Can Educational Policies Reduce Wealth Inequality?

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Abstract

This study examines the causal relationship between education and wealth accumulation using a U.S. panel dataset spanning two generations. Employing three identification strategies, the research finds that educational attainment significantly increases lifetime wealth, especially for tertiary education. A life-cycle heterogeneous agents model is developed and calibrated to assess the impact of educational policies on wealth distribution. The model evaluates policies to enhance education quality, financial literacy, and increase higher education quantity. The analysis reveals that increasing college-educated individuals and fostering long-term planning effectively reduces wealth inequality. These results contribute to understanding education's role in wealth disparities and generation.

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

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

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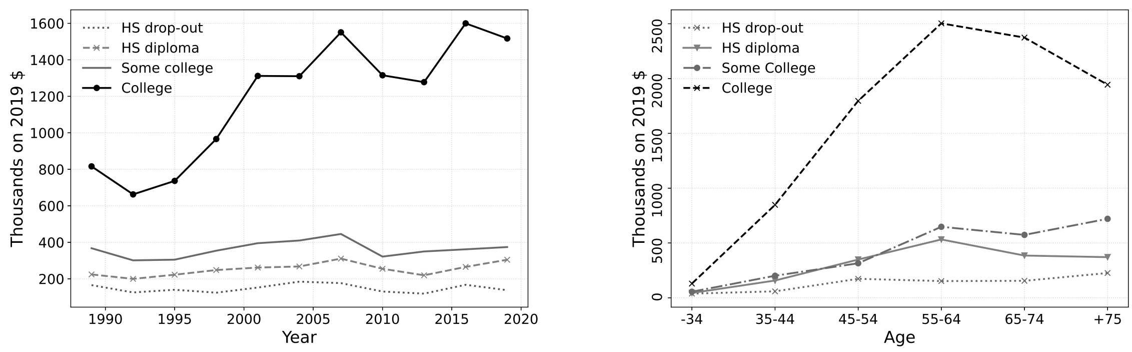
1 Introduction

In recent decades, wealth concentration at the top has risen in most countries, leading to increased wealth inequality.[1] In the U.S., the top 1% of households hold over 40% of the wealth, while the bottom 90% has seen little change since 1980. These disparities have fueled discussions on wealth accumulation mechanisms and barriers to economic mobility. Educational attainment plays a key role in these dynamics, revealing nuanced disparities often overlooked by general statistics.

Figure 1a illustrates the wealth distribution by educational level from 1989 to 2019, highlighting significant disparities between those with and without a college degree. Figure 1b shows 2019 life cycle wealth profiles by education, indicating distinct accumulation patterns for college graduates. However, factors like inherited wealth and privilege can obscure education's impact on wealth, complicating the direct correlation between education and wealth accumulation. These differences highlight the importance of examining how education influences 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.

Understanding how human capital investments impact wealth accumulation and inequality is crucial in economic research. This study addresses two questions: Does human capital investment enable consistent wealth accumulation throughout the life cycle? Can educational policies reduce wealth inequality? The paper aims to determine if a causal link exists and to analyze the mechanisms driving this relationship at different life stages, while also exploring the effectiveness of various educational policies.

Traditional economic studies have focused on the link between education and labor income, consistently finding a positive relationship (Card, 1999). Recently, attention has shifted to education's effects on net worth, though research is sparse due to data and causality challenges. Scandinavian studies have explored aspects like financial market participation and home ownership, but direct evidence of education's impact on wealth is

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

limited and inconclusive. For instance, Bingley and Martinello (2017) found no evidence that education influences retirement wealth in Denmark, while Fagereng, Guiso, Holm, and Pistaferri (2020) found no causal returns to schooling on wealth in Norway. Conversely, Girshina (2019) suggests a causal link in Sweden, with effects varying across the life cycle, though this study's limitation lies in measuring parental economic background through income rather than wealth.

Parental wealth significantly influences children's future outcomes, including educational achievements and economic returns.[2] Research by Charles and Hurst (2003) shows a strong link between parents' wealth and their children's outcomes before inheritances are passed on. Black et al. (2015) found that wealth transmission is largely influenced by the developmental environment and, to a lesser extent, genetics. Karagiannaki (2017) indicates that parental wealth is crucial for children's access to higher education, highlighting the significant and enduring impact of family wealth.

This paper investigates the causal link between education and wealth using multiple empirical strategies, addressing various sources of endogeneity. The analysis reveals a causal relationship between education and wealth across the life cycle, particularly for individuals with college and postgraduate education, with relationships varying by life-cycle stage and wealth distribution segment. The findings highlight labor income, productivity, and financial literacy as mechanisms through which education impacts wealth, enhancing individuals' ability to generate wealth through direct capital returns and increased labor income.

Having established a causal effect of tertiary education on wealth accumulation, a life cycle quantitative model is introduced. Recent research has incorporated idiosyncratic returns to wealth to better align 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, especially in the context of education's impact on wealth, remain underexplored. Integrating insights from wealth inequality research into this life cycle analysis offers a promising avenue to understand how education influences wealth accumulation over time. After exploring different features driving wealth accumulation in the quantitative model and validating its replication power, the study introduces educational policies aimed at reducing wealth inequality. Simulations suggest that increasing the share of college graduates and enhancing education quality and financial literacy can reduce wealth inequality, while higher returns to capital among college graduates can have the opposite effect.

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

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

2 Empirical Model

This section implements different econometric models to establish a causal relationship between education and wealth, addressing the challenge of unobserved variables such as parental education, wealth, and individual abilities. These factors can influence access to quality education and predispose individuals to higher socioeconomic status. Without a perfect natural experiment, it's essential to develop empirical approaches to control for these unobserved factors. Therefore, I propose three strategies to mitigate their influence and accurately isolate the impact of education on life-cycle wealth.

2.0.1 Control for Unobservables

The initial empirical strategy aims at controlling the main unobservable variables that are suspected to be affecting the estimates obtained through ordinary least squares (OLS). 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. The main specification follows:

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

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, X is a matrix of covariates that include: a measure of individual innate ability, parental wealth, parental presence, 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. The approach also includes birth-cohort effects.

After controlling for the variables considered unobservables, 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 Within Siblings Variation

To address additional endogeneity concerns, a within-siblings variation (WS) strategy is implemented. It compares 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:

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

Here, $D.W_{jt}$ represents the wealth difference between siblings j at time t, with $D.Educ_{jt}$ and $D.X_{jt}$ include differences in age, socioeconomic backgrounds and parental presence during upbringing, participation in gifted programs, and class repetition, as well as behavioral factors like breaking the law. γ_t accounts for 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.

2.0.3 Instrumental Variables

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 (CSL) and parental job loss (PJL) for an instrumental variables analysis (IV). These instruments help us isolate the effect of education on wealth more cleanly.

