The Production of Financial Literacy

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Abstract

We study the accumulation of financial competencies in a model of dynamic skill formation. We find evidence of complementarities between financial literacy and risk attitudes. Risk tolerance facilitates experimentation and learning-by-doing. Latent risk attitudes and financial literacy are unevenly distributed across households and do not align with general human capital. Linking estimates with data on household portfolios, we show that early-life differences in financial literacy may account for more than half of the standard deviation of wealth by age 60. Dynamic complementarities in skill formation imply that early interventions could reduce later-life inequality while boosting wealth growth.

Keywords: Financial literacy, inequality, wealth returns, skills, risk attitudes

1 Introduction

There is growing recognition that financial literacy has an important influence on households' financial health and long-term outcomes. Many adults struggle to understand basic concepts related to saving and investing (Lusardi and Mitchell, 2007) and this has lasting consequences for wealth growth, retirement and long-term welfare. Research often focuses on the correlation between households' socio-economic characteristics and their ability to make informed financial choices (Lusardi and Mitchell, 2014)and several studies highlight that inadequate financial competencies are often associated to life-cycle outcomes such as large debt (Gorbachev and Luengo-Prado, 2019; Gathergood, 2012) and low portfolio diversification (Gaudecker, 2015; Li, Li, and Wei, 2020).

Despite evidence on the costs of poor financial literacy, we have a limited understanding of the way such skills are developed. Do observable household traits (income, age, education) shape financial literacy? Do risk attitudes influence the acquisition of such skills? How do financial competencies evolve over the life-cycle? To examine these questions we develop a dynamic model of skill formation and explore the conditions under which key parameters can be identified and estimated. The objective is to shed light on the way different inputs contribute to the development of financial competencies and to establish to what extents these inputs align with general educational achievement and income.

Inequality in financial competencies exacerbates wealth inequality because gaps in investment returns, even as small as a yearly difference of 50 basis points (Gaudecker, 2015), get compounded into large differences over longer horizons. Lusardi, Michaud, and Mitchell (2017) estimate that financial knowledge may account for between 30 and 40 percent of retirement wealth inequality. Examining the dynamic formation of financial skills is helpful to understand potential drivers of returns' heterogeneity and their impact on long-term economic discrepancies. In this respect our work is related to empirical and theoretical research on the determinants of wealth heterogeneity (Benhabib, Bisin, and Zhu, 2011; Benhabib, Bisin, and Zhu, 2015; Hubmer, Krusell, and Smith Jr, 2021; Fagereng et al., 2020). For example, Fagereng et al. find that those with a college degree in Business or Economics enjoy higher average returns, consistent with the view that analytical skills lead to better choices. However, as we show in our descriptive analysis, education accounts for some of the variation in financial literacy but large differences prevail within groups of similarly educated individuals. This suggests that unobserved (latent) factors contribute to return heterogeneity above and beyond general human capital.

Our estimates suggest that financial competencies and risk attitudes are related. Higher risk tolerance enhances the dynamic accumulation of financial skills as individuals become more willing to engage in experimentation and learning-by-doing. Moreover, we find that risk attitudes interact with several other household traits in the dynamic process of skill formation.

To quantify the impact of early life differences, we consider the distribution of excess wealth growth (that is, excess unpredicted returns) across households and characterize the influence of heterogeneous traits that contribute to wealth inequality through financial literacy. Linking the acquisition of financial literacy to portfolio returns (Lusardi, Michaud, and Mitchell, 2017) we draw attention to less known aspects of their relationship, including (i) whether financial competencies affect choices in a non-linear way (for example, by requiring a minimum level or through increasing returns); (ii) whether specific inputs in the production of financial competencies are independently associated with the distribution of wealth; and (iii) whether traits that shape financial skills can be considered effective substitutes to household income in determining long-term wealth outcomes.

The empirical analysis relies on microdata from the "Panel of Household Finance in Germany", a survey covering the balance sheet, pension, income and demographic characteristics of a panel of households living in Germany. We use repeated observations for the same set of households to estimate a model of dynamic skill formation. In our sample, roughly 2/3 of adults have at least a basic level of financial literacy (Klapper and Lusardi, 2020); nonetheless, we identify significant effects of heterogeneity in financial competencies and emphasize that these insights may be of even greater practical value in places where savings and self-insurance play a larger role in buffering negative income shocks and shaping financial resilience (Lusardi and Mitchell (2011b)).

Our empirical approach builds on the one suggested in the context of life-cycle skills formation (Cunha, Heckman, and Schennach, 2010), where the focus is on the distinction between cognitive and non-cognitive traits that facilitate the accrual of productive human capital. This line of research has gained popularity in other contexts (see for example Attanasio et al., 2020; Attanasio, Meghir, and Nix, 2020). Our implementation can be summarized in three incremental steps. First, through an E-M algorithm, we approximate the data distribution by a mixture of Normals. Second, parameter estimates of the joint distribution of latent factors, including financial competencies, are obtained; in this respect we leverage multiple survey measures of financial literacy. In the final step, we generate a synthetic sample by randomly drawing combinations of latent factors and observable variables from the fitted mixtures of Normals. We then use these samples to estimate a dynamic production function describing the formation of financial competencies. Since data on the distribution of private portfolio returns can be obtained, the estimated distribution of latent financial skills can be mapped into the distribution of wealth growth.

The dynamic production of financial literacy amounts to a sequence of input choices whose dynamic complementarity can be estimated alongside the elasticity of substitution between pre-existing latent factors. We rely on multiple noisy measures from the survey to tease out three latent factors that enter as inputs in the production of financial literacy; these factors are the pre-existing stock of financial competencies, latent household resources and unobserved risk tolerance. We find evidence of strong dynamic complementarities so that existing financial knowledge begets higher literacy as people age. Since complementarities may result in an early crystallization of skills, this calls for policies that boost financial education from an early age such as the inclusion of personal finance notions in school curricula. Our findings suggest that even moderate exposure to such notions may increase individual welfare in the long term.

Latent attitudes towards risk appear important for the acquisition of financial competencies as they facilitate experimentation in unfamiliar activities and investments. Lower risk aversion is associated to faster accumulation of financial literacy as well as to a tighter relationship between financial competencies and portfolio returns. The latter observation suggests that financial literacy by itself may not be sufficient to induce significantly larger returns if individuals are unwilling to engage in somewhat uncertain endeavors. These findings are of interest when designing public policies aimed at reducing differences in lifetime wealth and retirement income, which have noticeably grown (Abbott and Gallipoli, 2022) over the past four decades.

2 Data

We use three waves of the German Panel of Household Finances (PHF 2011, 2014, 2017; Schmidt et al. 2019). The survey is conducted by the Bundesbank and contains information on households' balance sheets, pensions, incomes, employment and demographic characteristics. Some households are followed over time, while others are surveyed only once. We use a balanced panel consisting of the subset of households contacted in each of the three waves. The survey features information that can be used to directly gauge the evolution of financial knowledge among respondents over the sample period.

Measures of Financial Literacy. A financially knowledgeable person (FKP) is identified within each household. The FKP answers all questions related to assets, wealth, risk preferences and financial competencies. We include in the sample households whose FKP is the same in the three waves[1]. This restricts the sample to 1,567 households observed over three waves (4,701 household-year observations). The design of the survey provides direct information about socio-demographic and economic variables, including labor income, pensions, social and welfare transfers, rents, financial income, ownership of private companies, net wealth including real and financial assets but excluding public and occupational pension plans, the number of children less than 16 years old, and region of residence. The survey collects general questions, such as whether the household can make ends meet, and additional information about the characteristics of the FKP (marital status, gender, age, years of education, self-assessed attitudes to risk, patience in personal choices). Below we overview survey questions designed to elicit financial literacy (the exact wording, and possible answers, are in Appendix B):

- *Inflation:* Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
- *Diversification:* Buying a single company's stock usually provides a safer return than a stock mutual fund.
- *Compound interest rate 1:* Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the

[1] The FKP can change due to the household composition or the availability of the person at time of interview

account if you left the money to grow?

- *Compound interest rate 2:* Let's assume you have taken out a loan of $1,000 on which you're paying interest of 20% per annum. If you do not pay down any of the loan and interest is also charged on the accrued interest the following year, how many years would it take for the debt to double?

These hypotheticals assess the comprehension of basic financial notions: inflation, portfolio diversification and compounding interest rate. We create a dummy variable which is one if the answer is correct and zero otherwise. Table 1 reports the shares of respondents who correctly answered each of the four financial literacy questions in each wave. The question on compound interest was asked only in the third wave.

Table 1: Financial literacy questions. Share of people who answered correctly

Question	Wave 1	Wave 2	Wave 3
Q. inflation	0.940	0.929	0.938
Q. diversification	0.796	0.789	0.819
Q. compound interest 1	0.896	0.908	0.887
Q. compound interest 2	-	-	0.615

Descriptive Analysis Summary statistics of sample variables are shown in Tables 2 and 3. The sample is balanced in terms of location: North is the region with the lowest number of households at 17% of the total. As for marital status, about 2/3 of FKPs are married; singles are roughly 14% and divorced account for 10% of the sample. Widowed and separated make up the rest. Age patterns are consistent with marital status and the average age is 55.

Despite inequality in income and wealth, roughly 3/4 of households could make ends meet. As for risk attitudes and patience, less than one in twenty of respondents reported taking more than average risks in their financial investments and the average score in the risk self-assessment was 3.9 (where ten is being happy to take risks).

