age groups, as evidenced by the higher Gini coefficients compared to the base model. For instance, in early adulthood, the Gini coefficient increases from 0.60 in the base model to 0.68 in S1. Similarly, in mid and late adulthood, the Gini coefficients rise significantly to 0.85 and 0.88, respectively. This trend is also observed among college-educated individuals, where the Gini coefficient increases from 0.81 to 0.88. However, the inequality among non-college individuals remains unchanged.

It is important to note that these results are based on a specific scenario where the quality of education is improved by increasing the rates of return to capital for college graduates. This should not be interpreted to mean that improvements in educational quality across all aspects or degrees would necessarily yield similar effects. The broader concept of improving educational quality, particularly in ways that promote financial literacy and practical financial skills, could still offer significant benefits without the downside of increased inequality if it is accessible to the general population.

3.4.2 S2: Increasing the Share of College Graduates

The second policy simulation analyzes the impact of increasing the share of the population with a college degree on wealth distribution and inequality. This policy aims to increase the proportion of college-educated individuals, reflecting a hypothetical reduction in barriers to higher education access and affordability. Although the specific mechanisms for reducing these barriers are not detailed in this paper, the simulation represents the potential effects of such changes. By making higher education more accessible and affordable, the policy seeks to create a more educated workforce, promote social mobility, and reduce income and wealth disparities. We model this increase by adjusting the parameters that influence the probability of attaining a college degree, as detailed in section B.2 of the Appendix.

Table 14: Simulation Results: Quantity of Education

	Avg.	Percentage Wealth in the Top						Bottom
	Gini	1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S2: ↑ College Share	0.86	34.5	65.7	80.0	91.0	97.1	99.1	0.9

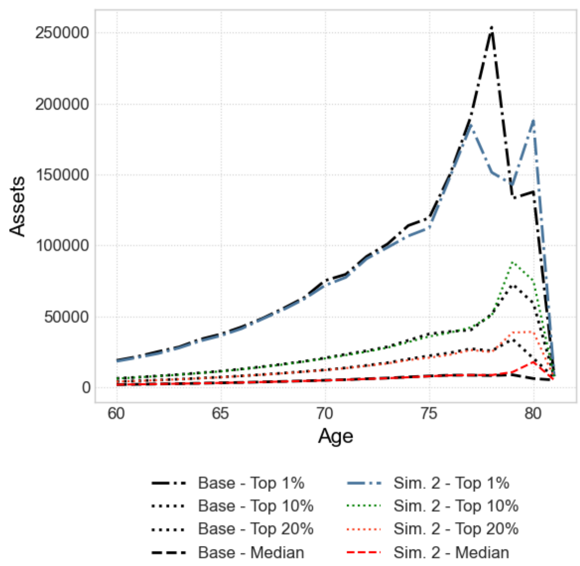
Source: Author's calculations.

The simulation results presented in table 14 indicate that a 30% increase in the share of individuals with a college education decreases the wealth Gini coefficient from 0.87 to 0.86, indicating a reduction in wealth inequality. This reduction in the Gini coefficient is primarily driven by changes at both ends of the wealth distribution. Specifically, the share of wealth held by the top 1% decreases by approximately 8%, reflecting a more equitable distribution of wealth among the wealthiest individuals. Additionally, the wealth held by the top 5%, 10%, and 20% also decreases. Conversely, the wealth held by the top 40% and 60% of the distribution increases, suggesting a shift in wealth towards the middle class. While the share of wealth held by the bottom 40% decreases by about 10%, the overall effect points to a redistribution that benefits the middle class, leading to a more balanced wealth distribution.[10]

