Skills, Education and Wealth Inequality

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Abstract

We study the link between individual skills, education, and wealth inequality through the channel of financial investment decisions. We present a simple model of individuals with heterogeneous ability in evaluating investment opportunities and a welfare-maximizing policymaker who subsidizes education using taxes on capital income. The key model insight reveals that education improves individuals' evaluation skills and prevents otherwise unskilled investors from making detrimental investment decisions, thus closing the gap between the top and bottom tails of wealth distribution. We provide consistent empirical evidence using individual-level data from the Dutch Household Survey (DHS). We document a positive and sizeable effect of education on both the level and returns to wealth due to the impact of education on stock market participation, after controlling for unobserved, individual ability. Our results suggest that policymakers can exploit the role of education to alleviate wealth inequality by promoting the stock market participation of unskilled individuals.

Keywords: Education, Inequality, Unobserved Ability, Financial Investments, Returns
JEL codes: I24, I26, I28, H30, H52

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1. Introduction

Inequality has dramatically increased over recent decades. Indeed, according to Oxfam's Annual Report 2022, the gap between the richest and the poorest is huge, with the top 1% of the world population having accumulated nearly 20 times the wealth of the bottom 50% since 1993. Policymakers and economists have attempted to explain how such a large concentration of wealth is controlled by such a small share of individuals. For instance, a growing strand of literature (Gabaix et al. (2016), Barth et al. (2020), Fagereng et al. (2020a)) argues that heterogeneity in individual ability, such as genetic talent and cognitive skills, explains highly heterogeneous returns to wealth and patterns of wealth accumulation across individuals. The intuition here is simple: skilled individuals are able to identify preferable investment opportunities that deliver higher returns, thus producing a highly positive correlation between the level and returns to wealth.

Our paper extends this line of research by studying the link between individual skills, education, and wealth inequality through the channel of financial investment decisions, both theoretically and empirically. To do this, we design a simple model of heterogeneous investors who evaluate different investment opportunities and allocate their wealth in such a way as to maximize consumption. The heterogeneous allocation of the initial endowment generates a large concentration of final wealth among the skilled investors. Next, we allow a social planner to supply free education to individuals using taxes on capital income. Education may partially correct the bias regarding the valuation of the investment pay-off, causing wealth inequality across individuals to decline because the fraction of the population that continues to make bad decisions is smaller. In the empirical analysis, we show that education has a positive and significant effect on both the level and returns to wealth through the channel of financial investment decisions, even after controlling for unobserved, individual ability. We then argue that education has the potential to reduce wealth inequality by enabling individuals endowed with low skills to make better investment decisions, thus narrowing the gap between the top and the bottom shares of the wealth distribution.

We provide several insights regarding the economic mechanism behind the relationship between skills, education, investment decisions, and wealth inequality by using a simple two-period model with heterogeneous individuals. Individuals are presented with three investment opportunities to allocate their initial wealth: a share of productive capital of a firm (the *stock market*), a lottery ticket with negative net present value, and a risk-less bank deposit. Individuals are endowed with equal wealth but heterogeneous cognitive skills affecting their ability to evaluate the investment pay-off: individuals have different beliefs about the probabilities involved in the gamble and they generally overweight the probability of success. More specifically, the less competent investors highly overestimate this probability, meaning they prefer to gamble than invest in the stock market, while the more competent investors optimally choose stocks. The heterogeneous allocation of the initial endowment generates inequality across individuals in the distribution of the final wealth, with a large concentration of wealth among the skilled investors. Next, we allow a social planner to supply free education to individuals, which may partially correct the bias regarding probabilities involved in the gamble. By improving individual abilities through education, the government makes the lottery less attractive, thus persuading unskilled investors to favor stocks over gambling. As a consequence, wealth inequality across individuals declines because the fraction of the population persisting in undertaking the bad investment decision is smaller.

We use a fair lottery as a stylized example of a bad investment opportunity for several reasons. First, lotteries are notorious for being strictly negative NPV investments, yet worldwide evidence suggests that gambling has become very popular over recent decades. Furthermore, the menu of financial assets that present lottery-style payoffs in stock and option markets has dramatically increased. Kumar (2009) and Kearney (2005) highlight that lottery-style investments are particularly popular among individuals with a low level of education and poor background because they either misunderstand the actual chances of success when gambling or simply because they are driven by behavioral attitudes (Guryan and Kearney

(2008)). Such investors exhibit a preference for gambling when investing in financial markets, looking for lottery-like stocks (Bhattacharya and Garrett (2009), Eraker and Ready (2015), Agarwal et al. (2020), Liu et al. (2020)), lottery-like options (Boyer and Vorkink (2014), Byun and Kim (2016)), or saving products (Cookson (2018), Filiz-Ozbay et al. (2015)). In a nutshell, investors may prefer to trade off expected returns for skewness when allocating their financial investments. Moreover, Calvet et al. (2007) and Calvet et al. (2009) show that poorly educated individuals tend to hold very under-diversified portfolios or bet on single stocks when participating in the stock market. In contrast, highly educated individuals display a preference for diversified asset allocation, meaning they typically hold shares of mutual funds rather than single stocks (Bonaparte et al. (2014)). Then, the lottery ticket and the share of the productive firm play in the model the role of these opposite types of investment opportunity, respectively.

The key model prediction is that education improves both the level and returns to wealth by increasing the individual's propensity to invest in the stock market thanks to a better ability to evaluate investment pay-off, conditional on heterogeneous individuals skills. We empirically test this prediction using individual-level data from the Dutch Household Survey (DHS), conducted by the Dutch National Bank (DNB). The DHS provides information regarding educational attainment, asset allocation, and wealth composition, as well as personal characteristics that may influence the financial investment decisions of the individual, such as age, gender, health status, risk aversion, household size, area of residence, and employment status. Our sample is representative of the Dutch population: 47.42% are college graduates, around 18% invest in the stock market (either directly or through mutual funds), and each individual allocates an average of 8% of their financial wealth to stocks. The Netherlands is among the most advanced European countries in terms of the proportion of its population that hold a college degree, including both university degrees and vocational training courses. On the other hand, the rate of participation in the stock market in the Netherlands is relatively higher compared to other European countries. Because the DHS does not release information regarding which stocks or funds the individual holds in her portfolio, we measure total returns on the individual's wealth using the yearly (log)-growth rate of the total wealth. Similarly, we proxy an individual's financial returns using the yearly (log)-growth rate of the financial wealth.

First, we measure individual skills by estimating unobserved, individual ability in a standard (log)-earnings regression on education and a polynomial in age that proxies for years of experience, as in Belzil and Hansen (2002). We document strong heterogeneity in the distribution of the unobserved ability across individuals, with a remarkable left tail that highlights a sizeable fraction of very unskilled individuals. We challenge our proxy of individual skills by replicating the empirical analysis of Barth et al. (2020), who use biological data on genetic endowment at the individual level, and we report consistent results. Then, after sorting individuals based on their unobserved ability, we show that skilled individuals display a higher propensity for investing in the stock market and risk-taking. Importantly, we uncover a positive assortative match between unobserved ability and both total and financial returns—that is, skilled individuals earn substantially higher returns to wealth than low-skilled individuals. The difference between the top and the bottom quartiles of the skills distribution is remarkable: the annual financial (total) returns are on average 5.18% (3.51%) in the top quartile and 0.79% (1.67%) in the bottom quartile.

Next, we estimate the effect of education on both the level and returns to wealth, when conditioning on the unobserved, individual ability. Specifically, we quantify both the *direct* effect of education and its *indirect* effect through the impact of education on the decision to invest in the stock market, by jointly estimating a simultaneous two-equation model. In the main equation, either wealth or the returns to wealth is the dependent variable, while the dummy variable representing the decision to participate in the stock market is the dependent variable in the auxiliary regression. Meanwhile, educational attainment and unobserved ability are the main explanatory variables in both of the estimated regressions. To assess the indirect effect of education through the decision to participate in the stock market, we include the dummy variable for the individual's stock market participation among the independent variables in the main regression. By doing so, we evaluate the effect of both education and unobserved ability on either the level or the returns to wealth through the impact that these explanatory variables have on stock market participation.

We find that both education and unobserved ability have a positive and significant effect on both total wealth and financial wealth through the channel of stock market participation. Specifically, holding a college degree increases the total (financial) wealth by 4.6% (4.4%) through the positive impact that higher education has on the propensity to participate in the stock market. Meanwhile, unobserved, individual ability increases the total (financial) wealth by 3.4% (3.3%) through the positive impact that high skills exert on the propensity to invest in the stock market. Importantly, the impact of both education and individual skills on the returns to both total and financial wealth matter only through the decision to participate in the stock market. Specifically, college-graduated individuals earn annual 0.4% extra-returns on financial wealth and 0.2% extra-returns on total wealth due to the positive effect of higher education on the propensity to invest in the stock market. Similarly, skilled individuals earn annual 0.3% extra-returns on financial wealth and 0.2% extra-returns on total wealth because of the positive effect of better unobserved ability on the propensity to invest in the stock market. These effects are highly statistically significant and economically important, accounting for a large fraction of the overall estimated extra-returns to total and financial wealth.

Finally, we corroborate our empirical findings by conducting a set of additional tests. We show that our results are quantitatively robust to alternative model specifications, alternative definitions of high education, and alternative sample time series selection. Interestingly, we also find that the beneficial effect of education on returns to wealth through stock market participation is significantly stronger when individuals invest in the stock market using shares of mutual funds rather than investing in stocks directly. This empirical evidence is consistent with the previous documented evidence that poorly educated individuals tend to prefer single stocks, as reflected in their adoption of gambling-like behaviors while better-educated individuals display a preference for well-diversified portfolios. In this spirit, this further result also supports our model's predictions. Intuitively, individuals with a higher level of education may be better able to identify, and thus display a preference for, well-diversified portfolios that have historically delivered higher risk-adjusted returns compared to single stocks.

Related Literature. Our paper speaks to the broad literature that has recently linked wealth inequality to heterogeneous individual skills. To do this, we attempt to characterize the different range of skills. First, skills may be strictly related to natural talent. Gabaix et al. (2016) rationalize inequality dynamics with idiosyncratic shocks to earnings secured by talents (i.e., "superstar" shocks). Using biological data, Barth et al. (2020) find that genetic endowment has a causal effect on educational attainment, wealth at retirement, and stock market participation. Moreover, individuals with lower genetic scores hold biased beliefs about the probabilities associated with simple economic events. Similarly, Lillard and Willis (2001) argue that probabilistic thinking enhances both the propensity to participate in the stock market and the ability to optimize asset allocation, thus ultimately explaining wealth accumulation over time. Meanwhile, Grinblatt et al. (2011) and Grinblatt et al. (2016) demonstrate that cognitive skills, as measured by IQ tests, positively predict stock market participation. Furthermore, as shown by Gennaioli et al. (2015), although direct transaction costs have now become negligible, less competent investors are likely to bear indirect costs that may limit their stock market participation, such as paying for asset management fees to reduce anxiety.

Individual skills may also be related to the ability to efficiently collect and process information about the stock market. Indeed, better-informed investors are more likely to join the stock market (Kacperczyk et al. (2019)) and select better investments without making investment mistakes (Calvet et al. (2007), Calvet et al. (2009)), whereas less sophisticated investors tend to avoid the stock market. Moreover, because information acquisition can be costly and available only to wealthier individuals, skills heterogeneity may exacerbate wealth inequality (Peress (2004), Lei (2019)).

Finally, individual skills may be influenced by human capital investment and educational attainment. Using survey data from the US, Kim (2022) finds that disparities in education contribute to wealth inequality through a skill-specific wage process. Fagereng et al. (2020b) documents a positive assortative match between schooling years and returns on bank deposits. Bianchi (2018) shows that literate households actively re-balance their portfolio and earn higher returns. In Lusardi et al. (2017), some investors may optimally choose to stay ignorant if education is too costly, so heterogeneous knowledge can endogenously boost wealth inequality over time. The common prediction across these papers is that there will be a positive relationship between education and wealth inequality—in other words, education enables individuals to identify better investment opportunities, thus increasing the gap between poor and wealthy individuals because the wealthy can afford the costs to acquire strong educations. However, we show that education can actually reduce inequality by improving individual ability to evaluate investment opportunities, which ultimately prevents unskilled investors from making detrimental investment decisions, which in turn closes the gap between the top and bottom tails of the population.

Paper Structure. The remainder of the paper is structured as follows. In the next section, we present the model and characterize the model equilibrium before presenting the main results through a numerical analysis. We then describe the data in Section 3 and conduct our empirical analysis in Section 4. After that, we estimate unobserved, individual skills and study the link between skills and both the level and returns to wealth in Section 4.1. The empirical results regarding the effect of education through the channel of stock market participation are described in Section 4.2. In Section 4.3, we present a set of additional results and robustness tests. Finally, Section 5 concludes the paper.