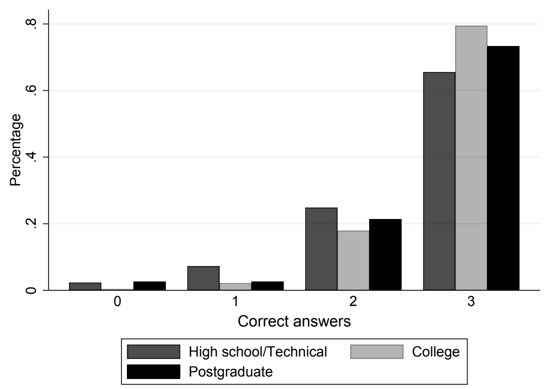
Figure 1 shows histograms of the share of correct answers for three financial literacy questions in the first wave, conditional on various covariates. After conditioning on age, education, gender and location, significant heterogeneity continues to be present in survey responses. In particular, while education and financial literacy are correlated, considerable variation in responses persists within each education group. Rather than being a gauge of general education, financial literacy exhibits independent variation. Age is negatively correlated with financial literacy (Figure 1b) but there is visible heterogeneity in the number of questions answered correctly in each age group. Married respondents have higher financial literacy, as one would expect in the presence of specialization within the household.

Table 2: Descriptive statistics. Categorical variables. Wave 1

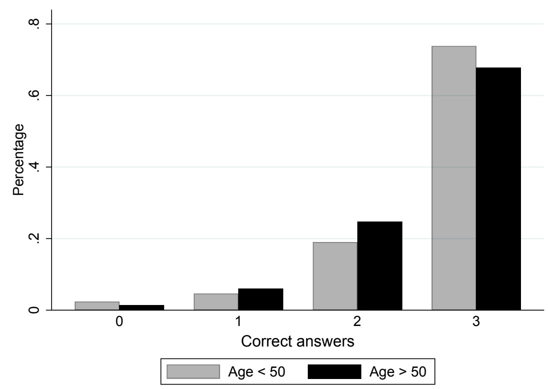
Household characteristics		FKP characteristics	
Make ends meet	0.731	Female	0.408
Risks above average	0.030	*Marital status*	
Region		Single	0.139
North	0.172	Divorced	0.101
West	0.273	Widowed	0.068
South	0.369	Married	0.666
East	0.186	Separated	0.026

Table 3: Descriptive statistics of non-categorical variables (wave 1 of survey). Income and wealth expressed in real (2017) Euros.

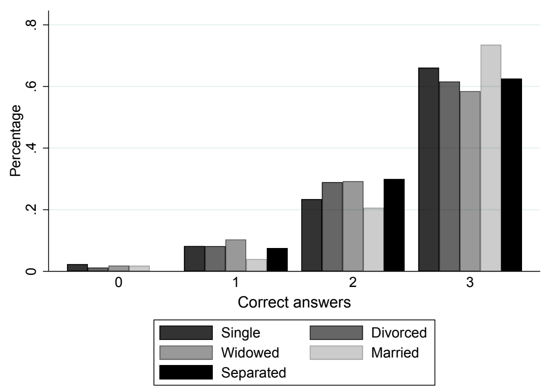
	Mean	sd	p10	p50	p90
Household characteristics					
Income	66,137	77,962	16,100	49,400	127,000
Wealth	438,317	2,096,601	2,830	194,500	854,500
Number of children	0.29	0.70	0	0	1
FKP characteristics					
Years of education	12.2	3.2	9	10	16
Age	55.3	14.6	34	57	72
Self-assessment Risk	3.9	2.3	1	4	7
Self-assessment Patience	4.6	2.5	1	5	8



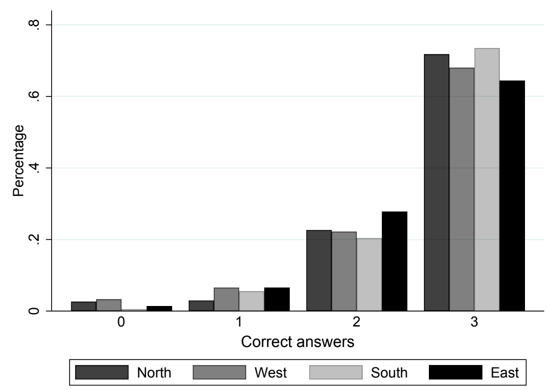
(a) Education



(b) Age



(c) Marital status



(d) Region

Figure 1: Histogram of the correct number of financial literacy questions in the first wave by age, education, marital status and region

3 Model

To explore the processes that shape financial competencies, we study a dynamic production function of an intangible output interpreted as financial knowledge. The production structure delivers estimable restrictions on different latent factors that contribute to skill development. The analysis imposes the canonical restrictions of a production function to recover the elasticity between inputs both within and between periods, and to assess the importance of distinct household characteristics, such as family resources and risk attitudes.

Estimates of the parameters that govern the evolution of skill formation are useful to account for the origins of heterogeneity in financial competencies across households and for the distribution of financial outcomes such as savings, debt, and the net return on wealth. Different unobserved factors can contribute to changes in financial competence, with the main one being the existing stock of financial competence itself. We model the latter as a latent variable observed with error through the survey questions on financial literacy included in the PHF. The two additional latent inputs in our analysis reflect, respectively, household resources derived from wealth and income, and risk tolerance. Higher pre-existing family resources are often described as an important factor in the production of financial knowledge as they imply awareness of the costs and benefits of administering assets and sustain expenditures into older age. Of course, financial literacy itself may shape household resources, requiring additional steps to assess their empirical impacts.

The unobserved risk tolerance factor, measured through questions about uncertainty and preferences, affects financial knowledge by expanding the choice set of less risk-averse individuals who are willing to consider more opportunities and devote attention to such matters. Our findings suggest that risk attitudes may be important for the learning-by-doing process that shapes financial literacy.

3.1 Dynamic Production of Financial Competencies

We consider a constant elasticity (CES) production function that links the financial literacy outcomes ($\theta^1_{i,t+1}$) to predetermined values of the existing stock of knowledge ($\theta^1_{i,t}$), as well as t broader household resources ($\theta^2_{i,t}$) and to risk preference measures ($\theta^3_{i,t}$). The approach allows to flexibly control for household and personal characteristics ($X_{i,t}$) through the productivity term (TFP), including age, gender, years of education, number of children and marital status of the FKP (Cunha, Heckman, and Schennach, 2010). Age may contribute to financial knowledge through different channels. For example, young people might accumulate skills through novel financial products, while those close to retirement must keep track of their finances despite the inevitable depreciation of knowledge due to aging (Lusardi and Mitchell, 2011a). Gender could play a role through variation in risk attitudes and pre-existing financial competence (Lusardi and Mitchell, 2008).

More years of education facilitate the acquisition of the analytical concepts necessary for financial planning even if the overlap between financial and non-financial competencies is imperfect. Finally, marital status might influence the production of financial literacy through mutual learning and specialization within the household.

Substitution between latent factors. A key parameter governing the production of financial knowledge is the elasticity of substitution among latent inputs in the production of financial competencies. Equation (1) presents a specification where all the inputs and controls are either lagged or time-invariant. Our interest lies in recovering the elasticity as well as the share parameter, as they jointly summarize the contribution of different layers of household heterogeneity to the dynamic production process. We assume stationarity of technology parameters but allow for age-varying productivity:

$$\theta^1_{i,t+1} = (s_1(\theta^1_{i,t})^\rho + s_2(\theta^2_{i,t})^\rho + (1 - s_1 - s_2)(\theta^3_{i,t})^\rho)^{\frac{1}{\rho}} exp[\alpha_0 + \alpha X_{i,t} + u_{i,t}] \tag{1}$$

Anchoring financial literacy. An advantage of the self-contained PHF survey data is that we can access measures of distinct financial outcomes in the cross-section of households. These measures are not directly used to estimate the production technology parameters but, rather, deliver a snapshot of household-level outcomes that depend on it. Linking cross-sectional measures such as total wealth growth to estimates of intangible financial knowledge (and other covariates) allows one to anchor the scale of the latent variable (θ^1) in a way that makes it interpretable (Cunha, Heckman, and Schennach, 2010). For illustration, we consider the case of the excess growth of net wealth. We compute these excess returns as follows:

1. Define and estimate net wealth changes as $r_{i,t} = \frac{w_{i,t}}{w_{i,t-1}} - 1$. This measure includes active saving, capital gains and reinvested dividends.
2. Regress wealth growth of household i between t and $t-1$ ($r_{i,t}$) on age, year and income polynomials, gender, number of children and adults, a dummy for geographical region, the value of the previous period's net wealth composition and lagged net wealth.
   The lagged values account for differentials in the returns across assets and for the possibility that richer households might have access to better investment opportunities.
3. Compute the predicted (fitted) wealth growth ($\hat{r}_{i,t}$) using estimates from the previous step.
4. Compute excess growth as the actual change in wealth minus the fitted values (three-year growth rates), that is:
   $$Z_{i,t} = r_{i,t} - \hat{r}_{i,t} \tag{2}$$
   Since $\hat{r}_{i,t}$ uses $t-1$ information, and there are only three waves in the PHF, the variable $Z_{i,t}$ can be computed for the last two waves.

