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THE EDUCATION PREMIUM IN RETURNS TO WEALTH

Elisa Castagno
Raffaele Corvino
Francesco Ruggiero

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Elisa Castagno[a], Raffaele Corvino[b,*], Francesco Ruggiero[c]

[a] *Collegio Carlo Alberto, Piazza Arbarello 8, Turin*
[b] *University of Torino and CeRP, Corso Unione Sovietica 218bis, Turin*
[c] *Bank of Italy, Via Nazionale 91, Rome*

Abstract

Using individual-level data from the Survey on Household Income and Wealth (SHIW), we estimate the extra-returns to wealth earned by highly educated individuals (*education premium*). Importantly, we quantify the fraction of the premium attributable to financial investment decisions, such as stock market participation and asset allocation. We find that college-graduated individuals earn annual returns to wealth that are 3.7% higher than those of their non-college-graduated peers, and we find that 19% of the extra-returns (0.7%) is due to the higher propensity to invest in the stock market. We show that this effect is particularly sizeable for college-graduated individuals with a major in Economics. Furthermore, we find that a university degree delivers 0.4% extra-returns to wealth as a result of the larger risky share of financial wealth held by college-graduated individuals. Finally, to rationalize our empirical results, we explore two economic mechanisms, namely portfolio diversification and participation persistence over time, both of which indicate a significant beneficial effect of education on returns to wealth.

Keywords: Education, Financial Investments, Returns to Wealth, Education Premium
JEL codes: I24, I26, I28, H30, H52

*Corresponding author. *Phone Number*: +39 3465316931.
Email addresses: elisa.castagno@carloalberto.org (Elisa Castagno), raffaele.corvino@unito.it (Raffaele Corvino), francesco.ruggiero@unina.it (Francesco Ruggiero)

1. Introduction

Wealth inequality and limited stock market participation are two critical and widely known stylized facts in developed economies, both of which have crucial implications for economic growth and efficiency. According to Fagereng et al. (2017), all investors should optimally invest in the stock market, yet the rate of stock market participation is persistently low across countries. This empirical evidence has prompted efforts to solve the so-called non-participation puzzle. The literature has recently linked these two stylized facts by introducing heterogeneity in individual skills as a main candidate to explain both heterogeneous patterns of wealth accumulation over time and heterogeneous profiles of financial investments. On the one hand, heterogeneity in skills is a valid candidate to rationalize limited participation as an alternative channel to more traditional mechanisms, such as participation costs (Fagereng et al. (2017)), income risk (Bonaparte et al. (2014), Bagliano et al. (2014), Bagliano et al. (2021)), and poor financial literacy (Van Rooij et al. (2011)). More specifically, skilled individuals make better investment decisions (Calvet et al. (2007), Calvet et al. (2009), Gennaioli et al. (2015), Kacperczyk et al. (2019)) and display a higher propensity for risk-taking and investing in the stock market (Barth et al. (2020)). On the other hand, heterogeneity in skills can also rationalize heterogeneous returns to wealth and the strong correlation between the level and returns to wealth observed in the data (Benhabib et al. (2011), Gabaix et al. (2016)). For instance, in a recent paper, Fagereng et al. (2020a) show that inherent skills are so important that education has no effect on returns to capital when conditioning on unobserved, individual ability.

In light of this, we set out to answer the following questions: Do highly educated individuals earn superior returns to wealth? And, if yes, what fraction of the extra-returns to wealth (*education premium*) is due to the heterogeneity in the financial investments across educational attainments? We address these two research questions by using individual-level data from the Survey on Household Income and Wealth (SHIW) by the Bank of Italy. We use the SHIW because it is the only publicly available source of data that contains individual-level information regarding demographic and personal characteristics; income; educational attainment and educational fields; stock market participation and asset allocation; savings and consumption. In addition, the SHIW includes a remarkable panel dimension and a relatively long time-series of data. As a result, the SHIW has been used widely in recent times by top scholars in household finance, such as Paiella and Pistaferri (2017) and Jappelli and Pistaferri (2020). In particular, by using information on savings and consumption, we can compute individual-level returns to wealth by following the approach of Lusardi et al. (2017), which we can then relate to individual-level information on education and financial investments.

The SHIW is organized in bi-annual waves, starting in 1980. We use all the waves of the SHIW from 1993, when data on the subject of individuals' university degree (e.g., Economics, Law, Medicine) started to be released. The SHIW contains highly detailed, individual-level information about both financial investments and education. Our sample is representative of the Italian population and highlights several stylized facts in continental European countries, such as a small fraction of graduated individuals, limited stock market participation, high risk aversion, and highly skewed distribution of both wealth and returns to wealth. We also observe in our sample a positive assortative match between the level and returns to wealth—that is, wealthy people earn on average substantially higher returns than poorer individuals. Moreover, wealthy individuals display a much higher rate of stock market participation and allocate a larger fraction of their financial wealth to stocks, either by using stocks directly or through mutual funds. When sorting individuals by wealth, we show that highly educated individuals display a higher propensity for risk-taking and investing in the stock market. However, we document ambiguous patterns in returns to wealth across educational attainments, with non-college-graduated individuals apparently obtaining higher returns than their college-graduated peers.

Next, we estimate the conditional differences in returns to wealth between college- and non-college-graduated individuals (the *education premium*). Importantly, we quantify the fraction of the premium attributable to financial investment decisions by using a simultaneous two-equation model. In the main regression, returns to wealth is the dependent variable while education and investment decision serve as the two main independent variables. We control for a large set of personal, observable characteristics, such as age, gender, risk aversion, household size, labor income, wealth, and a proxy of unobserved, individual ability that we estimate using the approach of Belzil and Hansen (2002). In the auxiliary regression, while using the same set of control variables as in the main regression, the investment decision is the dependent variable and education is the main covariate. By estimating the model, we can determine the direct, indirect, and total effects of education on returns to wealth, while also being able to compute the fraction of the education premium due to financial investment decisions as the ratio between the indirect effect and total effect of education. To be more precise, the indirect effect is a combination of the impact of education on the investment decision and the effect of the latter on the returns to wealth. We analyze two main investment decisions: stock market participation and asset allocation (the share of financial wealth allocated to the risky portfolio).

We document a sizeable education premium: college-graduated individuals earn annual returns to wealth that are 3.7% higher than those of non-college-graduated individuals when controlling for observable treats. Moreover, 19% of this excess return is caused by college-graduated individuals' higher propensity to invest in the stock market. The extra-return secured by graduated individuals and the beneficial effect of stock market participation due to higher education fall to 3.1% and 10%, respectively, when also conditioning on the unobserved ability. Nevertheless, both the premium and the indirect effect of education retain strong statistical significance. Interestingly, the higher propensity to invest in the stock market associated with a degree in Economics delivers 1.4% extra-returns to wealth out of a total 2.4% extra-returns to wealth secured by college-graduated individuals with an Economics major, which corresponds to an indirect effect of more than 50% of the overall extra-returns to wealth. This channel is still active but weaker in both magnitude and statistical significance for the STEM-graduated-individuals. Moreover, we find that a university degree delivers 0.4% extra-returns to wealth because of the larger risky share of financial wealth held by college-graduated individuals: the university degree increases the share of financial wealth allocated to the stock market by 3.9%, while an increase by 1% in the risky share is associated with extra-returns to wealth of 11.2%.

We challenge two mechanisms that may help to explain the beneficial effect of education on returns to wealth through the channel of financial investments: portfolio diversification and ownership dynamics. First, we estimate the simultaneous two-equation model using direct stockholding only, finding that the indirect effect of education is positive but not significant when considering either stock market participation or asset allocation. By contrast, when we estimate the model using mutual funds shareholding, we find that the indirect effect of education is positive and significant for both stock market participation and asset allocation—more specifically, better-educated individuals earn 0.3% extra-returns to wealth because of their higher propensity to participate in the stock market through mutual funds and 0.1% extra-returns to wealth because of a larger proportion of financial wealth allocated to shares of mutual funds. We also find that this effect is particularly sizeable for individuals with a major in Economics: their fraction of the education premium due to the higher propensity to hold mutual funds shares is 37.5%. The significantly higher propensity to invest in the stock market through well-diversified portfolios, such as shares of mutual funds, aligns with the evidence provided by Calvet et al. (2007) Calvet et al. (2009), who show that better-educated individuals are less likely to make investment errors, such as under-diversification.

Next, we study ownership dynamics at the individual level. Specifically, we compute each individual's frequency of participation in the stock market and the fraction of the risky portfolio traded by each individual over time. We document that better-educated individuals display a higher frequency of participation in the stock market over time—that is, they remain on the market longer than individuals with a lower education. This evidence is consistent with the significantly positive relationship between education and participation frequency documented by both Bonaparte et al. (2020) and Galaasen and Raja (2022). Furthermore, the higher persistence in stock market participation of highly educated individuals can be partially attributed to the better anxiety control of skilled investors while investing in financial markets (Gennaioli et al. (2015)).