The first instrument 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. The analysis employs a two-stage least squares method, with the first stage predicting schooling based on compulsory education laws, while controlling for parental wealth to account for possible violations of the exclusion restriction:

$$\mathrm{Schooling}_{it} = \beta_1\,\mathrm{CSL}_i + \beta_2\,\mathrm{Par.Wealth}_i + \epsilon_{it}, \tag{3}$$

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

$$\mathrm{W}_{it} = \alpha_0 + \alpha_1\,\mathrm{Schooling}_{it} + \alpha_2\,\mathrm{Par.Wealth}_i + \upsilon_{it}, \tag{4}$$

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.

While compulsory schooling laws provide valuable exogenous variation in educational attainment, some suggest they primarily affect high school attendance. They may not fully capture the impacts of tertiary education on wealth accumulation. Thus, a new instrument is introduced to address this limitation and complement the initial results: parental job loss during the child's final high school years. Parental job loss during this critical period introduces an exogenous shock to the family's financial stability, directly impacting the decision to pursue higher education. This event provides a source of exogenous variation that is particularly relevant for studying the effects of college education. To ensure the validity of this instrument, initial family wealth is controlled, isolating the educational pathway through which PJL affects wealth accumulation. The first stage is presented by:

$$\text{College}_{it} = \beta_1 \,\text{PJL}_i + \beta_2 \,\text{Par.Wealth}_i + \epsilon_{it}, \tag{5}$$

I specify the second stage as follows:

$$\text{W}_{it} = \alpha_0 + \alpha_1 \,\text{College}_{it} + \alpha_2 \,\text{Par.Wealth}_i + \upsilon_{it}, \tag{6}$$

The use of parental job loss as a complementary instrument offers a novel contribution to the literature on the effects of education and wealth. By introducing a shock that is both unexpected and financially impactful, this instrument provides a unique angle to understand the barriers to higher education.

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 dropouts to postgraduate studies.[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

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

16, and inheritance receipt.[5]

The data on parental job loss is obtained from the PSID, exploiting its inter-generational features. The PSID provides detailed information on the employment status of household heads, including the number of weeks unemployed each year. We calculate parental job loss by summing the hours of unemployment for each parent during the years when the child is between 15 and 18 years of age. This period is chosen because it represents the critical high school years, during which financial stability can significantly influence a child's decision to pursue higher education. 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 Empirical Results

The empirical findings, as detailed in Table 1, shed light on the relationship between education and wealth across the life cycle, analyzed through ordinary least squares regression. This analysis is divided into two different panels: panel (A) examines the impact of education as a continuous variable on wealth, while panel (B) explores the effects based on categorized educational levels.

Across both panels, education emerges as a significant predictor of wealth, highlighting 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. This effect escalates dramatically for individuals in their 60s, where education increases in wealth more than in previous age groups. Panel (B) separates the education variable into categories. The results highlight a progressive increase in wealth with higher education levels. For instance, individuals with a high school diploma see a wealth increment, which significantly amplifies for those with one to two years of college education. This trend continues, with postgraduate education showcasing the most substantial wealth gains, especially pronounced in the later life stages. For the remaining variables, inheritance and parental wealth consistently contribute positively across all models and life stages. Interestingly, the coefficients for parental education effects vary, showing a more positive and significant effect for fathers than mothers.

The study further investigates this relationship using the within-sibling variation strategy reported in table 2. The results, for the average life cycle and by categories of education are reported in the first column of the table, highlighting a consistently positive and significant effect of education on wealth across almost all categories except for postgraduate education. A detailed examination of life stage-specific impacts reveals that education's positive influence on wealth persists across all age groups. Higher education

[5] Summary statistics are presented in Table A3, a correlation matrix in Table A4, and a descriptive analysis of wealth by education and cohort in Table A5, all in the Appendix.

Table 1: 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)
(B) Education Categories on Wealth Over the Life Cycle					
	Avg	**Cohort**			
		30	**40**	**50**	**60**
Highschool	1220.52*	1832.99**	4196.66***	5523.55***	2089.51
	(611.31)	(629.30)	(649.82)	(867.19)	(1393.96)
Some College	2429.58***	1903.49**	5569.92***	6265.32***	8461.72***
	(677.35)	(697.32)	(768.53)	(966.68)	(1564.55)
College	2439.55**	5044.87***	10598.11***	10108.45***	10385.52***
	(783.29)	(791.38)	(866.67)	(1089.23)	(1685.97)
Postgraduate	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.

levels correlate with increased wealth accumulation throughout the life cycle.

College education shows substantial wealth gains, particularly for individuals in their 40s and 50s, while the lack of significance in the 30 age group may be attributed to a delayed entry into the labor market due to the time spent in education. Postgraduate education demonstrates significant wealth effects primarily for individuals in their 40s, but not consistently across other age groups. The negative sign in the first age group might be due to the opportunity cost of extended education. These inconsistencies could also be attributed to smaller sample sizes. The category 'Some College' education also

Table 2: Within Variation Regression: Effects of Education on Wealth

	Avg	**Cohort**			
		30	**40**	**50**	**60**
D.Highschool	1013.57^{+}	305.65	830.13	446.05	31983.15*
	(534.54)	(650.97)	(655.77)	(989.28)	(14720.33)
D.Some College	2605.85***	1671.88*	1729.37*	2948.22*	20230.82
	(616.07)	(706.41)	(853.63)	(1281.98)	(17346.99)
D.College	4985.44***	604.52	6665.88***	9253.42***	14464.63
	(986.05)	(1100.50)	(1369.20)	(2412.12)	(22087.41)
D.Postgraduate	747.67	−2691.06*	4075.86*	3204.44	40549.35
	(1172.68)	(1305.32)	(1669.10)	(3478.00)	(32783.38)
Observations	7887	3796	3078	1279	30
Adjusted R^2	0.02	0.04	0.05	0.07	0.00

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. Control variables include the difference between siblings in age, socioeconomic conditions, parental presence when young, and school performance. The constant term is included but not reported for brevity.

exhibits significant effects, though with varying magnitudes. While these findings align with the previous strategy in indicating education's role in wealth accumulation, the within-sibling variation method generates new insights. Specifically, it reveals that the causal effects of education on wealth are most pronounced for college and postgraduate education.

A third and final identification strategy, instrumental variables, is introduced to complement the analysis. It includes two different instruments to target different stages of education: compulsory schooling laws for basic education and parental job loss for higher education. Even though CSL affects tertiary education as shown by the first stage of the IV, some argue that this instrument does not target higher education. Therefore, parental job loss is included to address this limitation.

The first instrument leverages the exogenous variation provided by compulsory schooling laws across U.S. states to examine how mandated education minimums impact long-term wealth accumulation.[6] Using a two-stage least squares regression, the initial stage incorporates CSL as instrumental variables. Although detailed first-stage results are omitted for brevity, they confirm that higher schooling requirements are positively correlated with higher reported education in adulthood. Incorporating parental wealth into the analysis addresses potential concerns regarding the exclusion restriction, mitigating bias from shifts in compulsory schooling potentially delaying young individuals' entry into the labor market and prolonging financial dependence on parents. Table 3 presents the findings from this IV regression, reporting the average life cycle effects followed by effects separated by age groups.