Having recovered a cross-sectional distribution of excess returns, we examine their relationship with financial literacy as in:

$$Z_{i,t+1} = \gamma_0 + \gamma_1 \ln(\theta^1_{i,t+1}) + \epsilon_{i,t} \tag{3}$$

To anchor the production function to excess returns (Cunha, Heckman, and Schennach, 2010), we can cast it as :

$$(\theta^1_{i,t+1})^{\gamma_1} = (s_1(\theta^1_{i,t})^{\rho\gamma_1} + s_2(\theta^2_{i,t})^\rho + (1 - s_1 - s_2)(\theta^3_{i,t})^\rho)^{\frac{1}{\rho}} \exp[\alpha_0 + \alpha X_{i,t} - \gamma_0 + u_{i,t}] \tag{4}$$

We estimate equations (3) and (4) jointly. Anchoring the financial education latent variable to realized returns is useful to interpret parameter estimates and enhances their value for policy analysis.

3.2 The Measurement System

To estimate the distributions of latent variables we develop a measurement system that spells out the reduced-form relationship between a set of noisy measurements (M) and the latent variables (θ) (see Attanasio, Meghir, and Nix, 2020). The system consists of additively separable functional forms governed by parameters (Λ, Σ):

$$M = A + \Lambda \ln \theta + \Sigma \epsilon \tag{5}$$

The matrix Λ imposes the "zero restrictions" that define which noisy measure is related to a latent variable. Since a noisy measure is related to only one latent variable, the matrix Λ features a single non-zero entry in each row. We normalize the coefficient of the first measurement of each latent variable to one. For example, if we had two latent variables, each with three measurements, the matrix Λ would be:

$$\Lambda = \begin{bmatrix} 1 & 0 \\ \lambda_{2,1} & 0 \\ \lambda_{3,1} & 0 \\ 0 & 1 \\ 0 & \lambda_{2,2} \\ 0 & \lambda_{3,2} \end{bmatrix} \tag{6}$$

We consider three latent variables: financial literacy (θ_t^1), household resources (θ_t^2), and risk attitudes (θ_t^3). Denoting the survey wave by $t \in \{1, 2, 3\}$, the relationship between latent factor k and measurement j is:

$$m_{j,k,t} = a_{j,k,t} + \lambda_{j,k,t} \ln \theta_t^k + \epsilon_{j,k,t} \tag{7}$$

where $\epsilon_{j,k,t}$ are independently distributed Gaussian shocks. The system can accommodate different covariates that we later use for the estimation of the production function. In fact, covariates must be included to estimate the joint distribution of all the relevant observable variables. The variables that do not vary with time (in this system, all except θ^1) are normalized in both scale and location. The dynamic skill factor (θ^1) is not centered so that the measurement system can reflect its evolution over time.

Identification. Solving the measurement system requires at least three measures for each factor. As we show below, we employ three noisy measurements for θ^2 and θ^3, while for financial knowledge (θ^1), we use four measurements in the first two waves and five in the last wave. Identification is up to a normalization where the coefficient of the first measurement of each latent variable is set to one. This normalization is held across waves, making the scale of the latent variables consistent over time.

Noisy measures and latent variables. The measurements in vector M are obtained from the Panel of Household Finances (PHF) and are listed in Table 4. For financial literacy, we use questions related to inflation, portfolio diversification, interest compounding, and discretionary savings in the last twelve months. For the latent household resources we rely on three measurements. The first two are the reported values of income and wealth expressed in real terms (2017 Euros). The third is a categorical variable taking value one for households that report making ends meet easily or fairly easily. Finally, for the latent risk attitudes' factor we use two self-assessed scores on risk-taking and self-control in daily life (see Appendix C for details) and an explicit question about risk preferences when making financial decisions.

Table 4: Measurements

Measure	Wave 3	Wave 2	Wave 1
Financial education			
Q. inflation	x	x	x
Q. diversification	x	x	x
Q. compound interest 1	x	x	x
Q. compound interest 2	x		
Discretionary savings	x	x	x
Resources			
Income	x	x	x
Net wealth	x	x	x
Make ends meet	x	x	x
Risk preferences			
Self-assessed risk	x	x	x
Risk preference	x	x	x
Self-assessed patience	x	x	x

3.3 Estimation

Estimation consists of a sequence of steps (Attanasio, Meghir, and Nix, 2020). We begin by approximating the C.D.F. of the latent variables through a mixture of two Normal distributions (denoted as A and B):

$$F_\theta = \tau\Phi(\mu_A, \Omega_A) + (1-\tau)\Phi(\mu_B, \Omega_B). \tag{8}$$

The equation above, together with the measurement system in (5), imply that a mixture of Normals approximates also the C.D.F. of the measurements, that is

$$F_M = \tau\Phi(\Pi_A, \Psi_A) + (1-\tau)\Phi(\Pi_B, \Psi_B) \tag{9}$$

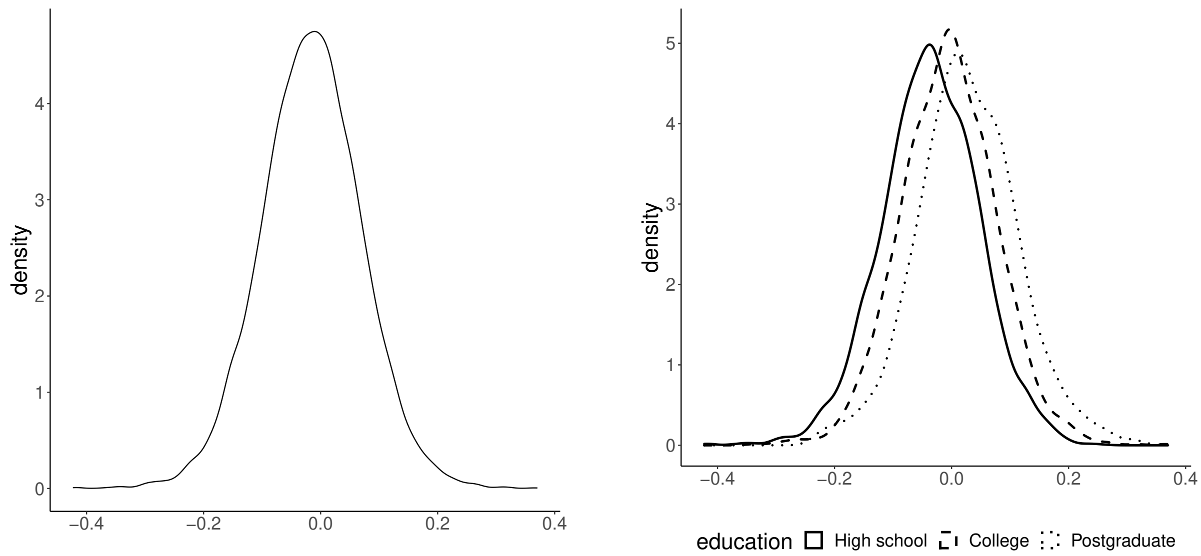
We estimate the parameters of the F_M distribution and of the production function in three steps:

1. We estimate $\tau, \Pi_A, \Psi_A, \Pi_B, \Psi_B$ in (9) using the E-M algorithm. Initially we guess values for (τ, Π_x, Ψ_x) and, through the E step of the algorithm, we estimate the probability that each observation is drawn from each C.D.F. Next, the M step employs conditional likelihood to estimate the parameters of the two Normal distributions. This process is repeated until numerical convergence in the parameter space is achieved.
2. Given parameters for F_M and the measurement system in (5), we use GMM to estimate the following relationships:
$$\begin{aligned} \Psi_x =& \Lambda^T\Omega_x\Lambda + \Sigma \\ \Pi_x =& A + \Lambda\mu_x. \end{aligned} \tag{10}$$
Since $x = A, B$, there are four systems of equations that describe first and second moments of the two Normal distributions on the right-hand side of (9). Given the constraints imposed in the Λ vector, and under an initial period normalization $(\tau\mu_{A,t=0}+(1-\tau)\mu_{B,t=0} = 0)$,[2] we can recover the unknown parameters in $\Lambda, \Omega_x, \Sigma, A, \mu_x$. That is, we choose the parameters to minimize the distance between empirical and theoretical moments derived from the equations in (10).
3. The third step involves drawing a sample from F_θ to estimate the production function in (1). Confidence intervals are obtained through bootstrap of all three steps.

4 Estimation Results

Figure 2 shows the density function of the latent financial literacy factor θ^1. The left panel refers to the most recent sample wave while the right panel shows density functions conditional on education.

[2]The normalization identifies the constant terms of the measurement system in the first period (Attanasio, Meghir, and Nix, 2020). Given stationarity, μ_A and μ_B are identified in subsequent periods since A is identified in the first period and the weight of the first measurement in the Λ matrix is one in each period.