2. The Model

We present a simple two-period model, with time denoted by t=$\{t_0, T\}$. The economy is populated by four types of agents: (I) N risk-neutral *individuals*, denoted by i=$\{1,..,N\}$, endowed at t_0 with initial wealth $W_{i,0}$; (II) a *firm* issuing stocks at t_0 to raise capital K and distributing the liquidation value D to the shareholders in T; (III) a bank paying out a risk-free interest rate equal to r to depositors; (IV) a social planner (the *government*) collecting taxes and distributing public goods to individuals. First, we describe the economy and the general version of the model: we characterize individuals, their investment opportunities, and the objective functions of individuals and social planner. Next, we detail the approach and the algorithm to obtain the model solution. Finally, we characterize the model equilibrium and present results in different scenarios obtained by using a numerical analysis.

2.1. The Individuals

At t_0, each individual i allocates the endowment across three investment opportunities: (I) a fair lottery with binary outcome, (II) a share of the firm that entitles to a share of the liquidation value, and (III) a bank deposit. We assume that individuals do not borrow, are endowed with equal initial wealth, and allocate the entire wealth in one investment opportunity only:

$$\mathcal{I}_i^l + \mathcal{I}_i^b + \mathcal{I}_i^m = 1,$$

where $\mathcal{I}_i^l$ is an indicator function equal to 1 if the individual plays the lottery, and zero otherwise, $\mathcal{I}_i^b$ is an indicator function equal to 1 if the individual stores the endowment into the bank deposit, and zero otherwise, $\mathcal{I}_i^m$ is an indicator function equal to 1 if the individual invests in stocks, and zero otherwise. While these assumptions do not affect the generality of the model, they improve tractability in order to obtain the model solution and characterize the model equilibrium.

At T, the payoffs of the investment opportunities are realized, the individual collects the payoff of the investment and uses the final wealth $W_{i,T}$ to consume a unique good with unit price P:

$$C_{i,T} = W_{i,T}/P,$$

with

$$W_{i,T} = h \cdot \left(\mathcal{I}_i^l \wedge \mathcal{I}_i^v \right) + d \cdot \mathcal{I}_i^m + W_0(1+r) \cdot \mathcal{I}_i^b, \tag{1}$$

where h is the lottery prize, $\mathcal{I}_i^v$ is an indicator function equal to 1 if the individual wins the lottery, and zero otherwise, and d is the share of the liquidation value D of the firm per unit of capital:

$$d = \frac{W_0}{K} D, \tag{2}$$

where K is the capital for production raised by the firm through equity issuance, that is equal to:

$$K = \sum_{i=1}^{N} W_0 \cdot \mathcal{I}_i^m = m \cdot N. \tag{3}$$

Thus, the share of the liquidation value of the firm entitled to an individual depends on the overall number of individuals who have allocated their wealth in stocks, where m is the share of individuals investing in stocks.

Each individual chooses how to allocate her wealth by maximizing her expected utility defined over consumption in T. Under the assumptions of unit price P and risk-neutrality, this problem is equivalent to maximize the expected final wealth:

$$\max_{\mathcal{I}_i^l, \mathcal{I}_i^m, \mathcal{I}_i^b} E_i[W_{i_T}] = q_i h \cdot \mathcal{I}_i^l + d_i \cdot \mathcal{I}_i^m + W_{i,0}(1+r) \cdot \mathcal{I}_i^b,$$

such that $\mathcal{I}_i^l + \mathcal{I}_i^m + \mathcal{I}_i^b = 1$, and where $q_i = E_i[\mathcal{I}_i^v]$ is the belief of individual i about the probability of winning the lottery.

2.2. Investment Opportunities

The firm. The firm raises capital K through equity issuance to produce an output Y of a unique good:

$$Y = AK^{\beta},$$

where the productivity of K in the firm's production technology is $\beta \in (0, 1)$, A denotes firm profitability, and K is defined in (3). The firm generates profits equal to

$$\pi = Y - c(Y),$$

where $c(Y)$ is a cost function that includes both fixed and proportional production costs, that we assume equal to zero without loss of generality. At time T, the firm pays taxes on profits at the corporate tax rate τ, liquidates its assets and distributes the liquidation value D to shareholders:

$$D = (1 - \tau) \max(\pi, 0).$$

Each shareholder receives a proportional share of D defined in (2), and the social planner collects a share τ of the before-tax profits.

Lottery. The structure of the lottery is simple, with only two outcomes: h and 0. For each individual, the expected value of the lottery depends on her individual belief q_i about the probability to win the lottery and the total lottery jackpot H:

$$q_i \cdot h + (1 - q_i) \cdot 0 = q_i H \alpha, \tag{4}$$

where α is the fraction of the amount H returned to individuals as a prize, with $\alpha \in [0, 1]$, and

$$H = \sum_{i=1}^{N} W_0 \cdot \mathcal{I}_i^l = l \cdot N, \tag{5}$$

where l denotes the share of individuals joining the gamble. We assume that the individual belief q_i is equal to the 'true' probability to win the lottery, p_i, and an individual bias γ_i that measures the wedge between the individual belief and the true probability to win the lottery:

$$q_i = \gamma_i p_i,$$

where p_i depends on the overall number of individuals who participate to the lottery:

$$p_i = \frac{W_0 \cdot \mathcal{I}_i^l}{H}.$$

We assume that the individual bias about the probability to win the lottery can be only upward: individuals can overestimate but cannot underestimate this probability, thus we impose $\gamma_i \geqslant 1$. Using equations (4) and (5), the expected value of the lottery for individual i reduces to

$$q_i \cdot h = \gamma_i p_i \alpha H = \gamma_i \alpha,$$

that is, the expected value of the lottery for the unbiased individual (i.e., γ_i=1) is equal to the fraction of H returned to the players as a prize. We assume $\alpha = (1 - \epsilon)$, where

ϵ is a strictly positive but negligible number.[1] While it is without loss of generality, this assumption guarantees that the lottery is a strictly negative NPV investment, in line with reality.

Bank Deposit. Individuals can store their initial wealth into a bank deposit. Bank deposits act as a storage technology, are available to all individuals at no costs, and allow individuals to transfer wealth to the next period. The bank rewards deposit at a risk-free interest rate equal to r. Thus, the individual receives $W_0(1 + r)$ when storing into the bank deposit the initial endowment.

2.3. The Government

The government raises funds through taxes on corporate profits and uses tax revenues to produce a public good and to provide free education to the individuals. We assume that the public good is non-rival, non-exclusionary and is equally distributed by the government to all the individuals. Because agents live only one period, the government has no motive to accumulate funds for the future. Thus, the government splits public income I between G and e, where G denotes the amount used by the government to produce the public good and e denotes the amount allocated by the government to finance the education supply:

$$I = G + e,$$

where $I = \tau \max(0, \pi)$. We denote by δ the fraction of public income allocated by the government to finance education, so $e = \delta I$ and $G = (1-\delta)I$, with δ determined in equilibrium. The public good affects individual utility directly because individuals consume the public good in T. In particular, individuals receive and consume $\lambda \cdot (G/N)$.

On the other hand, education affects individual consumption through the investment decision of individuals, by correcting their beliefs about the probabilities involved in the lottery, thus

[1] When $\alpha = 1$, the winner of the lottery is entitled to receive the entire jackpot.

ultimately affecting their final wealth. Specifically, we assume that the wedge between the individual belief about the probability to win the lottery and the true probability, after received public education, is equal to:

$$\hat{\gamma}_i = \gamma_i \cdot (1 - e_i/f),$$

where $e_i = e/N$ and f is the effectiveness of the education supply in terms of bias correction that is, individuals receive equal education and the effectiveness of the education supply is homogeneous across individuals.

We denote by $\mathcal{P}^*$ the optimal policy of the government, where $\mathcal{P}^* = \{\tau^*, \delta^*\}$: the government sets the corporate tax rate τ^* and the fraction δ^* of public income used for education to maximize the social welfare J. We adopt an utilitarian social welfare function as the sum of the N individuals' utility defined over both private consumption $C_{i,T}$ and public good G:

$$\{\tau^*, \delta^*\} = \arg\max J(\tau, \delta) = \sum_{i=1}^{N} U\left(C_{i,T}(\tau, \delta) + G(\tau, \delta)/N\right). \tag{6}$$

The government faces a two-fold trade-off: on the one hand, a higher tax rate reduces the value distributed by the firm to the shareholders, and thus private consumption. Meanwhile, a higher tax rate increases the public income and so the public good distributed to the individuals. On the other hand, education supply is costly for the government and reduces the fraction of public income available for individual consumption. However, education improves individual ability to evaluate the investment opportunities, thus leading to better investment decisions and ultimately increasing individual final wealth.[2] We describe the timeline of the model below:

[2] We assume that the government is unbiased when evaluating the individual's probability to win the lottery and computing the individual's expected value of the lottery. This is an important and realistic assumption that allows the social planner to choose a public policy that (partially) drives and corrects the individual decision when allocating the endowment.

Time t_0:

- Individuals are endowed with equal wealth and heterogeneous skills
- The government sets the corporate tax rate and supplies education
- Individuals receive education and update their beliefs
- Individuals observe the tax rate and allocate their initial endowment
- The firm raises capital through stock issuance and uses capital to produce the output
- The bank stores individuals' wealth into risk-less deposits

Time T

- The bank returns to the depositors the initial wealth plus a risk-less interest rate
- The firm is liquidated and the liquidation value is distributed to shareholders
- The government collects taxes on corporate profits
- The government uses tax revenues to produce the public good and to pay costs for education supply
- Individuals receive the payoff from their investment, the public good from the government and consume the final wealth

2.4. Model Equilibrium

We design the model as a two-stage sequential game with the government acting as a leader. In the first stage, the government sets the policy in terms of corporate tax rate and education supply. In the second stage, each individual allocates the initial endowment on the basis of the government policy. By anticipating the individuals' allocation, the government chooses the optimal policy which maximizes total welfare. We solve the model numerically by backward induction. The main challenge in finding the solution is that the allocation of each individual depends on the allocation of the other individuals. For instance, the individual decides whether to allocate the wealth in stock on the basis of the expected return from the stock. Though, the return generated by the stock depends on the capital raised by the firm through equity issuance, which, in turn, depends on the overall number of individuals who invest in stocks and purchase a share of the firm. We detail our approach to obtain the model solution in Appendix A.

In this section, we present the results from a numerical analysis. We assume a unit initial endowment equal across individuals and a unit price for the consumption good. We assume a risk-free interest rate equal to 1% and we set $\gamma = 0.75$.[3]. We begin by presenting a friction-less scenario, in which all individuals have homogeneous, correct beliefs about the probability to win the lottery and there is no social planner. Next, we introduce heterogeneous beliefs across individuals and the welfare-maximizing government. We describe the equilibrium allocation of the individuals and the optimal policy of the government. We finally provide implications in terms of total welfare, wealth inequality and stock returns. In scenario, we report our results for increasing values of the aggregate profitability parameter A. We use A as a measure of the state of the economy, thus we interpret low and high values of A as bad and good states of the economy.

Baseline Scenario. In our friction-less, baseline set-up, individuals are endowed with homogeneous skills and so they have homogeneous, correct beliefs about the probability to win the lottery. Moreover, we remove the government from the economy, thus there is no tax on the corporate profits and no education is provided by the government. The baseline scenario is described by the following set of parameters:

[3]We borrow the value of the parameter governing the returns to scale on production capital from the corporate finance literature.

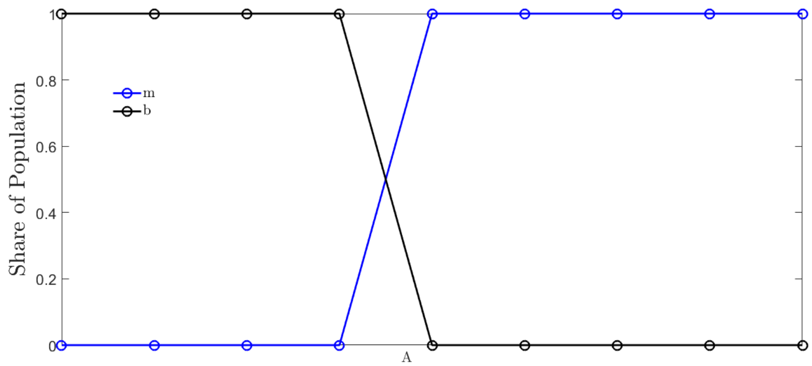

Figure 1. Baseline Model: Equilibrium Allocation. The figure shows the equilibrium allocation in the baseline scenario for increasing levels of the profitability parameter (A) in the firm production function. We report the proportion of population investing in stock (m, blue line), and using the bank deposit (b, black line).

- $\gamma_i = 1, \;\; q_i = p_i \quad \forall i$
- $\delta = 0, \;\; \tau = 0$

We present our baseline results in Figure 1. When individuals assess correctly the probabilities involved in the lottery, they interpret correctly the lottery as a negative NPV investment. As a result, there is no motive to gamble and thus the lottery is ruled-out regardless the state of the economy. Then, since individuals are homogeneous along all the dimensions, all the individuals prefer either using the bank deposit to transfer wealth into the next period if economic conditions are bad or buying stocks when economic conditions improve.