The IV regression outcomes confirm a robust causal relationship between education and wealth for the average and throughout life. However, when separating education from a continuous variable into categories, it was found that lower levels of education do not

[6]Figure A1 in the appendix illustrates the heterogeneity in compulsory attendance across states.

Table 3: I.V. Regression: Compulsory Schooling Laws

(a) Avg. Education

	Avg	**Cohort 30**	**Cohort 40**	**Cohort 50**	**Cohort 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**	**Cohort 40**	**Cohort 50**	**Cohort 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**	**Cohort 40**	**Cohort 50**	**Cohort 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.

have significant effects, nor for the average or the different life cycle stages. The only statistically significant effects were found for college and postgraduate education. These results are reported in panels (b) and (c) of Table 3, revealing a larger marginal wealth increase for college-educated individuals than the general education average. These results suggest the notion that higher educational attainment—particularly at the college and postgraduate levels—plays a significant role in wealth accumulation throughout the life cycle, although with varied significance across different stages.

Table 4: I.V. Regression: Compulsory Schooling Laws on Tertiary Education

	Avg	**Cohort 30**	**Cohort 40**	**Cohort 50**	**Cohort 60**
Tertiary	29958.92**	20842.69+	28197.41***	38114.43***	67838.94**
	(11405.44)	(10863.86)	(5829.78)	(7650.73)	(24456.19)
First Stage					
CSL	0.02***	0.01***	0.02***	0.01***	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
F-statistic	35.83	15.28	49.34	47.66	11.09
Observations	10281	1389	3912	3681	1243

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.

To address concerns regarding the validity of using compulsory schooling laws as an instrument for higher education, I created a binary variable distinguishing between tertiary education and non-tertiary education. By focusing on the first stage, the analysis aims to demonstrate that CSL has a significant impact on higher education attainment, thereby mitigating concerns about omitted variable bias and supporting the robustness of the IV strategy. The results, presented in Table 4, demonstrate a significant positive effect of CSL on the likelihood of obtaining tertiary education across various age cohorts. The first stage results, which are significant, confirm that compulsory schooling laws indeed have a substantial positive impact on educational attainment beyond high school. Additionally, these effects are observed across all age groups and supported by robust F-statistics, reinforcing the validity of CSL as an instrument for higher education.

The second instrument utilizes the exogenous variation introduced by parental job loss during a child's high school years to investigate how financial disruptions impact long-term wealth accumulation. This approach examines how unexpected financial shocks to a family during critical educational periods influence a child's educational attainment, especially tertiary education, and subsequent wealth. The results of this second instrument are presented in table 5. The first stage results are also omitted for brevity but they show a significant effect of parental job loss on education and more importantly, on tertiary education.

Table 5: I.V. Regression: Parental Job Loss

(a) Avg. Education				
	Avg	**Cohort**		
		30	**40**	**50 - 60**
Education	3027.88	3213.60*	8687.91***	6810.09+
	(2912.45)	(1346.76)	(2626.93)	(4042.22)
F-statistic	41.49	32.58	22.01	19.56
Observations	11310	4050	4131	1398

(b) Tertiary Education				
	Avg	**Cohort**		
		30	**40**	**50 - 60**
Tertiary	19150.10	23802.79*	57676.22*	62512.97
	(19246.83)	(11040.08)	(22440.22)	(53107.25)
F-statistic	39.49	26.60	13.30	9.55
Observations	11310	4050	4131	1398

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 parental job loss during the final years of high school. Year and cohort effects are included. Parental wealth is included but not reported for brevity.

The results using parental job loss during high school years as an instrument are consistent with the findings from the first instrument, compulsory schooling laws. The results demonstrate a robust relationship between education and wealth accumulation. Even though the average education effect is not statistically significant, the life cycle effects across different age cohorts are statistically significant, indicating that the impact of education on wealth becomes more pronounced over time.

In terms of tertiary education, the results confirm that the effects are predominantly significant for higher levels of education. The significance levels are generally lower with parental job loss as the instrument compared to the first instrument. This could be attributed to the more targeted nature of parental job loss, which captures financial disruptions specific to high school years rather than a broader educational policy impact. Despite this, the results remain significant, underscoring the validity of the instrument. The lower significance levels do not undermine the findings; instead, they highlight the nuanced understanding that financial shocks during high school have a more direct but perhaps slightly less broad impact on long-term wealth accumulation. These results further confirm that the effects of education on wealth are not significant at lower levels of education but are substantial for tertiary education.

2.3 Additional Empirical Analysis

2.3.1 Parental Income vs Parental Wealth

The regression results in Table A6 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 A6 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.

2.3.2 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

$$Q_q(W_{it}) = \alpha_q + \beta_{0q}\, Educ_i + \beta_{1q}\, X_i + \beta_{2q}\, SD_{it} + \gamma_t + \upsilon_{itq} \tag{7}$$

where the equation 7 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 A7 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 6.

Table 6: Quantile Regression: Effects of Education on Wealth

	(A) Quantiles of Wealth Distribution					
	0.10	**0.25**	**0.50**	**0.75**	**0.95**	**0.99**
Highschool	2233.98***	906.30*	3472.00***	4739.12***	3829.28**	7582.75***
	(557.24)	(430.68)	(486.34)	(559.06)	(1212.89)	(879.15)
Some College	431.57	1336.53*	5652.41***	7088.34***	6250.97***	8841.04***
	(593.41)	(576.08)	(546.04)	(623.92)	(1174.98)	(1084.64)
College	850.80	5178.97***	10924.69***	12501.78***	10550.40***	14881.19***
	(924.38)	(731.30)	(590.12)	(606.71)	(1204.03)	(1629.12)
Postgraduate	−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)
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**
Highschool	3288.23***	2976.58***	4647.41**	4422.23***	2063.75	−1332.98+
	(428.65)	(551.23)	(1699.36)	(1080.78)	(1311.62)	(764.11)
Some College	3939.58***	4930.85***	8209.59***	7379.38***	10804.34***	2450.88*
	(628.42)	(651.10)	(1767.93)	(1161.26)	(1977.45)	(1109.39)
College	7845.91***	11137.99***	12725.15***	12094.71***	12963.23***	7232.86***
	(704.80)	(774.17)	(1810.63)	(1452.85)	(1613.91)	(1006.09)
Postgraduate	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)
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, cohort effects and other variables are included. 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.

The results obtained in table 6 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.