Importantly, we show that a higher participation frequency is positively and significantly associated with higher returns to wealth and corroborate the evidence that the beneficial effect of education through the channel of financial investments is particularly relevant for individuals with a major in Economics: more than 50% of the overall education premium in returns to wealth (1.6% out of 2.4%) is due to the higher participation frequency displayed by Economics-graduated individuals. Nevertheless, the higher persistence in stock market participation of better-educated individuals does not imply that they are more passive than their non-college-graduated peers. In fact, we do not find any significant difference in portfolio re-balancing across educational attainments nor across heterogeneous types of university degree. Indeed, Bianchi (2018) shows that investors with better financial literacy are more likely to actively trade on stock markets. Overall, then, our results highlight that well-diversified portfolios and long-term investments deliver better risk-adjusted returns compared to direct stock-holding and short-term strategies, such as entry and exit from the market.

Related Literature. Our paper speaks to the vast literature on the link between education and financial investments. Calvet et al. (2007) and Calvet et al. (2009) show that highly educated individuals carry out more proficient portfolio choices. Kacperczyk et al. (2019) and Lei (2019) highlight the superior ability of skilled individuals to process and manage information in financial markets. Moreover, higher education is often found to be a strong predictor of stock market participation and risk-taking (Bonaparte et al. (2014), Fagereng et al. (2017), Bonaparte et al. (2020), Bagliano et al. (2021)). Specifically, our analysis connects to the recent, growing literature that tries to quantify the effect of educational attainment on returns to capital. Fagereng et al. (2020b) shed light on a positive assortative match between schooling years and returns on bank deposits. Fagereng et al. (2020a) document a causal effect of education on returns to labor, but they do not find there to be any significant impact of education on returns to capital when conditioning on unobserved ability, using an instrumental variables approach. In contrast, a contemporaneous study by Altmejd et al. (2022) finds strong evidence that financial education affects stock market participation, risk-taking, and portfolio returns.

Our main contribution to this strand of literature is the estimate of the fraction of the extra-returns to wealth earned by better-educated individuals through a more proficient allocation of their financial wealth, namely the participation to the stock market and portfolio choice. We also uncover two economic mechanisms that help to explain the indirect effect of education on returns to wealth through the financial investments channel. In a companion paper, Castagno et al. (2023) explore the link between individual skills, education, and wealth inequality through the channel of financial investments, both theoretically and empirically. They argue that education has the potential to reduce wealth inequality by allowing individuals endowed with low skills to undertake better investment decisions, thus narrowing the gap between the top and the bottom shares of the wealth distribution. In this paper, we use data from the SHIW to compute a better measure of returns to wealth and we include asset allocation in addition to stock market participation as an investment decision. Moreover, we disentangle direct stockholding from mutual funds shareholding and we assess the degree of heterogeneity across different university fields.

Paper Structure. Our paper proceeds as follows. In the next section, we describe the data and present preliminary evidence regarding the relationship between education, financial investments, and returns to wealth. Empirical results regarding the quantitative impact of education, both directly and through the channel of the financial investment decisions, are presented in Section 3. In Section 4, we study two potential economic mechanisms. Section 5 concludes the paper.

2. Data and Preliminary Evidence

We use data from the SHIW, which was conducted by the Bank of Italy. The SHIW is organized in bi-annual waves, starting in 1980. 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 on income and wealth components, educational attainment, and a large set of personal characteristics. Such information is either provided at the household level or at the individual level, with individual-level information referring to the household's head. We map individuals onto households using the unique household identifier, after which we build a unique individual-household identifier. Given that the head of a household may change over time, we create a flag that allows us to track changes in the household's head. If there is a change in the household's head over time, we consider it a new household.

We use all the waves of the SHIW from 1993, when data regarding the specific major of individuals' university degrees (e.g., Economics, Law, Medicine) was first released. For each wave, we merge the different sections of the survey using the unique identifier at the individual level, after which we merge waves over time and use the individual-level identifier to follow individuals over time. We drop individuals either older than 75 or younger than 18. Given that the focus of our analysis is the individual-level returns to 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 40,665 individual-year observations from 8,113 unique individuals.[1] Our main variables of interest

[1]When using the entire sample of individuals, results are substantially unchanged and available upon

are the educational attainment, portfolio choice, and wealth composition at the individual level. We also 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, among others. We provide a complete list of variables with short descriptions in Table 1.

[Table 1 about here.]

Education. We identify the highest degree of education achieved by each individual using a ranking variable spanning from 1 to 6, where 1 stands for no educational achievement and 6 denotes top educational achievement, namely a post-graduate degree. The complete list of education rank includes the following: primary school (2), low-secondary school (3), high-secondary school (4), and university degree (5). We then construct a dummy variable that takes a value equal to 1 if the individual has a *University* degree, and zero otherwise, which corresponds to values of the categorical variable equal to either 5 or 6, and zero otherwise (1 to 4). We denote the individual as *College*-graduated when the dummy variable is equal to 1. We also have information about the specific field of university degree obtained by the individual. The university majors are classified by the SHIW as follows: (a) Mathematics, Physics, Chemistry, and Biology; (b) Engineering; (c) Architecture; (d) Medicine and Veterinary Medicine; (e) Economics & Statistics; (f) Political Sciences; (g) Law; (h) Literature, Philosophy, Psychology, Languages. To ensure that each sub-sample of individuals holding a given university major is sufficiently populated, we include (a), (b), and (c) in the so-called STEM subject and consider (f) and (g) to be in the same group.

Wealth and Investments. The survey contains data regarding individuals' total wealth and its composition, for each wave. In particular, wealth is classified into two major components: financial wealth and real wealth. Financial wealth mostly includes financial assets held

request.

by the individual: checking accounts, savings or deposit accounts, insurance policies, bonds, stocks and mutual funds, and derivatives. Real wealth includes real estate and durable and luxury goods. In addition, the SHIW provides information about the decision to invest in the stock market, either directly by holding stocks or indirectly through mutual funds. This decision is described in the dataset by a dummy variable taking a value equal to 1 if the individual has either been holding stocks or investing in mutual funds over the course of the year, and zero otherwise. We can also determine whether the individual has invested in the stock market by using stocks only (without using mutual funds) or by holding shares of mutual funds only (without using stocks directly). Moreover, we have information about the share of financial wealth held in stocks or mutual funds at the individual level, in each wave. Our sample confirms that the rate of participation in the stock market in Italy is relatively lower compared to other developed European countries: on average, less than 15% of the individuals invest in the stock market either directly or through mutual funds and around 7% of the financial wealth is allocated to the stock market. We also recover information about risk attitude based on individuals' answers to a specific question from the psychological section of the survey. For this, we use a ranking variable ranging between 1 and 4, with 1 signaling preference for risk-taking and 4 denoting the highest degree of risk aversion.

Returns to Wealth. Importantly, the SHIW contains information about individuals' consumption and savings in each wave. Hence, we are able to compute a measure of returns to wealth using the approach of Lusardi et al. (2017):

$$W_{i,t} = (W_{i,t-1} + X_{i,t-1} - C_{i,t-1}) \cdot (1 + WR_{i,t}), \tag{1}$$

where $W_{i,t}$ is the total wealth of the individual i at wave t, X_t is the net labor income, $C_{i,t}$ is the consumption expenditure, and $WR_{i,t}$ is the *wealth returns* earned by the individual i

at wave t, which is equal to

$$WR_{i,t} = \frac{W_{i,t}}{W_{i,t-1} + S_{i,t-1}} - 1, \tag{2}$$

where $W_{i,t-1}$ and $S_{i,t-1}$ denote the total wealth and savings, respectively, of the individual i at wave $t-1$. Due to the bi-annual frequency of the survey waves in the SHIW, we assume that individuals' returns are constant across the two years between two subsequent waves, $t-1$ and t. We then input half of the bi-annual returns as a proxy of an individual's annual returns to obtain an individual-level measure of annual returns to wealth.

Summary Statistics. We summarize the data in Table 2. The average age is around 54 and almost two-thirds of the individuals are male (which is in line with the stylized fact that the Italian household head is usually a man). Indeed, the graduation rate is notoriously low in Italy: slightly more than 10% of individuals hold a university degree. In particular, one-third of them hold a major in Humanistic sciences, more than one-quarter graduate in a STEM subject, and only around 10% of college-graduated individuals have a major in Economics or Statistics. Moreover, the level of risk aversion is high (the mean value is 3.34 on a scale ranging from 1 to 4, where 1 means that the individual is a risk seeker and 4 means that the individual is risk averse) and 35% of the individuals live in urban areas. Wealth distribution is positively skewed: the mean (283,100 euros) is substantially higher than the median (182,130 euros), a feature that is common across countries. Real wealth accounts for approximately 90% of total wealth. The positive skewness is particularly remarkable in the financial component of wealth: the average financial wealth (36,260 euros) is more than three times larger than the median financial wealth (10,020 euros). The distribution of the wealth returns is highly positively skewed too: individuals earn, on average, an annual rate of returns to wealth equal to 4.32%, but the median return to wealth is substantially negative (-3.94%). In addition, we document a huge difference between the top and the bottom tails of the wealth returns distribution: the 95th percentile is 88.17% while the 5th percentile is

-49.03%.

