Can Educational Policies Reduce Wealth Inequality?

Fernando Loaiza

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Abstract

This study examines the relationship between education and wealth accumulation using U.S. panel data spanning two generations. Employing multiple identification strategies, the analysis finds that educational attainment significantly increases lifetime wealth, with particularly strong effects for college and postgraduate education. Building on these empirical results, the paper develops and calibrates a life-cycle heterogeneous-agent model to evaluate how educational policies shape the distribution of wealth. The model simulates two policies: expanding access to higher education and improving education quality. These simulations show that increasing college attainment reduces wealth inequality by broadening access to high-return educational investments. In contrast, improvements in education quality raise productivity and returns among college graduates but may increase wealth inequality when gains accrue disproportionately to already advantaged individuals. The results highlight education's dual role in promoting economic mobility and shaping wealth inequality.

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

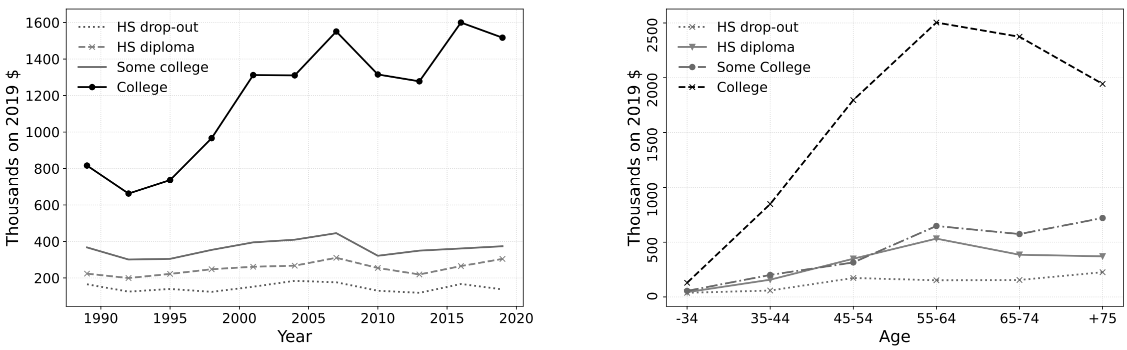
JEL Codes: D15 · D31 · E21 · I24 · I26

*Contact: Max Planck Institute for Innovation and Competition, Herzog-Max-Str. 4, 80333, Munich, Germany. Email: fernando.loaiza@ip.mpg.de.

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% have 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.

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

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 identification challenges. Scandinavian studies have explored aspects like financial market participation and home ownership, but direct evidence of education's impact on wealth is 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 link between education and wealth using multiple empirical strategies, addressing various sources of endogeneity. The analysis reveals a 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

[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).

on wealth, remain underexplored. Integrating insights from the wealth inequality literature into this life-cycle framework provides a structured way to examine how education influences wealth accumulation over time.

After introducing and validating the model's ability to replicate key features of the wealth distribution, the analysis considers educational policies operating along two distinct margins. The first is the extensive margin, which captures policies that expand access to higher education and increase the share of college-educated individuals. By broadening access to high-return educational investments, such policies reduce wealth inequality and promote upward mobility among individuals from less wealthy backgrounds. The second is the intensive margin, which reflects improvements in education quality among those who attain higher education. Higher-quality education raises productivity and enhances the efficiency with which educated individuals translate savings into wealth, a mechanism captured in the model through higher returns to capital for college graduates. While these quality improvements can increase aggregate wealth and economic efficiency, they may also lead to higher wealth inequality if the associated gains accrue disproportionately to already advantaged households.

The remainder of the paper is organized as follows. The econometric analysis is presented in Section 2 to explore the relationship between education and wealth. Section 3 simulates educational policies' effects on wealth inequality using a quantitative life cycle model. Finally, Section 5 presents concluding remarks and further research ideas.

2 Empirical Analysis

2.1 Empirical Model

This section implements different econometric models to establish a clear relationship between education and wealth. Without a perfect natural experiment, it is essential to develop empirical approaches that control for unobserved heterogeneity across individuals. To this end, I employ a random effects (RE) panel model, which allows for unobserved individual-specific factors that are constant over time while retaining time-invariant variables of interest. This approach mitigates potential bias arising from omitted variables that differ across individuals but remain stable over time, thereby improving the precision of the estimated effect of education on wealth.

The baseline specification is given by:

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

where the indices i and t represent individuals and time, respectively. The dependent variable Y_{it} is total wealth, which varies over time. The key explanatory variables include both time-invariant and time-varying covariates. The time-invariant variables are Education$_i$, measured as the individual's completed years of schooling, and X_i, a set of background characteristics recorded at age 16, including parental wealth, parental education, and proxies for individual ability; these variables do not change over the life cycle and therefore remain constant across all survey waves. Additional time-invariant factors are race and sex. In contrast, the time-varying controls D_{it} include demographic characteristics that evolve over time, such as age. The model also includes year fixed effects γ_t, which capture aggregate shocks common to all individuals in a given wave. Finally, c_i represents an unobserved, time-invariant individual-specific component, and υ_{it} is the idiosyncratic error term. The random effects specification is appropriate in this context because core explanatory variables, particularly education and family-background measures, are time-invariant and would otherwise be absorbed by a fixed effects estimator.