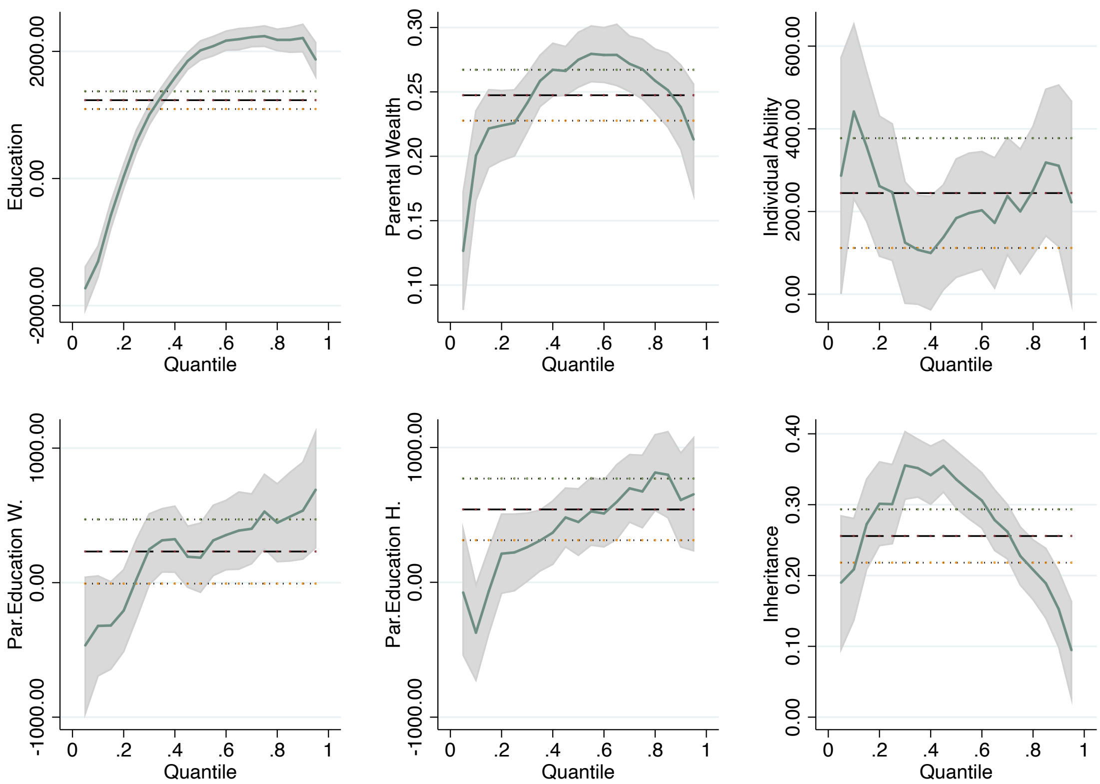


Figure 2: Education per Quantile of Wealth

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

2.4 Mechanisms of Transmission

To 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 7 is productivity and it is described as the individual's ability to generate income through labor or capital. The way this mechanism works would be that education enhances skills and knowledge, which can increase an individual's productivity in the workforce Gintis (1971). This increased productivity is often rewarded with higher labor income Card (1999), bonuses, and opportunities for investment income, such as rent.

Table 7: Wealth's Regression Mechanisms: Productivity Effect

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

Note: Source: PSID. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are heteroskedastic robust. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

The variables included in this mechanism are income obtained from labor, work bonuses, and rents. In this case, labor income is directly tied to productivity at work, however, this variable can also be considered as measuring the known income effect. This means that if individuals obtain more income, this would allow them to accumulate higher wealth over time. In this analysis, bonuses are the main measure of labor productivity as they are often awarded for exceptional performance or productivity at work. Lastly, the rent obtained reflects income from property investments, which can be considered a form of capital productivity. The results suggest that these variables serve as a good mechanism as they increase the value of wealth while attenuating the effect of the highest educational categories. Even though their effects are different, the three variables show significant results. Similar results are presented in table A13 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 8: Wealth's Regression Mechanisms: Financial Literacy

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

Note: Source: PSID. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Standard errors are heteroskedastic robust. Time, socio-demographics, inheritance, parental education and wealth, and cohort effects are included. Socio-demographic variables include age, sex, and race of individuals. The constant term is included but not reported for brevity.

Table 8 explores the three different types of assets that might explain the transmission of education on wealth. The first one is through directly held stocks. Individuals with higher educational attainment tend to increase their probability of owning stocks Campbell (2006), and higher stock market participation Bertaut (1998). The results of this mechanism are reported in column A with positive and significant results.

The second is through annuities and retirement accounts with positive and statistically significant results presented in column (B). In general, the idea is that highly educated individuals will participate more in annuities and individual retirement accounts (IRA). This was examined by Bingley and Martinello (2017) who found that individuals with higher levels of education will increase the value of pension annuity claims. The dynamics could drive highly educated individuals to invest in retirement accounts, thus wealth during retirement would not suffer directly, for example, from negative medical expenses.

Table 9: Wealth's Regression Mechanisms: Financial Behavior

Dependent Variable: Wealth		
	(A)	**(B)**
Highschool	1277.80*	949.33
	(508.51)	(613.50)
Some College	1828.73**	2062.60**
	(571.34)	(690.39)
College	1323.68*	2044.10*
	(658.18)	(794.41)
Postgraduate	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.

The third variable of table 8 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.

The last mechanism trying to explain the main results is financial behavior which relates to 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 9 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 9 report negative and statistically significant effects of money problems on wealth. Similar results for the two mechanisms are presented in tables A14 and A15 for wealth with home equity in the Appendix.

3 Quantitative Model

After exploring the effects of education on net worth and discovering that only a strong case for causality can be made for college and postgraduate-educated individuals, a quantitative partial equilibrium life cycle model aims to explore potential scenarios for educational reforms. 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.

$$E_0 \left[\sum_{t=0}^{T} \left(\prod_{i=0}^{t} \beta_i \right) s_t \, u(c_t) + (1 - s_t) \, \theta(b_t) \right] \tag{8}$$

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.

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{9}$$

The utility derived from bequests follows De Nardi (2004)

$$\theta(b) = \theta_1 \Big(1 + \frac{b}{\theta_2}\Big)^{1-\gamma} \tag{10}$$

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:

$$y_t = h_t \, \xi_t \tag{11}$$

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.

$$\xi_{t+1} = \begin{cases} \mu & \text{pr } \pi \\ \phi_{t+1}/(1-\pi) & \text{pr } (1-\pi) \end{cases} \tag{12}$$

During all the working stages, labor income is obtained by the equation 11. The transitory shock ξ_t, presented in equation 12, 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 $\phi \in [\underline{\phi}, \bar{\phi}]$.

$$h_t = G \, \psi_t \, h_{t-1}, \tag{13}$$

Equation 13 can be seen as the permanent income part of the process and consists of its previous value, a parameter G_t that represents a permanent income growth factor and a mean-one IID permanent shock ψ_t that satisfies $\mathrm{E}_t[\psi_{t+n}] = 1 \;\; \forall \, n \geq 1$ and $\psi \in [\underline{\psi}, \bar{\psi}]$. The distribution of the shocks follows:

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

Labor income shocks are independent across agents.[7] 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.[8] This means that there are idiosyncratic rates of return to capital following:

$$\log R_t = \bar{u}_r + \eta_t^r \ \bar{w}_r \tag{14}$$

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.[9]

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.

$$\log \beta_t = \bar{u}_\beta + \eta_t^\beta \ \bar{w}_\beta \tag{15}$$

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:

$$F_{\beta R} := \lim_{n \to T} \left(E \prod_{t=1}^{n} \beta_t \ R_t \right)^{1/n} < 1 \tag{16}$$

The value $F_{\beta R}$ in equation (16) can be thought of as the long run (geometric) average gross rate of return discounted to present value to ensure existence and stability.