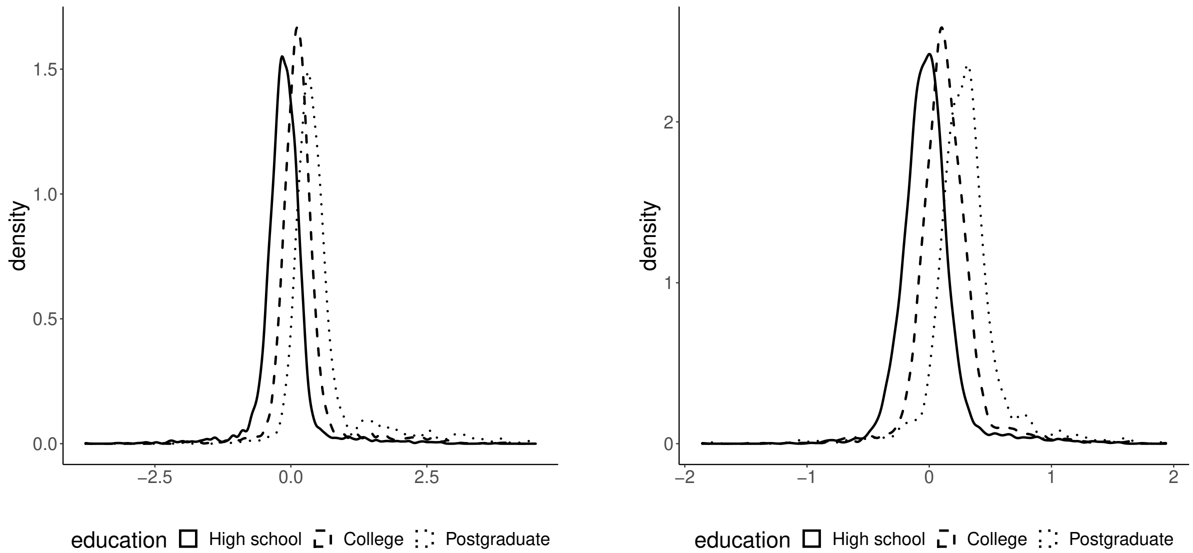


(a) Unconditional density. (b) Density conditional on education.

Figure 2: Density of latent financial literacy in survey wave 3. Unconditional (left panel) and conditional on education (right panel).

The coefficient of variation (CV) of the unconditional distribution of the latent financial literacy factor is 5.36. This indicates significant dispersion, which is only partly reduced when conditioning on education group. The high school group has the lowest CV at around 2.25; more educated individuals have higher financial literacy on average. The conditional distributions of different education groups overlap to an extent that suggests that standard measures of human capital are a poor proxy of financial competencies. Put differently, within each education group, there is sufficient variation in financial literacy to suggest that observed education is an inaccurate approximation for it. Figure 3 shows the densities of latent factors reflecting household resources (θ_3^2) and risk attitudes (θ_3^3), conditional on education.[3] It is the case that more educated individuals enjoy more resources and are more willing to accept risks (higher θ^3).

[3]The latent factor θ^3 reflects the willingness to accept risk. This is because the coefficients in matrix Λ put positive weight on measurements that take higher values for individuals who are more willing to take risks. In this sense θ^3 increases with willingness to take risks.



(a) Household resources latent factor (θ_3^2). (b) Risk attitudes latent factor (θ_3^3).

Figure 3: Density of estimated latent factors in latest survey wave, by education.

When looking at gender differences (Figure 4), our estimates suggest slightly higher financial literacy among men, although the distributions are similarly dispersed and overlap with each other over most of their ranges. It is worth emphasizing that our estimates presented below suggest that women tend to have higher TFP in the production of financial competencies; together with the results in Figure 4, these findings indicate large potential gains from gender-targeted policies that encourage the acquisition of such skills.

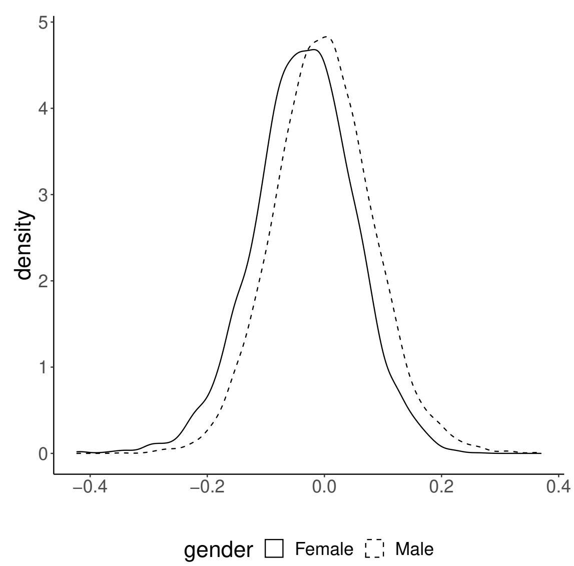


Figure 4: Density of latent financial literacy factor in latest survey wave 3, by gender.

4.1 Measurement System: Estimates

Appendix E summarizes the estimates of the measurement system's mixture parameters. Table 23 shows that the probability of each mixture (τ) lies far from the boundaries (either zero or one) and that the means of most factors are different. The latter observation confirms that using more than one Normal distribution is necessary to correctly approximate the distribution of data.

Estimates of the loadings in matrix Λ are in Table 24. In the case of financial education, the diversification measurement carries the highest weight, while the compound interest question has the lowest. The latent factor for household resources depends mostly on income and wealth, while 'making ends meet' has a lower weight. This suggests that income and wealth are often sufficient on their own to identify the resources available to a household.

Finally, the weights used to define the latent risk attitudes factor confirm that θ_3^3 should be viewed as a measure of the willingness to take risk. The self-assessment question on self-control and patience has limited impact, while the two noisy measures of risk-taking have a strong influence. Among the latter, the preference measure carries a higher weight, which is comforting since this question is specifically designed to gauge the willingness to accept risk in financial investments.

Signal versus noise: a decomposition. Using the estimates of the measurement system we can break down each measure into signal and noise components. This decomposition leverages the additively separable structure of the system. From equation (7), the variance of a measurement variable can be written as the sum of a signal, for example $\lambda_{j,k,t}^2 var(\ln \theta_t^k)$, and a noise component, for example $var(\epsilon_{j,k,t})$. Table 5 shows that, for financial literacy, the question on diversification has the highest share of signal in all waves. This is also the question with the lowest share of correct answers (Table 1). The noisy measures of wealth and income shape the household resources latent factor; in contrast, "making ends meet" adds mostly noise. Finally, the signal for the latent risk attitudes factor largely derives its information content from the risk attitude questions.

Table 5: Share of signal in each measure

Wave	3	2	1
Financial education			
Q. inflation	0.09	0.19	0.03
Q. diversification	0.25	0.35	0.25
Q. compound interest 1	0.05	0.35	0.01
Q. compound interest 2	0.23		
Discretionary savings	0	0.15	0
Resources			
Income	0.11	0.18	0.41
Net wealth	0.74	0.58	0.32
Make ends meet	0.01	0.01	0.01
Risk preferences			
Self-assessed risk	0.04	0.02	0.02
Risk preference	0.25	0.97	0.93
Self-assessed patience	0	0	0

4.2 Production Function Estimates

From the estimated C.D.F. of the latent factors we draw a random sample to estimate the production function in (1).

Endogeneity of household resources. As the input θ^2 (household resources) can introduce endogeneity bias, we use a control function approach and begin by estimating a reduced-form equation for latent household resources using a set Y of instruments. That is:

$$\ln \theta^2_{i,t} = \beta_0 + \beta_1 \ln \theta^1_{i,t} + \beta_2 \ln \theta^3_{i,t} + \beta_3 X_{i,t} + \beta_4 Y_{i,t} + \nu_{i,t} \tag{11}$$

Specifically, we use regional variation in wealth per capita to instrument changes in household resources. Next, under the assumption that $\mathbb{E}(u_{i,t}|\theta_t, X_{i,t}, Y_{i,t}) = b\nu_{i,t}$, we include $\hat{\nu}_{i,t}$ as an additional regressor (the control function) when estimating (4). The endogeneity of θ^2 can be tested by examining the significance of its coefficient.

Financial literacy production: parameter estimates. Table 6 shows estimation results. The impact of lagged financial education is around 0.25, indicating persistence and dynamic complementarity. The risk attitude factor has a similar gradient. Household resources have an estimated effect close to 0.5. This points to two interesting findings. First, higher resources enhance the acquisition of financial competencies. This might occur through more opportunities for investment which, in turn, generate higher financial knowledge. Second, lower aversion to risk implies more readiness to invest in financial products and these decisions require learning more about returns and the way they vary.

The elasticity is estimated quite precisely around 1.0 ($\hat{\rho} = 0.003$). This denotes complementarity between inputs and implies that public policies to increase financial knowledge should operate through multiple channels. Regarding the effect of covariates, two results are especially salient. Women apear to accumulate financial knowledge faster. It is important to note this suggests that women have higher productivity when accumulating financial knowledge despite lower initial financial knowledge (see Figure 4 and Lusardi and Mitchell, 2008). The policy implications is that investing in women's financial literacy generates high returns.

Table 6: Production function. 90% confidence intervals based on 100 replications in square brackets. Marital status dummies included, see Table 14 for full results

	Financial knowledge
Finlit	0.258
	[0.084,0.579]
Resources	0.516
	[0.273,0.756]
age	0.012
	[-0.017,0.042]
age^2	-0.001
	[-0.001,0.001]
female	0.028
	[-0.001,0.057]
children	0.003
	[-0.02,0.022]
education	-0.117
	[-0.155,-0.064]
ρ	0.003
	[-0.107,0.018]

The role of non-financial education. Figure 5 shows the average value of the latent financial literacy factor by age and education group. The life-cycle profile for high-school graduates seems somewhat steeper than for more educated individuals, which suggests the possibility of a catch-up process. These patterns are consistent with the negative estimates of the education gradient in Table 6. To illustrate this point, consider two individuals, i and j, with the same characteristics including initial financial competence ($\theta^1_{i,t} = \theta^1_{j,t}$), but different levels of education ($educ_i > educ_j$). Using equation (1), the difference in financial literacy in $t+1$ is approximately

$$\ln\left(\frac{\theta^1_{i,t+1}}{\theta^1_{i,t}}\right) - \ln\left(\frac{\theta^1_{j,t+1}}{\theta^1_{j,t}}\right) = \alpha_{educ}(educ_i - educ_j). \tag{12}$$

If financial literacy for j grows faster, the LHS is negative and $\alpha_{educ} < 0$. As in the case of gender, heterogeneity reflects the pace of growth in financial competencies rather than their initial levels.