2.1.1 Within Siblings Variation

To address 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:

$$\Delta \mathrm{Y}_{jt} = \alpha_0 + \alpha_1 \,\Delta\mathrm{Education}_{jt} + \alpha_2 \,\Delta \mathrm{X}_{jt} + \gamma_t + \upsilon_{jt}, \tag{2}$$

Here, ΔY_{jt} represents the wealth difference between siblings j at time t, with $\Delta Education_{jt}$ and ΔX_{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.

2.1.2 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:

$$\text{Education}_{it} = \beta_1\,\text{CSL}_i + \beta_2\,\text{Par.Wealth}_i + \delta_i + \gamma_c + \epsilon_{it}, \tag{3}$$

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 $Education_{it}$, which is included in the second stage to estimate the effect of endogenous schooling on wealth using compulsory schooling as an instrumental variable. I specify the second stage as follows:

$$\text{Y}_{it} = \alpha_0 + \alpha_1\,\widehat{\text{Education}}_{it} + \alpha_2\,\text{Par.Wealth}_i + \delta_t + \gamma_c + \upsilon_{it}, \tag{4}$$

Here, Y_{it} indicates an individual's net worth. It also includes year fixed effects δ_t and cohort fixed effects γ_c. 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. 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.

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:

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

I specify the second stage as follows:

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

The use of parental job loss as a complementary instrument offers a novel contribution to the literature on the effects of education and wealth. While compulsory schooling laws primarily influence high school completion, previous studies have shown that these reforms also have spillover effects on postsecondary attainment by shifting educational expectations, delaying labor-market entry, and leading to spillover effects on college enrollment and not just high school completion (Lochner (2010); Lavecchia et al. (2016)). This mechanism broadens their relevance for studying long-term wealth accumulation, as individuals exposed to stricter schooling laws are more likely to pursue further education. Conversely, parental job loss operates at the upper educational margin, directly affecting the transition from high school to college by tightening family liquidity constraints precisely when higher-education decisions are made (Stevens and Schaller (2011); Charles et al. (2018)). Hence, the two instruments capture complementary dimensions of exogenous variation, policy-induced and financially driven, jointly addressing endogeneity while identifying both the extensive and intensive margins of education's impact on wealth.

2.2 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. All analyses use the Core–Immigrant family weights provided in each PSID wave.

Both samples exclusively consider biological relationships to minimize unobserved heterogeneity. Household wealth is total net worth excluding home equity. Because wealth data often include zero and negative values and exhibit substantial right-skewness, I apply a generalized inverse hyperbolic sine (IHS) transformation. This transformation accommodates non-positive values while mitigating the influence of extreme outliers, providing a log-like interpretation without requiring strict positivity. A scaling parameter is used following best practice in the literature to enhance numerical stability, given the wide range of monetary values observed.[4]

Education is modeled categorically, grouped into five levels based on years of schooling completed, ranging from high school dropouts (High school D.O.) to postgraduate studies.[5] Additional controls include parental wealth and education, captured from the earliest available PSID waves to approximate conditions when the Focus Unit was young, leveraging the survey's intergenerational design to account for family background. A family-level IQ measure serves as a proxy for ability, and I further control for age, sex, race, family structure by age 16, and inheritance receipt.[6]

[4]Details and formal definitions of the IHS transformation are provided in Appendix A.2.

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

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

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.

2.3 Empirical Results

The empirical findings, as detailed in Table 1, shed light on the relationship between education and wealth across the life cycle, using a random effects regression. This analysis explores the effects based on categorized educational levels. Education emerges as a significant predictor of wealth, highlighting its important role in wealth accumulation. 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 is significantly amplified 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 levels correlate with increased wealth accumulation throughout the life cycle.

Table 1: RE Regression: Effects of Education on Wealth

	Avg	Cohort 30	Cohort 40	Cohort 50	Cohort 60
High school	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. Socio-demographic variables include age, sex, and race. The constant term is included but not reported for brevity.

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

	Avg	Cohort 30	Cohort 40	Cohort 50	Cohort 60
D.High school	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.

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 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 effects of education on wealth are most pronounced for tertiary education.

The final identification strategy, instrumental variables, is introduced to complement the analysis. 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. An initial regression is provided in Table A5 in the Appendix. The IV regression outcomes confirm a robust 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 have significant effects, nor for the average, nor for the different life cycle stages. The only statistically significant effects were found for college and postgraduate education. 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 3: I.V. Regression: Compulsory Schooling Laws on Tertiary Education

	Avg	**Cohort**			
		30	**40**	**50**	**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 → College	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 3, demonstrate a significant positive effect of CSL on the likelihood of obtaining a 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 4. 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 4: I.V. Regression: Parental Job Loss

	Avg	**Cohort**		
		30	**40**	**50 - 60**
Tertiary	19150.10	23802.79*	57676.22*	62512.97
	(19246.83)	(11040.08)	(22440.22)	(53107.25)
First Stage				
PJL → College	-0.069^{**}	-0.085^{***}	-0.062^{**}	0.045
	(0.021)	(0.024)	(0.022)	(0.035)
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.