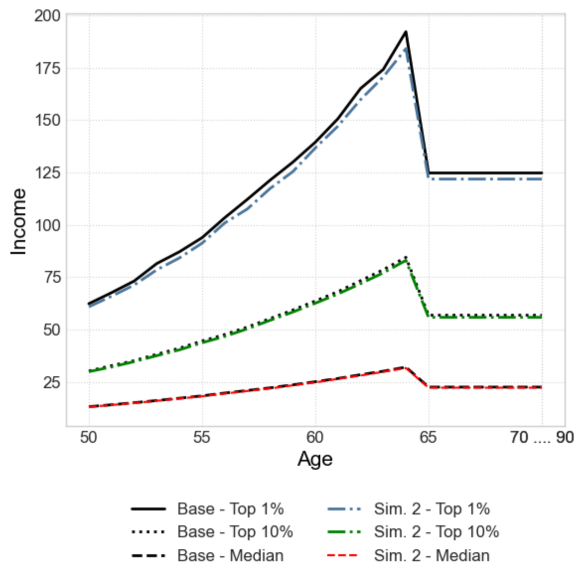
Additional results are presented in Table B3 in the Appendix. The results confirm that increasing the quantity of education (S2) has a similar impact on wealth inequality across age and educational categories. For example, among college-educated individuals, the category affected by the policy, the Gini coefficient decreases indicating a slight improvement in equality.

Having established the main results of the educational policies' impact on wealth distribution and inequality, we now turn to the channels driving the observed reduction in wealth inequality. Figure 3 examines whether changes in assets and income drive these changes by analyzing their life cycle profiles, differentiated by education level. For college-educated individuals, the assets of the top 1% decrease slightly, while the assets

[10]Non-linear effects are explored in the Appendix B.4.



(a) Direct



(b) Indirect

Figure 3: Simulation 2 Mechanisms: Direct and Indirect Effects
Note: The life cycle profiles of assets are presented in figure 3a and of income in 3b.

of those in the top 10%, 20%, and median increase. This shift reflects a redistribution of wealth within the college-educated population, aligning with the overall reduction in wealth inequality observed in Table 14. In contrast, the income profiles for the top 20% and median among college-educated individuals remain relatively stable, with only the top 1% experiencing a slight reduction in their income life cycle profile.

These findings highlight the dual channels through which increased access to higher education influences wealth distribution: direct effects of education on asset accumulation and indirect effects via labor income. The policy's impact on assets is more pronounced, contributing significantly to the observed wealth redistribution. Although there are changes in labor income, particularly for the top 1%, these effects are smaller in magnitude compared to the changes in assets. The results obtained previously in Section 2.5 corroborate these findings, demonstrating the substantial role of the direct effect of education on assets and the relatively lower indirect effect via labor income.[11]

An additional simulation is reported in section B.6 in the Appendix that combines the improvements in quality of education and the increase in the share of college graduates. These results highlight the complexity of interacting policies. While increasing the share of college graduates alone tends to reduce wealth inequality by increasing the share of the middle class, the simultaneous enhancement of education quality through higher returns to capital disproportionately benefits those already at the top of the wealth distribution.

[11]Additional results showing the impact of educational policies on wealth inequality are presented in Table B.5.

3.4.3 S3: Enhancing Long-Term Planning and Financial Literacy

An additional educational policy considered aims to incentivize savings and long-term financial planning specifically for individuals with a college education. This policy might involve integrating comprehensive financial literacy programs into college curricula, designed to improve students' understanding of personal finance, investment strategies, and the benefits of long-term financial planning. Alternatively, it could include other initiatives that enhance future-oriented financial behavior, such as personalized financial advising or mandatory financial planning workshops. As a result, the policy is expected to exogenously reduce the average discount factor for college graduates from 0.96 to 0.93, reflecting an increased propensity for future-oriented financial behavior among this group.