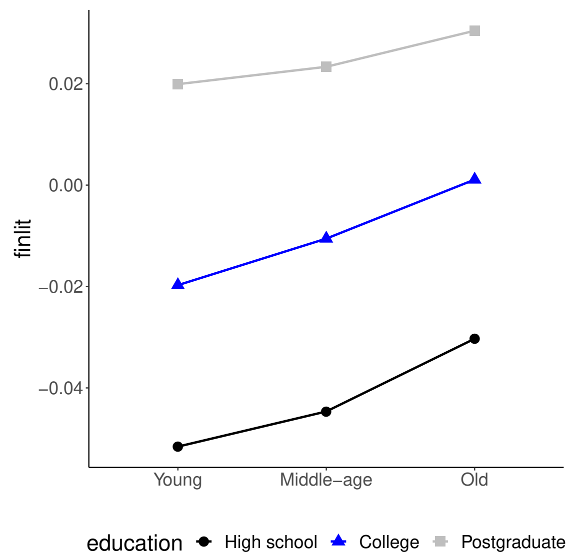


Figure 5: Average latent financial literacy (wave 3) by education group and age

The coefficient on the variable representing the residuals from the reduced-form equation of resources is strongly significant. The control variables have a joint p-value of 0.000 and an F test of 39.0, which suggests that they are effective in accounting for the endogeneity of θ^2.

4.3 Wealth Changes and Financial Competencies

We can estimate the parameters dictating the accumulation of financial competencies, equation (4), alongside the relationship between these competencies and wealth growth, as in equation (3). This analysis builds on the 'anchoring' approach discussed in Section 3 and has two advantages. First, it allows to cast the level of financial knowledge (θ^1) in the metric of wealth growth and to facilitate interpretation. Second, it becomes possible to quantify the impact of financial education on wealth dynamics, which provides insights on the relationship between returns heterogeneity and human capital (Fagereng et al., 2020), but unlike previous work it focuses on latent measures of financial competencies that are the by-product of previous skills and investments. The focus on the dynamic accumulation process makes policy design, and potential policy impacts, more transparent.

Joint estimation of (4) and (3) results in a new set of parameter values, reported in Table 7. Production parameter estimates are similar to those in Table 6. Latent household resources have the highest weight while financial literacy has a dynamic gradient of 0.17, which is consistent with intertemporal complementarities. The elasticity of substitution between contemporaneous inputs is close to one and precisely estimated.

Table 7: Estimated parameters for th production function and anchor equation. The 90% confidence intervals, based on 100 replications, are in square brackets. Marital status dummies included, see Table 15 for full results.

Finlit	0.17
	[0,0.97]
Resources	0.674
	[0.018,0.827]
age	0.026
	[-0.016,0.065]
age^2	-0.001
	[-0.002,0.001]
female	0.028
	[-0.012,0.051]
children	-0.008
	[-0.03,0.02]
education	-0.12
	[-0.154,-0.005]
ρ	0
	[-0.127,0.021]
γ_0	-0.013
	[-0.024,0.087]
γ_1	1.145
	[0.051,2.797]

From financial literacy to wealth growth. Joint estimation of the financial literacy technology and the excess return equation delivers a measure of the pass-through from financial competencies to wealth growth. The point estimate of this pass-through (the semi-elasticity γ_1 in equation (3)) is positive and just above 1.1. Since the standard deviation of $\ln(\theta_3^1)$ is 0.09, a one standard deviation increase in financial competencies induces, on average, an extra wealth return of roughly 10% in three years. This is approximately an extra return on wealth of 3.2% annually.

Put differently, moving a person from the first quartile of the latent financial literacy distribution to its median (from -0.07 to +0.04) would imply an extra return on wealth of roughly 13%, close to 4% annually. These extra returns would have a big impact over longer time intervals and if compounded until retirement.

Figure 6 shows the distribution of estimates for the pass-through parameter γ_1, based on 100 bootstrap replications. The distribution of the semi-elasticity γ_1 is unimodal and exhibits a thick right tail, suggesting that excess returns from higher financial literacy are, on average, sizable and positive.

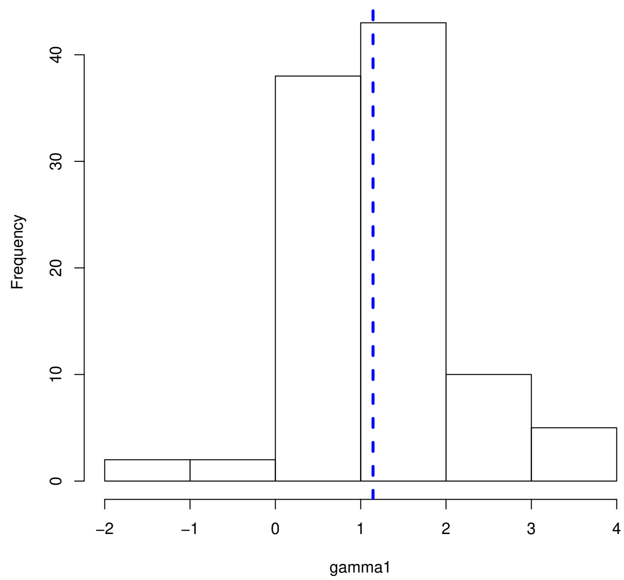


Figure 6: Density of γ_1. Dotted line is central estimate.

4.4 The Uneven Impact of Financial Literacy on Wealth Changes

Figure 6 illustrates that the pass-through from financial competencies to wealth growth is positive but imprecisely estimated. This suggests the possibility of heterogeneous pass-through across households. To assess the empirical relevance of age differences and risk attitudes we re-estimate the model for separate sub-samples.

Financial literacy and age. In Table 8 we show estimates of production function parameters for a sub-sample of households whose FKP is older than 55 and a sub-sample of younger FKPs.

Among the similarities, we note that the elasticity of substitution among inputs is similar across age groups and close to one. Education has a negative gradient at all ages, which is consistent with the differential accumulation across education groups and the catch-up effects discussed in the previous section. The point estimate of the gender gradient is positive in both age group.

Table 8: Production function and anchor equation by age. 90% confidence intervals based on 100 replications in square brackets. Marital status dummies included, see Table 16 for full results

	Young	Old
Finlit	0.134	0.206
	[-0.037,0.896]	[0.053,0.918]
Resources	0.714	0.653
	[0.065,0.864]	[0.045,0.841]
female	0.031	0.024
	[-0.006,0.07]	[-0.019,0.045]
children	-0.008	-0.015
	[-0.036,0.017]	[-0.027,0.014]
education	-0.122	-0.117
	[-0.146,-0.016]	[-0.158,-0.013]
ρ	0.001	-0.001
	[-0.129,0.034]	[-0.145,0.039]
γ_0	0.031	-0.031
	[-0.059,0.205]	[-0.076,0.085]
γ_1	1.446	1.013
	[0.074,3.377]	[-0.114,2.754]

Point estimates of the pass-through from financial competencies to wealth growth (γ_1) are quite different. Among younger households the estimated pass-thorugh is significant and almost 1/3 higher than for the whole population; for older households the coefficient is close to one and not significant. Differences are apparent also in financial literacy production parameters, as the weight of lagged financial literacy (s_1) is 0.13 for the young and 0.21 for the old. This contrasts with the trend of the weight of resources, which is decreasing with age, suggesting a progressive crystallization of financial competencies as age progresses. Taken together, these patterns indicate that the accumulation of financial literacy may depend on learning by doing and that the learning process might be more productive and vigorous at younger ages. Earlier life financial choices not only increase households' wealth over longer horizons but may play an important role in the dynamic accumulation of financial literacy through learning by doing. This observation has non trivial policy implications as it suggests that early investments in financial competencies may contribute to household welfare through different and complementary channels. Figure 7 shows the distribution of the pass-through parameter γ_1 in the two age groups.