Heterogeneous Background. We now introduce heterogeneity across individuals. We assume that individuals have heterogeneous skills endowment, as in Barth et al. (2020) and Grinblatt et al. (2011). Because of such heterogeneous background of competences, individuals possess heterogeneous ability to assess the chance the win the lottery, and so they have heterogeneous beliefs about the probability to succeed in the gamble. We encompass this friction in the model by using a distribution for γ_i: $\gamma_i \in (1, \overline{\gamma})$, where $\overline{\gamma}$ denotes the most severe degree of probability over-weighting across individuals, thus we obtain a distribution for q_i:

$$q_i \in (p_i, \overline{\gamma} p_i),$$

where the skilled individual has γ_i=1 and estimates correctly the probability to win the lottery.[4] We display the equilibrium allocation in this scenario in Figure 2, for moderate ($\overline{\gamma} = 2$) and severe ($\overline{\gamma}$=5) degrees of bias.

As soon as $\overline{\gamma} > 1$ that is, when individuals overestimate the probability to succeed in the lottery, they may be willing to join the lottery. In particular, the less skilled individuals prefer gambling than either storing the wealth in the bank deposit or buying the stock. The share of population who allocates the initial wealth in the lottery decreases when the state of the economy is higher, as the firm generates higher revenues and so the investment in stock becomes more attractive. Obviously, the share of population who joins the gamble is larger when the bias about the probability to succeed in the gamble is higher.

The Education Effect. In this section, we introduce the social planner, which we briefly refer to as the *government*. The objective of the government is to maximize social welfare, defined as the sum of individuals' consumption. To do so, the government raises funds through taxes on corporate profits and uses tax revenues to: i) implement a free education program; ii) produce a public consumption good equally distributed across individuals; iii) a combination of (i) and (ii). The government may launch the free education program to correct the biased beliefs of individuals about the probability to succeed in the gamble, thus improving their abilities of evaluating investment opportunities. The government is aware that pushing the individual allocation towards stocks is a dominant choice for sufficiently high states of the economy. Meanwhile, a higher stock market participation rate increases total

[4]We assume a Uniform distribution defined over the support $[1, \overline{\gamma}]$.

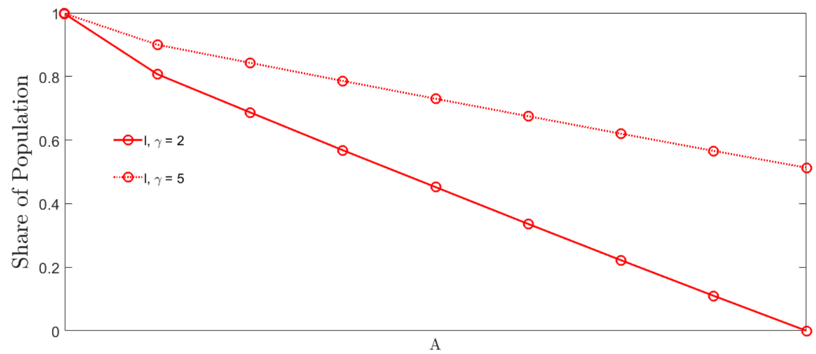

Figure 2. Heterogeneous Skills: Equilibrium Allocation. The figure shows the equilibrium allocation in the scenario with heterogeneous, biased beliefs about the probability to win the lottery, for increasing levels of the parameter (A) in the firm production function. Heterogeneous beliefs are defined by $\gamma_i \in (1, \overline{\gamma})$. We report the proportion of population investing in stock (m, blue lines) and joining the gamble (l, red lines) when $\overline{\gamma}$=5 (solid lines) and when $\overline{\gamma}$=10 (dashed lines).

welfare, as the lottery is a strictly negative NPV investment. The government knows that the propensity to invest in stocks grows when the individual is more educated. Therefore, the government sets the policy parameters to push individuals to invest in the stock for sufficiently high states of the economy, when maximizing social welfare.

In Figure 3, we highlight the optimal policy of the government, in terms of corporate tax rate and education supply. When economic conditions are poor, the government does not supply public education and does not charge any tax on profits. In low states of the economy, the government finds optimal that part of the population stays away from the stock market, because the cost to supply education is not compensated by a sufficient welfare gain. This outcome aligns with the results of Lusardi et al. (2017), in which investors may prefer to stay ignorant and away from the market if education is too costly. In this case, only the more competent individuals allocate their wealth to the stock, regardless the free education supply.

When economic conditions improve, the optimal policy of the government changes substantially: in high states of the economy, the government raises taxes on profits and uses tax revenues to fund the education program. When receiving education, individuals relocate

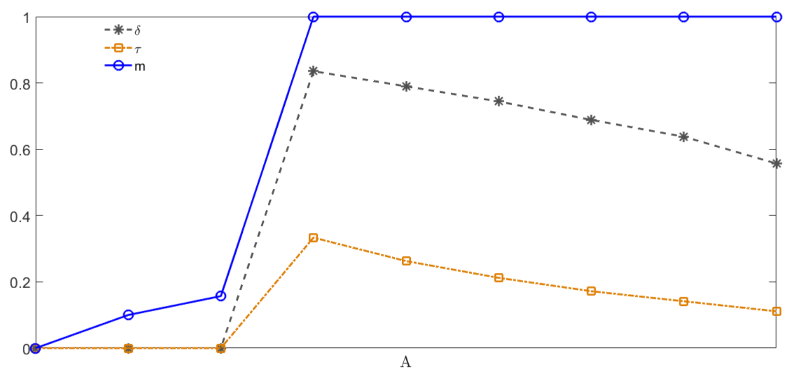

Figure 3. The Education Effect: Equilibrium Allocation and Policy. The figure shows the optimal policy of the government in terms of corporate tax rate (τ, dashed line) and share of tax revenues allocated to education supply (δ, dotted line), and the proportion of population investing in stock (m, solid line), for increasing levels of the profitability parameter (A) in the firm production function.

their portfolio towards the stock market: all the individuals who were gambling turn to purchase a share of the productive capital of the firm. The funds used by the government to supply free education gradually decline when capital profitability increases: the amount of education required to push individuals towards the stock market is lower when the stock generates higher returns. Then, the government prefers to raise the share of tax revenues allocated to the production of the public good: in high states of the economy, the government has additional funds to produce and distribute a larger amount of the public consumption good, which definitely enhances the total welfare.

Welfare Analysis. We now present the welfare implications of our model results. In Figure 4, we display the total welfare, defined as the average utility across individuals from consumption at time T, where individual consumption is the sum of individual wealth and the individual share of public good provided by the social planner. Obviously, welfare increases in the higher states of the economy across all the scenarios. The baseline model, in which all the individuals have homogeneous skills endowment, and thus equal and correct beliefs about the gambling probabilities, represents the first-best scenario in terms of total welfare. Then, the difference between the total welfare in the baseline case and the total welfare in

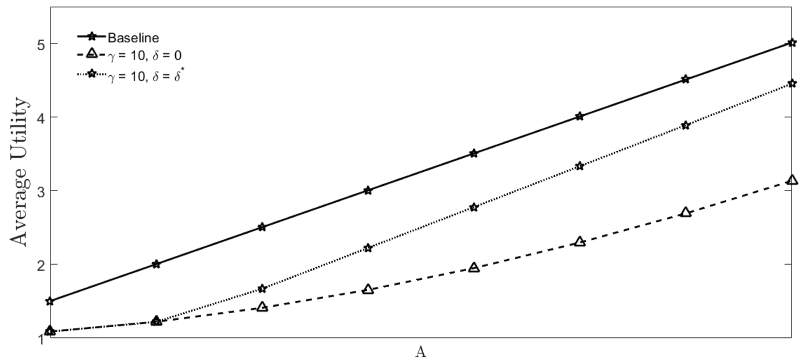

Figure 4. Total Welfare The figure shows the total welfare in different scenarios for increasing levels of the profitability parameter (A) in the firm production function. Total welfare is computed as the average individual utility at time T across individuals. The scenarios are the followings: *Baseline* (solid line); Biased beliefs ($\bar{\gamma} = 10$) and NO government ($\delta = 0$); Biased beliefs and education supply ($\delta = \delta = \delta^*$).

the alternative scenarios is the dead-weight loss due to the individuals' bias in evaluating investment opportunities. This loss grows proportionally with the severity of the bias (i.e, $\bar{\gamma}$). Next, we show that the government can partially reduce the welfare loss. In particular, the government achieves this target by supplying free education, which allows the otherwise unskilled investors to switch towards better wealth allocation.

Wealth Inequality. In the first-best equilibrium, individuals are homogeneous along all the dimensions, thus they choose equal wealth allocation. As a result, all individuals have equal wealth in T and there is no inequality in the economy. In contrast, when individuals have heterogeneous skills endowment, they opt for heterogeneous wealth allocation and thus wealth is unequally distributed across individuals in T. Then, skills heterogeneity induces inequality, which is the outcome of a bad investment decision undertaken by part of the population due to the incompetence in the evaluation of the investment. When the bias about the probability to win the lottery is moderate ($\bar{\gamma}$=5), inequality displays a hump-shaped trend with respect to the state of the economy. Inequality is low either when few individuals invest in stocks but the return generated from the stock is poor or when the stock return is high and most of people are in the stock market. Instead, when the bias is severe ($\overline{\gamma}$=10), inequality grows in high states of the economy. Because of the high degree of overestimation of the probability to succeed in the lottery, a large share of the population disregards the stock market and joins the gamble despite the economic boom. Then, fewer, skilled individuals catch the boom, relocate the portfolio towards stocks, and share the (big) liquidation value of the firm.

The implication of the government policy on wealth inequality is striking. Inequality drops to zero when the government start supplying education to individuals, thus pushing the otherwise unskilled investors away from gambling. As a result, all the individuals invest in stocks and equally split the liquidation value of the firm, thus collecting equal wealth in T. Importantly, there is a straightforward and neat map between total welfare and wealth inequality. There is no inequality in the first-best, baseline model, as individuals allocate their wealth equally. In contrast, inequality grows with better economic conditions when individual skills are heterogeneous and beliefs are biased. However, the government is able to reduce inequality by using a combination of both free education and public consumption good. Beside improving the individual ability in evaluating investment opportunities, and thus pushing individuals towards better wealth allocation, the government generates also a wealth redistribution effect, by providing the individuals with a public consumption good through taxes on capital gain.

We also assess wealth inequality in terms of concentration of wealth in the top 5% of the wealth distribution. Obviously, because all the individuals undertake identical portfolio allocation, the top 5% holds exactly 5% of the total wealth in T in the baseline scenario. In contrast, wealth concentration in the top tail of the wealth distribution lifts when individuals have heterogeneous beliefs and there is no education supply. In particular, such wealth concentration is hump shaped with respect to A. The intuition is simple: when A is low, the return generated by the stock is also low, thus the few individuals who invest in the firm stock collect a final wealth moderately higher than those joining the lottery. On the other hand, when A is sufficiently high, the return generated by the stock is high enough

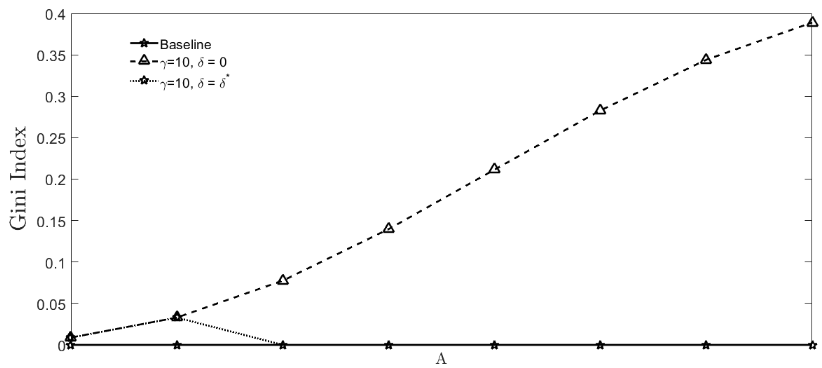

Figure 5. Wealth Inequality The figure shows the Wealth inequality in different scenarios for increasing levels of the profitability parameter (A) in the firm production function. Wealth inequality is defined as the Gini index computed on the distribution of the individuals' wealth at T. The scenarios are the followings: *Baseline* (solid line); Biased beliefs ($\bar{\gamma} = 10$) and NO government ($\delta = 0$); Biased beliefs and education supply ($\delta = \delta = \delta*$).