Table 15: Simulation Results: Long-Term Planning

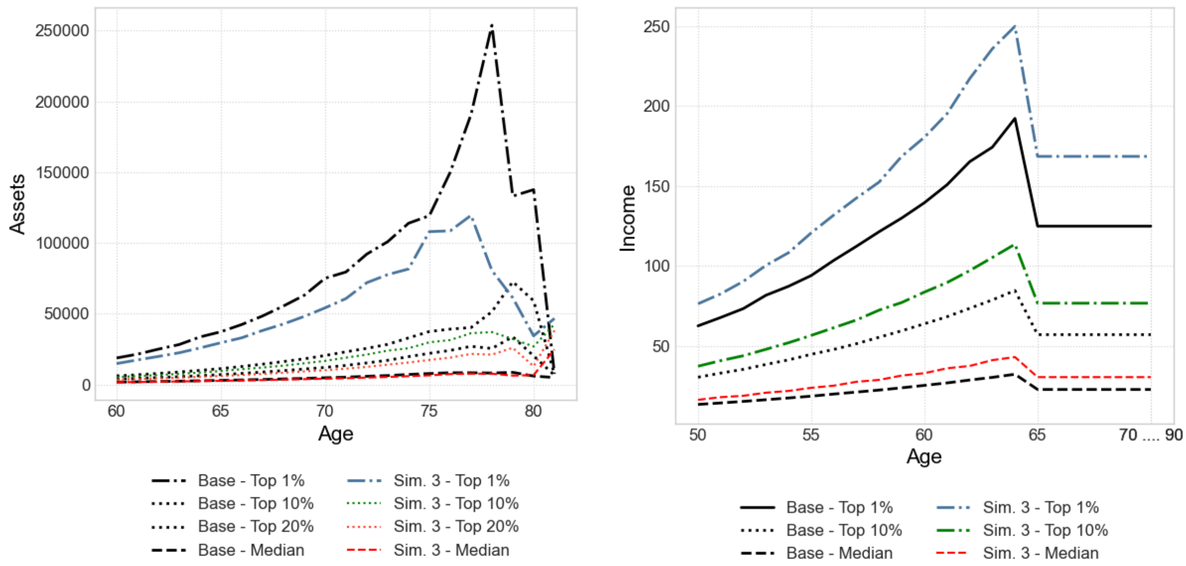
	Avg.	**Percentage Wealth in the Top**						**Bottom**
	Gini	1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S3: ↑ Long-term planning	0.85	34.2	65.6	79.5	89.9	96.4	98.8	1.2

Source: Author's calculations.

The simulation results, presented in Table 15, show that enhancing financial literacy and long-term planning for college graduates has a notable impact on wealth distribution. Under this policy, the average Gini coefficient decreases to 0.85 from 0.87 in the model with direct and indirect effects of education. This indicates a reduction in wealth inequality. The wealth held by the top 1% decreases from 37.4% to 34.2%, and similar reductions are observed across the top 5%, 10%, and 20% of the wealth distribution. Additionally, the wealth share of the bottom 40% increases slightly from 1.0% to 1.2%.

This reduction in wealth inequality is more significant than that achieved by increasing the share of college graduates. Not only does the wealth held by the top 1% decrease more substantially, but the wealth held by the bottom 40% of the population also increases, compared to the decrease found in the previous policy. These results suggest that policies aimed at improving financial literacy and encouraging long-term financial planning among college graduates can contribute to a more equitable distribution of wealth. By fostering a culture of savings and strategic investment within this educated demographic, such policies can mitigate the concentration of wealth at the top and enhance financial stability for a broader segment of the population.

To understand the mechanisms driving the impact of this policy, it is essential to analyze whether the observed effects are primarily driven by changes in assets or income. These changes are presented in figure 4. The asset profiles indicate that the policy leads to notable changes in wealth accumulation. For the top 1%, the asset levels in the simulation are generally lower than in the baseline model, particularly noticeable from age 65 onwards. This reduction suggests that the policy encourages a more balanced distribution of assets among the wealthiest individuals. The top 10% and top 20% groups also show reduced asset levels under the policy, though the median group's assets have a slight increase, indicating that the policy has a leveling effect on asset distribution.



(a) Direct

(b) Indirect

Figure 4: Simulation 3 Mechanisms: Direct and Indirect Effects
Note: The life cycle profiles of assets are presented in figure 4a and of income in 4b.