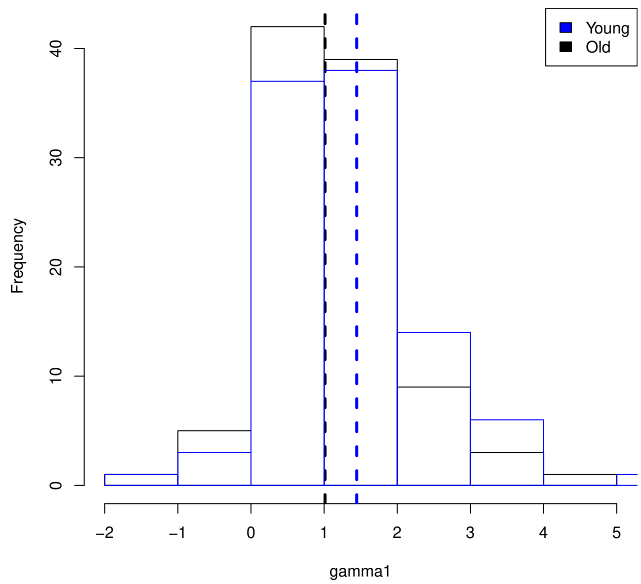


Figure 7: Density of γ_1 by age. Dotted line is central estimate

Risk attitudes and learning-by-doing. Table 8 suggests that, among younger households, financial literacy may have a stronger gradient on wealth returns. This is consistent with the view that early life learning plays a role in the dynamic accumulation of both skills and wealth. To examine this hypothesis, in Table 9 we report estimates of technology and pass-through parameters after dividing the sample of young households according to latent risk attitudes. If learning by doing is a direct contributor to the development of financial literacy, risk attitudes would play an important role insofar they facilitate (or hinder) experimentation. As mentioned above, we begin by splitting the sample of younger households in those below and above the median of the latent factor θ^2; in this way we distinguish between households with stronger aversion to risk (those below the median θ^2) and those more willing to accept risks and experiment (above median θ^2). Findings suggest that financial literacy does play a more salient role in the dynamic accumulation of new skills and wealth among less risk averse households. We estimate a γ_1 close to one and not significant in the low θ^2 sample while its estimate exceeds two and is significant among households that are more willing to accept risks. In addition, Table 9 shows that financial literacy is less persistent among households that are more willing to accept risk (the Finlit share in production is 0.063 vs 0.242 depennding on risk attitudes). These estimate corroborate the view that young households that are more willing to accept risk are better able to move away from their initial level of financial literacy and lend support to the hypothesis that households with higher risk tolerance manage to accumulate more wealth while growing their financial literacy at the same time through learning by doing.

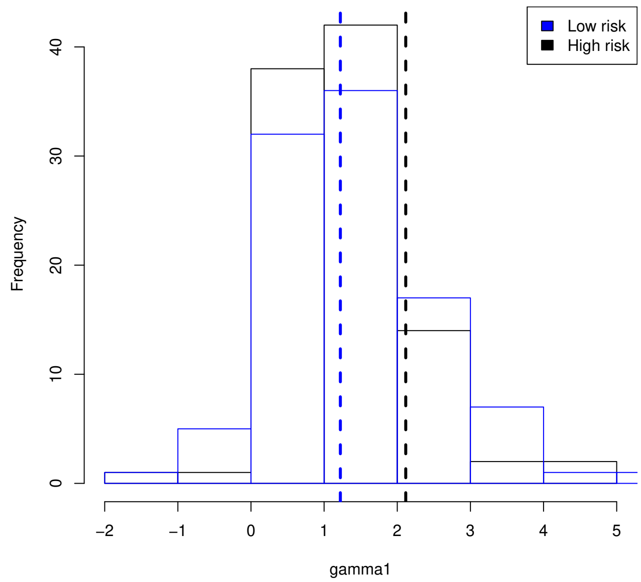


Figure 8: Density of the semi-elasticity of excess returns (γ_1) to financial literacy. By risk preferences, conditional on young age group. Dotted line is central estimate.

Table 9: Production function and anchor equation by risk level for young. 90% confidence intervals based on 100 replications in square brackets. Marital status dummies included, see Table 17 for full results

	High risk aversion	Low risk aversion
Finlit	0.242	0.063
	[-0.004,0.948]	[-0.039,0.806]
Resources	0.639	0.767
	[0.034,0.828]	[0.188,0.944]
Constant	0.172	-0.346
	[-0.142,0.481]	[-0.535,0.187]
female	0.034	0.021
	[-0.016,0.07]	[-0.024,0.073]
children	0.008	-0.02
	[-0.024,0.032]	[-0.037,0.037]
education	-0.139	-0.092
	[-0.166,-0.007]	[-0.179,-0.029]
ρ	-0.028	0.033
	[-0.274,0.042]	[-0.123,0.062]
γ_0	0.263	-0.203
	[-0.077,0.576]	[-0.521,0.237]
γ_1	1.222	2.116
	[-0.103,3.449]	[0.19,3.311]

Marital status. Does marital status matter for the dynamics of financial literacy and wealth growth? Table 10 shows differences in the loadings of latent factors in the production of financial literacy for married and non-married households (by marital status of the FKP). For married individuals, the weight of the lagged financial literacy and latent family resources add up to almost one, while for those not married they add up to around 0.6, indicating that unobserved risk tolerance (not reported) has a higher weight in their skill formation process. Moreover, the point estimate of γ_1 (the semi-elasticity of excess wealth returns to financial literacy) is approximately twice as large in the sample of non-married households, although imprecisely estimated.

Table 10: Production function and anchor equation by marital status. The 90% confidence intervals, based on 100 replications, are in square brackets.

	Not married	Married
Finlit	0.118	0.284
	[-0.051,0.569]	[0.045,1.02]
Resources	0.51	0.727
	[0.215,0.633]	[-0.026,0.98]
Constant	0.203	-0.189
	[0.091,0.351]	[-0.224,-0.012]
age	0.028	-0.001
	[-0.012,0.084]	[-0.026,0.046]
age^2	-0.003	0
	[-0.003,0.003]	[-0.001,0.001]
female	0.022	0.031
	[-0.001,0.057]	[-0.009,0.059]
children	0.006	-0.031
	[-0.018,0.04]	[-0.045,0.013]
education	-0.091	-0.125
	[-0.133,-0.046]	[-0.171,0.005]
ρ	0.001	-0.028
	[-0.084,0.058]	[-0.339,0.009]
γ_0	0.182	-0.108
	[0.058,0.356]	[-0.157,0.016]
γ_1	1.829	0.894
	[0.185,3.418]	[-0.043,2.793]

This difference does not depend on age composition, as shown in Table 11 which reports estimates by marital status conditioning on a age and focusing on younger couples. Instead, these discrepancies suggest the possibility of decreasing returns to financial competencies which become more apparent in couples where specialization results in more literate FKPs. We examine this hypothesis further down.

Table 11: Production function and anchor equation by marital status for young (younger than 55). The 90% confidence intervals, based on 100 replications, are in square brackets.

	Not married	Married
Finlit	0.156	0.127
	[-0.054,0.545]	[0.063,0.993]
Resources	0.486	0.917
	[0.232,0.686]	[0,0.976]
Constant	0.174	-0.232
	[-0.011,0.508]	[-0.32,0.111]
female	0	0.058
	[-0.023,0.055]	[-0.008,0.084]
children	0.001	-0.036
	[-0.028,0.032]	[-0.071,0.008]
education	-0.091	-0.146
	[-0.135,-0.044]	[-0.165,-0.002]
ρ	-0.003	-0.099
	[-0.106,0.098]	[-0.545,0.017]
γ_0	0.188	-0.123
	[0.007,0.507]	[-0.236,0.202]
γ_1	2.047	1.145
	[0.557,3.643]	[-0.066,2.872]

5 Accounting for Wealth Inequality

The estimates in the previous sections can be used to examine how the dispersion of a variable, e.g. inequality in latent resources θ_t^2, translates into wealth growth. Below we illustrate this by using baseline estimates (Table 7) to simulate the evolution of financial competencies and wealth growth for a cross-section of households. In particular, we employ model parameters to approximate the distributions of latent values. Then, we examine the distributions of the dependent variables (output) for the same cross-section of households. For this last step we use the production and pass-through equations reported below:

$$\begin{aligned}
\ln(\hat{\theta}_{i,2}^1) &= \frac{1}{\hat{\gamma}_1}\left[\frac{1}{\hat{\rho}}(\hat{s}_1(\theta_{i,1}^1)^{\hat{\rho}\hat{\gamma}_1} + \hat{s}_2(\theta_{i,1}^2)^{\hat{\rho}} + (1-\hat{s}_1-\hat{s}_2)(\theta_{i,1}^3)^{\hat{\rho}}) + \hat{\beta} + \hat{\alpha}X_{i,1}\right] \\
\ln(\hat{\theta}_{i,3}^1) &= \frac{1}{\hat{\gamma}_1}\left[\frac{1}{\hat{\rho}}(\hat{s}_1(\hat{\theta}_{i,1}^2)^{\hat{\rho}\hat{\gamma}_1} + \hat{s}_2(\theta_{i,2}^2)^{\hat{\rho}} + (1-\hat{s}_1-\hat{s}_2)(\theta_{i,2}^3)^{\hat{\rho}}) + \hat{\beta} + \hat{\alpha}X_{i,2}\right] \\
\hat{Z}_{i,2} &= \hat{\gamma}_0 + \hat{\gamma}_1\ln(\hat{\theta}_{i,2}^1) \\
\hat{Z}_{i,3} &= \hat{\gamma}_0 + \hat{\gamma}_1\ln(\hat{\theta}_{i,3}^1)
\end{aligned}$$

It is also possible to design counterfactual exercises such that latent inputs (e.g. family resources, risk tolerance) are replaced with their cross-sectional averages; this is useful to illustrate the impact of equalizing latent conditions across households.

Counterfactual returns on wealth. We first consider the case of latent household resources and substitute $\theta^2_{i,t}$ by $\bar{\theta}^2_t = \frac{1}{N}\sum \theta^2_{i,t}$. By shutting down heterogeneity in latent resources we gauge their effects on the mean and variance of wealth growth.

Figure 9 superimposes the the counterfactual distribution of predicted wealth growth to the actual distribution for college-level households; to reduce confounding effects, both distributions are conditional on the FKP being aged between 40 and 60. Forcing latent household resources to be equal to their cross-sectional average results in a rightward shift in the distribution of wealth growth. That is, the average value of θ^2 implies more abundant resources for a majority of the households which is associated to better excess returns on average The dispersion of wealth growth rates becomes marginal higher after equalizing latent family resources, consistent with the notion that households may engage in investments that carry marginally more risk.