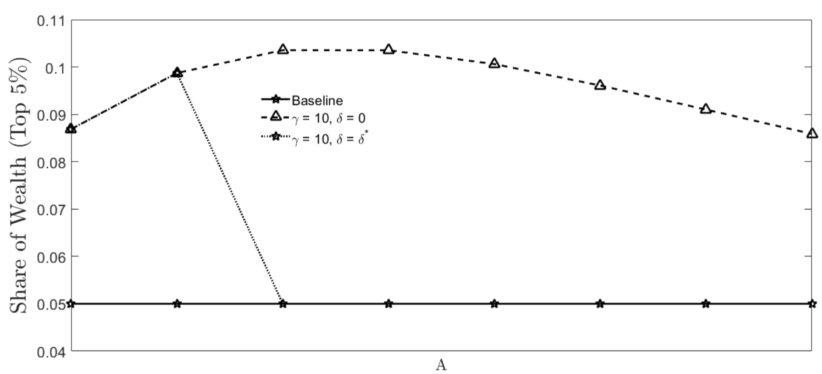

Figure 6. Wealth Concentration The figure shows the share of the final aggregate wealth held by the 5% of the individuals with highest skills–that is, the top 5% of the individuals with least bias about the the probability to win the lottery, in different scenarios for increasing levels of the profitability parameter (A) in the firm production function. The scenarios are the followings: *Baseline* (solid line); Severe bias ($\bar{\gamma} = 10$) and NO government ($\delta = 0$); Severe bias and education supply ($\delta = \delta = \delta*$).

to push most of the individuals into the stock market. Then, wealth concentration is more pronounced for mild economic conditions, when still a limited share of the population prefers the stock market to the lottery despite a higher stock return, which now allows the more competent individuals to collect substantially larger final wealth compared to the less skilled ones.

Government Efficiency. We finally introduce an additional dimension in the model set-up, namely the *government's efficiency*, through the parameter λ into the objective function of the welfare planner. In particular, individuals receive and consume a fraction of the public good equal to $\lambda(G/N)$. When $\lambda = 1$, the government is neutral and does not create nor destroy resources, thus distributing to the individuals an amount of public good exactly equal to G. The government destroys value when λ <1: individuals effectively enjoy only a residual fraction λ of the amount raised and used by the government to produce the public good, so $(1 - \lambda) \cdot G$ quantifies the public resources wasted because of inefficiency. At the opposite, the government generates a surplus when λ >1.

We then solve the model by assuming either $\lambda = 0$ (*Inefficient* Government) or $\lambda = 2$ (*Efficient* Government), and we report results in Figure 7. The optimal allocation of the individuals is equivalent across the two scenarios: the proportion of the population investing in the stock market is equal regardless the level of λ. Nevertheless, the optimal policy of the government that induces such equivalent individual allocation clearly depends on the government's efficiency. When λ=0, the government raises taxes only to supply free education, without producing any public good, so δ is always equal to 1. Then, when the aggregate productivity grows, the government gradually decreases the tax rate, because the education supply needed to push individuals towards the stock market is lower as the stock becomes inherently more attractive, thus the government needs to raise a lower income from taxes. Instead, when λ=2, the government splits the public income between education supply and production of the public good. Then, the share of public income allocated to education supply in order to push individuals towards the stock market decreases when A increases, because the stock is more profitable. However, the optimal tax rate is higher when A increases: when stock returns are sufficiently high to avoid capital drain from the stock market, the efficient government raises taxes to produce the public good, thus increasing the total welfare.

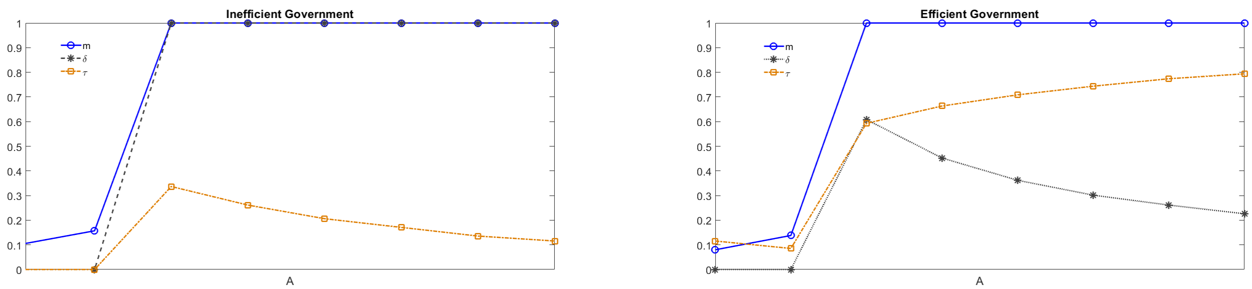

Figure 7. Government Efficiency: Equilibrium Allocation and Policy. The figure shows the optimal policy of the government in terms of corporate tax rate (τ, dashed line) and share of tax revenues allocated to education supply (δ, dotted line), and the proportion of population investing in stock (m, solid line), for increasing levels of the profitability parameter (A) in the firm production function. The left panel displays results when $\lambda = 0$ (*Inefficient* Government). The right panel displays results when $\lambda = 2$ (*Efficient* Government).

3. The Data

We use data from the Dutch Household Survey (DHS), which has been conducted in yearly waves by the Dutch National Bank since 1993. In each wave, variables are grouped into different homogeneous sections, such as income, wealth, household and personal characteristics, and economic and psychological features. The dataset thus provides information about income and wealth components, educational attainment, and a large set of personal characteristics, including age, gender, health status, risk aversion, household size, area of residence, and employment status. The data are provided at either the household level or at the individual level and include information about financial investments and asset allocation. We use all the waves of the DHS from 1993 to 2022. For each wave, we merge the different sections of the survey using a unique identifier at the individual level, after which we merge the waves over time. To create the individual-level identifier that we use to follow individuals over time, we combine the unique household-level identifier and the within-household individual identifier. While this procedure implies that household-level data are potentially attributed to multiple individuals, such data are typically recorded for one individual per household only, with survey questions usually being addressed to the household head. We therefore drop individuals who are either older than 75 or younger than 18, giving us an unbalanced panel of 27 yearly observations and a total of 96,127 individual-year observations from 24,726 unique individuals. Our main variables of interest are the educational attainment, portfolio choice, and wealth composition at the individual level. Given that the focus of our analysis is the individual-level returns on wealth over subsequent years, we further select in our sample only the individuals who are interviewed for at least three consecutive years. This procedure leaves us with a final sample of 75,198 individual-year observations across 11,098 unique individuals.[5]

Education. We identify the highest degree of education achieved by each individual using a ranking variable spanning from 0 to 5, where 0 stands for no educational achievement and 5 denotes top educational achievement, namely a university degree. The complete list of education rank includes primary school (1), high school (2), pre-university degree (3), vocational training (4), and university degree (5). Due to the specific nature of the education system in the Netherlands, in which vocational colleges are typically grouped together with university institutions, we consider as a *college* degree both a university degree and a vocational training course. We then create a dummy variable taking the value of 1 if the individual has a *college* degree, and zero otherwise. The Netherlands is notable for being one of the most advanced European countries in terms of the proportion of its population that holds a college degree—indeed, in our sample, 47.42% of the individuals are graduates.

Wealth and Investments. The survey also contains data regarding individuals' total wealth for each year as well as its composition. Generally, wealth is classified into two major components: financial wealth and real wealth. Financial wealth primarily comprises financial assets held by the individual: checking accounts, savings or deposit accounts, insurance policies, bonds, stocks and mutual funds, and derivatives. Real wealth includes real estate and

[5] When using the entire sample of individuals, the results remain largely unchanged and are available upon request.

durable and luxury goods. Importantly, the DHS provides information about the decision to invest in the stock market, either directly by holding single stocks or through shares of mutual funds. This decision is described in the dataset by a dummy variable taking a value equal to 1 if the individual has been holding stocks or investing in mutual funds throughout the year, and zero otherwise. Moreover, we have information about the share of financial wealth held in stocks or mutual funds at the individual level. Our sample confirms that the rate of participation in the stock market in the Netherlands is higher than that of other European countries: on average, around 18% of individuals invest in the stock market either directly or through mutual funds, while more than 7% of individuals' financial wealth is allocated to the stock market. We also recover information about risk attitude based on the answer to a specific question in the psychological section of the survey. For this, we use a ranking variable ranging from 1 to 7, with 1 signaling preference for risk-taking and 7 standing for the highest degree of risk aversion. In a similar vein to Bonaparte et al. (2014) and Bagliano et al. (2021), who also adopt the DHS as a main data source in their study, we finally consider a large set of personal characteristics that may indirectly affect financial investment decisions: age, gender, health status, household size, area of residence, and employment status. We provide a complete list of variables with a short description in Table 1.

[Table 1 about here.]

Returns to Wealth. Unfortunately, the DHS does not contain information regarding which stocks or funds the individual holds in her portfolio, meaning we are not able to compute an exact measure of returns on the financial investments. Also, the DHS does not release information about consumption and savings, which means we cannot follow the approach of Lusardi et al. (2017) in measuring returns to wealth. Thus, we compute two different proxies of returns to wealth to assess the performance of the individual investments. First, we consider the yearly (log)-growth rate of the total wealth as a measure of total returns.

Second, we consider the yearly (log)-growth rate of financial wealth as a measure of financial returns. The two measures of returns to wealth are computed as follows:

$$TR_{i,t} = \ln\left(\frac{W_{i,t}}{W_{i,t-1}}\right) \qquad \text{(Total Returns)},$$
$$FR_{i,t} = \ln\left(\frac{FW_{i,t}}{FW_{i,t-1}}\right) \qquad \text{(Financial Returns)},$$

where $W_{i,t}$ is the total wealth of the individual i at year t, and $FW_{i,t}$ is the financial wealth of the individual i at year t.

[Table 2 about here.]

Summary Statistics. We summarize the data in Table 2. The average age is around 50, self-assessed health status is generally good (the mean value is almost 4 on a scale ranging from 1 to 5, with 5 being excellent health status), and only 18.83% of the individuals in the sample are retired. The sample is also balanced in terms of gender: slightly more than half of the individuals are male. The level of risk aversion is moderate (the mean value is 4.56 on a scale ranging from 1 to 7, where 1 stands for risk seeking and 7 is the highest degree of risk aversion) and 38.62% of the individuals live in urban areas. Wealth distribution is positively skewed: the mean (194,920 euros) is substantially higher than the median (77,130), a feature that is common across countries. Real wealth accounts for around 80% of total wealth. However, the positive skewness is particularly remarkable in the financial component of wealth: the average financial wealth (35,740 euros) is more than twenty times as large as the median financial wealth (1,460 euros). The annual (log)-growth rates of total and financial wealth, which are our measures of total and financial returns, are 2.67% and 2.51%, respectively. We interpret these numbers as follows: individuals earn, on average, an annual rate of return equal to 2.67% on their total wealth and an annual rate of return equal to 2.51% on their financial wealth, respectively.

4. Empirical Results

We now empirically test the relationship between individual skills, education, and both the level and returns to wealth through the channel of financial investment decisions. First, we estimate the individual, unobserved ability and link our measure of individual skills to educational attainment, financial investments, and both the level and returns to wealth. Next, we disentangle the direct, indirect, and total effects of education on both the level and returns to wealth using a simultaneous two-equation model. Lastly, we run a battery of robustness checks and provide further results. In the Appendix, we offer additional evidence consistent with the main model's ingredients and predictions by using individual-level data from the 1993 wave of the DHS, which contains information about participation in lotteries.[6]

4.1. Skills Heterogeneity

We estimate individual skills by following the approach of Belzil and Hansen (2002). We estimate a standard (log)-earnings regression on education and a polynomial in age that proxies for years of experience:

$$\ln(z_{i,t}) = \gamma_1 e_{i,t} + \gamma_2 a_{i,t} + \gamma_3 a_{i,t}^2 + h(e_{i,t}, a_{i,t}, g_i) + f_i + \epsilon_{i,t}, \tag{7}$$

where $\ln(z_{i,t})$ are the log-earnings of individual i at year t; $e_{i,t}$ is the education rank attainment of individual i at year t; $a_{i,t}$ stands for age; and $h(e_{i,t}, a_{i,t}, g_i)$ is a polynomial up to the fourth order in education, age, and gender g_i, as in Bonaparte et al. (2014). In equation (7), the time-invariant covariate f_i identifies the unobserved, individual ability that we interpret as an exogenous, inherent skill endowment. $\epsilon_{i,t}$ denotes the error term. We estimate equation (7) using OLS and individual fixed-effects to capture the unobserved ability f_i. We display the distribution of the estimated $\hat{f}_i$ in Figure 8, which highlights great heterogeneity

[6] We show that education is the only predictor, among a large set of personal observable characteristics, with statistical significance for both the decision to play a lottery and participate in the stock market: better-educated individuals prefer to invest in stocks and avoid gambling.