The income profiles reveal that the policy impacts income levels, especially for the top 1%. The income for the top 1% in the simulation is higher than the baseline but the top 10% and median groups see slight improvements in income under the policy. This suggests that while the policy enhances earnings potential, it also promotes a more balanced income distribution as individuals approach retirement. Comparing this with the policy of increasing the share of college graduates, which also reduces inequality but through different mechanisms, we see distinct impacts. The financial literacy policy achieves a more balanced wealth distribution by reducing the concentration of wealth at the top and increasing the wealth of the bottom 40%.

It seems that the financial literacy policy reduces wealth inequality more effectively than increasing the share of college graduates because it directly enhances individuals' financial decision-making and planning skills. By equipping college graduates with comprehensive financial literacy, they become more adept at managing their finances, saving consistently, and making informed investment choices. This targeted approach addresses the root causes of financial mismanagement and disparities in wealth accumulation. In contrast, merely increasing the share of college graduates boosts overall asset and income levels but does not specifically tackle the underlying financial behaviors that contribute to wealth inequality. Therefore, financial literacy leads to a more balanced and equitable distribution of wealth by fostering prudent financial habits and strategic investments, making it a more effective policy for reducing inequality.

4 Conclusions

The unequal accumulation of wealth can significantly hinder individuals' ability to afford crucial investment opportunities, including higher education, ultimately affecting their life outcomes. This raises the question of whether investing in education is worthwhile given these disparities. This research investigates the causal relationship between education and wealth accumulation, exploring whether this relationship holds across different education levels and throughout the life cycle, and examines whether educational policies can reduce these wealth disparities.

The first part of this research employs an econometric analysis using three identification strategies aiming to isolate the effect of education on wealth. The findings indicate that there are wealth returns to education, with a strong causal effect evident for individuals with college and postgraduate education. Notably, these results remain significant even after controlling for parental wealth, an important factor that previous studies often overlooked. Furthermore, quantile regressions reveal that the impact of education on wealth varies across different points of wealth distribution. The analysis also investigates mechanisms such as productivity effects, financial behavior, and financial literacy. These mechanisms play a significant role in explaining how education influences wealth accumulation for college graduates. The results highlight that while education does increase wealth, its effects are more pronounced and consistent among those with higher educational attainment.

After finding that there is a causal effect of education on wealth for individuals with college and postgraduate education, 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 quantitative model includes unique features that generate a skewed wealth distribution and mechanisms that transmit educational effects on wealth for college graduates. This quantitative model explores educational policies and provides counterfactual simulations. These educational policies aim at increasing access to higher education, improving the quality of education, and enhancing financial literacy. The simulation results reveal that while increasing access to higher education and more long-term planning tend to reduce wealth inequality, improving the quality of education, by enhancing returns to capital for college graduates, may increase inequality.

Future research should explore the effects of early childhood and primary education interventions on later-life wealth accumulation and inequality, expanding the scope beyond higher education. Additionally, investigating the broader economic impacts of educational policies, such as how increasing access to higher education and improving education quality affect overall economic growth, is essential. While improving the quality of education may increase wealth inequality by enhancing returns to capital for college graduates, it could also drive significant economic growth. Moreover, examining the effects of educational policies on social mobility is crucial for understanding whether improved education access and quality lead to greater upward mobility.

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Appendix

A Econometric Analysis: Additional Information

A.1 Description and Summary of Variables

Table A1: 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 2.2).
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 A2: 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 A3: 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.