[Table 2 about here.]

2.1. Descriptive Evidence

We now identify several patterns in the data on educational attainment, financial investments, and returns to wealth by sorting individuals according to their initial wealth. We start by identifying initial wealth in the sample, denoted by $W_{i,0}$, as the first available data on total wealth at the individual level. After that, we group individuals into quartiles of initial wealth and, within each quartile, we compute the share of individuals holding a university degree, the share of individuals investing in the stock market, the average share of financial wealth held in stocks—either directly or through mutual funds—and the average returns to wealth.

In panel A of Table 3, we document a strong and positive correlation between level and returns to wealth: the richest individuals earn on average annual returns to their wealth equal to 18.56%, while the average returns to wealth are 7.59%, 4.21%, and -15.70% within the third, second, and bottom wealth classes, respectively. We also document a strong correlation between initial wealth and financial investment decisions: only 3.76% of individuals in the bottom wealth class invest in the stock market and they hold on average 2.90% of their financial wealth in stocks, either directly or through mutual funds; meanwhile, 31.39% of the richest individuals invest in the stock market and they hold on average 14.04% of their financial wealth in stocks; rich individuals also display substantially higher graduation rates compared to individuals from lower wealth quartiles.

Next, we compute the share of individuals investing in the stock market, the average share of financial wealth held in stocks, and the average returns to wealth within each initial wealth class, after sorting individuals according to their educational attainment. In panel B of Table 3, we show that education is strongly and positively correlated with both the decision to participate in the stock market and the fraction of financial wealth allocated to stocks, even after controlling for initial wealth. For example, in the top (bottom) wealth class, the stock market participation rate is 40.28% (9.35%) for college-graduated individuals and 28.93% (3.45%) for non-college-graduated individuals. Similarly, the share of financial wealth allocated to stocks is, on average, equal to 17.87% (5.78%) for college-graduated individuals and 13.63% (2.71%) for non-college-graduated individuals. Differences in participation rate and risky share across educational attainments hold within each quartile regardless of whether the investment in the stock market involves either stocks directly only or mutual funds only. On the other hand, we observe counter-intuitive patterns in terms of returns to wealth: apparently, non-college-graduated individuals earn greater returns to wealth than their graduated peers in each wealth quartile with the exception of the bottom wealth class. Lastly, we compute the share of individuals investing in the stock market, the average share of financial wealth held in stocks, and the average returns to wealth for each sub-sample of individuals holding a different university major. Unsurprisingly, individuals graduated in Economics display the highest rate of stock market participation and the highest average share of financial wealth invested in the stock market. Differences in participation rate and risky share are particularly large for investments in the stock market through stocks directly. In fact, individuals graduated in STEM and Politics exhibit rates of stock market participation through mutual funds and average share of financial wealth held in mutual funds in line with those graduated in Economics. Interestingly, Economics-graduated individuals report, on average, much higher returns to wealth (10.33%) than individuals holding any other university major.

[Table 3 about here.]

2.2. Unobserved Ability

To construct a proxy of individual skills, we follow the approach of Castagno et al. (2023), based on Belzil and Hansen (2002). For this, we estimate a standard (log)-earnings regression on education and a polynomial in age that proxies for years of experience:

$$\ln(z_{i,t}) = \gamma_1 e_{i,t} + \gamma_2 a_{i,t} + \gamma_3 a_{i,t}^2 + h(e_{i,t}, a_{i,t}, g_i) + f_i + \epsilon_{i,t}, \tag{3}$$

where $\ln(z_{i,t})$ represents 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). 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 (3) using OLS and individual fixed-effects to capture the unobserved ability f_i. Using the SHIW data, we obtain a distribution of $\hat{f}_i$ in line with that obtained by Castagno et al. (2023) using the DHS data (Figure 1). Moreover, by using our proxy of individual skills, we replicate the regression analysis of Barth et al. (2020), who employ biological data and information regarding individual-level genetic endowment, and we support in our sample their evidence: individual skills are positively associated with both total and financial wealth, risk-taking, and a higher propensity to participate in the stock market. We detail the results in the Online Appendix.

3. The Education Premium

In this section, we quantify the fraction of the extra-returns to wealth earned by college-graduated individuals through the channel of financial investment decisions. To do this, we estimate a structural regression model by using a mediator variable that describes either the decision to participate in the stock market (Section 3.1) or the individual's share of the financial wealth allocated to the stock market (Section 3.2). By doing so, we disentangle the direct and indirect effects of education on returns to wealth, where the latter identifies the fraction of the conditional difference in returns to wealth across educational attainment (the *education premium*) due to the financial investment decisions. Lastly, we study heterogeneity in the education premium across different fields of university degree (Section 3.3).

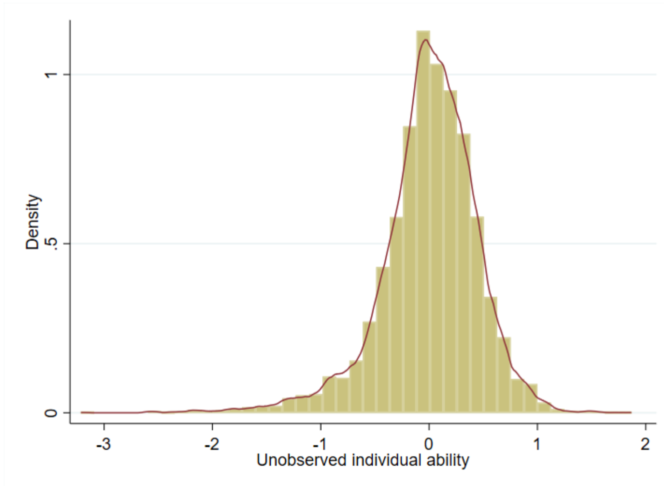

Figure 1. Sample Distribution of Unobserved Ability. The figure reports the sample distribution of the unobserved, individual ability $\hat{f}_i$. We obtain $\hat{f}_i$ by estimating equation (3) using OLS. The data are from the Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

3.1. Stock Market Participation

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 both education and stock market participation on returns to wealth and the impact of education on the decision to invest in the stock market:

$$WR_{i,t} = \beta_0 + \beta_1 \mathcal{I}^{\mathcal{P}}_{i,t} + \beta_2 Edu_{i,t} + \beta_3 Skills_i + \beta_4 W_{i,t-1} + X'_{i,t}\gamma + \epsilon_{i,t} \tag{4}$$

$$\mathcal{I}^{\mathcal{P}}_{i,t} = \delta_0 + \delta_1 Edu_{i,t} + \delta_2 Skills_i + \delta_3 W_{i,t-1} + X'_{i,t}\gamma + \nu_{i,t} \tag{5}$$

where $WR_{i,t}$ is the returns to wealth earned by the i-th individual in year t, computed using equation (2); $\mathcal{I}^{\mathcal{P}}_{i,t}$ is the dummy variable equal to 1 if the individual i invests in the stock market in year t, either directly or through mutual funds, and zero otherwise; $Edu_{i,t}$ is the dummy variable equal to 1 if the individual i holds a university degree in wave t, and zero otherwise; $Skills_i$ is the unobserved ability of individual i estimated in regression (3); $X_{i,t}$ 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 (4) and (5), we also control for the individual-level, lagged value of wealth, denoted by $W_{i,t-1}$. 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 returns to wealth. 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 as a dependent variable in equation (5). In doing so, we quantify the effect of education on the propensity to participate in the stock market by estimating equation (5). Then, the indirect effect of education on the dependent variable $WR_{i,t}$ is given by the product between the impact of education on the decision to participate in the stock market (δ_1) and the impact of the stock market participation on $WR_{i,t}$ (β_1). As a result, the *total* effect of education on $WR_{i,t}$ is given by the sum of the direct and indirect effects:

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

We estimate the two-simultaneous equation model and report results in Table 4. We report results about the regression equation (4) in Panel A and the regression equation (5) in Panel B. In column (1), we control for a large set of personal characteristics, such as age, gender, household size, and labor income, and we find that education has a positive and significant impact on stock market participation (panel B) as well as a positive and significant impact on wealth returns (panel A). Meanwhile, stock market participation is positively and significantly associated with higher wealth returns (panel A). In column (2), we support this result by controlling for the individual, unobserved ability estimated in equation (3): education retains statistical significance even after conditioning on unobserved ability in both the regressions. By contrast, our estimate of skills has a significant impact only on wealth returns, but individual skills are positively but not significantly associated with a higher propensity to invest in the stock market.