2.4 Mechanisms

To understand the effects of education on wealth, it is important to consider the mechanisms that are driving the main results. While the literature often highlights income effects, descriptive patterns suggest that other factors are also associated with education and wealth. In this subsection, I discuss three sets of potential channels, i.e., increased productivity, financial literacy, and financial behavior, not as associated mechanisms identified in the data. McKay (2013) suggests that individuals with higher education might be better equipped to learn, search, and assess risk and the trade-offs of choosing good investments. However, it is argued here that this is done via financial literacy and financial behavior. These regressions do not identify causal mechanisms but describe correlates consistent with model channels.

The first mechanism presented in table 5 is productivity, and it is described as the individual's ability to generate income through labor or capital. The way this mechanism works would be that education enhances skills and knowledge, which can increase an individual's productivity in the workforce Gintis (1971). This increased productivity is often rewarded with higher labor income Card (1999), bonuses, and opportunities for investment income, such as rent.

The variables included in this mechanism are income obtained from labor, work bonuses, and rents. In this case, labor income is directly tied to productivity at work; however, this variable can also be considered as measuring the known income effect. This means

Table 5: Wealth's Regression Mechanisms: Productivity Effect

Dependent Variable: Wealth			
	(A)	**(B)**	**(C)**
High school	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.

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 could 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.

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 et al. (2023), enabling individuals to make more informed decisions about investments and financial products, which can lead to greater wealth accumulation.

Table 6: Wealth's Regression Mechanisms: Financial Literacy

	Dependent Variable: Wealth			
	(A)	**(B)**	**(C)**	**(D)**
High school	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 6 explores the three different types of assets that might explain the transmission of education on wealth. The first one is through directly held stocks. Individuals with higher educational attainment tend to increase their probability of owning stocks Campbell (2006), and higher stock market participation Bertaut (1998). The results of this mechanism are reported in column A with positive and significant results.

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

The third variable of table 6 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

Table 7: Wealth's Regression Mechanisms: Financial Behavior

Dependent Variable: Wealth		
	(A)	**(B)**
High school	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.

collection for investment purposes. In a similar manner to 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, 2025), 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 7 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 7 report negative and statistically significant effects of money problems on wealth.

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.

3.1 Environment

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.

$$E_0 \left[\sum_{t=0}^{T} \left(\prod_{i=0}^{t} \beta_i \right) s_t \, u(c_t) + (1 - s_t) \, \theta(b_t) \right] \tag{7}$$

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.

$$u(c) = \frac{c^{1-\gamma}}{1-\gamma} \tag{8}$$

The utility derived from bequests follows De Nardi (2004)

$$\theta(b) = \theta_1 \left(1 + \frac{b}{\theta_2}\right)^{1-\gamma} \tag{9}$$

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:

$$y_t = h_t \, \xi_t \tag{10}$$

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.

$$\xi_{t+1} = \begin{cases} \mu & \text{pr } \pi \\ \phi_{t+1}/(1-\pi) & \text{pr } (1-\pi) \end{cases} \tag{11}$$

During all the working stages, labor income is obtained by the equation 10. The transitory shock ξ_t, presented in equation 11, 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 $\phi \in [\underline{\phi}, \bar{\phi}]$.

$$h_t = G \; \psi_t \; h_{t-1}, \tag{12}$$

Equation 12 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:

$$\log R_t = \bar{u}_r + \eta_t^r \; \bar{w}_r \tag{13}$$

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

[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 et al. (2016) and Fagereng, Guiso, Malacrino, and Pistaferri (2020).

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.

$$\log \beta_t = \bar{u}_\beta + \eta_t^\beta \; \bar{w}_\beta \tag{14}$$

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:

$$F_{\beta R} := \lim_{n \to T} \left(E \prod_{t=1}^{n} \beta_t \; R_t \right)^{1/n} < 1 \tag{15}$$

The value $F_{\beta R}$ in equation (15) can be thought of as the long run (geometric) average gross rate of return discounted to present value to ensure existence and stability.

3.2 Household Recursive Problem

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

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

$$v(\bar{z}_t) = \max_{c_t} \left\{ u(c_t) \ + \ \beta_t s_t E_t \left[v_{t+1}(\bar{z}_{t+1}) \right] + (1 - s_t)\theta(a_t) \right\} \tag{16}$$

s.t.

$$a_t = m_t - c_t \tag{17a}$$

$$y_{t+1} = (\psi_{t+1} \; G \; h_t) \; \xi_{t+1} \tag{17b}$$

$$m_{t+1} = R_{t+1} \; a_t + \; y_{t+1} \tag{17c}$$

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

$$v(\bar{z}_t) = \max_{c_t} \left\{ u(c_t) \ + \ \beta_t s_t E_t \left[v_{t+1}(\bar{z}_{t+1}) \right] \ + \ (1 - s_t)\theta(a_t) \right\} \tag{18}$$

s.t.

$$a_t = m_t - c_t \tag{19a}$$

$$m_{t+1} = R_{t+1} \; a_t + \; p_{t+1} \tag{19b}$$

3.3 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 8.