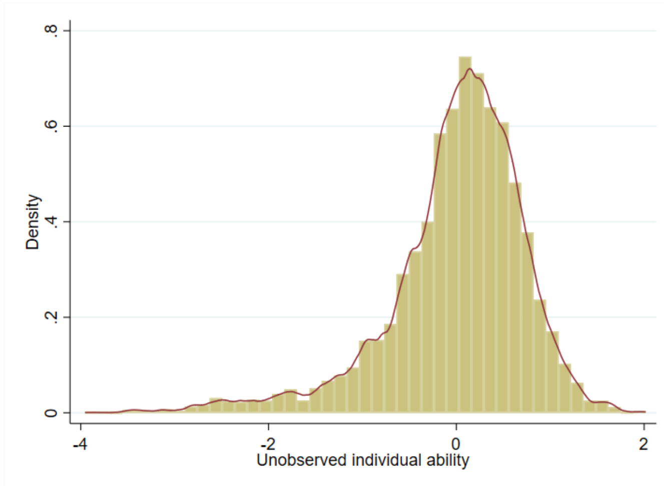

Figure 8. Sample Distribution of Unobserved Ability. The figure reports the sample distribution of the unobserved, individual ability $\hat{f}_i$. We obtain $\hat{f}_i$ by estimating equation (7) using OLS. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

across individuals, is hump-shaped with an average equal to 0.18, and spans between -1.39 (5-*th* percentile) and 0.97 (95-*th* percentile). Interestingly, the individual skills distribution displays a remarkable left tail that highlights a sizeable fraction of very unskilled individuals. For comparison, the distribution of $\hat{f}_i$ is highly similar to the distribution of the genetic score across individuals reported by Barth et al. (2020), which is also hump-shaped and centered around zero, roughly spanning over a range between -2 and 2.

Descriptive Evidence. To present preliminary evidence on the relationship between individual skills, educational attainment, financial investments, and returns to wealth, we sort individuals according to their estimated unobserved ability and then use these groupings to form quartiles. Then, within each quartile, we compute the share of individuals with a college degree, the share of individuals who invest in the stock market, the average share of financial wealth held in stocks, and the average financial and total returns.

First, we document a positive and monotonic relationship between unobserved ability and graduation rate: the share of individuals who hold a college degree is 29.90% within the bottom skill class, 38.94% in the second quartile, 58.37% in the third quartile, and 78.77% in the top skill class. We also observe a positive and monotonic pattern in terms of stock market participation and asset allocation across skill classes. The participation rate in the stock market is 31.85% in the top quartile and 9.36% in the bottom quartile. Similarly, individuals endowed with the best unobserved ability allocate more than 14% of their financial wealth to either stocks or mutual funds, while the share of financial wealth invested in the stock market drops to less than 5% in the bottom skill class. In addition, in our sample, we find support for the common prediction that there is a positive assortative match between individual abilities and returns to wealth. More specifically, we document a stark difference in terms of average returns to both financial and total wealth between the top skill class and the lower skill quartiles. Skilled individuals earn, on average, annual financial and total returns equal to 5.18% and 3.51%, respectively. In contrast, the average financial returns drop to 2.83%, 1.50%, and 0.79% within the third, second, and bottom quartiles. Similarly, the average total returns drop to 3.15%, 2.36%, and 1.63% within the third, second, and bottom quartiles.

We next condition on the educational attainment. Within each skill class, individuals with a college degree display both a higher propensity to invest in the stock market and a larger share of the financial wealth allocated to stocks. However, the relationship between educational attainment and returns to both total and financial wealth within each skill quartile is mixed. College-graduated individuals earn higher financial returns than their non-graduated peers only in the third, second, and bottom quartiles as well as higher total returns only in the third and bottom quartiles.

[Table 3 about here.]

Regression Analysis. We corroborate our proxy of individual, unobserved skill endowment by following the approach of Barth et al. (2020) to test the effect of individual skills on wealth, risk aversion, and propensity to participate in the stock market. We simply replicate the regression analysis of Barth et al. (2020) by employing similar dependent variables and by using our measure of individual skill as the main explanatory variable, thus further conditioning on a set of additional controls. In Table 4 (panel A), we show that individual skills are positively associated with total wealth when we include usual controls, such as age, gender, household, and year fixed-effects (column (2)). The regression coefficient of individual skills remains positive and highly significant even when controlling for the educational attainment of the individual (column (3)), the individual's labor income (column (4)), and for both education and labor income (column (5)). We obtain results that are quantitatively and qualitatively very similar when using as dependent variables either financial wealth (panel B) or real wealth (panel C).

[Table 4 about here.]

Furthermore, we validate the negative relationship between individual skills and risk aversion in Table 5: the most skilled individuals display a significant preference for risk taking (column (1)). In column (3), we support one of the main findings of Barth et al. (2020): individuals endowed with high skills have a greater propensity to participate in the stock market. In addition, we test the relationship between skills and asset allocation, which is not documented in Barth et al. (2020), and we report a positive and significant effect of skill endowment on the share of financial wealth allocated to stocks: the most skilled individuals invest a larger fraction of their financial wealth in the stock market. In columns (2)–(4)–(6), we test the robustness of our regression results by controlling for the initial wealth and we obtain similar findings, although the regression coefficients on the unobserved ability are smaller in magnitude.

[Table 5 about here.]

4.2. The Education Effect

To study the effect of education on both the level and returns to wealth through the channel of financial investment decisions, we estimate a structural regression model by using a mediator variable that describes the decision to participate in the stock market. By doing so, we disentangle the direct and indirect effects of education on both the level of wealth and the returns to wealth. Specifically, we design the following simultaneous two-equation model to quantify both the *direct* effect of education and its *indirect* effect, by jointly estimating the impact of education on the decision to invest in the stock market:

$$Y_{i,t} = \beta_0 + \beta_1 OwnSTKMF_{i,t} + \beta_2 * Edu_{i,t} + \beta_3 * Skills_i + \beta_4 * (F)W_{i,t-1} + X'_{i,t}\gamma + \epsilon_{i,t}, \quad (8)$$

$$OwnSTKMF_{i,t} = \delta_0 + \delta_1 * Edu_{i,t} + \delta_2 * Skills_i + \delta_3 * (F)W_{i,t-1} + X'_{i,t}\gamma + \nu_{i,t}, \quad (9)$$

where $OwnSTKMF_{i,t}$ is a dummy variable equal to 1 if the individual i invests in the stock market (either directly or through mutual funds) at year t, and zero otherwise; $Edu_{i,t}$ is a dummy variable equal to 1 if the individual i holds a college degree in year t, and zero otherwise; $Skills_i$ is the unobserved ability of individual i estimated in regression (7); $X_{i,t}$ is a vector of personal characteristics of the individual i at year t (such as age, household size, risk aversion, and employment status), which we include as additional controls in both the regression equations; and $\epsilon_{i,t}$ and $\nu_{i,t}$ are two orthogonal error terms. In both the equations (8) and (9), we also control for the individual-level, lagged value of the (financial) wealth, denoted by $(F)W_{i,t-1}$. Specifically, we use the lagged total wealth when the dependent variable Y is either total wealth or total returns and we use the lagged financial wealth when the dependent variable Y is either financial wealth or financial returns. Under the assumption of normal distribution for both $\epsilon_{i,t}$ and $\nu_{i,t}$, we jointly estimate the two-equation model using maximum likelihood.

Through the first equation, we quantify the direct effect of education as well as the effect of the stock market participation dummy on Y. To assess the indirect effect of education through the decision to participate in the stock market, we use the dummy variable of stock market participation in equation (9). By doing this, we quantify the effect of education on the propensity to participate in the stock market by estimating equation (9). The indirect effect of education on the dependent variable Y is then given by the product between the impact of education on the decision to participate in the stock market (δ_1) and the impact of stock market participation on Y (β_1). As a result, the *total* effect of education on Y is given by the sum of the direct and indirect effects:

$$\begin{aligned} \text{Direct effect} &= \beta_2 \\ \text{Indirect effect} &= \beta_1\delta_1 \\ \text{Total effect} &= \beta_2 + \beta_1\delta_1 \end{aligned}$$

First, we use either total or financial wealth as dependent variable Y, the results of which we report in columns (1) and (2) of Table 6. In panel A, we document a positive and significant relationship between education and both total and financial wealth as well as a positive and significant relationship between stock market participation and both total and financial wealth. The impact of education on financial wealth is slightly larger in magnitude compared to the impact on total wealth. Meanwhile, in panel B, we report in columns (1) and (2) a positive and significant impact of education on the decision to invest in the stock market—that is, holding a college degree significantly increases the propensity to participate in the stock market, and this continues to be the case after controlling for unobserved ability and lagged wealth. Consistently, we confirm that individual skills are positively and significantly associated with stock market participation across different model specifications (columns (1) to (4)). Plus, we corroborate a positive and significant link between unobserved ability and both total wealth and financial wealth.

Next, we focus on returns to wealth by using either returns to total wealth or returns to financial wealth as a dependent variable Y, the results of which we report in columns (3) and (4) of Table 6 (panel A). We find that stock market participation has a positive and significant impact on both financial and total returns. However, the impact of stock market participation on financial returns is substantially larger in magnitude compared to the impact on total returns—that is, investing in stocks increases annual financial returns by 6.1% and annual total returns by 3.5%. Meanwhile, in panel B, we provide evidence in columns (3) and (4) of the positive and significant effect of education on the decision to invest in stocks. However, the direct relationship between education and returns to wealth as well as between individual skills and returns to wealth is positive but statistically weak.

We then report the direct, indirect, and total effects of education and unobserved skills on the level and returns to wealth in Table 7. Education has a positive and significant impact (both directly and through stock market participation) on both total and financial wealth. Both the direct and indirect effects on financial wealth are similar in magnitude to those on total wealth: holding a college degree increases the total (financial) wealth by 4.6% (4.4%) through the positive impact that higher education has on the propensity to participate in the stock market. On the other hand, the unobserved, individual ability increases the total (financial) wealth by 3.4% (3.3%) through the positive impact that high skills exert on the propensity to invest in the stock market.

Importantly, the impact of both education and individual skills on the returns to both total and financial wealth occur only through the decision to participate in the stock market. More specifically, college-graduated individuals earn annual 0.4% extra-returns on financial wealth and 0.2% extra-returns on total wealth thanks to the positive effect of higher education on the propensity to invest in the stock market. Similarly, skilled individuals earn annual 0.3% extra-returns on financial wealth and 0.2% extra-returns on total wealth due to the positive effect of better unobserved ability on the propensity to invest in the stock market. These effects are highly statistically significant and economically important, accounting for a large fraction of the overall estimated extra-returns to total and financial wealth.

[Table 6 about here.]

[Table 7 about here.]

4.3. Additional Results & Robustness

Lastly, we perform a set of additional checks and robustness tests. First, we limit the sample time series up to 2019 in order to control for the potential confounding effects of the COVID-19 pandemic. This means that we exclude from our analysis the last three survey waves (i.e., 2020 to 2022) and highlight that our results are unaffected by the sample time series restriction (Table 8). Moreover, in the estimated regressions presented in Table 6, we employ individual-level, lagged financial wealth as a control variable when the dependent variable is either financial wealth or financial returns. Instead, we now use the individual-level, lagged total wealth as a control variable and find that, across all model specifications, our results are unaltered (Table 9). Next, we further stress the relevance of individual skills in our empirical analysis by excluding our individual-level measure of unobserved ability from the estimated regression equations, the results of which we report in Table 10. While the beneficial effect of education on both the level and returns to wealth retains statistical and economical significance, its magnitude is now larger. Intuitively, better education now partially absorbs the previously documented positive and significant impact of the omitted unobserved ability. As an additional robustness test, we also employ a stricter definition of *college* degree by only classing those individuals with a university degree as college graduates. This means that individuals who have undergone vocational training are allocated to the non-college-graduated group. In Table 11, we show that, after applying these changes, our results generally hold, which suggests that the highest level of education is a major driver of our findings.

Finally, we test in our sample the prediction that highly educated individuals exhibit a propensity for well-diversified portfolios rather than single stocks and study whether this preference has an impact on both the level and returns to wealth. To do this, we use information on whether individuals hold stocks either directly or through shares of mutual funds. To reflect this, in each wave t, the DHS includes a dummy variable ($OwnSTK_{i,t}$) equal to 1 if the individual i has invested in the stock market by using stocks directly, and zero otherwise. Similarly, the dummy variable $OwnMF_{i,t}$ is equal to 1 if the individual i has invested in the stock market through mutual funds, and zero otherwise. We then use the variables $OwnSTK_{i,t}$ and $OwnMF_{i,t}$ as mediator variables in the simultaneous two-equation model presented in Section 4. Specifically, we use either $OwnSTK_{i,t}$ or $OwnMF_{i,t}$ as a mediator variable to study the effect of education on wealth and returns to wealth through the channel of stock market participation, following the approach outlined in Section 4. We report our results on direct stockholding in Table 12 and on mutual funds shareholding in Table 13. First, we confirm that better-educated individuals display a significantly higher propensity to invest in the stock market using shares of mutual funds compared to their non-college-graduated peers, but there are no significant differences across college- and non-college-graduated individuals in terms of their preference for direct stockholding. Importantly, we find that mutual funds shareholding is strongly associated with higher returns to wealth but that this relationship is substantially weaker when using direct stockholding. Moreover, it transpires that the beneficial, indirect effect of education on returns to wealth through stock market participation is positive and statistically significant only when using shares of mutual funds. This finding suggests that the mechanism through which education improves wealth returns is by increasing the propensity of the individual to invest in the stock market using well-diversified portfolios which have historically delivered higher risk-adjusted returns than single stocks.

[Table 8 about here.]