We report the corresponding direct, indirect, and total effects of education on returns to wealth in columns (1) and (2) of Table 5, respectively. As can be seen from the table, when controlling for observable traits, college-graduated individuals earn annual returns to wealth 3.7% higher than non-college-graduated individuals. Moreover, 19% of this excess return is attributable to the higher propensity to invest in the stock market. The extra-returns secured by graduated individuals and the beneficial effect of stock market participation due to higher education are 3.1% and 10%, respectively, when also controlling for unobserved abilities.

3.2. Asset Allocation

We next quantify the effect of education on both the level and returns to wealth through the channel of the individual's asset allocation. To do so, we estimate the structural regression model by using the risky share of the financial wealth as a mediator variable in the simultaneous two-equation model described in Section 3.1:

$$WR_{i,t} = \beta_0 + \beta_1 \alpha_{i,t} + \beta_2 Edu_{i,t} + \beta_3 Skills_i + \beta_4 W_{i,t-1} + X'_{i,t}\gamma + \epsilon_{i,t} \tag{6}$$

$$\alpha_{i,t} = \delta_0 + \delta_1 Edu_{i,t} + \delta_2 Skills_i + \delta_3 W_{i,t-1} + X'_{i,t}\gamma + \nu_{i,t} \tag{7}$$

where $\alpha_{i,t}$ is the share of the financial wealth allocated by the individual i to stocks at year t, either directly or through mutual funds. With the exception of the mediator variable, the independent variables in the equations (6) and (7) are equal to those presented in the equations (4) and (5), respectively. We jointly estimate the regressions (6) and (7), and report the results in panel A and panel B of Table 4, respectively. In column (3), we find that education has a positive and significant impact on the proportion of financial wealth allocated to the stock market (panel B) as well as a positive and significant impact on wealth returns (panel A). However, the latter is not statistically significant when we condition on the unobserved ability (column (4)). Accordingly, we find that a university degree delivers an extra-return of 0.4% due to the larger risky share of financial wealth held by college-graduated individuals: the university degree increases the share of financial wealth allocated to the stock market by 3.9% while an increase by 1% in the risky share is associated with an extra-return to wealth equal to 11.2%. However, this beneficial, indirect effect of education on returns to wealth is statistically weaker when including individual skills in the estimated regressions. By contrast, individual skills are positively associated with the risky share, with this channel accounting for around 16% of the total impact of skills on returns to wealth.

[Table 4 about here.]

[Table 5 about here.]

[Table 6 about here.]

3.3. University Fields

We now investigate heterogeneity in the education premium on returns to wealth across different university fields by using information on the specific major undertaken by each college-graduated individual in the sample. We estimate the simultaneous two-equation model using either stock market participation (equations (4) and (5)) or asset allocation ((equations (6) and (7)) as a mediator variable, and we interact the dummy variable *Education* with a set of dummy variables, each of them taking a value equal to 1 if the individual has obtained a degree in a given field, and zero otherwise. We report the results regarding the direct, indirect, and total effects in Table 6.

Panel A highlights a positive and sizeable indirect effect of an Economics degree on returns to wealth through stock market participation. Importantly, the impact of an Economics degree on returns to wealth matters only through the decision to participate in the stock market. The higher propensity to invest in the stock market associated with an Economics degree delivers 1.4% extra-returns to wealth out of a total 2.4% extra-returns to wealth secured by college-graduated individuals with an Economics major, which corresponds to an indirect effect of more than 50% of the overall extra-returns to wealth. This channel is still active but weaker both in magnitude and statistical significance for the graduates with STEM degrees. However, a major in STEM is associated with significant extra-returns to wealth (4.1%). We also report a sizeable impact of education on returns to wealth for individuals graduated in Human sciences. Interestingly, this sub-sample of individuals is the only group for which we find a negative indirect effect, though this is not significant. In line with the results presented in columns (3) and (4) of Table 4, we barely observe a significant indirect effect of education on returns to wealth for any university field when using the risky share of financial wealth as a mediator variable.

4. The Economic Mechanisms

This section addresses the mechanisms that may explain the link between education and returns to wealth through the channel of financial investment decisions. We identify two potential mechanisms, namely portfolio diversification and ownership dynamics. To examine the first mechanism, we disentangle the individual's investments in the stock market through direct stockholding from stock market participation through shares of mutual funds (Section 4.1). We then assess the second mechanism by computing both the individual's frequency of participation in the stock market and the fraction of the risky portfolio traded by the individual over time (Section 4.2).

4.1. Stock vs Mutual Funds

The SHIW provides information on whether the individual holds stocks either directly or through shares of mutual funds. In each wave t, the SHIW 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. From the SHIW, we also know the fraction of financial wealth allocated to stocks directly by the individual i in the wave t ($PropSTK_{i,t}$) and the fraction of financial wealth allocated to shares of mutual funds by the individual i in the wave t ($PropMF_{i,t}$). We use the variables $OwnSTK_{i,t}$, $OwnMF_{i,t}$, $PropSTK_{i,t}$, and $PropMF_{i,t}$ as mediator variables in the simultaneous two-equation model presented in Section 3. In particular, we use either $OwnSTK_{i,t}$ or $OwnMF_{i,t}$ as a mediator variable to study the impact of education on wealth returns through the channel of stock market participation, following the approach outlined in Section 3.1. Next, we use either $PropSTK_{i,t}$ or $PropMF_{i,t}$ as a mediator variable to study the impact of education on wealth returns through the channel of asset allocation, following the approach outlined in Section 3.2. We present the results in Tables 7 to 9 and Tables 10 to 12, respectively.

In Table 7, we show that college-graduated individuals display a higher propensity to invest in stocks directly only when ignoring the unobserved ability (Panel B, column (1)). Indeed, when including the individual skills in the set of control variables, this effect loses statistical significance (Panel B, column (2)). Similarly, direct stockholding is no longer associated with higher wealth returns when controlling for the individual skills (Panel A, column (2)). We report an analogous pattern for asset allocation: higher education is associated with a larger share of financial wealth allocated to direct stockholding, unconditionally on the individual skills (Panel B, column (3)), but this effect disappears when controlling for the unobserved ability (Panel B, column (4)). However, an increase in the risky share held in stocks directly is associated with higher wealth returns regardless of whether individuals' skills are included in the estimated regressions (Panel A, columns (3) and (4)). This effect is economically relevant: an additional 1% of risky share held through stocks directly delivers annual 11.2% extra-returns to wealth. We then show in Table 8 that the indirect effect of education on wealth returns through direct stockholding is positive but not significant when controlling for unobserved ability, either using the participation dummy or the risky share of financial wealth as a mediator variable. Additionally, we demonstrate that this effect is not significant for any university major (Table 9).

[Table 7 about here.]

[Table 8 about here.]

[Table 9 about here.]

In Table 10, we report substantial differences in our results when estimating the education premium through stock market investments using shares of mutual funds. First, we find that highly educated individuals exhibit a significantly higher propensity to invest in the stock market through mutual funds, both unconditionally and conditionally on unobserved ability (Panel B, columns (1) and (2)). Similarly, highly educated individuals allocate a significantly larger fraction of their financial wealth to stocks using shares of mutual funds, both unconditionally and conditionally on unobserved ability (Panel B, columns (3) and (4)). However, both the magnitude and statistical significance of the university dummy are stronger when we do not include skills in the estimated regressions: a university degree is associated with an additional 1.4% (2.7%) share of financial wealth allocated to mutual funds when (without) controlling for individual skills. Moreover, both stock market participation through mutual funds (Panel A, columns (1) and (2)) and a larger share of financial wealth allocated to stocks through mutual funds (Panel A, columns (3) and (4)) are associated with higher wealth returns. We also note that the magnitude of the regression coefficients associated with both the participation dummy for mutual funds and the risky portfolio allocated to mutual funds are very similar to those reported for direct stockholding.

We then report in Table 11 the fraction of the education premium attributable to the higher propensity to hold shares of mutual funds and show that this indirect effect of education on returns to wealth is now positive and statistically significant, both unconditionally and conditionally on unobserved ability. More specifically, we find that highly educated individuals earn 0.3% extra-returns to wealth because of their higher propensity to participate in the stock market through mutual funds (column (2)) and 0.1% extra-returns to wealth because a larger proportion of financial wealth allocated to shares of mutual funds (column (4)). This beneficial effect of education accounts for around 10% of the overall education premium when considering stock market participation and around 3% when focusing on asset allocation. These figures are higher when ignoring unobserved ability (columns (1) and (3), respectively). Interestingly, we find that the beneficial effect of education on wealth returns through stock market participation using shares of mutual funds is both sizeable and significant only for individuals holding a major in Economics: the fraction of the education premium due to the higher propensity to hold mutual funds shares is 37.5%. This fraction drops to 6.45% when considering the allocation of financial wealth to mutual funds and is not statistically significant for any university major.