The counterfactual exercise where we equalize risk attitudes induces a small decrease in average wealth growth and very little change in dispersion. This finding suggests that there exists a subset of high resources and risk-tolerant households that end up losing in the counterfactual scenario as they are no longer able to enjoy the high excess returns of the baseline distribution. This group, however, is not very large and the counterfactual distribution is extremely close to the baseline one.

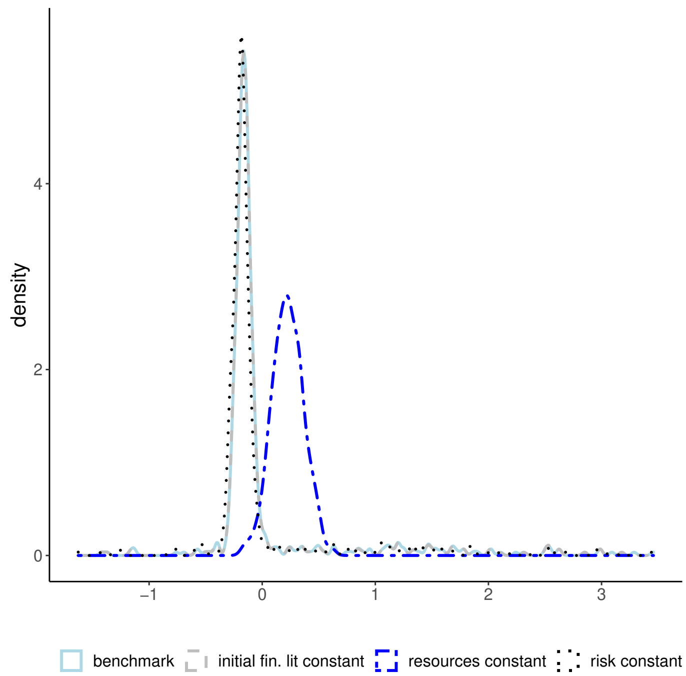
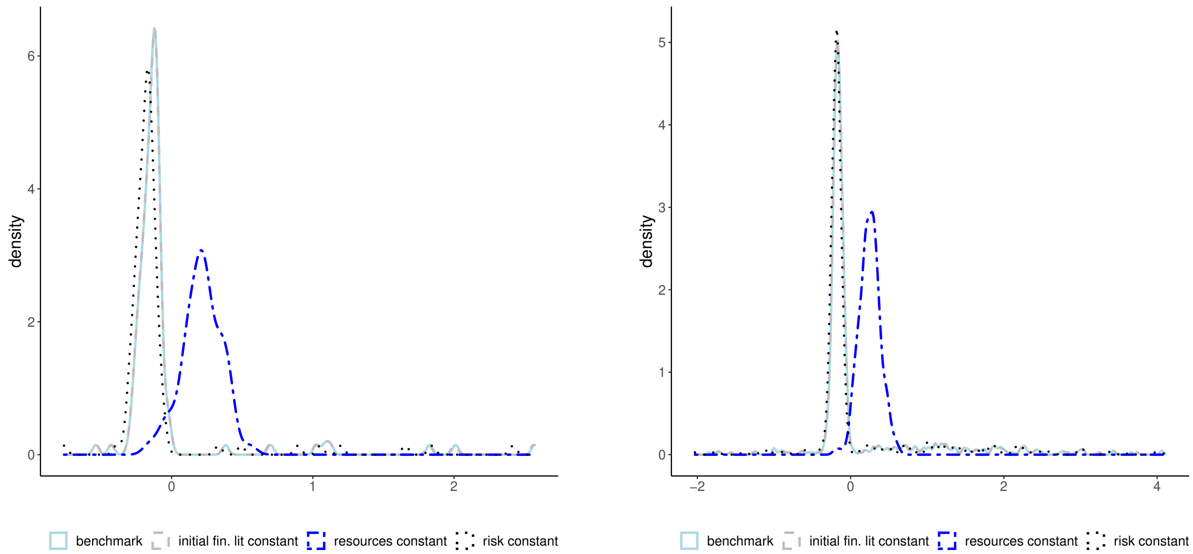


Figure 9: Actual and counterfactual distributions of wealth growth (returns) in the last sample period. Sample of college graduates; age between 40 and 60.

The importance of latent factors at different ages. To illustrate the importance of latent factors at different ages, we perform (Figure 10) simulations for college-level households in other age groups. Specifically, we consider FKPs younger than 40 as well as FKPs older than 60. When comparing these counterfactuals to those in Figure 9, we find that risk attitudes play a more central role in early life and their impact on wealth returns become progressively weaker in households where the FKP is above age 40, almost dissipating by age 60. The same pattern is observed in the counterfactual where we equalize latent household resources, as the impact on return heterogeneity is larger for younger households.



(a) Density age less than 40

(b) Density age more than 60

Figure 10: Density: excess wealth growth in period three, FKP with college degree

5.1 Financial Literacy and Wealth Inequality over the Life-Cycle

Leveraging the age-specific estimates shown in Section 4.4, we examine the life-cycle evolution of wealth and financial literacy for households that only differ in initial characteristics.

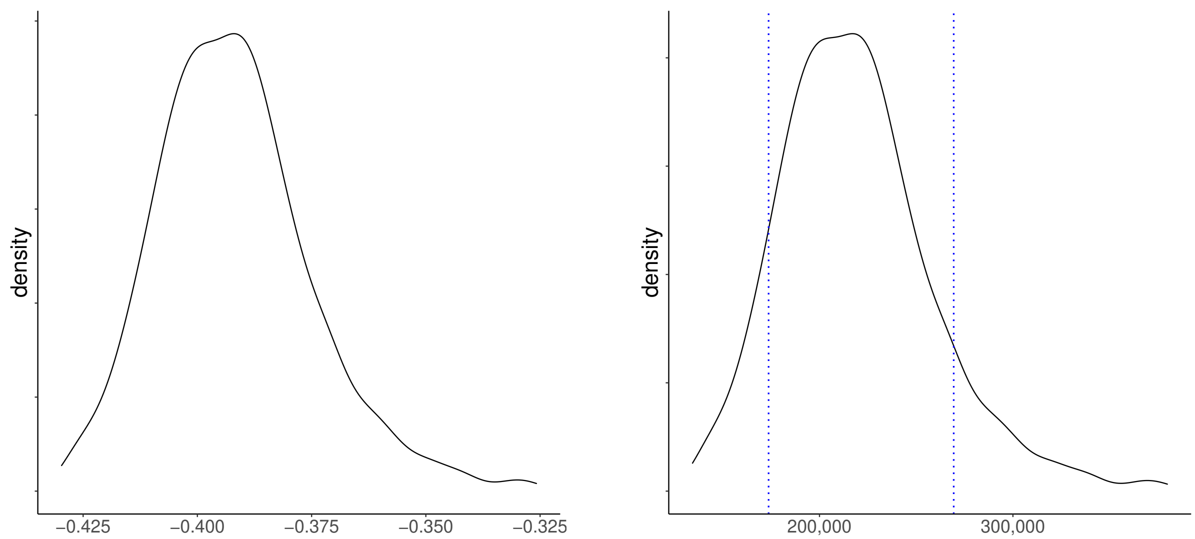
We begin by considering wealth inequality and its dependence on the initial stocks of latent financial literacy. How much of the observed wealth heterogeneity can be attributed to early life differences in the unobserved financial literacy factor? First, we simulate the accumulation of wealth and skills for a sample of one hundred households starting at age 30 with the same level of initial wealth (EUR \$16,000), which is the median value in the PHF for households below age 30. Using estimates of the matrix Λ, we generate a value for the latent θ^2 factor (household resources).[4]

Next, we set the latent risk attitudes factor (θ^3) to the sample median. This implies that households only differ in their initial level of latent financial literacy (θ^1), for which we assign the percentiles $1, 2, 3, \ldots, 100$ in the sample. Using the parameterized equations (3) and (4) for different age groups (Table 8), we can then generate wealth and financial literacy trajectories over a 30 year horizon and project their values at age 60.

Figure 11 shows the distribution of both these outcomes after thirty years. It is apparent that more wealth dispersion is induced by differences in early life endowments of financial literacy. The standard deviation in the distribution of later life wealth is EUR \$ 40,000

[4]The latent factor θ^2 varies with income. We restrict household income to its cross-sectional average to avoid confounding effects on θ^2.

and the median is EUR $220,000. If we can compare these outcomes to values observed in the PHF between age 30 and 60, we see that latent financial literacy accounts for a significant portion of wealth inequality. Using the PHF microdata, we estimate wealth dispersion (standard deviation) among households below age 30 at around EUR $305,000; when we consider households where the FKP is at age 60 the same metric reaches EUR $ 830,000. Simply comparing real and simulated changes over the life cycle, heterogeneity in initial financial literacy would account for roughly 8% of the change in wealth inequality (40,000 out of 525,000). A similar contribution is obtained when looking at changes in the wealth gap between the 10th and 90th percentiles of wealth: the change in the 90-10 gap in our simulations is EUR $96,000; in the PHF data the 90-10 gap grows from 245,000 for those aged 30 or less to 1,310,000 at age 60. Therefore the distance between the 10th and 90th percentiles increases by EUR $1,065,000 in data and latent initial financial literacy accounts for roughly 9%. These are clearly lower bounds of the true impact of early life endowments of financial literacy because the counterfactual exercise ignore the covariation of initial conditions in latent factors.