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.

Consistent with the empirical evidence presented in Section 2, education is introduced through an ex-ante classification of individuals into college and non-college types at the beginning of the life cycle. College attainment probabilities are calibrated using logistic regression estimates reported in Appendix B.2, yielding population shares of 34% college-educated and 66% non-college individuals.

Education affects wealth accumulation through two channels. First, college-educated

Table 8: 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

individuals face higher expected labor income over the life cycle. This is implemented through an education-specific permanent income premium calibrated to match empirically observed earnings differentials between college and non-college workers. The calibration allows for additional dispersion in permanent income among college-educated individuals, reflecting heterogeneity in career paths and returns to skills documented in the literature (e.g., Card (1999), Heckman et al. (2006)).

Second, education directly affects wealth accumulation through higher average returns to capital. While returns remain heterogeneous across individuals, the mean return for college-educated households is higher than for non-college households, increasing from 1.04 to approximately 1.12 on average. This return differential captures education-related differences in financial sophistication, asset market participation, and investment efficiency documented in the empirical literature (e.g., Campbell (2006), Black et al. (2018), Ma et al. (2020)).

Calibration targets are derived from 2019 U.S. data from the Survey of Consumer Finances and include the wealth Gini coefficient and wealth shares across percentiles. Table 9 reports the model's ability to replicate these moments. The calibrated model reproduces substantial wealth concentration at the top of the distribution and generates a level of wealth inequality comparable to that observed in the data, providing a credible quantitative baseline for the policy experiments that follow. As an additional validation exercise, Table B2, in the Appendix, compares wealth inequality generated by the calibrated model with U.S. data from the Panel Study of Income Dynamics (PSID), by age group and education level. The model closely matches wealth inequality, especially in mid and late adulthood and among college-educated individuals, which are the groups most directly affected by the policy experiments analyzed in the paper.

Table 9: Calibration Results: Wealth Distribution

	Avg.	**Percentage Wealth in the Top**						**Bottom**
	Gini	1%	5%	10%	20%	40%	60%	40%
U.S. Data 2019	0.82	37.4	65.4	76.7	87.5	96.4	99.7	0.2
Model + Direct & Indirect Effects	0.84	38.1	66.7	78.7	88.5	95.6	98.5	1.5

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

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 improving education quality on wealth accumulation and inequality by increasing the economic returns to education for college graduates. Higher education quality equips individuals with stronger cognitive and non-cognitive skills, improved financial knowledge, and greater capacity to evaluate and manage investment opportunities. As a result, educated individuals are able to allocate assets more efficiently and achieve higher returns on their savings over the life cycle.

In practice, education quality improvements may reflect better teacher quality, modernized curricula, skill-based programs, improved digital access, or the integration of financial education and planning components into college training. These interventions enhance individuals' ability to make informed financial decisions and to translate savings into wealth more effectively, without necessarily altering their preferences or saving motives.

The simulation results in Table 10 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.

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

Table 10: Simulation Results: Quality of Education

	Avg. Gini	Percentage Wealth in the Top						Bottom
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.84	38.1	66.7	78.7	88.5	95.6	98.5	1.5
S1: ↑ Avg. Rates of Return	0.88	43.6	73.4	84.3	92.1	97.0	99.0	1.0

Source: Author's calculations.

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

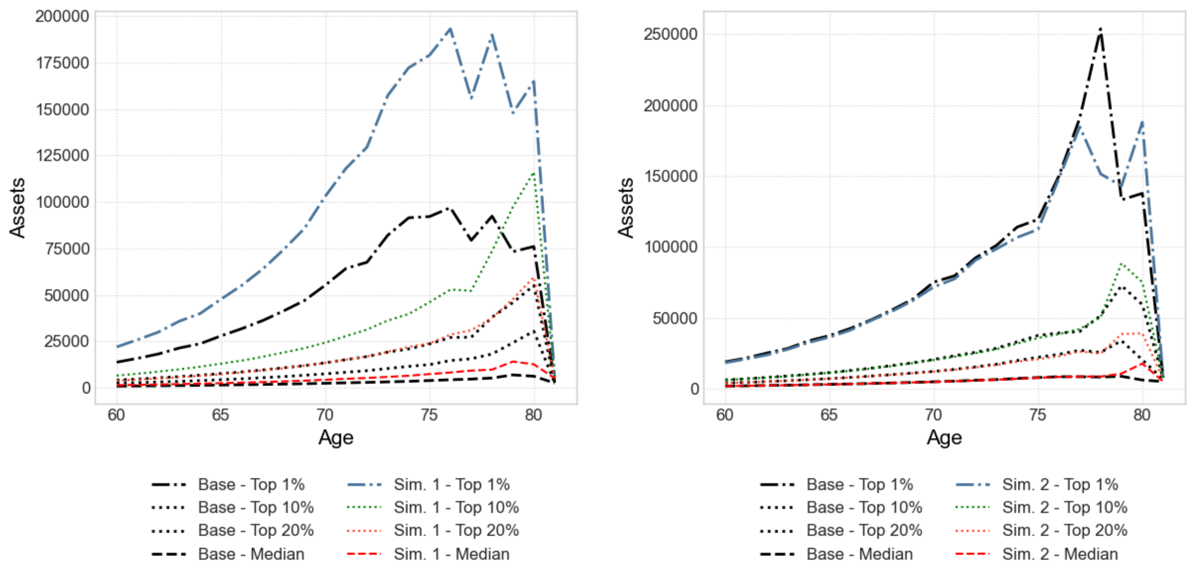
This policy simulation examines the impact of increasing the proportion of the population with a college degree on wealth distribution and inequality. It reflects a hypothetical reduction in barriers to higher education access and affordability, aiming to create a more educated workforce, promote social 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 11: Simulation Results: Quantity of Education