[Table 10 about here.]

[Table 11 about here.]

[Table 12 about here.]

4.2. Participation Frequency and Turnover

We address the second mechanism by computing the individual-level stock market participation frequency and portfolio re-balancing. More precisely, we compute the individual's participation frequency as the number of waves in which the individual participates in the stock market either directly or through mutual funds and we scale it by the total number of waves in which the individual reports information about financial investments. By doing this, we obtain an individual-level measure of relative participation frequency. We then compute the absolute change in stock ownership between two subsequent waves $t-1$ and t for each individual and scale it by the risky share held at wave $t-1$. Thus, we obtain an individual-level measure of risky portfolio turnover.

First, we study the relationship between education and both participation frequency and portfolio re-balancing using a simple OLS regression, and we report the results in Table 13. In column (1), it can be seen that education is significantly and positively associated with participation frequency after controlling for unobserved ability, labor income, wealth, and a large set of personal characteristics—more specifically, a college-graduated individual has a 4.7% higher relative frequency of stock market participation compared to a non-college graduated peer. Next, we disentangle heterogeneous university degrees, finding that the positive assortative match between education and frequency is significant for individuals with a major in Economics, who display 15.3% higher participation frequency compared to other individuals (column (2)). STEM-graduated individuals also display a significantly superior propensity to remain in the market for longer (7.3%). The results hold when we interact the University dummy with the specific University major (column (3)). In contrast, we do not find any significant difference in portfolio re-balancing across college- and non-college-graduated individuals either across different university fields (columns (4) to (6)).

[Table 13 about here.]

Overall, our results suggest that the higher persistence in stock market participation of better-educated individuals does not imply that they are more passive than their non-college-graduated peers. We support this argument by estimating the simultaneous two-equation model using either participation frequency or portfolio re-balancing as a mediator variable, the results of which are presented in Table 14. On the one hand, we confirm that education increases participation frequency, both conditionally and unconditionally on the unobserved ability, and that the link between education and portfolio turnover is not statistically significant. On the other hand, we find that higher persistence in stock market participation delivers higher returns to wealth: an increase of 1% in the relative frequency delivers slightly less than 0.10% higher returns on wealth. By contrast, we do not find evidence that a more active portfolio management yields extra-returns to wealth.

Lastly, by using results presented in Table 14, we compute the direct, indirect, and total effects of education on returns to wealth. We report the effects in Table 15. In column (1), we show that around one-quarter of the overall education premium in returns to wealth (0.9% out of 3.7%) is attributable to the higher participation frequency displayed by better-educated individuals compared to their non-college-graduated peers. Meanwhile, when additionally controlling for the unobserved ability (column (2)), we find that the fraction of the premium attributable to the higher participation frequency induced by better education is approximately 13% (0.4% out of 3.1%). This indirect effect also retains statistical significance. The beneficial, indirect effect of education on returns to wealth through portfolio turnover accounts only for around 1% and is not statically significant, both with and without individual skills included in the estimated regressions (columns (3) and (4), respectively). In Table 16, we report the direct, indirect, and total effects of education on returns to wealth when estimating the simultaneous two-equation model using data on the university fields. We corroborate once more the evidence that the beneficial effect of education through the channel of financial investments is particularly relevant for individuals with a major in Economics (Panel A). Specifically, more than 50% of the overall education premium in returns to wealth (1.6% out of 2.4%) is attributable to the higher participation frequency displayed by Economics-graduated individuals. This fraction drops to 8% for STEM-graduated individuals and is not significant for other fields. Finally, in Panel B, we confirm the lack of significance of portfolio turnover for returns to wealth, documented in Table 14, for any university field.

[Table 14 about here.]

[Table 15 about here.]

[Table 16 about here.]

5. Conclusions

In this paper, we define education premium as the extra-returns to wealth earned by college-graduated individuals compared to their non-college-graduated peers. We find that the education premium is sizeable after controlling for both observable, personal treats and individual, unobserved ability. Furthermore, we find that an important fraction of the premium is attributable to the higher propensity for risk-taking and investing in the stock market of better-educated individuals. We refer to this channel as the indirect effect of education on the returns to wealth and show that it is particularly large for college-graduated individuals holding a major in Economics.

To understand the economic rationale behind our empirical results, we document a significantly higher propensity for well-diversified portfolios as well as a higher persistence in stock market participation over time among better-educated individuals, before showing that both mechanisms positively and significantly contribute to the education premium. These results can serve as a foundation for future academic research into the link between education and portfolio choices and their impact on both the level and returns to wealth. Moreover, our paper can help policymakers to form better-calibrated responses to the slow development of financial markets, particularly in lower-education environments.

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Table 1 Definitions of variables

Variable	Definition
Age	Years old.
Male	One if male and zero otherwise.
University	One if holds a University degree and zero otherwise.
University Fields	One if holds a University degree in (see below) and zero otherwise.
- Economics	Economics and Statistics
- Politics	Law and Political Sciences
- Medicine	Medicine or Veterinary Medicine
- STEM	Mathematics, Physics, Chemistry, Biology, Engineer, Architecture
- Humanistic	Literature, Philosophy, Psychology, Languages
Retired	One if retired and zero otherwise.
Risk aversion	Perception of risk (rating from 1 to 4, where 1 is risk seeker and 4 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 directly and/or through mutual funds (MF) and zero otherwise.
OwnSTK	One if owns stocks directly and zero otherwise.
OwnMF	One if owns stocks through Mutual Funds and zero otherwise.
PropSTKMF	Fraction of financial wealth invested in stocks directly or through mutual funds.
PropSTK	Fraction of financial wealth invested in stocks directly.
PropMF	Fraction of financial wealth invested in stocks through mutual funds.
Participation Frequency	Number of waves in which individual participates to the stock market.
Relative Frequency	Ratio between Participation Frequency and total number of waves the individual is surveyed.
Share Rebalancing	Fraction of risky share bought or sold by the individual.
Wealth Return	Returns to wealth computed using formula in Lusardi et al. (2017).

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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Variable	Obs	Mean	Std. Dev.	p5	Median	p95
Age	40,655	54.08	12.18	33	55	72
Male	40,655	65.10%	47.67%	0	1	1
University	40,655	10.91%	31.18%	0	0	1
University Fields						
- Economics	4,238	11.85%	32.32%	0	0	1
- Politics	4,238	17.18%	37.72%	0	0	1
- Medicine	4,238	12.10%	32.62%	0	0	1
- STEM	4,238	26.31%	44.04%	0	0	1
- Humanistic	4,238	32.56%	46.87%	0	0	1
Retired	40,655	35.70%	47.91%	0	0	1
Risk Aversion	24,100	3.34	0.76	2	4	4
HH Size	40,655	2.86	1.28	1	3	5
Urban	40,655	7.49%	26.33%	0	0	1
Total Wealth (x1,000)	40,655	283.10	511.75	0.51	182.13	877.83
Financial Wealth (x1,000)	40,655	36.26	125.94	0.00	10.02	131.88
Other Wealth (x1,000)	40,655	258.23	466.05	0.21	170.46	793.41
OwnSTKMF	40,655	14.53%	35.24%	0	0	1
OwnSTK	40,655	4.63%	21.01%	0	0	1
OwnMF	40,655	7.01%	25.53%	0	0	1
PropSTKMF	33,834	7.76%	20.51%	0	0	63.16%
PropSTK	33,834	2.71%	11.50%	0	0	19.05%
PropMF	35,008	5.03%	16.61%	0	0	45.45%
Participation Frequency	40,655	14.53%	25.92%	0	0	0.75%
Relative Frequency	13,603	23.99%	19.78%	0	0.20%	0.60%
Share Rebalancing	2,674	70.35%	94.03%	4.04%	42.79%	269.00%
Wealth Return	30,898	4.32%	48.88%	-49.03%	-3.94%	88.17%

Table 3 Patterns by Wealth and Education

The table reports descriptive evidence about educational attainment, financial investments, and wealth returns, by sorting individuals on their initial wealth. We identify initial wealth in the sample as the first available data on total wealth at the individual-level and we group individuals into quartiles. In panel A, for each wealth quartile, we report the share of individuals holding a University degree (*UniDegree*), the share of individuals investing in the stock market - either directly or through mutual funds (*Participation*), directly only (*Only Stock*), through mutual funds only (*Only MF*) - the average share of financial wealth held in stocks - either directly or through mutual funds (*Risky Share*), directly only (*Stock Share*), through mutual funds only (*MF Share*) - and the average return to wealth (*Wealth Return*). In Panel B, we compute the same quantities in each wealth quartile, after sorting individuals on their educational attainment. Within each wealth quartile, we split individuals into two sub-samples: University graduated and non-University graduated. In Panel C, we compute the same quantities within each group of individuals holding a specific type of University degree. The data are from the Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