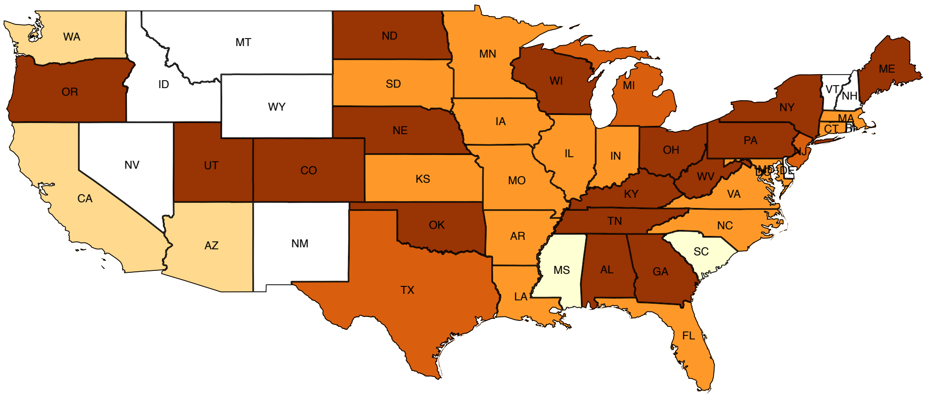
Table A4: Correlation Matrix

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***

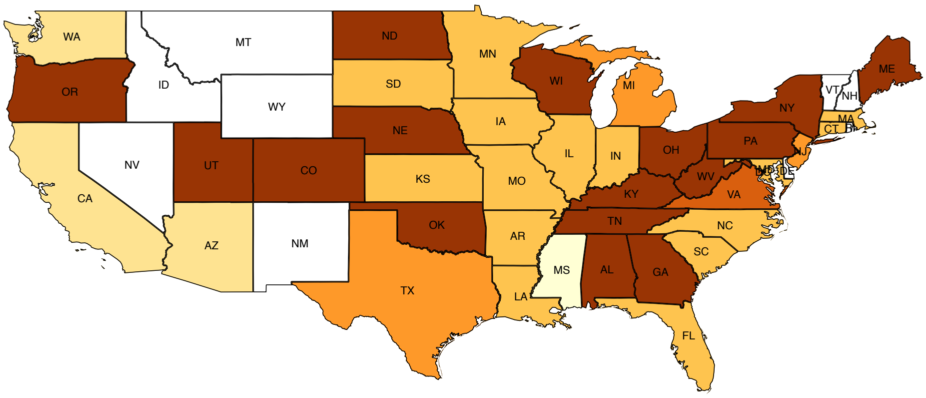
Note: Source: Panel Study of Income Dynamics. Significance levels are denoted as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Data in this analysis is used with sampling weights.

A.2 U.S. Compulsory Schooling Laws

(a) 1965



(b) 1972



(c) 1978

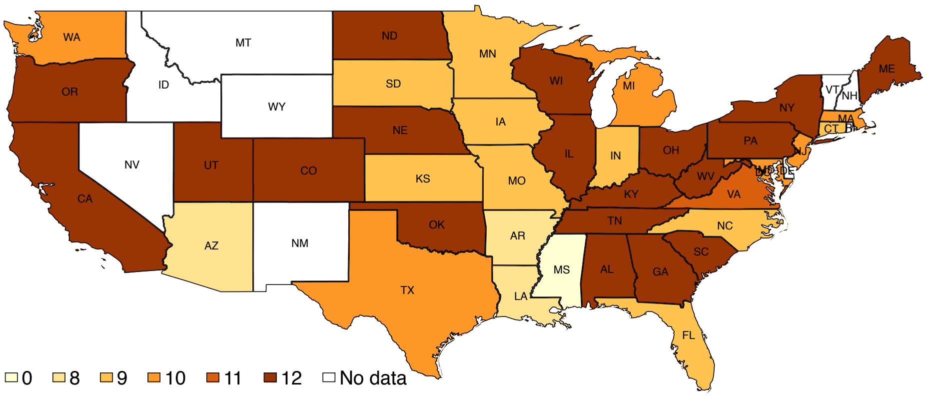


Figure A1: Evolution of Compulsory Education Laws
Note: The compulsory years of education in the U.S. by state in 1965, 1972 and 1978.

A.3 Additional Results: Parental Wealth versus Income

Table A5: 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.

A.4 Additional Empirical Results: Quantile Regression

Table A6: 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.

A.5 Additional Empirical Results: Wealth including Home Eq.

Table A7: 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 A8: 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 A9: 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 A10: 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 A11: 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 A12: 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 A13: 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 A14: 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.