	Avg. Gini	Percentage Wealth in the Top						Bottom
		1%	5%	10%	20%	40%	60%	40%
Model + Direct & Indirect Effects	0.84	38.1	66.7	78.7	88.5	95.6	98.5	1.5
S2: ↑ College Share	0.85	37.7	67.2	79.8	89.8	96.5	98.8	1.2

Source: Author's calculations.

Table 11 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] 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) Simulation 1

(b) Simulation 2

Figure 2: Simulations Direct Effects
Note: The life cycle profiles of assets are presented in figure 2a for simulation 1 and in 2b for simulation 2. Source: Author's calculations.

Figure 2 compares asset life-cycle profiles under Simulation 1 and Simulation 2 relative to the baseline. In Simulation 1, asset accumulation diverges sharply at the top of the distribution: the top 1% exhibits substantially higher assets than in the baseline, while gains for the top 10%, top 20%, and the median are more modest. This pattern suggests that improvements in education quality disproportionately raise wealth at the top by increasing returns to capital. In contrast, Simulation 2 shows more uniform deviations from the baseline across the distribution. Asset accumulation rises for the top 10%, top 20%, and the median, while the top 1% experiences relatively smaller gains. This flatter divergence is consistent with an extensive-margin effect, whereby expanding access to higher education broadens wealth accumulation and limits increases in concentration at the top.

[10]Non-linear effects are explored in the Appendix B.6.

An additional simulation is reported in section B.7 in the Appendix that combines the improvements in quality of education and the increase in the share of college graduates. These results highlight the complexity of interacting policies. While increasing the share of college graduates alone tends to reduce wealth inequality by increasing the share of the middle class, the simultaneous enhancement of education quality through higher returns to capital disproportionately benefits those already at the top of the wealth distribution.

4 Discussion

The findings of this study carry important implications for education and wealth policy. They suggest that educational interventions can serve as powerful tools to mitigate inequality, but their effectiveness depends on how well they address underlying disparities in opportunity and behavior. Policies that broaden access to higher education, through targeted scholarships, income-contingent loans, or public university expansion, can help offset the constraints imposed by parental wealth and improve long-term wealth accumulation among lower-income groups. Consistent with the empirical evidence, the direct effects of education on wealth operate primarily at the tertiary level, while earlier educational interventions are likely to influence wealth accumulation indirectly by shaping skills, preferences, and access to higher education rather than wealth itself. However, expanding access alone may not suffice if differences in early human capital formation persist. Investments in early childhood and primary education are therefore essential to equalize cognitive and non-cognitive skills before wealth gaps become entrenched.

Beyond access, the quality of education plays a central role in shaping wealth outcomes. Improvements in education quality, through better instruction, curricula, and skill formation, enhance individuals' productivity and their ability to make effective economic and financial decisions. Embedded within such quality improvements are elements such as financial knowledge, long-term planning capacity, and risk management skills, which strengthen the mechanisms through which education translates into wealth by improving saving and investment behavior across the distribution. At the same time, reforms that raise education quality should be designed with attention to their potential regressive effects: improving quality in already advantaged institutions may increase inequality by amplifying returns for high-income families. A comprehensive policy approach that combines early investment, broad access, and high-quality education is therefore essential to ensure that education serves not only as a driver of productivity but also as a foundation for inclusive wealth accumulation.

Several limitations should be noted. First, parental wealth and education are used as proxies for intergenerational advantage and may not fully capture informal transfers, social networks, or cultural capital that influence both educational attainment and wealth accumulation. This makes the use of multiple identification strategies particularly valuable, as they help mitigate potential bias arising from unobserved aspects of family background. Second, reported wealth may underrepresent top or informal assets, leading to a slight compression of observed inequality but without altering the direction of the estimated causal effects. Finally, the quantitative model operates in partial equilibrium and therefore does not account for potential general equilibrium feedbacks, such as wage or price adjustments resulting from large-scale education reforms. These limitations, however, do not affect the internal validity of the results but rather delineate the scope of their interpretation.

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 improvements in education quality may increase wealth inequality by boosting returns for college graduates, they may also generate substantial gains in aggregate productivity and economic growth, highlighting the need to balance inequality reduction with economic advancement. Further research could also benefit from the use of administrative data, which would allow for more precise measurement of wealth, intergenerational links, and educational trajectories over the life cycle, thereby improving the accuracy and policy relevance of the estimates.