3.1 Household Recursive Problem

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

[7]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.

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

[9]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).

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:

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

s.t.

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

$$y_{t+1} = (\psi_{t+1} \ G \ h_t) \ \xi_{t+1} \tag{18b}$$

$$m_{t+1} = R_{t+1} \ a_t + \ y_{t+1} \tag{18c}$$

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:

$$v(\bar{z}_t) = \max_{c_t} \Big\{ u(c_t) \ + \ \beta_t s_t E_t \left[v_{t+1}(\bar{z}_{t+1}) \right] \ + \ (1 - s_t)\theta(a_t) \Big\} \tag{19}$$

s.t.

$$a_t = m_t - c_t \tag{20a}$$

$$m_{t+1} = R_{t+1} \ a_t + \ p_{t+1} \tag{20b}$$

3.2 Calibration

The model simulates $n = 100,000$ households, starting work at age 20 and retiring at 65. Each period is one year, with a maximum age of 90, spanning 70 periods. Household preferences use a relative risk aversion coefficient $\gamma = 1.5$ from Attanasio et al. (1999) and Gourinchas and Parker (2002). One-period survival probabilities s_t come from Bell et al. (1992). The summary of the parameters is presented in Table 10.
The labor income process, based on Carroll et al. (2015), Carroll et al. (1992), and DeBacker et al. (2013), includes an income growth factor $G = 1.03$, reflecting the U.S. average GDP per capita growth rate (1947-2014). The unemployment insurance replacement rate is $\mu = 0.15$ with a probability of $\mu = 0.07$. Pensions during retirement are a fraction $\kappa = 0.70$ of permanent income at retirement. Variances for permanent and transitory shocks are $\sigma^2_\psi = 0.01$ and $\sigma^2_\phi = 0.01$ respectively, matching uncertain income processes. The average rate of return to capital is 1.04%, with a mean value $\bar{u}r = 0.0238$

and $\bar{w}r = 0.215$, sourced from Ma et al. (2020). The average discount factor $\beta = 0.96$ is set by parameters $\bar{u}\beta = 0.91$ and $\bar{w}\beta = 0.004$. Details on the discretization process are in section B.1 in the Appendix.

Probabilities of receiving an inheritance in five-year intervals were derived from PSID data, generating random inheritances to match empirical averages. A parameter was included to reflect that 97% of the population does not receive any inheritance. The model's fit to real data is discussed in section B.3 in the Appendix. The initial asset distribution uses a Weibull distribution with mean $\mu_m = 0.27955$ from PSID data, including a zero fraction parameter of 0.33 to reflect those with no initial assets. Initial human capital distribution is lognormal, with parameters $\mu_p = 0.23425$ and $\sigma_p = 0.21865$ from PSID data. Bequest parameters θ_1 and θ_2 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). The values $\theta_1 = 9.30$ and $\theta_2 = 11.37$ produce a model ratio of 1.16, ensuring alignment with the empirical data.

3.3 Calibration Results

The next step is to observe the model's outcome to see if it reflects key aspects of real-world wealth distribution. Calibration targets are derived from 2019 U.S. data from the Survey of Consumer Finances, including metrics like the Gini coefficient and the percentage of wealth held by various percentile groups. The goal is to ensure the model accurately reflects distributional patterns observed in real-world data. Table 11 shows that the model, incorporating idiosyncratic rates of return to capital, heterogeneous discount

Table 10: 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

factors, intergenerational links, and idiosyncratic labor income, reasonably approximates the wealth distribution. It captures key aspects of wealth accumulation, especially at the distribution's extremes, and produces a Gini coefficient that, while lower than the real data, indicates significant wealth inequality. These initial results serve as a foundation for further refinement by incorporating the role of education in wealth accumulation, which is expected to improve the model's alignment with real-world data, especially in capturing educational impacts on wealth distribution and inequality.

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

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

3.3.1 Exogenous Effects of Education

Section 2 demonstrated that education causally affects wealth accumulation for college and postgraduate individuals. To incorporate this into the life cycle model, individuals are classified as either college or non-college based on their human capital and wealth at the first period of life. The probability of college attendance is calculated using logistic regression parameters detailed in subsection B.2 in the Appendix, aligning the model's classification with the real distribution: 34% college-educated and 66% non-college.

Classifying individuals into college and non-college categories is significant only if these distinctions manifest observable differences. As discussed in section 2, education impacts wealth through labor income and rates of capital returns, influencing financial asset participation (Loaiza, 2021). Literature shows education increases the probability of owning stocks (Campbell, 2006), risk-taking in financial markets (Black et al., 2018), returns on risky assets (Ehrlich, Hamlen, & Yin, 2008), pension annuity values (Bingley & Martinello, 2017), and lowers stock market entry costs (Cooper & Zhu, 2016). Education also facilitates 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 12.

Table 12: Main Calibration Target: Wealth Distribution

	Avg. Gini	Percentage Wealth in the Top						Bottom
		1%	5%	10%	20%	40%	60%	40%
U.S. Data 2019	0.82	37.4	65.4	76.7	87.5	96.4	99.7	0.2
Model	0.66	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 12, 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 incorporates intergenerational links, idiosyncratic shocks, and education's direct and indirect effects on wealth to capture disparities between college and non-college individuals over their life cycle. Validating the model against empirical data ensures its robustness. Table 13 presents validation outcomes, comparing key metrics from the model with U.S. data from the PSID for 2019. These metrics reflect wealth inequality trends across different life stages and education levels.

Table 13: 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 examines the impact of educational policies on wealth distribution and inequality using counterfactual simulations based on a selected model. The baseline model incorporates education's direct and indirect effects on wealth accumulation. The goal is to determine if educational policies can reduce wealth inequality by targeting initial opportunities rather than solely economic outcomes. Previous studies, such as Keller (2010), have shown that educational expenditures significantly enhance income distribution with an equalizing effect. Three types of policies are analyzed: improving education quality, increasing the share of college graduates, and enhancing long-term financial planning. These policies aim to increase higher education access and improve returns to education for college graduates through better quality and financial literacy.

3.4.1 S1: Improving the Quality of Education

This policy examines the effects of enhancing education quality on wealth accumulation and inequality by increasing the returns to education for college graduates. Improved education quality equips individuals with better skills and knowledge, enabling more effective investment decisions and higher returns on capital. This can be achieved through better teacher quality, modernized curricula, skill-based programs or better digital access. The modeling approach involves exogenously increasing the average rates of return to capital for college graduates.

The simulation results in Table 14 show that a 5% increase in returns to capital for college graduates significantly affects wealth distribution, increasing the wealth Gini coefficient by about 7%. This rise in inequality is driven by a 33% increase in wealth held by the top 1%, while the bottom 40% sees a 70% decrease, highlighting a concentration of wealth among the wealthiest.