B Life Cycle Model: Additional Information

B.1 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

$$v(\bar{z}_t) = \max_{c_t} \Big\{ \frac{(\mathbf{c}_t h_t)^{1-\gamma}}{1-\gamma} + \beta_t E_t v_{t+1}(\bar{z}_{t+1}) \Big\} \tag{B1a}$$

$$\frac{v(\bar{z}_t)}{h_t^{1-\gamma}} = \max_{c_t} \Big\{ \frac{(\mathbf{c}_t h_t)^{1-\gamma}}{(1-\gamma)h_t^{1-\gamma}} + \beta_t E_t \frac{v_{t+1}(\bar{z}_{t+1})}{h_t^{1-\gamma}} \Big\} \tag{B1b}$$

$$v_t(\bar{\mathbf{z}}) = \max_{c_t} \Big\{ \frac{\mathbf{c}_t^{1-\gamma}}{1-\gamma} + \beta_t E_t \Big[\frac{v_{t+1}(\bar{z}_{t+1})}{h_t^{1-\gamma}} \frac{h_{t+1}^{1-\gamma}}{h_{t+1}^{1-\gamma}} \Big] \Big\} \tag{B1c}$$

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:

$$v_t(\bar{\mathbf{z}}) = \max_{c_t} \Big\{ u(\mathbf{c}_t) + \beta_t E_t \Big[(G\psi_{t+1})^{1-\gamma} v_{t+1}(\bar{\mathbf{z}}_{t+1}) \Big] \Big\} \tag{B2}$$

s.t.

$$\mathbf{m}_{t+1} = \frac{R_{t+1}}{G\psi_{t+1}}(\mathbf{m}_t - \mathbf{c}_t) + \xi_{t+1} \tag{B3}$$

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

$$\mathbf{c}_i = \mathrm{E}_t\left[\beta_t R_t \left(G\psi_{t+1}\mathbf{c}^*_{t+1}\left(\frac{R_{t+1}}{\psi_{t+1}}\mathbf{a}_i + \xi_{t+1}\right)\right)^{-\rho}\right]^{-\frac{1}{\rho}} \tag{B4}$$

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

$$\mathbf{a}_i = \mathbf{m}_i - \mathbf{c}_i \;\Leftrightarrow\; \mathbf{m}_i = \mathbf{a}_i + \mathbf{c}_i \tag{B5}$$

4. Then repeat for each period the same procedure.

B.2 Estimation Probability of Attending College

The primary objective here is to explore the key factors influencing the decision to attend college. To achieve this, logistic regression was applied using the Panel Study of Income Dynamics data from 2019, offering a contemporary snapshot of how socioeconomic factors impact educational decisions during early adulthood.
The relationship between parental education, family wealth, and the probability of attending college is modeled as follows:

$$\mathrm{logit}(P(\mathrm{college})) = \beta_0 + \beta_1 \cdot \mathrm{Par.Wealth} + \beta_2 \cdot \mathrm{Par.Education} \tag{B6}$$

This equation encapsulates the log odds of college attendance as a function of parental wealth and education, suggesting that both factors may play a crucial role in shaping educational outcomes.

Table B1: Logistic Regression Results for Predicting College Attendance

	Coefficient	Std. Error
Par.Education	0.72003***	(0.03299)
Par.Wealth	0.00000947***	(0.00000230)
Constant	-1.5998***	(0.09602)

Note: Significance levels are denoted as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Source: PSID, 2019.

The coefficients derived from the logistic regression model provide insights into the factors influencing college attendance. A positive coefficient for parental education suggests that an increase in the parents' educational attainment significantly raises the likelihood of their children attending college. Similarly, the coefficient for parental wealth indicates that even small increases in family wealth can enhance college attendance probabilities.