5 Conclusions

Wealth inequality can constrain access to key investments such as education, shaping individuals' economic trajectories over the life cycle. This paper examined whether education remains a pathway to wealth accumulation in the presence of such disparities and, critically, whether educational policies can be effective tools for reducing wealth inequality.

Using multiple identification strategies, the empirical analysis provides robust evidence that education has a causal effect on wealth accumulation, with effects concentrated at the tertiary level. College and postgraduate attainment generate large and persistent wealth gains, whereas lower levels of education show limited or statistically insignificant effects once endogeneity is addressed. Moreover, these effects emerge primarily in mid- and late adulthood, consistent with cumulative processes of saving, investment, and capital returns over the life cycle. These effects remain after controlling for parental wealth, indicating that tertiary education can operate as a channel of intergenerational mobility. Descriptive evidence on mechanisms suggests that productivity, financial behavior, and financial literacy are important pathways through which education translates into wealth, especially among highly educated individuals.

Building on these empirical findings, the life-cycle model with heterogeneous agents clarifies how different educational policies affect the wealth distribution through distinct margins. Policies that expand access to higher education, the extensive margin, reduce wealth inequality by broadening participation in high-return educational investments and shifting wealth accumulation toward the middle of the distribution. In contrast, policies that improve education quality solely by increasing returns to capital among college graduates, the intensive margin, raise aggregate productivity but may increase wealth inequality when the associated gains accrue disproportionately to already advantaged households.

The central implication is that educational policies can reduce wealth inequality, but not all educational policies do so. Distributional outcomes depend critically on policy design and on whether reforms target access, returns, or both. The empirical evidence points to direct wealth effects primarily at the tertiary level, while earlier educational interventions are likely to influence wealth accumulation indirectly, by shaping skills, behaviors, and access to higher education rather than wealth itself. Quality-enhancing reforms are not inherently inequality-reducing in isolation; however, when combined with policies that expand educational access or strengthen financial capability more broadly, they can contribute to more inclusive wealth accumulation.

These findings highlight education's dual role in wealth distribution. Education can promote upward mobility and inclusion when opportunities are widely shared, yet it can reinforce inequality when improvements primarily amplify returns for the highly educated. Recognizing this distinction is essential for designing education systems and policy packages that foster productivity growth while also supporting a more equitable distribution of wealth.

Data Availability

The data used in this study come from the Panel Study of Income Dynamics (PSID), which is publicly available upon registration from the PSID website. All data sources are described in detail in the paper and its appendix. Replication code will be made available upon publication.

Declaration of Competing Interests

The author declares that there are no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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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.
Education	Highest year of education completed. Education is classified into 5 categories (detailed in subsection A.3).
Par. Wealth	Parental net worth reported when the child was young.
Par.Education W.	Highest year of education completed by the mother.
Par.Education H.	Highest year of education completed by the father.
Par. Income	Total parental income reported when the child was young.
Ability	IQ score tests as a proxy for ability with results that range from zero to thirteen.
Parents	Reports as “1” if the individual lived with both parents until 16 years old and “0” otherwise.
Inheritance	Value of inheritance received by the individual.
Age	Current age of each individual in a particular year.
Race	*Race* is reported as ”1” if White and ”0” for others.
Sex	*Sex* is reported as ”1” for males and ”0” for females.
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.

A.2 Inverse Hyperbolic Sine Transformation of Wealth Variable

Household net worth in the PSID exhibits substantial right-skewness and includes zero and negative values. To accommodate these features while retaining all observations, the analysis applies an inverse hyperbolic sine (IHS) transformation to net worth. The IHS transformation preserves non-positive values and provides a log-like transformation for large values without requiring strict positivity. Formally, the inverse hyperbolic sine transformation is defined as:

$$\operatorname{asinh}(x) = \ln!\left(x + \sqrt{x^2+1}\right). \tag{A1}$$

A generalized, scaled version of the transformation is given by:

$$\mathrm{IHS}_\lambda(x) = \frac{1}{\lambda}\operatorname{asinh}(\lambda x) = \frac{1}{\lambda}\ln!\left(\lambda x + \sqrt{(\lambda x)^2+1}\right), \tag{A2}$$

where $\lambda > 0$ is a scaling parameter. In the baseline analysis, $\lambda = 0.0001$ is used to improve numerical stability given the wide range of net worth values. As a robustness check, specifications using $\lambda = 1$ yield qualitatively similar results.

A.3 Descriptive Analysis

Table A4: 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.4 Additional Results: Instrumental Variables

Table A5: I.V. Regression: Compulsory Schooling Laws

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

Note: Source: Panel Study of Income Dynamics. Standard errors in parentheses. Significance levels are denoted as follows: $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The instrument is the years of compulsory schooling by state. Year and cohorts effects are included. Parental wealth is included but not reported for brevity.

A.5 Additional Results: Parental Wealth versus Income

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 it 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.