[Table 9 about here.]

[Table 10 about here.]

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

5. Conclusions

A recent strand of literature (Benhabib et al. (2011), Gabaix et al. (2016)) argues that idiosyncratic, persistent shocks to wealth may certainly foster a significant correlation between the level and returns to wealth and thus wealth accumulation over time, which justifies such tick right tail of the wealth distribution observed in the data. Whether individual abilities, such as genetic talent and cognitive skills, can explain idiosyncratic returns to wealth is an open and intriguing question that is receiving growing attention in the academic debate on wealth inequality. We contribute to this important discussion by exploring whether education can alleviate wealth inequality by allowing otherwise unskilled individuals to make proficient investment decisions, thus ultimately closing the gap between the top and bottom tails of the wealth distribution. Our results are encouraging: education has a positive, significant, and sizeable impact on both the level and returns to wealth through the channel of financial investment decisions when conditioning on unobserved, individual abilities. Based on these findings, we recommend that policymakers strongly promote public education in order to address worldwide limited stock market participation and huge wealth inequality.

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Acknowledgements. We are grateful to Elsa Fornero, Giovanna Nicodano, Francesca Parodi, Beniamino Pisicoli, Paolo Sodini and seminar participants at the NETSPAR International Pensions Workshop 2023, the Global Finance Conference 2023, the Leuven Economics of Education Conference 2023, the Quantitative Finance Workshop 2023, the ESOMAS Department (University of Torino) brown bag series 2022, the CeRP Workshop on Financial Literacy 2021, for their useful feedback on the paper. Raffaele Corvino and Francesco Ruggiero acknowledge financial support by the Observatoire de l'Espargne Europeenne (OEE).

Appendix A Model Solution

We detail here our numerical approach to obtain the model solution. First, we define a grid of values for δ and τ both bounded between 0 and 1. Then, for each possible combination of δ and τ, we determine the equilibrium denoted by the triple

$$\{m^*(\delta,\tau), l^*(\delta,\tau), b^*(\delta,\tau)\}, \tag{A1}$$

that are the shares of individuals investing in stocks, joining a gamble, and storing money into the bank deposit, respectively, for a given value of δ and τ. To determine the equilibrium, we proceed as follows. We set the first combination of δ and τ, that we denote by $\{\delta^1,\tau^1\}$. Next, we start from an arbitrary value of m, denoted by m^0 and so $K^0 = m^0 \cdot N$. Given K^0, each individual chooses whether to invest in stocks, join a gamble, or use the bank deposit, by maximizing expected utility over final consumption, as defined in (1). By solving (**??**) for all the individuals, we obtain a triple

$$\{m^{'}(K^0,\delta^1,\tau^1), l^{'}(K^0,\delta^1,\tau^1), b^{'}(K^0,\delta^1,\tau^1)\},$$

that are the shares of individual investing in stocks, joining a gamble, and saving money into the bank deposit, respectively, given $K = K^0$, $\delta = \delta^1$, and $\tau = \tau^1$. We also denote by $C_i^{'}$ the value of C_i corresponding to the i-th individual choice based on K^0 and $\{\delta^1,\tau^1\}$. We then update K using $K^{'} = m^{'} \cdot N$ and find the new triple $\{m^{''}(K^{'},\delta^1,\tau^1), l^{''}(K^{'},\delta^1,\tau^1), b^{''}(K^{'},\delta^1,\tau^1)\}$ resulting from the individual choice based now on $K^{'}$ and $\{\delta^1,\tau^1\}$. We compute $C_i^{''}$, that is the value of C_i corresponding to the i-th individual choice based on $K^{'}$ and $\{\delta^1,\tau^1\}$, and determine the difference between $C_i^{''}$ and $C_i^{'}$ for each individual, that we denote by ΔC_i. We iterate the procedure until convergence, that we define as follows:

$$|\Delta C_i| < \epsilon \quad \forall i,$$

where $|\Delta C_i|$ is the absolute value of ΔC_i and ϵ is sufficiently small; that is, there is no individual who has incentive to deviate from the current allocation of the endowment, given $\delta = \delta^1$ and $\tau = \tau^1$. When we reach convergence, we store the solution as the equilibrium triple $\{m^*(\delta^1, \tau^1), l^*(\delta^1, \tau^1), b^*(\delta^1, \tau^1)\}$. We repeat this process for each combination of δ^j and τ^j, with j going from 1 to n, where n is the length of the grids of δ and τ. Thus, we obtain a matrix n x n of equilibrium triples denoted by $\{m^*(\delta^j, \tau^j), l^*(\delta^j, \tau^j), b^*(\delta^j, \tau^j)\}$.

For each element of this matrix, that is for each equilibrium triple, we compute social welfare by using the welfare utility function defined in (6). Thus, we obtain a matrix n x n of potential values of $J(\delta, \tau)$, denoted by $J^j = J(\delta^j, \tau^j)$, corresponding to different combinations of δ and τ. We select within this matrix the highest J^j, thus finding the pair of values of δ and τ that maximize J. This pair is the combination of δ and τ corresponding to the highest value of J. As a result, we finally obtain the corresponding equilibrium triple, as defined in (A1):

$$\{m^*(\delta^*, \tau^*), l^*(\delta^*, \tau^*), b^*(\delta^*, \tau^*)\}.$$

Appendix B Investing or Gambling? Evidence from the 1993 wave

In this Section, we focus on the 1993 wave that contains information about the decision to participate to a gamble at the individual level. This sample includes 2,794 households and 5,091 individuals. Our main variables of interest are: *Stock*, that is a dummy variable equal to 1 if the individual has invested in the stock market either directly or through mutual funds in the previous year, and zero otherwise; *Lottery*, that is a dummy variable equal to 1 if the individual has participated at least once to a gamble in the previous year, and zero otherwise; In addition, we consider a set of personal characteristics which may influence the individual behaviour, such as education, labour income, employment, wealth, age, family size, gender, health, financial literacy, and risk aversion. Variables are described in table 14.

[Table 14 about here.]

We summarize the data in Table 15. The sample is relatively young: the average age is less than 43, 15% of the individuals has obtained a college degree, and the average level of education is 2.31 on a 1-5 scale, where 5 is the top education level. The sample is balanced across genders. The vast majority of individuals has an occupation: 8% is unemployed and 10% is retired. The self-valuation of the financial literacy is relatively low while the individuals are generally highly risk-averse.

We confirm in our sample the stylized fact of a limited participation to the stock market: 18% of the individuals hold stocks, either directly or through mutual funds, in line with participation rates in early 1990s in other developed countries, such as US and UK. The fraction of individuals who have joined a gamble is exactly twice than the one investing in stocks. Moreover, we document a strong dichotomy between stock market participation and gambling: only 4% of individuals have both invested in stocks and joined a gamble, which means that roughly 90% of those gambling do not invest in stocks and almost 80% of those participating to the stock market have not played a lottery.

[Table 15 about here.]

We offer graphical evidence about the relationship between education and preference for stocks or gambling in Figure 9. We split the individuals in quartiles according to their education rank and we compute the participation rates to the stock market and lottery within each quartile. For each quartile, we also compute the average share of financial wealth allocated to stocks either directly or through mutual funds. We execute the same analysis using quartiles of individual wealth. We document a clear pattern of stock market participation and shareholding across both education and wealth quartiles. The participation rates to the stock market for the top and bottom education grades are 0.25 and 0.11, respectively,

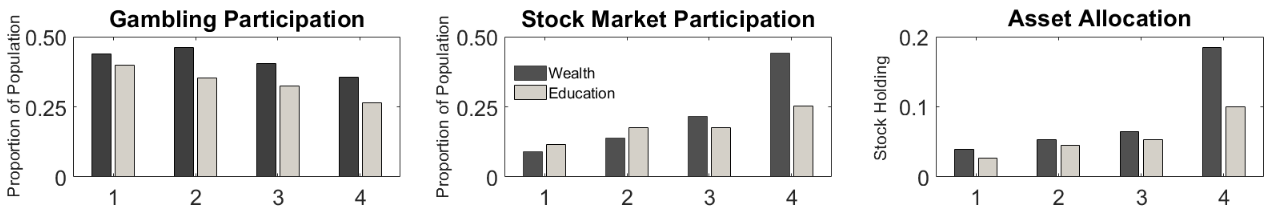

Figure 9. Investment Decisions. Education and Wealth quartiles. The figure reports evidence about participation rates to gambling and stock market, and about asset allocation decision, for quartiles of wealth and education rank. We split individuals in quartiles according to total wealth and education grade. Then, for each quartile, we report the fraction of individuals who has joined a lottery at least once in the year (left panel), the fraction of individuals who has participated to the stock market during the year (mid panel), and the average share of financial wealth allocated to stocks either directly or through mutual funds.

and are 0.44 and 0.09 for the top and bottom wealth quartiles, respectively. Similarly, the average shares of financial wealth allocated to stocks for the top and bottom education sub-samples are 0.10 and 0.02, respectively, and are 0.18 and 0.04 for the top and bottom wealth sub-samples, respectively. Instead, the pattern of the participation rates to the lottery is monotonic across education quartiles but is hump-shaped across wealth quartiles. This evidence suggests that preference for gambling is more sensitive to the level of education than to the level of wealth of the individual. Stepping down from top to bottom education ranks, the fraction of individuals who have joined a gamble increases from 0.26 to 0.40.

Next, we relate the decision to participate to the stock market and join a gamble, to individual observable characteristics by using a probit analysis. We regress the dummy variables Stock and Lottery over a set of personal traits and we report results in Table 16.

[Table 16 about here.]

Our main finding is that the education achievement is the only characteristic with explanatory power for both the decision to invest in stocks (columns (1)-(2)) and for the decision to play a lottery (columns (3)-(4)). Specifically, the level of education is the only statistically significant predictor of the decision to play a lottery, by using either a dummy variable for the college degree (*College*, column (3)) or a categorical ranking variable (*School*, column (4)) for the education grade. On the other hand, the level of education is among the few significant predictors of the decision to participate to the stock market, more than wealth, risk aversion, and financial literacy (columns (1)-(2)). In particular, the education rank is positively correlated with stock market participation and negatively correlated with gambling: more educated individuals are less willing to join a gamble and more likely invest in stocks. While displaying opposite signs, the estimated regression coefficients for both College and Education are very similar in magnitude across columns (1)-(2) and (3)-(4), respectively. Moreover, our estimates are economically significant. The propensity to invest in stocks of an individual in principle indifferent between stock and lottery increases by 12% when the individual obtains a college degree. Meanwhile, the propensity to join a gamble drops by 12%. In fact, the probability that a dummy variable Y takes value equal to 1, according to the probit model, is given by

$$P(Y = 1) = \Phi\left(\sum_{k=1}^{K} \beta_k X_k\right), \tag{B2}$$

where Φ stands for the cumulative distribution function of a standard normal variable, β_k is the coefficient estimated with the probit regression for the variable k, and X_k is the value of the k-th independent variable. Therefore, the marginal effect of the k-th variable on $P(Y = 1)$ is simply given by

$$\frac{\partial P(Y = 1)}{\partial X_k} = \frac{\partial \Phi(\beta' X)}{\partial X_k} = \phi(\beta' X)\beta_k, \tag{B3}$$

where ϕ stands for the probability distribution function of a standard normal variable, and $\beta' X$ is the equivalent in matrix notation of the argument of Φ in (B2). In this example, we are considering two individuals with original propensity to participate to the stock market or join a gamble equal to 50%, that corresponds to $\beta' X = 0$, since $\beta' X = \Phi^{-1}(P(Y_{i,t} = 1))$, where Φ^{-1} stands for the inverse of the cumulative distribution function of a standard normal variable. When $\beta' X = 0$, $\phi(\beta' X)$ is approximately equal to 0.40, then the probability that an individual without a college degree and propensity to participate to the stock market equal to 50% increases by 12% once obtained the college degree (0.297*0.40). Similarly, the probability that an individual without a college degree and propensity to join a gamble equal to 50% drops by 12% once obtained the college degree (0.299*0.40).

In Table 16, we also report results from a Tobit model estimation, in which the dependent variable is the share of financial wealth allocated to stocks either directly or through mutual funds (columns (5) and (6)) and the share of financial wealth allocated to stocks only (columns (7) and (8)). In line with probit regression results about stock market participation, we find that education significantly and positively affects individual shareholding, when using either a dummy variable for the college degree (columns (5) and (7)) or a categorical ranking variable (column (6) and (8)) for the education grade.

Table 1 Definitions of variables

Variable	Definition
Age	Years old.
Male	One if male and zero otherwise.
College	One if holds either a vocational training or University degree and zero otherwise.
University	One if holds a University degree and zero otherwise.
Retired	One if retired and zero otherwise.
Health status	Self-assessed general health status (rating from 1 to 5, where 1 is poor and 5 is excellent).
Risk aversion	Perception of risk (rating from 1 to 7, where 1 is risk seeker and 7 is risk averse).
HH Size	Household size (number of people in the household).
Urban	One if living in an urban area and zero otherwise.
Total Wealth	Net worth (Total Assets - Total Liabilities).
Financial Wealth	Financial component of Total Wealth.
OwnSTKMF	One if owns stocks or mutual funds shares and zero otherwise.
OwnSTK	One if owns stocks directly and zero otherwise.
OwnMF	One if owns mutual funds shares and zero otherwise.
PropSTKMF	Fraction of financial wealth invested in stocks.
Total Return	(log)-Growth rate of total wealth.
Financial Return	(log)-Growth rate of financial wealth.