PANEL A: Initial Wealth

Quartile	Uni Degree	Participation	Only Stock	Only MF	Risky Share	Stock Share	MF Share	Wealth Return
Poor	5.26%	3.76%	1.20%	2.29%	2.90%	0.92%	1.93%	-15.70%
25-50th	6.30%	7.63%	2.44%	4.20%	4.40%	1.44%	2.95%	4.21%
50-75th	10.42%	15.33%	4.73%	8.49%	7.90%	2.55%	5.37%	7.59%
Rich	21.67%	31.39%	10.14%	13.06%	14.04%	5.27%	8.79%	18.56%

PANEL B: Initial Wealth and Education

	Participation		**Only Stock**		**Only MF**		**Risky Share**		**Stock Share**		**MF Share**		**Wealth Return**	
Quartile	No Uni	Uni	No Uni	Uni	No Uni	Uni	No Uni	Uni	No Uni	Uni	No Uni	Uni	No Uni	Uni
Poor	3.45%	9.35%	1.12%	2.62%	2.10%	5.79%	2.71%	5.78%	0.86%	1.76%	1.80%	3.87%	-15.72%	-15.26%
25-50th	7.04%	16.40%	2.24%	5.47%	3.99%	7.35%	4.13%	8.03%	1.321%	3.20%	2.81%	4.88%	4.31%	2.78%
50-75th	14.46%	22.86%	4.47%	6.99%	8.07%	12.09%	7.43%	11.92%	2.38%	3.97%	5.08%	7.80%	8.06%	3.61%
Rich	28.93%	40.28%	9.35%	13.03%	12.35%	15.62%	12.99%	17.87%	4.80%	6.98%	8.19%	10.91%	19.97%	13.45%

PANEL C: University Fields

Quartile	Participation	Only Stock	Only MF	Risky Share	Stock Share	MF Share	Wealth Return
Economics	42.43%	16.14%	14.14%	19.09%	9.54%	9.64%	10.33%
Law/Politics	29.95%	9.07%	13.60%	14.41%	5.22%	9.15%	6.74%
Medicine	27.88%	9.55%	11.50%	12.14%	4.47%	7.64%	6.80%
STEM	31.93%	8.52%	14.44%	15.16%	5.07%	9.94%	6.08%
Humanistic	22.17%	7.17%	10.29%	11.46%	3.91%	7.58%	5.65%

Table 4 The Education Effect: Structural Equation Model.
The table reports results from Maximum Likelihood estimation using data described in Section 2. We estimate the simultaneous two-equation model described in equations (4) and (5). In Panel A, we report estimation results about equation (4), in which we use as dependent variable the *Wealth Returns* as defined in Section 2. In columns (1) and (2), the main independent variables are the individuals' decision to participate to the stock market (*OwnSTKMF*) - either directly or through mutual funds - and the educational attainment (*Education*). *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 University degree, and zero otherwise. In columns (3) to (4), the main independent variables are the risky share of financial wealth held in stocks - either directly or through mutual funds (*PropSTKMF*) and the educational attainment (*Education*). In columns (2) and (4), we also control for the unobserved, individual ability (*Skills*) computed by estimating equation (3) using OLS. In columns (1) to (4), we control for the lagged, individual-level (log)-Wealth. In columns (1) to (4), we include year-fixed effects and demographic, personal characteristics, such as age, age squared, gender, and household size, but we suppress the coefficients of control variables to save in space. In Panel B, we report estimation results about equation (5), in which we use as dependent variable either the individuals' decision to participate to the stock market (columns (1) and (2)) or the risky share of financial wealth held in stocks (columns (3) and (4)). Model specifications and other 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A	Wealth Returns	Wealth Returns	Wealth Returns	Wealth Returns
Total Wealth$_{t-1}$	-0.030***	-0.30***	-0.63***	-0.055***
	(0.004)	(0.005)	(0.004)	(0.006)
OwnSTKMF	0.080***	0.085***		
	(0.009)	(0.012)		
PropSTKMF			0.112***	0.119***
			(0.17)	(0.024)
Education	0.030***	0.028**	0.042***	0.039***
	(0.009)	(0.011)	(0.009)	(0.012)
Skills		0.046***		0.031**
		(0.013)		(0.014)
Panel B	OwnSTKMF		PropSTKMF	
Total Wealth$_{t-1}$	0.042***	0.040***	0.019***	0.019***
	(0.002)	(0.003)	(0.001)	(0.002)
Education	0.091***	0.041**	0.039***	0.016
	(0.014)	(0.018)	(0.008)	(0.010)
Skills		0.097		0.048
		(0.014)		(0.010)
Controls	YES	YES	YES	YES
Observations	19,310	9,922	15,928	8,240

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

Table 5. The Education Effect: *Direct* and *Indirect* Effects.
The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in Table 4, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (4) and (5) using data described in Section 2. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In columns (1) and (2), the mediator variable is the individuals' decision to participate to the stock market (*OwnSTKMF*) - either directly or through mutual funds. In columns (3) and (4), the mediator variable is the risky share of financial wealth held in stocks - either directly or through mutual funds (*PropSTKMF*). 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 3. *Skills* is the unobserved, individual ability computed by estimating equation (3) 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Wealth Returns	OwnSTKMF	OwnSTKMF	PropSTKMF	PropSTKMF
Direct Effect:				
Education	0.030***	0.028**	0.042***	0.039***
	(0.009)	(0.011)	(0.009)	(0.012)
Skills		0.046***		0.031**
		(0.013)		(0.014)
Indirect Effect:				
Education	0.007***	0.003**	0.004***	0.002
	(0.00)	(0.002)	(0.001)	(0.001)
Skills		0.008***		0.006***
		(0.002)		(0.002)
Total Effect:				
Education	0.037***	0.031***	0.047***	0.041***
	(0.009)	(0.011)	(0.009)	(0.012)
Skills		0.055***		0.037**
		(0.12)		(0.014)

Table 6. University Fields: *Direct* and *Indirect* Effects.
The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In Panel A, the mediator variable is the individuals' decision to participate to the stock market (*OwnSTKMF*) - either directly or through mutual funds. In Panel B, the mediator variable is the risky share of financial wealth held in stocks - either directly or through mutual funds (*PropSTKMF*). 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 3. We report direct, indirect, and total effects for each field of University degree, as described in Table 1. We control for the unobserved, individual ability computed by estimating equation (3) using OLS. The data are from the Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A: Participation

Wealth Returns	Economics	Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.010	-0.014	0.017	0.036*	0.054***
	(0.029)	(0.024)	(0.027)	(0.019)	(0.019)
Indirect Effect:					
OwnSTKMF	0.014***	0.004	0.002	0.005*	-0.001
	(0.005)	(0.003)	(0.004)	(0.003)	(0.002)
Total Effect:					
	0.024	-0.010	0.019	0.041**	0.053***
	(0.029)	(0.024)	(0.027)	(0.019)	(0.020)

Panel B: Asset Allocation

Wealth Returns	Economics	Law/Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.010	-0.003	0.036	0.045**	0.065***
	(0.035)	(0.026)	(0.029)	(0.020)	(0.020)
Indirect Effect:					
PropSTKMF	0.004	0.004	-0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Total Effect:					
	0.014	0.001	0.035	0.047	0.066***
	(0.035)	(0.026)	(0.030)	(0.020)	(0.020)

Table 7 The Education Effect: Structural Equation Model. Stocks directly
The table reports results from Maximum Likelihood estimation using data described in Section 2. We estimate the simultaneous two-equation model described in equations (4) and (5). In Panel A, we report estimation results about equation (4), in which we use as dependent variable the *Wealth Returns* as defined in Section 2. In columns (1) and (2), the main independent variables are the individuals' decision to participate to the stock market (*OwnSTK*) directly and the educational attainment (*Education*). *OwnSTK* is a dummy variable equal to 1 if the individual holds stocks directly in year t, and zero otherwise. *Education* is a a dummy variable equal to 1 if the individual holds a University degree, and zero otherwise. In columns (3) to (4), the main independent variables are the risky share of financial wealth held in stocks directly (*PropSTK*) and the educational attainment (*Education*). In columns (2) and (4), we also control for the unobserved, individual ability (*Skills*) computed by estimating equation (3) using OLS. In columns (1) to (4), we control for the lagged, individual-level (log)-Wealth. In columns (1) to (4), we include year-fixed effects and demographic, personal characteristics, such as age, age squared, gender, and household size, but we suppress the coefficients of control variables to save in space. In Panel B, we report estimation results about equation (5), in which we use as dependent variable either the individuals' decision to participate to the stock market (columns (1) and (2)) through direct stockholding or the risky share of financial wealth held in stocks directly (columns (3) and (4)). Model specifications and other 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A	Wealth Returns	Wealth Returns	Wealth Returns	Wealth Returns
Total Wealth$_{t-1}$	-0.27***	-0.028***	-0.061***	-0.54**
	(0.003)	(0.005)	(0.004)	(0.006)
OwnSTK	0.069***	0.071		
	(0.016)	(0.022)		
PropSTK			0.118***	0.112**
			(0.034)	(0.051)
Education	0.035***	0.031***	0.045***	0.041***
	(0.009)	(0.011)	(0.010)	(0.012)
Skills		0.052***		0.034**
		(0.013)		(0.014)
Panel B	OwnSTK		PropSTK	
Total Wealth$_{t-1}$	0.013***	0.012***	0.007***	0.006***
	(0.001)	(0.010)	(0.001)	(0.001)
Education	0.025***	0.007	0.012**	0.001
	(0.008)	(0.010)	(0.005)	(0.006)
Skills		0.032***		0.022***
		(0.008)		(0.005)
Controls	YES	YES	YES	YES
Observations	19,310	9,922	15,928	8,240