Table 14: 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 in table B3 in section B.5 of the Appendix show that improving education quality (S1) increases wealth inequality across all age groups, with higher Gini coefficients compared to the base model. In early adulthood, the Gini coefficient rises from 0.60 to 0.68; in mid and late adulthood, it increases to 0.85 and 0.88, respectively. Among college-educated individuals, the Gini coefficient rises from 0.81 to 0.88, while inequality among non-college individuals remains unchanged. These results reflect a scenario where improving education quality increases returns to capital for college graduates. It should not imply that all improvements in educational quality lead to increased inequality. Enhancing financial literacy and practical financial skills accessible to the general population could offer significant benefits without increasing inequality.

3.4.2 S2: Increasing the Share of College Graduates

This policy simulation examines the impact of increasing the proportion of the population with a college degree on wealth distribution and inequality. It reflects a hypothetical reduction in barriers to higher education access and affordability, aiming to create a more educated workforce, promote social mobility, and reduce income and wealth disparities. This is modeled by adjusting parameters influencing the probability of attaining a college degree, as detailed in section B.2 of the Appendix.

Table 15: Simulation Results: Quantity of Education

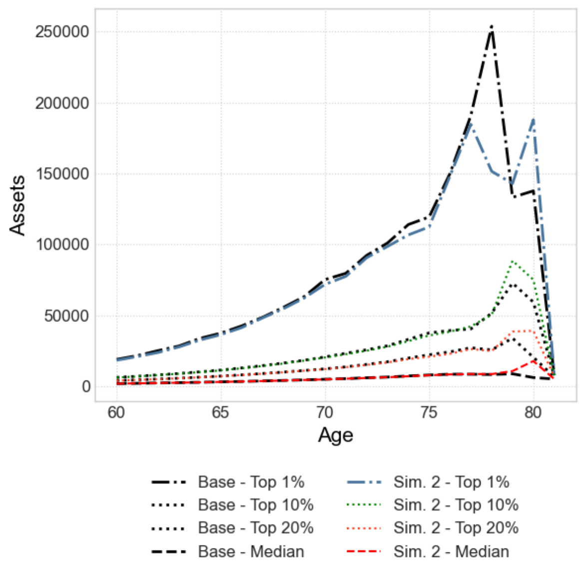
	Avg. Gini	Percentage Wealth in the Top						Bottom
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S2: ↑ College Share	0.86	34.5	65.7	80.0	91.0	97.1	99.1	0.9

Source: Author's calculations.

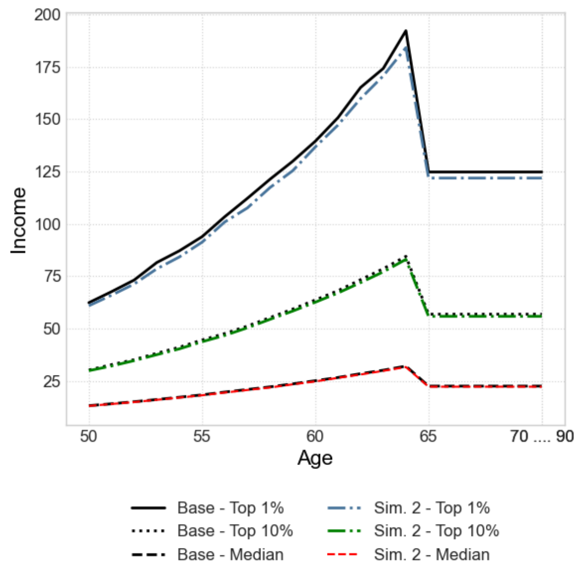
Table 15 shows that a 30% increase in the share of college-educated individuals reduces the wealth Gini coefficient from 0.87 to 0.86, indicating decreased wealth inequality. This reduction is driven by a decrease in the wealth share of the top 1%, top 5%, top 10%, and top 20%, while the wealth share of the top 40% and 60% increases, suggesting a shift towards the middle class. Although the bottom 40% sees a slight decrease, the overall effect benefits the middle class, leading to a more balanced wealth distribution.[10]

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

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.



(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.

Figure 3 analyzes the mechanisms behind the reduction in wealth inequality by examining changes in assets and income life cycle profiles by education level. For college-educated individuals, the assets of the top 1% decrease slightly, while assets of the top 10%, 20%, and median increase, reflecting a redistribution of wealth. Income profiles for the top 20% and median remain stable, with only the top 1% experiencing a slight reduction.
These findings highlight the dual channels through which increased access to higher education influences wealth distribution: direct effects on asset accumulation and indirect effects via labor income. The impact on assets is more pronounced, significantly contributing to wealth redistribution. Changes in labor income, particularly for the top 1%, are smaller in magnitude compared to asset changes. These results align with Section 2.4, demonstrating the substantial role of education on assets and a 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

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

to capital disproportionately benefits those already at the top of the wealth distribution.

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 16: Simulation Results: Long-Term Planning

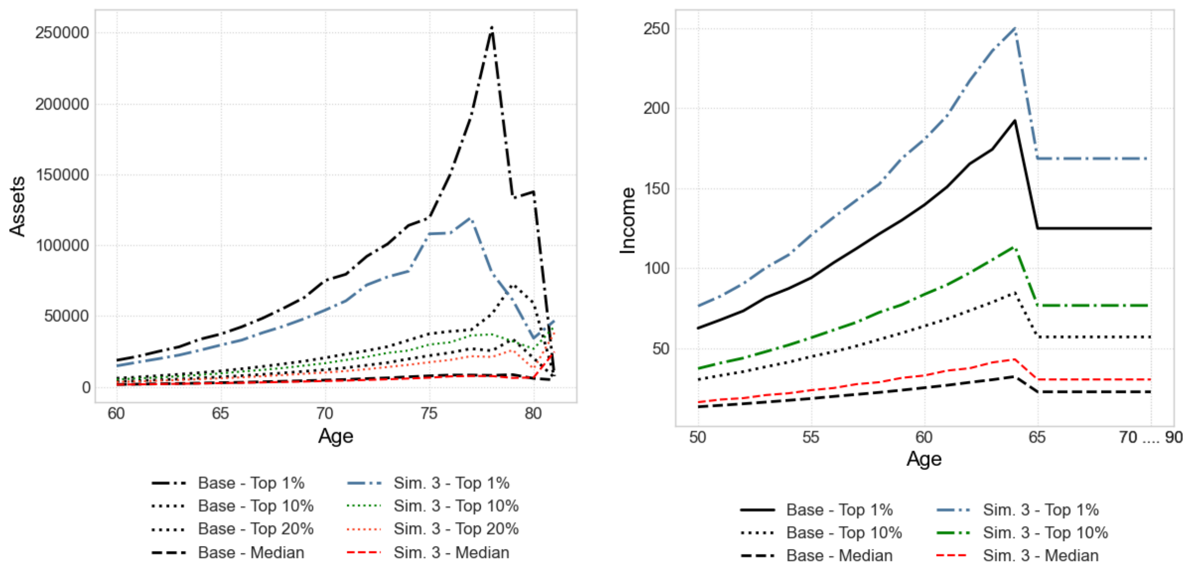
	Avg. Gini	**Percentage Wealth in the Top**						**Bottom**
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
S3: ↑ Long-term planning	0.85	34.2	65.6	79.5	89.9	96.4	98.8	1.2

Source: Author's calculations.