Table 2 Summary statistics
This table reports the summary statistics for the variables used in the empirical analysis. We report the total number of observations, the mean, the standard deviation, the 5th, 50th and 95th percentiles. The definitions of the variables are in Table 1. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

Variable	Obs	Mean	Std. Dev.	p5	Median	p95
Age	47,797	50.94	14.11	28	51	72
Male	47,797	56.25%	49.61%	0	1	1
College	47,730	50.09%	50.00%	0	1	1
University	47,730	12.70%	33.30%	0	0	1
Retired	47,254	18.83%	39.10%	0	0	1
Health status	42,738	3.88	0.73	3	4	5
Risk Aversion	39,156	4.56	2.08	1	5	7
HH Size	47,797	2.51	1.27	1	2	5
Urban	43,492	38.62%	48.69%	0	0	1
Total Wealth (x1,000)	47,797	194.92	287.50	-0.94	77.13	650.55
Financial Wealth (x1,000)	47,797	35.74	96.91	0.00	1.46	150.25
Other Wealth (x1,000)	47,797	163.24	248.90	0.00	23.50	549.90
OwnSTKMF	47,797	18.13%	38.52%	0	0	1
PropSTKMF	43,227	8.00%	25.72%	0.00%	0.00%	63.54%
Total Return	33,402	2.67%	72.35%	-126.03%	0.00%	140.51%
Financial Return	32,196	2.51%	66.22%	-118.01%	0.00%	123.21%

Table 3 Individual Skills and Financial Investments: Descriptive Evidence
The table reports descriptive evidence about educational attainment, financial investments, and wealth returns, by sorting individuals on their estimated skills. We proxy individual skills using the unobserved, individual ability computed by estimating equation (7) using OLS. Then, we group individuals into quartiles. In panel A, for each skill quartile, we report the share of individuals holding a College degree (*College Share*), the share of individuals investing in the stock market (*Market Share*), the average share of financial wealth held in stocks - either directly or through mutual funds (*Equity Share*), the average financial and total returns. The definitions of the variables are in Table 1. Total returns and financial returns are detailed in Section 3. In Panel B, we compute the same quantities in each skill quartile, after sorting individuals on their educational attainment. Within each skill quartile, we split individuals into two sub-samples: college graduated and non-college graduated. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

PANEL A: Patterns by Unobserved Skills

Quartile	College Share	Market Share	Equity Share	Fin. Return	Tot. Return
Unskilled	29.90%	9.36%	4.65%	0.79%	1.63%
25-50th	38.94%	15.55%	6.03%	1.50%	2.36%
50-75th	58.37%	20.27%	7.96%	2.83%	3.15%
Skilled	78.77%	31.85%	14.41%	5.18%	3.51%

PANEL B: Patterns by Unobserved Skills and Education

	Market Share		**Equity Share**		**Fin. Return**		**Tot. Return**	
Quartile	No College	College	No College	College	No College	College	No College	College
Unskilled	7.88%	12.81%	3.82%	6.43%	0.22%	1.99%	1.02%	3.14%
25-50th	13.15%	19.36%	5.60%	6.70%	0.58%	2.90%	2.36%	2.32%
50-75th	14.51%	24.37%	5.45%	9.68%	1.80%	3.49%	3.12%	3.16%
Skilled	26.52%	33.29%	10.89%	15.33%	7.65%	4.53%	5.15%	3.07%

Table 4 Household Wealth Regressions
The table reports results from OLS regression using data described in Section 3. The dependent variable is either the (log)-Total Wealth (Panel A), the (log)-Financial Wealth (Panel B), or the (log)-Other Wealth (Panel C). We use identical model specification and independent variables across Panels A, B, and C. The main independent variable ($\hat{f}_i$) is the unobserved, individual ability computed by estimating equation (7) using OLS. In column (1), we do not include additional controls. In column (2), we control for demographic, personal characteristics, such as age, age squared, gender, and household size. In columns (3) and (4), we control for the individual's educational attainment (*Education*) and the (log)-labour net income (*Labour Income*), respectively. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. In column (5), we include the entire set of control variables. In columns (2) to (5), we also include year-fixed effects. In columns (2) to (5), we suppress the coefficients of control variables to save in space. The definitions of the variables are in Table 1. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	PANEL A: (log)-Total Wealth				
	(1)	(2)	(3)	(4)	(5)
$\hat{f}_i$	1.130***	1.097***	1.014***	0.939***	0.840***
	(0.021)	(0.023)	(0.024)	(0.032)	(0.033)
Education			0.299***		0.309***
			(0.023)		(0.023)
Labour Income				0.164***	0.179***
				(0.025)	(0.025)
Observations	30,141	30,141	30,141	30,141	30,141
R2	0.152	0.314	0.319	0.316	0.320
Controls		X	X	X	X
	PANEL B: (log)-Financial Wealth				
	(1)	(2)	(3)	(4)	(5)
$\hat{f}_i$	1.162***	1.137***	1.045***	1.070***	0.962***
	(0.019)	(0.021)	(0.022)	(0.030)	(0.031)
Education			0.330***		0.335***
			(0.023)		(0.023)
Labour Income				0.070***	0.085***
				(0.036)	(0.036)
Observations	30,757	30,757	30,757	30,757	30,757
R2	0.158	0.273	0.278	0.273	0.278
Controls		X	X	X	X
	PANEL C: (log)-Other Wealth				
	(1)	(2)	(3)	(4)	(5)
$\hat{f}_i$	1.006***	1.003***	0.944***	0.849***	0.778***
	(0.023)	(0.026)	(0.029)	(0.037)	(0.039)
Education			0.194***		0.203***
			(0.025)		(0.025)
Labour Income				0.164***	0.175***
				(0.030)	(0.030)
Observations	26,059	26,059	26,059	26,059	26,059
R2	0.110	0.235	0.237	0.236	0.238
Controls		X	X	X	X

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5 Risk Aversion and Stock Market Participation
The table reports results from OLS regression using data described in Section 3. The dependent variable is either the individual's *Risk Aversion* (columns (1) and (2)), the share of individuals investing in the stock market (columns (3) and (4)), or the average share of financial wealth held in stocks - either directly or through mutual funds (columns (5) and (6)). We identify the individual's risk aversion by using a categorical variable ranging between 1 and 7, where 7 stands for high risk aversion. The main independent variable ($\hat{f}_i$) is the unobserved, individual ability computed by estimating equation (7) using OLS. In columns (1) to (6), we control for the individual's educational attainment (*Education*) and the (log)-labour net income (*Labour Income*) as well as for demographic, personal characteristics, such as age, age squared, gender, and household size. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. In columns (2), (4), and (6), we also control for the individual's initial wealth by sorting individuals in quartiles (*Wealth Class*). In columns (1) to (6), we also include year-fixed effects. In columns (1) to (6), we suppress the coefficients of control variables to save in space. The definitions of the variables are in Table 1. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	(1) Risk Aversion	(2) Risk Aversion	(3) Market Share	(4) Market Share	(5) Equity Share	(6) Equity Share
$\hat{f}_i$	-0.218***	-0.117***	0.071***	0.026***	0.028***	0.012***
	(0.031)	(0.031)	(0.005)	(0.005)	(0.003)	(0.003)
Education	-0.518***	-0.482***	0.095***	0.078***	0.048***	0.042***
	(0.025)	(0.025)	(0.004)	(0.004)	(0.003)	(0.003)
Labour Income	-0.032	-0.017	0.003	-0.003	-0.001	-0.004
	(0.025)	(0.025)	(0.004)	(0.004)	(0.002)	(0.002)
Wealth class		-0.211***		0.095***		0.036***
		(0.013)		(0.002)		(0.002)
Observations	29,427	29,427	33,862	33,862	31,041	31,041
R2	0.094	0.102	0.089	0.135	0.040	0.054
Controls	X	X	X	X	X	X

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6 The Education Effect: Structural Equation Model.
The table reports results from Maximum Likelihood estimation using data described in Section 3. We estimate the simultaneous two-equation model described in equations (8) and (9). In Panel A, we report estimation results about equation (8), in which we use as dependent variable either the (log)-*Total Wealth* (column (1)), the (log)-*Financial Wealth* (column (2)), the *Total Returns* (column (3)) or the *Financial Returns* (column (4)). *Total Returns* and *Financial Returns* are defined in Section 3. In columns (1) to (4), the main independent variables are the following: the individuals' decision to participate to the stock market (*OwnSTKMF*), the educational attainment (*Education*), and the unobserved, individual ability (*Skills*) computed by estimating equation (7) using OLS. *OwnSTKMF* is a dummy variable equal to 1 if the individual holds stocks either directly or through mutual funds in year t, and zero otherwise. *Education* is a a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. In columns (1)-(3) and (2)-(4), we control for the lagged, individual-level (log)-Total Wealth and (log)-Financial Wealth, respectively. We include year-fixed effects and demographic, personal characteristics, such as age, age squared, gender, and household size, we suppress the coefficients of control variables to save in space. In Panel B, we report estimation results about equation (9), in which we use as dependent variable the individuals' decision to participate to the stock market (*OwnSTKMF*). Model specifications and independent variables in Panel B are equivalent to those described for Panel A. Standard errors are clustered at the individual-level. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	Panel A			
	Total Wealth	Financial Wealth	Total Returns	Financial Returns
	(1)	(2)	(3)	(4)
Total Wealth$_{t-1}$	-0.025***		0.001	
	(0.009)		(0.003)	
Financial Wealth$_{t-1}$		0.019***		-0.001
		(0.006)		(0.003)
OwnSTKMF	0.786***	0.702***	0.035***	0.061***
	(0.045)	(0.059)	(0.012)	(0.013)
Education	0.278***	0.309***	0.006	0.001
	(0.053)	(0.071)	(0.010)	(0.011)
Skills	0.856***	0.863***	0.011	0.009
	(0.043)	(0.059)	(0.008)	(0.008)
	Panel B			
	OwnSTKMF			
	(1)	(2)	(3)	(4)
Total Wealth$_{t-1}$	0.007***		0.007***	
	(0.002)		(0.002)	
Financial Wealth$_{t-1}$		0.004**		0.004**
		(0.002)		(0.002)
Education	0.058***	0.062***	0.057***	0.063***
	(0.011)	(0.012)	(0.012)	(0.013)
Skills	0.043***	0.047	0.049***	0.049***
	(0.007)	(0.008)	(0.007)	(0.008)
Controls	Yes	Yes	Yes	Yes
Observations	17,225	15,221	15,973	13,319

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. The Education Effect: *Direct* and *Indirect* Effects.
The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnSTKMF*, which is both an independent variable in (8) and the dependent variable in (9). *OwnSTKMF* is a dummy variable equal to 1 if the individual holds stocks either directly or through mutual funds in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	Total Wealth (1)	Financial Wealth (2)	Total Returns (3)	Financial Returns (4)
Direct Effect:				
Education	0.278***	0.309***	0.006	0.001
	(0.053)	(0.071)	(0.010)	(0.011)
Skills	0.856***	0.863***	0.011	0.009
	(0.043)	(0.059)	(0.008)	(0.008)
Indirect Effect:				
Education	0.046***	0.044***	0.002**	0.004***
	(0.009)	(0.009)	(0.001)	(0.001)
Skills	0.034***	0.033***	0.002***	0.003***
	(0.006)	(0.006)	(0.001)	(0.001)
Total Effect:				
Education	0.324***	0.353***	0.008	0.005
	(0.054)	(0.072)	(0.010)	(0.011)
Skills	0.889***	0.896***	0.012	0.012
	(0.043)	(0.060)	(0.008)	(0.008)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8. The Education Effect: *Direct* and *Indirect* Effects. Excluding Covid
The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnSTKMF*, which is both an independent variable in (8) and the dependent variable in (9). *OwnSTKMF* is a dummy variable equal to 1 if the individual holds stocks either directly or through mutual funds in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2019.

	Total Wealth (1)	Financial Wealth (2)	Total Returns (3)	Financial Returns (4)
Direct Effect:				
Education	0.255***	0.304***	0.005	0.000
	(0.056)	(0.075)	(0.011)	(0.012)
Skills	0.885***	0.890***	0.019**	0.015*
	(0.045)	(0.061)	(0.008)	(0.009)
Indirect Effect:				
Education	0.049***	0.050***	0.002**	0.004***
	(0.010)	(0.010)	(0.001)	(0.001)
Skills	0.033***	0.032***	0.002***	0.003***
	(0.006)	(0.007)	(0.001)	(0.001)
Total Effect:				
Education	0.304***	0.353***	0.007	0.004
	(0.057)	(0.076)	(0.011)	(0.012)
Skills	0.918***	0.922***	0.021**	0.018**
	(0.046)	(0.062)	(0.008)	(0.009)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9. The Education Effect: *Direct* and *Indirect* Effects. Controlling for Total Wealth
The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnSTKMF*, which is both an independent variable in (8) and the dependent variable in (9). *OwnSTKMF* is a dummy variable equal to 1 if the individual holds stocks either directly or through mutual funds in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022. Here we use total wealth as a control variable in both the equations (8) and (9) in columns (1) to (4).