Table A6: Parental Income and Wealth

Dependent Variable: Wealth		
	(A)	**(B)**
High school	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.6 Quantile Regression

This analysis is introduced after the main 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

$$Q_q(W_{it}) = \alpha_q + \beta_{0q}\, Educ_i + \beta_{1q}\, X_i + \beta_{2q}\, SD_{it} + \gamma_t + \upsilon_{itq} \tag{A3}$$

where the equation A3 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 RE 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 results obtained in table A7 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 than those on top of the wealth distribution. These estimates obtained from the quantile regression can be appreciated more clearly in the figure A1, 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.

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**
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**
High school	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.

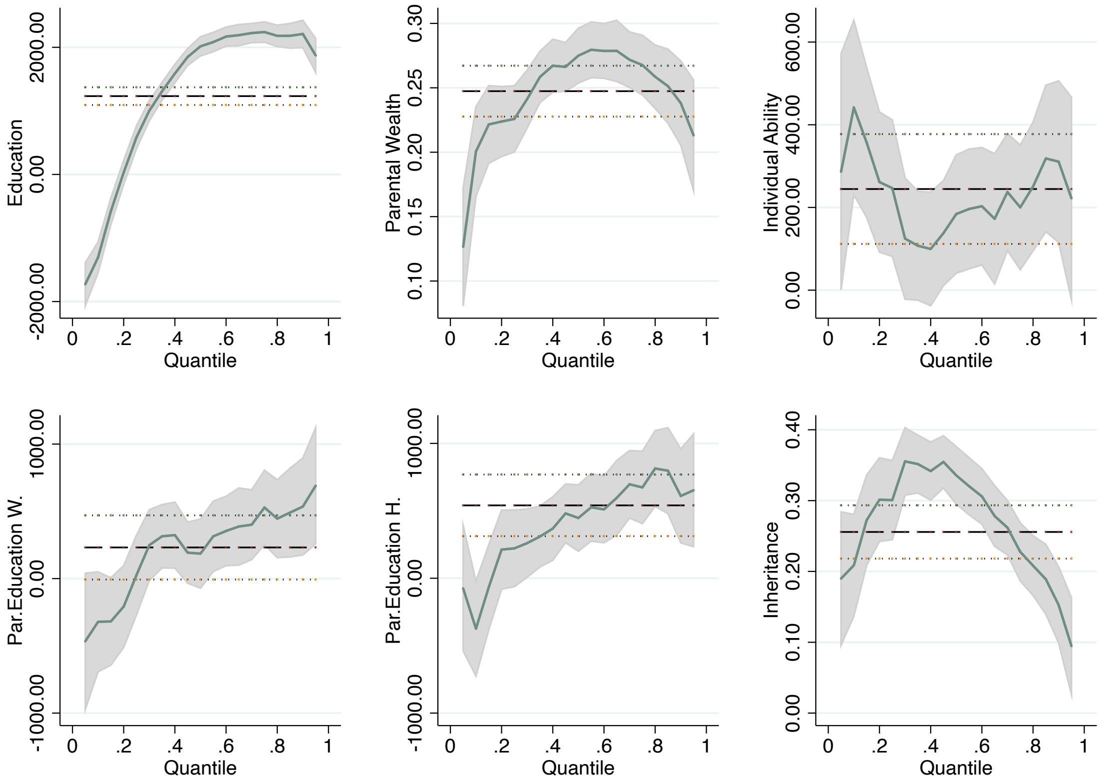

Figure A1: Education per Quantile of Wealth

Note: The graph shows the results of the quantile regression for some variables on household wealth, excluding 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.

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 (15). The process of discretization of β_{t+1}, R_{t+1}, ψ_{t+1} and ξ_{t+1} is done by a standard Gauss-Hermite quadrature transforming the shocks into β^i, R^i, ψ^i and ξ^i respectively, with 8 quadrature points and weights π^i_β, π^i_R, π^i_ψ and π^i_ξ also associated. This method simplifies the root-finding process done by the time iteration, reduces the computational time, and increases accuracy and efficiency even during its implementation on more complex models. The main idea of EGM is to start with the assets $\mathbf{a}_t$ accumulated at the end of each period, to analytically calculate the optimal policy rule, i.e., consumption $\mathbf{c}_t$, to provide as output market resources $\mathbf{m}_t$ at the beginning of the same period endogenously. The algorithm for solving the finite dynamic programming

household problem with uncertain labor and capital income follows:
Algorithm:

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

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

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

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

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

4. Then repeat for each period the same procedure.

B.2 Estimation Probability of Attending College

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

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

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

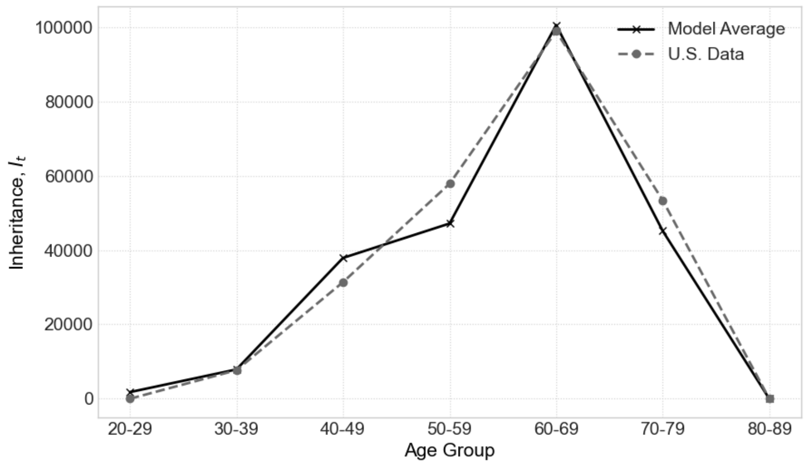

Figure B1: Average Inheritance by Age

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 Wealth Inequality by Age and Education