Table 16 shows that enhancing financial literacy and long-term planning for college graduates reduces wealth inequality. The average Gini coefficient drops to 0.85 from 0.87, and the wealth share of the top 1% decreases from 37.4% to 34.2%. The wealth held by the top 5%, 10%, and 20% also declines, while the bottom 40% sees a slight increase from 1% to 1.2%. This reduction in wealth inequality is more significant than increasing the share of college graduates. The financial literacy policy decreases the wealth of the top 1% and increases the wealth of the bottom 40%, suggesting it is more effective in promoting a more equitable wealth distribution. These policies foster savings and strategic investment, reducing wealth concentration and enhancing financial stability for a broader population.

To understand the mechanisms driving this policy's impact, Figure 4 analyzes changes in assets and income. 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.

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



(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.

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%.

The financial literacy policy reduces wealth inequality more effectively than increasing the share of college graduates by directly improving financial decision-making and planning skills. By equipping college graduates with comprehensive financial literacy, they manage finances better, save consistently, and make informed investment choices. This approach addresses the root causes of financial mismanagement and wealth disparities, leading to a more balanced and equitable wealth distribution through prudent financial habits and strategic investments.

4 Conclusions

Wealth inequality can hinder access to crucial investments like higher education, affecting life outcomes. This study investigates whether investing in education is worthwhile amidst these disparities, exploring the causal relationship between education and wealth accumulation across various education levels and life stages, and examines the potential of educational policies to reduce wealth disparities.

The first part of this research uses econometric analysis with several identification strategies 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, even after controlling for parental wealth. Quantile regressions show that education's impact on wealth varies across the wealth distribution. The analysis also explores mechanisms such as productivity effects, financial behavior, and financial literacy, revealing that education's influence on wealth is stronger and more consistent among those with higher education.

Building on the causal link between education and wealth for college and postgraduate individuals, this research simulates educational policies aimed at reducing wealth inequality using a life cycle quantitative model with heterogeneous agents. The model, which includes features generating skewed wealth distribution and mechanisms transmitting educational effects on wealth, explores policies to increase higher education access, improve education quality, and enhance financial literacy. Simulations show that while increasing access to higher education and promoting long-term planning reduce wealth inequality, improving education quality may increase inequality by enhancing returns to capital for college graduates.

Future research should investigate the impact of early childhood and primary education on later-life wealth and inequality, expanding beyond higher education. Additionally, examining the broader economic impacts of educational policies, such as overall economic growth and social mobility, is essential. While better education quality might increase wealth inequality by boosting returns for college graduates, it could also drive significant economic growth, highlighting the need to balance inequality reduction with economic advancement.

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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 A.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.
Compulsory Schooling Laws (CSL)	Compulsory schooling laws are the minimum years of education that an individual had as law in a respective state when 14 years of age.
Parental Job Loss (PJL)	Parental job loss is calculated by summing the hours of unemployment for each parent during the years when the child is between 15 and 18 years of age.

Table A2: Classification of the Educational Variable

Level	Year	Pct.
High school D.O.	0-11	15.1
High school	12	32.7
College	13-14	20.2
College	15-16	20.4
Post-graduate	17	11.6

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 Descriptive Analysis

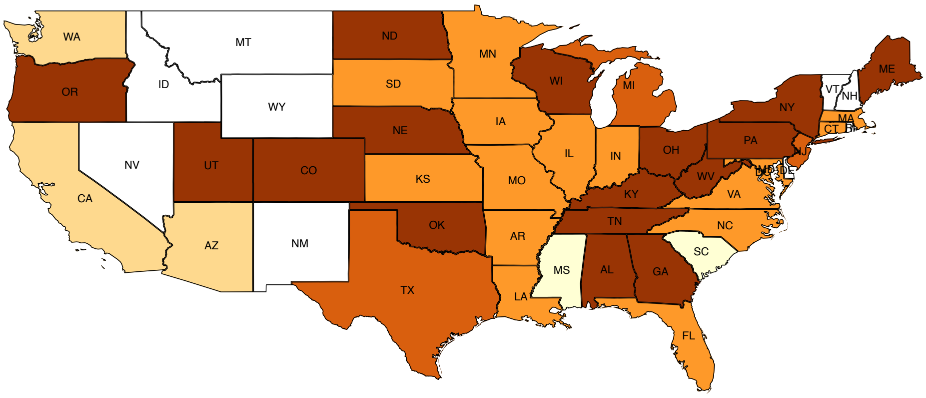
Table A5: Mean Wealth by Education and Cohort

	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)

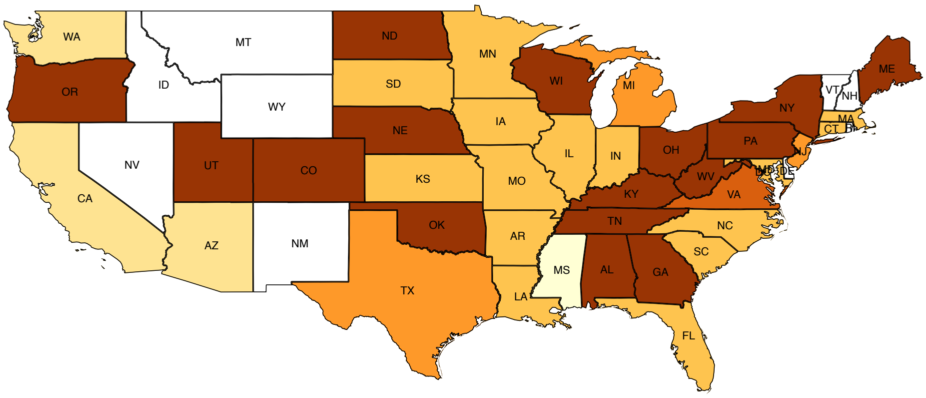
Note: Source: Panel Study of Income Dynamics, 1999 to 2019. The median value in parentheses. The data is used with sampling weights.

A.3 U.S. Compulsory Schooling Laws

(a) 1965



(b) 1972



(c) 1978

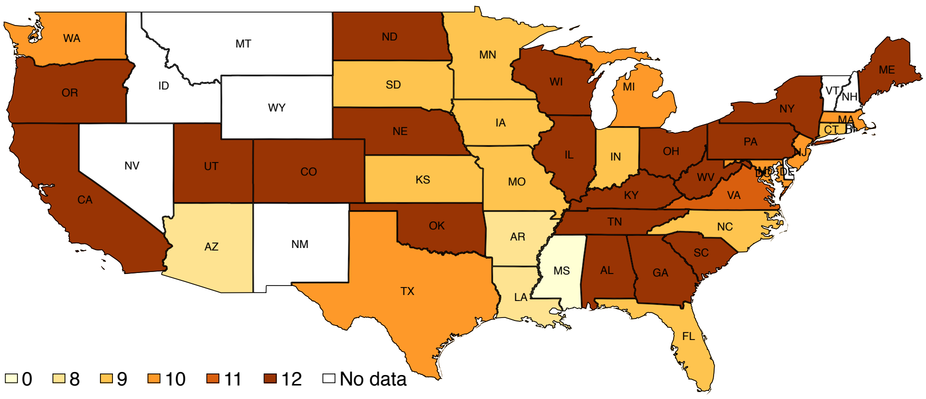


Figure A1: Evolution of Compulsory Education Laws
Note: The compulsory years of education in the U.S. by state in 1965, 1972 and 1978.