	Total Wealth (1)	Financial Wealth (2)	Total Returns (3)	Financial Returns (4)
Direct Effect:				
Education	0.278***	0.330***	0.006	-0.004
	(0.053)	(0.065)	(0.010)	(0.010)
Skills	0.856***	0.846***	0.011	0.020***
	(0.043)	(0.052)	(0.008)	(0.008)
Indirect Effect:				
Education	0.046***	0.041***	0.002**	0.004***
	(0.009)	(0.008)	(0.001)	(0.001)
Skills	0.034***	0.032***	0.002***	0.004***
	(0.006)	(0.006)	(0.001)	(0.001)
Total Effect:				
Education	0.324***	0.371***	0.008	0.000
	(0.054)	(0.066)	(0.010)	(0.010)
Skills	0.889***	0.879***	0.012	0.023***
	(0.043)	(0.053)	(0.008)	(0.008)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10. The Education Effect: *Direct* and *Indirect* Effects. Unconditional on Skills
The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnSTKMF*, which is both an independent variable in (8) and the dependent variable in (9). *OwnSTKMF* is a dummy variable equal to 1 if the individual holds stocks either directly or through mutual funds in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022. Here we do not include *Skills* as a control variable in both the equations (8) and (9) in columns (1) to (4).

	Total Wealth (1)	Financial Wealth (2)	Total Returns (3)	Financial Returns (4)
Direct Effect:				
Education	0.665***	0.714***	0.014	0.007
	(0.052)	(0.070)	(0.009)	(0.010)
Skills	NO	NO	NO	NO
Indirect Effect:				
Education	0.074***	0.073***	0.003***	0.005***
	(0.010)	(0.011)	(0.001)	(0.001)
Skills	NO	NO	NO	NO
Total Effect:				
Education	0.739***	0.787***	0.017*	0.012
	(0.053)	(0.071)	(0.009)	(0.010)
Skills	NO	NO	NO	NO

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11. The Education Effect: *Direct* and *Indirect* Effects. University only
The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnSTKMF*, which is both an independent variable in (8) and the dependent variable in (9). *OwnSTKMF* is a dummy variable equal to 1 if the individual holds stocks either directly or through mutual funds in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a University degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	Total Wealth	Financial Wealth	Total Returns	Financial Returns
	(1)	(2)	(3)	(4)
Direct Effect:				
Education	0.328***	0.387***	-0.006	-0.005
	(0.059)	(0.082)	(0.013)	(0.014)
Skills	0.891***	0.903***	0.013*	0.010
	(0.041)	(0.058)	(0.007)	(0.008)
Indirect Effect:				
Education	0.062***	0.056***	0.002**	0.004***
	(0.015)	(0.015)	(0.001)	(0.002)
Skills	0.040***	0.039***	0.002***	0.004***
	(0.006)	(0.006)	(0.001)	(0.001)
Total Effect:				
Education	0.389***	0.443***	-0.004	-0.001
	(0.060)	(0.084)	(0.012)	(0.014)
Skills	0.931***	0.942***	0.015	0.013
	(0.042)	(0.058)	(0.007)	(0.008)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12. The Education Effect: *Direct* and *Indirect* Effects. Direct stockholding

The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnSTK*, which is both an independent variable in (8) and the dependent variable in (9). *OwnSTK* is a dummy variable equal to 1 if the individual holds stocks directly in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	Total Wealth (1)	Financial Wealth (2)	Total Returns (3)	Financial Returns (4)
Direct Effect:				
Education	0.304***	0.330***	0.008	0.004
	(0.054)	(0.072)	(0.010)	(0.011)
Skills	0.876***	0.882***	0.012	0.011
	(0.043)	(0.059)	(0.008)	(0.008)
Indirect Effect:				
Education	0.020***	0.023***	0.001	0.002**
	(0.006)	(0.007)	(0.000)	(0.001)
Skills	0.014***	0.014***	0.000	0.001**
	(0.004)	(0.005)	(0.000)	(0.001)
Total Effect:				
Education	0.324***	0.353***	0.008	0.005
	(0.054)	(0.072)	(0.010)	(0.011)
Skills	0.889***	0.896***	0.012	0.012
	(0.043)	(0.060)	(0.008)	(0.008)

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13. The Education Effect: *Direct* and *Indirect* Effects. Mutual funds shares
The table reports the direct and indirect effects of *Education* and *Skills* on both wealth and returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in table 6, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (8) and (9) using data described in Section 3. Specifically, we estimate the direct effect from equation (8) and we compute the indirect effect by combining results from simultaneous estimation of equations (8) and (9). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (8) through the impact on *OwnMF*, which is both an independent variable in (8) and the dependent variable in (9). *OwnMF* is a dummy variable equal to 1 if the individual holds stocks though mutual funds in year t, and zero otherwise. We then compute the total effect as the sum of the direct and indirect effects. Detailed formula for both direct and indirect effects are provided in Section 4. *Skills* is the unobserved, individual ability computed by estimating equation (7) using OLS. *Education* is a dummy variable equal to 1 if the individual holds a College degree, and zero otherwise. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank. Data are on annual basis and cover waves from 1993 to 2022.

	Total Wealth (1)	Financial Wealth (2)	Total Returns (3)	Financial Returns (4)
Direct Effect:				
Education	0.291***	0.323***	0.007	0.002
	(0.053)	(0.072)	(0.010)	(0.011)
Skills	0.865***	0.875***	0.011	0.010
	(0.043)	(0.059)	(0.008)	(0.008)
Indirect Effect:				
Education	0.033***	0.030***	0.002**	0.003***
	(0.007)	(0.007)	(0.001)	(0.001)
Skills	0.025***	0.022***	0.002***	0.002***
	(0.005)	(0.005)	(0.001)	(0.001)
Total Effect:				
Education	0.324***	0.353***	0.008	0.005
	(0.054)	(0.072)	(0.010)	(0.011)
Skills	0.889***	0.896***	0.012	0.012
	(0.043)	(0.060)	(0.008)	(0.008)

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14   Definitions of variables. Wave 1993

Variable	Definition
Stock	One if owns stocks either directly or through mutual funds and zero otherwise.
Lottery	One if has joined a gamble and zero otherwise.
Both	One if own stocks or mutual funds and has also joined a gamble, and zero otherwise.
Share (STK & MF)	Fraction of financial wealth invested in stocks either directly or through mutual funds.
Share (STK)	Fraction of financial wealth invested in stocks only.
Bank	One if has bank deposits and zero otherwise.
Ln(NetWorth)	Log of net worth.
Ln(NetIncome)	Log of net income.
HH size	Household size (Number of people in the household).
Age	Years old.
College	One if college graduated and zero otherwise.
Education	Level of education (rating from 1 to 5, where 5 is the top education level).
Male	One if male and zero otherwise.
Unemployed	One if unemployed and zero otherwise.
Retired	One if retired and zero otherwise.
Health	Health rating (1-5, with 5 being in good).
Fin. Literacy	Level of financial knowledge (rating from 1 to 7, where 7 stands for top self-valuation of financial knowledge).
Risk aversion	Perception of risk (rating from 1 to 7, where 7 is belief that investing in stocks is very risky).

Table 15 Summary statistics. Wave 1993

This table reports the summary statistics for the variables used in the empirical analysis. The data are from the Dutch Household Servey (DHS) by the Dutch National Bank for the wave 1993. We report the mean, the standard deviation, the 1st, 50th, and 99th percentiles. N is the total number of observations. The definitions of the variables are in Table 14.

Variable	Mean	Standard Deviation	p1	Median	p99	N
Stock	0.18	0.38	0	0	1	5091
Lottery	0.36	0.88	0	0	1	3953
Both	0.04	0.20	0	0	0	3953
Bank	0.30	0.46	0	0	1	5091
PropStock	0.05	0.23	0	0	0.14	3469
PropLottery	0.04	6.67	0	0.01	0.18	1870
Ln(NetWorth)	11.78	1.78	9.10	12.38	13.29	2244
Ln(NetIncome)	10.40	1.08	9.08	10.59	11.42	3223
HH Size	2.85	1.31	1	2	5	4799
Age	42.74	15.21	23	42	65	4799
College	0.15	0.36	0	0	1	5091
Education	2.31	1.49	1	2	5	5091
Male	0.52	0.50	0	1	1	4799
Unemployed	0.08	0.28	0	0	0	5091
Retired	0.10	0.30	0	0	0	4799
Health	4.08	0.77	3	4	5	4796
Fin. Literacy	2.27	2.69	0	2	6	4810
Risk Aversion	5.08	1.68	3	5	7	3037

Table 16 Probit and Tobit Analysis. Wave 1993

This table reports results from regression estimates about the decision to participate to the stock market, join a lottery, and about the asset allocation decision. Columns (1) to (4) report results from Probit regressions, in which the independent variable is either *Stock* (columns (1)-(2)) or *Lottery* (columns (3)-(4)), where *Stock* is a dummy variable equal to 1 if the individual has invested in the stock market either directly or through mutual funds in the previous year and zero otherwise, and *Lottery* is a dummy variable equal to 1 if the individual has participated at least once to a gamble in the previous year and zero otherwise. Columns (5) to (8) report results from Tobit regressions. In columns (5) and (6), the dependent variable is the *Share* of financial wealth held in stocks either directly or through mutual funds (STK & MF). In columns (7) and (8), the dependent variable is the *Share* of financial wealth held in stocks only (STK). The definitions of the independent variables are in Table 14. We report in parentheses the robust standard errors and ***,**,* over the regression coefficients denote statistical significance at the 0.1%, 1%, and 5% significance levels, respectively. The data are from the Dutch Household Survey (DHS) by the Dutch National Bank for the wave 1993. N is the total number of observations.

	Probit Model				**Tobit Model**			
	Stock		**Lottery**		**Share (STK& MF)**		**Share (STK)**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Costant	-6.865***	-7.085***	0.872	1.117	-4.682***	-4.579***	-6.124***	-5.898***
	(0.792)	(0.781)	(0.557)	0.(548)	(0.809)	(0.791)	(1.397)	(1.352)
Ln(NetWorth)	0.270***	0.273***	-0.046	-0.048	1.145***	1.072***	1.779***	1.653***
	(0.045)	(0.045)	(0.025)	(0.025)	(0.323)	(0.319)	(0.566)	(0.533)
Ln(NetIncome)	0.138*	0.143*	-0.038	-0.049	0.056	0.039	-0.003	-0.022
	(0.067)	(0.066)	(0.051)	(0.051)	(0.041)	(0.041)	(0.056)	(0.056)
HH Size	-0.040	-0.037	-0.017	-0.021	0.009	0.017	-0.003	-0.001
	(0.037)	(0.037)	(0.029)	(0.029)	(0.022)	(0.021)	(0.033)	(0.033)
Age	0.011*	0.011*	-0.003	-0.003	0.009***	0.010***	0.013 ***	0.013***
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)
College	0.297**		-0.299**		0.162***		0.171**	
	(0.097)		(0.086)		(0.052)		(0.078)	
Education		0.071**		-0.048*		0.093***		0.106***
		(0.025)		(0.028)		(0.022)		0.035
Male	-0.006	-0.010	0.192	0.189	0.055	0.063	0.074	0.076
	(0.131)	(0.131)	(0.096)	(0.096)	(0.085)	(0.085)	(0.136)	(0.134)
Unemployed	-0.799	-0.816	0.116	0.134				
	(0.590)	(0.583)	(0.281)	(0.279)				
Retired	0.326*	0.321	-0.091	-0.080	0.136	0.136	0.140	0.140
	(0.149)	(0.149)	(0.126)	(0.126)	(0.089)	(0.088)	(0.132)	(0.132)
Health	0.011	0.014	-0.034	-0.039	0.001	-0.009	-0.012	0.024
	(0.058)	(0.058)	(0.046)	(0.046)	(0.035)	(0.035)	(0.053)	(0.053)
Fin. Literacy	0.243***	0.242***	0.012	0.011	0.098***	0.095***	0.137***	0.135***
	(0.023)	(0.023)	(0.017)	(0.017)	(0.014)	(0.014)	(0.024)	(0.024)
Risk Aversion	-0.084**	-0.083**	0.022	0.021	-0.044***	-0.043***	-0.082***	-0.082***
	(0.027)	(0.027)	(0.021)	(0.021)	(0.016)	(0.016)	(0.024)	(0.024)
Pseudo R2	0.218	0.217	0.014	0.011	0.234	0.243	0.247	0.256
N	1,498	1,498	1,459	1,459	844	844	844	844