In the baseline calibration, college-educated individuals receive a permanent income premium equivalent to an average increase of approximately 40 percent relative to non-college individuals, consistent with estimates of lifetime earnings differentials in the U.S. To capture heterogeneity in returns to education, the model introduces additional dispersion in permanent income for college-educated individuals, implemented as an additive shock with standard deviation 0.15.

Table B2 reports wealth Gini coefficients generated by the model and observed in the PSID for 2019, by age group and education level. The model closely matches wealth inequality in mid and late adulthood, replicating a Gini coefficient of 0.79 for individuals aged 60–79, identical to the data. In early adulthood (20–39), the model generates lower wealth inequality than observed in the data, reflecting more limited dispersion in initial asset accumulation. Similarly, the model understates inequality among non-college individuals.

By contrast, wealth inequality among college-educated individuals is closely matched, with a Gini coefficient of 0.81 in both the model and the data. These validation results are particularly relevant given that the policy experiments focus on education quality and the expansion of tertiary education. While the model understates inequality at early stages

Table B2: Validation: Wealth Gini Coefficient

	U.S. Data	**Model**
Age		
Early Adulthood (20–39 y.o.)	0.82	0.68
Mid Adulthood (40-59 y.o.)	0.81	0.79
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.

of the life cycle and among non-college households, it captures the key distributional patterns for the population segments most affected by the policies analyzed in the paper.

B.5 Simulations: Additional Results

Table B3: Classification of Wealth Gini Coefficient

	Model	**S1**	**S2**
Age			
Early Adulthood (20–39 y.o.)	0.68	0.72	0.68
Mid Adulthood (40-59 y.o.)	0.79	0.82	0.78
Late Adulthood (60-79 y.o.)	0.79	0.81	0.83
Education			
College	0.81	0.83	0.81
Non-College	0.66	0.66	0.66

Note: Author's calculations.

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 two specific simulations: S1, which focuses on improving the quality of education, and S2, which increases the share of college graduates. These findings are consistent with the main results, where improving education quality (S1) exacerbates wealth inequality, while increasing access to education (S2) help mitigate it.

B.6 Simulation: Non-linearity

The simulation results indicate that increasing the share of college-educated individuals affects wealth inequality in a non-linear manner. As shown in Table B4, a modest increase in college attainment produces only limited changes in the wealth distribution, while a larger expansion leads to a more pronounced reduction in inequality. When the college share is doubled, the wealth Gini coefficient declines from 0.84 to 0.83, and the wealth share of the top 1% falls substantially from 38.1% to 33.1%. These results suggest that the inequality-reducing effects of higher education operate primarily through the extensive

Table B4: Simulation Results: Wealth Distribution

	Avg. Gini	Percentage Wealth in the Top 1%	5%	10%	20%	40%	60%	Bottom 40%
Model + Direct & Indirect Effects	0.84	38.1	66.7	78.7	88.5	95.6	98.5	1.5
S2: ↑ College Share	0.85	37.7	67.2	79.8	89.8	96.5	98.8	1.2
S2: ↑ College Share x2	0.83	33.1	62.2	75.9	87.7	95.8	98.6	1.4

Source: Author's calculations.

margin and become quantitatively meaningful only when access to college is sufficiently broad.

B.7 Simulation: Impact of Combined Education Policies

A final policy simulation combines the two previous interventions by simultaneously increasing the share of college-educated individuals and improving education quality through higher returns to capital for college graduates. This simulation captures the interaction between the extensive and intensive margins of higher education. The results, reported in Table B5, indicate that the combined policy leads to an increase in wealth inequality relative to the baseline with direct and indirect education effects. The average Gini coefficient rises from 0.87 to 0.88, reflecting a modest but non-negligible increase in overall wealth concentration. The wealth share of the top 1% increases from 37.4% to 42.2%, with similar upward shifts across the top 5%, 10%, and 20% of the distribution. At the same time, the wealth share of the bottom 40% declines slightly, from 1.0% to 0.8%.

Table B5: Simulation Results: Quantity-Quality Trade-off

	Avg. Gini	Percentage Wealth in the Top 1%	5%	10%	20%	40%	60%	Bottom 40%
Model + Direct & Indirect Effects	0.87	37.4	68.6	81.8	91.2	96.9	99.0	1.0
↑ Quantity ↑ Quality	0.88	42.2	72.7	84.6	93.0	97.7	99.2	0.8

Source: Author's calculations.