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

Table 8. The Education Effect: *Direct* and *Indirect* Effects. Stocks directly

The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in Table 7, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (4) and (5) using data described in Section 2. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In columns (1) and (2), the mediator variable is the individuals' decision to participate to the stock market directly (*OwnSTK*). In columns (3) and (4), the mediator variable is the risky share of financial wealth held in stocks directly (*PropSTK*). 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 3. *Skills* is the unobserved, individual ability computed by estimating equation (3) 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Wealth Returns	OwnSTK	OwnSTK	PropSTK	PropSTK
Direct Effect:				
Education	0.035***	0.031***	0.045***	0.041***
	(0.009)	(0.011)	(0.010)	(0.012)
Skills		0.052***		0.034**
		(0.013)		(0.014)
Indirect Effect:				
Education	0.002**	0.000	0.001**	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Skills		0.002***		0.002**
		(0.001)		(0.01)
Total Effect:				
Education	0.037***	0.031***	0.046***	0.041***
	(0.009)	(0.011)	(0.009)	(0.012)
Skills		0.054***		0.036**
		(0.012)		(0.014)

Table 9. University Fields: *Direct* and *Indirect* Effects. Stocks directly
The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In Panel A, the mediator variable is the individuals' decision to participate to the stock market directly (*OwnSTK*). In Panel B, the mediator variable is the risky share of financial wealth held in stocks directly (*PropSTK*). 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 3. We report direct, indirect, and total effects for each field of University degree, as described in Table 1. We control for the unobserved, individual ability computed by estimating equation (3) using OLS. The data are from the Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A: Participation

Wealth Returns	Economics	Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.021	-0.010	0.019	0.039**	0.055***
	(0.029)	(0.024)	(0.027)	(0.019)	(0.020)
Indirect Effect:					
OwnSTK	0.003	0.001	-0.001	0.002	-0.002
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
Total Effect:					
	0.024	-0.009	0.018	0.041**	0.053***
	(0.030)	(0.024)	(0.027)	(0.019)	(0.020)

Panel B: Asset Allocation

Wealth Returns	Economics	Law/Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.012	-0.000	0.037	0.047**	0.067***
	(0.035)	(0.026)	(0.030)	(0.020)	(0.020)
Indirect Effect:					
PropSTK	0.002	0.002	-0.002	-0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Total Effect:					
	0.014	0.002	0.035	0.047**	0.066***
	(0.035)	(0.026)	(0.030)	(0.020)	(0.020)

Table 10 The Education Effect: Structural Equation Model. Mutual Funds
The table reports results from Maximum Likelihood estimation using data described in Section 2. We estimate the simultaneous two-equation model described in equations (4) and (5). In Panel A, we report estimation results about equation (4), in which we use as dependent variable the *Wealth Returns* as defined in Section 2. In columns (1) and (2), the main independent variables are the individuals' decision to participate to the stock market through mutual funds (*OwnMF*) and the educational attainment (*Education*). *OwnMF* is a dummy variable equal to 1 if the individual holds stocks through mutual funds in year t, and zero otherwise. *Education* is a a dummy variable equal to 1 if the individual holds a University degree, and zero otherwise. In columns (3) to (4), the main independent variables are the risky share of financial wealth held in stocks through mutual funds (*PropMF*) and the educational attainment (*Education*). In columns (2) and (4), we also control for the unobserved, individual ability (*Skills*) computed by estimating equation (3) using OLS. In columns (1) to (4), we control for the lagged, individual-level (log)-Wealth. In columns (1) to (4), we include year-fixed effects and demographic, personal characteristics, such as age, age squared, gender, and household size, but we suppress the coefficients of control variables to save in space. In Panel B, we report estimation results about equation (5), in which we use as dependent variable either the individuals' decision to participate to the stock market through mutual funds (columns (1) and (2)) or the risky share of financial wealth held in mutual funds shares (columns (3) and (4)). Model specifications and other 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A	Wealth Returns	Wealth Returns	Wealth Returns	Wealth Returns
Total Wealth$_{t-1}$	-0.028***	-0.029***	-0.060***	-0.054***
	(0.003)	(0.005)	(0.004)	(0.027)
OwnMF	0.072***	0.077***		
	(0.009)	(0.014)		
PropMF			0.106***	0.115***
			(0.018)	(0.027)
Education	0.032***	0.029**	0.043***	0.040***
	(0.009)	(0.011)	(0.009)	(0.011)
Skills		0.050***		0.035***
		(0.013)		(0.013)
Panel B	OwnMF		PropMF	
Total Wealth$_{t-1}$	0.029***	0.028***	0.013***	0.014***
	(0.002)	(0.002)	(0.001)	(0.001)
Education	0.066***	0.034**	0.027***	0.014*
	(0.012)	(0.015)	(0.007)	(0.008)
Skills		0.065***		0.026***
		(0.012)		(0.007)
Controls	YES	YES	YES	YES
Observations	19,310	9,922	16,993	8,862

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

Table 11. The Education Effect: *Direct* and *Indirect* Effects. Mutual Funds
The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in Table 10, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (4) and (5) using data described in Section 2. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In columns (1) and (2), the mediator variable is the individuals' decision to participate to the stock market through mutual funds (*OwnMF*). In columns (3) and (4), the mediator variable is the risky share of financial wealth held in stocks through mutual funds (*PropMF*). 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 3. *Skills* is the unobserved, individual ability computed by estimating equation (3) 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Wealth Returns	OwnMF	OwnMF	PropMF	PropMF
Direct Effect:				
Education	0.032***	0.029**	0.043***	0.040***
	(0.009)	(0.011)	(0.009)	(0.011)
Skills		0.050***		0.035***
		(0.013)		(0.013)
Indirect Effect:				
Education	0.005***	0.003**	0.002***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Skills		0.005***		0.003***
		(0.001)		(0.001)
Total Effect:				
Education	0.037***	0.031***	0.045***	0.041***
	(0.008)	(0.011)	(0.009)	(0.011)
Skills		0.055***		0.038***
		(0.012)		(0.013)

Table 12. University Fields: *Direct* and *Indirect* Effects. Mutual Funds

The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In Panel A, the mediator variable is the individuals' decision to participate to the stock market through mutual funds (*OwnMF*). In Panel B, the mediator variable is the risky share of financial wealth held in stocks through mutual funds (*PropMF*). 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 3. We report direct, indirect, and total effects for each field of University degree, as described in Table 1. We control for the unobserved, individual ability computed by estimating equation (3) using OLS. The data are from the Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A: Participation

Wealth Returns	Economics	Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.015	-0.013	0.017	0.038**	0.053***
	(0.029)	(0.023)	(0.027)	(0.019)	(0.019)
Indirect Effect:					
OwnMF	0.009**	0.004	0.002	0.003	0.001
	(0.004)	(0.002)	(0.003)	(0.002)	(0.002)
Total Effect:					
	0.024	-0.009	0.019	0.041**	0.054***
	(0.030)	(0.024)	(0.027)	(0.019)	(0.020)

Panel B: Asset Allocation

Wealth Returns	Economics	Law/Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.029	0.003	0.032	0.046**	0.059***
	(0.032)	(0.025)	(0.027)	(0.019)	(0.018)
Indirect Effect:					
PropMF	0.002	0.001	0.002	0.002	0.001
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)
Total Effect:					
	0.031	0.004	0.034	0.048**	0.060***
	(0.032)	(0.025)	(0.027)	(0.019)	(0.018)