B.3 Life Cycle Model: Inheritance's Fit

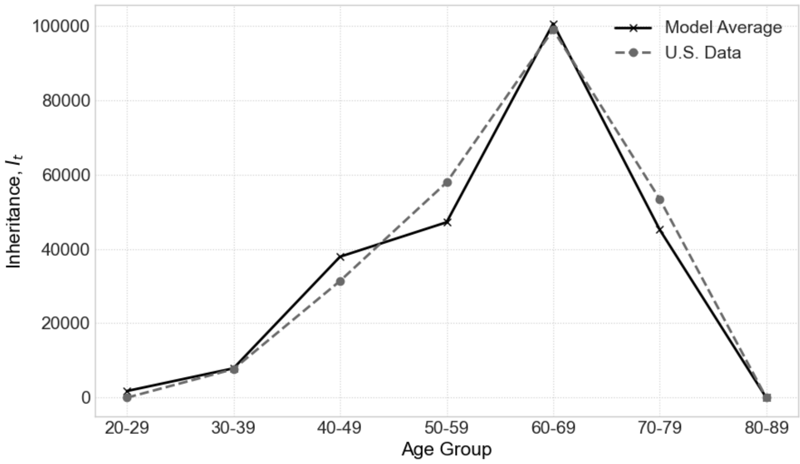


Figure B1: Average Inheritance by Age
Note: The figure compares the model's average inheritance received by individuals with the real data. Source: Panel Study of Income Dynamics, 2019.

B.4 Simulation 2: Non-linearity

The simulation results demonstrate a linear trend in the changes observed across different scenarios. As the share of individuals with a college education increases, the wealth Gini coefficient, the share of wealth held by the top 1%, and the share of wealth held by the bottom 40% all exhibit consistent percentage changes. Specifically, the reductions in the wealth Gini coefficient and the top 1% wealth share, as well as the share of wealth held by the bottom 40%, roughly double from the main model to the first simulation, and again from the first to the second simulation. This pattern indicates that the changes in wealth distribution metrics are linear in response to the equal percentage increase in the share of college-educated individuals.

Table B2: Simulation Results: Wealth Distribution

	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S2: ↑ College Share	0.86	34.5	65.7	80.0	91.0	97.1	99.1	0.9
S2: ↑ College Share x2	0.85	31.8	62.6	77.7	90.2	97.2	99.1	0.8

Source: Author's calculations.

B.5 Life Cycle Model: Additional Results

In addition to validating the main model, further simulations were conducted to explore the impact of different educational policies on wealth inequality. The additional results are presented in Table B3, comparing the model outcomes under three specific simulations: S1, which focuses on improving the quality of education, S2, which increases the share of college graduates and S3, which enhances long-term planning. These findings are consistent with the main results, where improving education quality (S1) exacerbates wealth inequality while increasing access to education (S2) and enhancing planning (S3) helps mitigate it.

Table B3: Classification of Wealth Gini Coefficient

	Model	**S1**	**S2**	**S3**
Age				
Early Adulthood (20–39 y.o.)	0.60	0.68	0.61	0.59
Mid Adulthood (40-59 y.o.)	0.71	0.85	0.69	0.69
Late Adulthood (60-79 y.o.)	0.79	0.88	0.77	0.77
Education				
College	0.81	0.88	0.80	0.79
Non-College	0.66	0.66	0.66	0.66

Note: Author's calculations.

B.6 Life Cycle Model: Impact of Combined Education Policies

A final policy simulation integrates the first two policies: increasing the proportion of college-educated individuals and enhancing the returns to education by raising the rates of return to capital for college graduates.

Table B4: Simulation Results: Quantity-Quality Trade-off

	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S3: ↑ Quantity vs. Quality	0.92	45.6	77.5	89.9	96.8	99.1	99.7	0.3

Source: Author's calculations.

The simulation results, presented in Table B4, indicate that the dominant effect is an increase in wealth inequality. Specifically, the average Gini coefficient increases from 0.87 to 0.92, suggesting a rise in overall wealth inequality. Interestingly, the increase in the share of wealth held by the top 1% in the combined policy scenario (22%) is less pronounced than the increase observed with only the improvement in education quality (33%). This suggests that while both policies contribute to wealth inequality, the negative effects of higher returns to capital are somewhat mitigated by the broader access to higher education. However, the combined effect still results in an overall increase in inequality, indicating the dominant influence of improving education quality.