A.4 Additional Results: Parental Wealth versus Income

Table A6: Parental Income and Wealth

Dependent Variable: Wealth	(A)	(B)
Highschool	1211.87*	1220.52*
	(616.73)	(611.31)
Some College	2350.31***	2429.58***
	(678.62)	(677.35)
College	2492.54**	2439.55**
	(781.36)	(783.29)
Postgraduate	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.5 Additional Empirical Results: Quantile Regression

Table A7: 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.6 Additional Empirical Results: Wealth including Home Eq.

Table A8: 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
Highschool	2062.37**	2881.70***	5662.70***	7053.99***	5483.54***
	(741.49)	(722.36)	(752.65)	(983.32)	(1512.25)
Some College	3320.32***	3971.31***	7381.58***	9529.15***	11283.67***
	(812.40)	(784.44)	(877.38)	(1071.25)	(1654.55)
College	2986.74**	7834.79***	11988.29***	11631.05***	11246.22***
	(910.27)	(852.16)	(945.82)	(1157.99)	(1849.08)
Postgraduate	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 A9: Within Variation Regression: Effects of Education on Wealth Eq.

	Avg	Cohort			
		30	**40**	**50**	**60**
D.Highschool	1668.24**	1046.06	−45.21	3542.62*	31297.24*
	(643.20)	(747.92)	(884.70)	(1403.17)	(13512.95)
D.Some College	2915.30***	1980.17*	751.57	4278.54*	20247.66
	(724.82)	(795.63)	(1105.85)	(1710.04)	(18812.04)
D.College	6731.26***	2599.18*	7470.59***	13269.61***	23501.78
	(1096.14)	(1232.52)	(1602.01)	(2812.31)	(22701.28)
D.Postgraduate	3829.04**	−787.96	7354.71***	6195.54	65973.99*
	(1316.20)	(1462.66)	(1972.27)	(3815.55)	(22870.05)
Observations	7887	3769	3033	1259	30
Adjusted R^2	0.02	0.06	0.05	0.07	0.00

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. Control variables include the difference between siblings in age, socioeconomic conditions, parental presence when young, and school performance. The constant term is included but not reported for brevity.

Table A10: I.V. Regression: Compulsory Schooling Laws 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 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	-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 A12: 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**
Highschool	2131.75***	2775.01***	6230.38***	4936.36***	4216.07***	7641.05***
	(368.36)	(642.88)	(702.31)	(793.98)	(802.08)	(968.96)
Some College	3254.44***	6195.79***	8762.64***	8291.40***	6474.96***	7978.07***
	(581.49)	(692.72)	(752.52)	(841.49)	(918.88)	(1663.60)
College	3235.12***	10101.19***	13166.38***	11218.82***	9414.03***	14035.97***
	(972.01)	(837.33)	(758.48)	(817.41)	(915.63)	(1605.56)
Postgraduate	−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**
Highschool	4819.51***	6803.47***	8569.74***	3711.13	6512.26***	−2586.65*
	(585.39)	(989.76)	(1362.75)	(3041.18)	(1034.40)	(1195.71)
Some College	6439.31***	10206.93***	9673.67***	8024.00*	13234.05***	3989.41***
	(736.61)	(1099.56)	(1313.99)	(3131.52)	(1428.89)	(746.63)
College	13125.38***	15443.11***	13622.44***	8975.96**	14945.21***	5441.49
	(1124.07)	(1029.90)	(1373.37)	(3247.68)	(1548.77)	(3463.22)
Postgraduate	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 A13: Wealth's Regression Mechanisms: Productivity Effect

	Dependent Variable: Wealth Eq.		
	(A)	**(B)**	**(C)**
Highschool	1903.34**	2053.13**	2095.13**
	(728.65)	(739.84)	(737.75)
Some College	3062.58***	3310.81***	3362.41***
	(803.05)	(810.54)	(807.71)
College	2374.06**	2934.63**	3023.21***
	(902.91)	(908.89)	(905.08)
Postgraduate	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 A14: Wealth's Regression Mechanisms: Financial Literacy

	Dependent Variable: Wealth Eq.			
	(A)	**(B)**	**(C)**	**(D)**
Highschool	2199.43**	2455.67***	1953.27**	2073.33**
	(708.53)	(680.28)	(720.53)	(738.45)
Some College	3205.31***	3446.90***	3162.64***	3332.60***
	(767.65)	(745.58)	(794.80)	(809.53)
College	2567.11**	2694.43**	2890.18**	3015.72***
	(868.36)	(837.09)	(888.73)	(906.99)
Postgraduate	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 A15: Wealth's Regression Mechanisms: Financial Behavior

	(A)	**(B)**
Highschool	2290.04***	1694.38*
	(639.95)	(741.87)
Some College	3075.20***	2769.95***
	(711.41)	(823.71)
College	2451.19**	2337.67*
	(787.15)	(921.31)
Postgraduate	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 (16). 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:

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

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

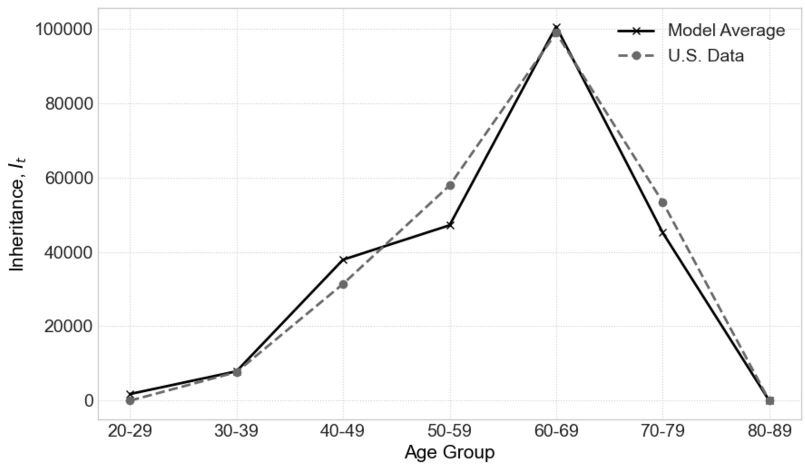


Figure B1: Average Inheritance by Age
Note: The figure compares the model's average inheritance received by individuals with the real data. Source: Panel Study of Income Dynamics, 2019.

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.