Table 13 Frequency & Rebalancing. OLS Estimation
The table reports results from OLS regression using data described in Section 2. In columns (1) to (3), the dependent variable is the number of waves in which the individual participates to the stock market (i.e., $OwnSTKMF = 1$) as a fraction of the total number of waves the individual provides information on financial investments (*Frequency*). *Frequency* takes values between 0 and 1. In columns (4) to (6) the dependent variable is the fraction of risky share traded (either bought or sold) by the individual as a fraction of the risky share held by the individual in the previous wave (*Rebalancing*). The main independent variable is the individual's educational attainment and the unobserved, individual ability ($\hat{f}_i$) computed by estimating equation (3) using OLS. In columns (1) to (6), we control for the (log)-labour income (*Labour Income*), demographic and personal characteristics, such as age, gender, and household size, as well as the individual's initial wealth by using the *Wealth Class* variable that denotes quartiles of initial wealth as described in Table 3. *Education* is a dummy variable equal to 1 if the individual holds a University degree, and zero otherwise. *University Fields* is a dummy variable equal to 1 if the individual holds a University degree in a specific field, and zero otherwise. 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

	(1) Frequency	(2) Frequency	(3) Frequency	(4) Rebalancing	(5) Rebalancing	(6) Rebalancing
Education	0.047***			0.040		
	(0.007)			(0.060)		
Economics		0.153***			-0.060	
		(0.023)			(0.115)	
Politics		0.029*			0.019	
		(0.017)			(0.091)	
Medicine		-0.009			0.052	
		(0.020)			(0.162)	
STEM		0.073***			0.041	
		(0.012)			(0.100)	
Humanistic		0.018*			0.103	
		(0.010)			(0.130)	
Education*Economics			0.154***			-0.060
			(0.023)			(0.115)
Education*Politics			0.030*			0.019
			(0.017)			(0.091)
Education*Medicine			-0.008			0.052
			(0.020)			(0.162)
Education*STEM			0.073***			0.041
			(0.012)			(0.100)
Education*Humanistic			0.018*			0.104
			(0.010)			(0.130)
Skills	0.135***	0.134***	0.134***	-0.068	-0.059	-0.060
	(0.008)	(0.008)	(0.008)	(0.092)	(0.094)	(0.094)
Labour Income	-0.005	-0.004	-0.004	0.014	0.0140	0.015
	(0.006)	(0.006)	(0.006)	(0.079)	(0.079)	(0.079)
Wealth Class	0.071***	0.071***	0.071***	0.058**	0.056**	0.056**
	(0.002)	(0.002)	(0.002)	(0.027)	(0.027)	(0.027)
Observations	15,559	15,559	15,559	1,155	1,155	1,155
R2	0.191	0.194	0.195	0.034	0.035	0.035
Controls	YES	YES	YES	YES	YES	YES

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

Table 14 The Education Effect: Structural Equation Model. Frequency & Rebalancing
The table reports results from Maximum Likelihood estimation using data described in Section 2. We estimate the simultaneous two-equations model described in equations (4) and (5). In Panel A, we report estimation results about equation (4), in which we use as dependent variable the *Wealth Returns* as defined in Section 2. In columns (1) and (2), the main independent variables are the number of waves in which the individual participates to the stock market (i.e., $OwnSTKMF = 1$) as a fraction of the total number of waves the individual provides information on financial investments (*Frequency*) and the educational attainment (*Education*). *Frequency* takes values between 0 and 1. *Education* is a a dummy variable equal to 1 if the individual holds a University degree, and zero otherwise. In columns (3) to (4), the main independent variables are the fraction of risky share traded (either bought or sold) by the individual as a fraction of the risky share held by the individual in the previous wave (*Rebalancing*) and the educational attainment (*Education*). In columns (2) and (4), we also control for the unobserved, individual ability (*Skills*) computed by estimating equation (3) using OLS. In columns (1) to (4), we control for the lagged, individual-level (log)-Wealth. In columns (1) to (4), we include year-fixed effects and demographic, personal characteristics, such as age, age squared, gender, and household size, but we suppress the coefficients of control variables to save in space. In Panel B, we report estimation results about equation (5), in which we use as dependent variable either the participation frequency (columns (1) and (2)) or the share rebalancing (columns (3) and (4)). Model specifications and other 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A	Wealth Returns	Wealth Returns	Wealth Returns	Wealth Returns
Total Wealth$_{t-1}$	-0.030***	-0.031***	-0.122***	-0.147***
	(0.004)	(0.005)	(0.020)	(0.028)
Frequency	0.094***	0.097***		
	(0.012)	(0.017)		
Rebalancing			0.016*	0.016
			(0.009)	(0.013)
Education	0.028***	0.027**	0.067***	0.072**
	(0.009)	(0.011)	(0.023)	(0.031)
Skills		0.045***		0.016
		(0.013)		(0.024)
Panel B	Frequency		Rebalancing	
Total Wealth$_{t-1}$	0.043***	0.039***	0.065***	0.033
	(0.002)	(0.002)	(0.022)	(0.026)
Education	0.097***	0.044**	0.048	0.084
	(0.013)	(0.017)	(0.049)	(0.062)
Skills		0.102***		0.036
		(0.013)		(0.053)
Controls	YES	YES	YES	YES
Observations	19,310	9,922	1,689	938

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

Table 15. The Education Effect: *Direct* and *Indirect* Effects. Frequency & Rebalancing

The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. We obtain both direct and indirect effects by using the estimation results presented in Table 14, in which we report the Maximum Likelihood estimate of the simultaneous two-equation model described in equations (4) and (5) using data described in Section 2. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In columns (1) and (2), the mediator variable is the number of waves in which the individual participates to the stock market (i.e., $OwnSTKMF = 1$) as a fraction of the total number of waves the individual provides information on financial investments (*Frequency*). *Frequency* takes values between 0 and 1. In columns (3) and (4), the mediator variable is the fraction of risky share traded (either bought or sold) by the individual as a fraction of the risky share held by the individual in the previous wave (*Rebalancing*). 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 3. *Skills* is the unobserved, individual ability computed by estimating equation (3) 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 Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Wealth Returns	Frequency	Frequency	Rebalancing	Rebalancing
Direct Effect:				
Education	0.028***	0.027**	0.067***	0.072**
	(0.009)	(0.011)	(0.023)	(0.031)
Skills		0.045***		0.016
		(0.013)		(0.024)
Indirect Effect:				
Education	0.009***	0.004**	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Skills		0.010***		0.001
		(0.002)		(0.001)
Total Effect:				
Education	0.037***	0.031***	0.068***	0.073**
	(0.009)	(0.011)	(0.023)	(0.031)
Skills		0.055***		0.017
		(0.012)		(0.024)

Table 16. University Fields: *Direct* and *Indirect* Effects. Frequency & Rebalancing
The table reports the direct and indirect effects of *Education* and *Skills* on returns to wealth. Specifically, we estimate the direct effect from equation (4) and we compute the indirect effect by combining results from simultaneous estimation of equations (4) and (5). We define as indirect effect the marginal impact that the independent variable has on the dependent variable of (4) through the impact on the mediator variable, which is both an independent variable in (4) and the dependent variable in (5). In Panel A, the mediator variable is the number of waves in which the individual participates to the stock market (i.e., $OwnSTKMF = 1$) as a fraction of the total number of waves the individual provides information on financial investments (*Frequency*). *Frequency* takes values between 0 and 1. In Panel B, the mediator variable is the fraction of risky share traded (either bought or sold) by the individual as a fraction of the risky share held by the individual in the previous wave (*Rebalancing*). 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 3. We report direct, indirect, and total effects for each field of University degree, as described in Table 1. We control for the unobserved, individual ability computed by estimating equation (3) using OLS. The data are from the Italian Survey on Household Income and Wealth (SHIW) by Bank of Italy. Data are on bi-annual basis and cover waves from 1993 to 2020.

Panel A: Participation Frequency

Wealth Returns	Economics	Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.008	-0.014	0.016	0.035*	0.053***
	(0.030)	(0.024)	(0.027)	(0.019)	(0.020)
Indirect Effect:					
Frequency	0.016***	0.005	0.003	0.005*	0.000
	(0.006)	(0.004)	(0.005)	(0.003)	(0.002)
Total Effect:					
	0.024	-0.009	0.019	0.040**	0.053****
	(0.030)	(0.024)	(0.027)	(0.019)	(0.020)

Panel B: Portfolio Turnover

Wealth Returns	Economics	Politics	Medicine	STEM	Humanistic
Direct Effect:					
	0.073	0.030	0.068	0.081*	0.099**
	(0.087)	(0.058)	(0.075)	(0.045)	(0.044)
Indirect Effect:					
Rebalancing	0.000	0.001	0.004	0.002	0.000
	(0.002)	(0.002)	(0.004)	(0.002)	(0.002)
Total Effect:					
	0.073	0.031	0.072	0.083*	0.099**
	(0.087)	(0.058)	(0.075)	(0.045)	(0.044)

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