(a) Financial literacy (θ^1)

(b) Wealth

Figure 11: Densities of wealth distributions at age 60, allowing only for initial heterogeneity in θ^1 (initial fin. literacy stocks). Wealth obtained after simulating wealth growth over 30 year horizons. Dotted lines are 10th and 90th percentiles.

The interaction between financial literacy and risk attitudes. The counterfactual exercise above ignores some sources of heterogeneity that have been shown to contribute to wealth dispersion. For example, if risk tolerance (θ^3) and financial literacy are correlated, the impact of initial conditions on wealth inequality would be different.

Our estimates suggest that θ^3 and θ^2 have a positive correlation of about 0.2. Therefore, households with higher initial financial literacy are, on average, more willing to accept risks. A confounding factor related to risk-tolerance is portfolio choice. In the simulations shown above all households are assumed to hold the same portfolio (housing, stocks, private businesses are constrained to be the same) and the expected wealth growth only changes with the level of wealth. However, financial literacy and risk attitudes do affect the likelihood of investing in assets such as stocks, creating further dispersion between households.

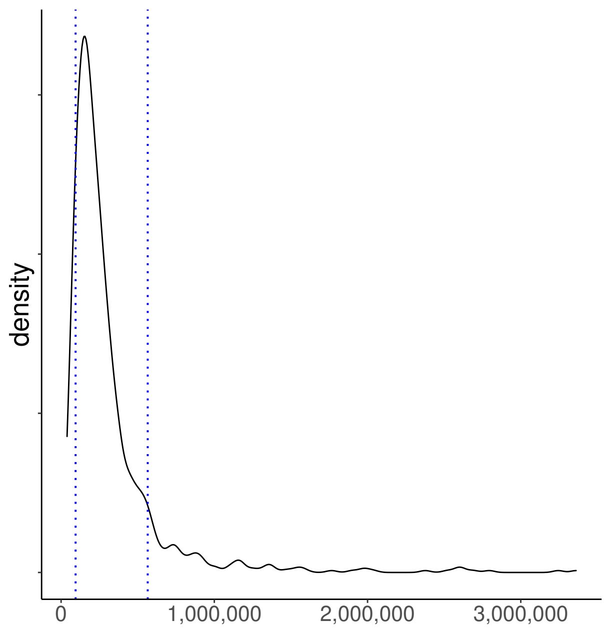


Figure 12: Density of wealth at age 60, for simulated paths over 30 year horizons. Allow for initial household heterogeneity in θ^1 and θ^3. Dotted lines are 10th and 90th percentiles.

To illustrate the importance of risk attitudes for wealth accumulation a natural second step is to allow for them in the counterfactual analysis. To this purpose we generate a sample of households that differ in initial financial literacy θ^1 as well as risk tolerance θ^3.[5] After simulating the evolution of both portfolio returns and skills over a thirty year horizon, we plot the cross-sectional wealth distribution in Figure 12. This exercise shows that (i) average wealth is higher than in Figure 11, and (ii) the dispersion (standard deviation) grows a lot more. Allowing for heterogeneity in risk tolerance, and for its positive correlation with financial literacy, results in a standard deviation of EUR \$348,000 by age 60. This accounts for about 2/3 of the actual growth in wealth dispersion in the PHF data. The gap between

[5]We consider households younger than 31 and trim outlying observations in the risk tolerance distribution, 2.5% on each side.

the 10th and 90th percentiles is EUR \$470,000, which is roughly 44% of the change observed in data between age thirty and sixty.

These results point to the importance of financial literacy for wealth inequality, and confirm that heterogeneity in initial skill endowments interacts with risk attitudes over the life-cycle, suggesting the presence of a learning-by-doing process shaping financial literacy over time.

5.2 Returns to Financial Literacy across Households

The evidence above suggests that excess returns to financial literacy do vary across subsets of the population. This can be due to differences in either the conditional distributions of financial literacy or in the semi-elasticity of excess returns.

In Table 12 we report, for the whole sample and for various sub-populations, estimates of three statistics: (1) the median excess returns in each sample; (2) 10^{th}, 50^{th} and 90^{th} percentiles of financial literacy values; and (3) point estimates (and confidence intervals) for the semi-elasticity of excess return to financial literacy (γ_1).

The estimates are obtained after jointly re-estimating the production function and excess return equations on the different sub-samples of households. In all samples, the distance between the 10^{th} and $90th$ percentiles of $\ln(\theta^1_{i,3})$ is around 0.2 unit (while the unit of measure is irrelevant, the differences can be compared across samples). Therefore, the impact on wealth accumulation of moving from the 10^{th} to the 90^{th} percentile of financial literacy is around $0.2 \times \gamma_1$ in all sub-samples.

When we consider estimates for the whole population sample, this would imply that the excess wealth return for high-literacy households is 23% over three years (that is, $0.2 \times 1.145 = 0.23$, or roughly 7% per year). This is a large magnitude when compared to the median excess return in the population, which is 2.6% over three years (0.8% annually).

Table 12: Estimates, for different sub-samples, of: (1) the median excess returns; (2) 10^{th}, 50^{th} and 90^{th} percentiles of financial literacy values; and (3) point estimates and confidence intervals for the semi-elasticity of excess return to financial literacy (γ_1). The model is re-estimated for each sub-sample.

Group	Median $Z_{i,3}$	Percentiles $\log(\theta^1_{I,3})$			$\hat{\gamma}_1$
		p10	p50	p90	
All	0.026	-0.122	-0.015	0.091	1.145
					[0.051,2.797]
Young	0.103	-0.134	-0.021	0.080	1.446
					[0.074,3.377]
Old	-0.004	-0.117	-0.013	0.096	1.013
					[-0.114,2.754]
Young - High risk aversion	0.106	-0.143	-0.033	0.060	1.222
					[-0.103,3.449]
Young - Low risk aversion	0.101	-0.120	-0.007	0.094	2.116
					[0.19,3.311]
Not - married	0.093	-0.144	-0.036	0.064	1.829
					[0.185,3.418]
Married	-0.004	-0.108	-0.004	0.103	0.894
					[-0.043,2.793]
Young - Not married	0.227	-0.152	-0.041	0.058	2.047
					[0.557,3.643]
Young - Married	0.026	-0.114	-0.007	0.091	1.145
					[-0.066,2.872]

The median excess return from financial literacy varies starkly across samples and is very high among young households, especially the non-married ones where it stands at almost 10 times the median return in the sample of all households. These differences are consistent with the estimates of the semi-elasticity γ_1 across sub-samples, which suggests that younger and unmarried households have more to gain from changes in their financial literacy.

We see these findings as further evidence of decreasing returns to financial literacy. For example, older and married households tend to have higher stocks of financial literacy, which might explain why incremental gains in these skills carry lower excess returns to those households.

Table 13: Point estimates of the semilasticity of excess returns to financial literacy (γ_1) for samples corresponding to different terciles of financial literacy θ^1 (Tercile 1 is the lowest financial literacy set). The 90% confidence intervals, based on 100 replications, are in square brackets. Control variables for gender, age, education, children and marital status are included. For a full set of results see Table 22 in the Appendix.

	Tercile 1	Tercile 2	Tercile 3
γ_1	1.905	1.753	-0.087
	[0.214,3.854]	[-2.537,4.237]	[-1.16,2.281]

To examine the hypothesis that excess returns vary with the underlying stock of financial literacy, we split the household sample into terciles based on their stock of finacial competencies and re-estimate the model (both the technology and anchor equations). Results in Table 13 indicate that, in fact, households with higher financial literacy may benefit less, on average, from incremental gains in such skills. While semi-elasticities are imprecisely estimated, this is consistent with the hypothesis that latent financial competencies have heterogeneous impacts on wealth and tend to be especially beneficial to households with lower initial skill endowments.

6 Conclusions

We use a non-linear model to estimate the way different factors, observable and latent, affect the development of financial literacy over time. We rely on noisy measurements of financial competencies, risk attitudes and household resources to recover the structural parameters of the model and we illustrate that latent financial competencies can help account for much of the variability in several outcomes over the life cycle.

Financial competencies exhibit high persistence and initial conditions do matter. This implies strong dynamic complementarities in production of such skills. At the same time, other factors such as risk attitudes and household resources have a first-order effect on financial literacy especially among younger households. The estimated elasticity of substitution between different inputs at a point in time is around 1.0 and is precisely estimated. Socioeconomic background plays an important role in the accumulation of financial competencies but it is not sufficient to explain heterogeneity in such skills. In particular, we find that risk attitudes can be extremely important at young ages as they facilitate experimentation and learning by doing. This is consistent with the relatively high positive correlation between latent risk tolerance and financial literacy. The behavioural heterogeneity across households with otherwise similar resources may result in very different life cycle outcomes.

In counterfactual exercises we show that early life heterogeneity in latent financial literacy and risk attitudes can account for a large share (up to and above $1/2$) of the growth in wealth dispersion across households in PHF data from Germany over thirty years.

We link measures of financial outcomes, such as wealth growth, to the cross-sectional distribution of latent variables, and provide a transparent mapping that clarifies the contribution of different inputs in the production od financial literacy to families' long-term economic welfare. This is valuable information for governments and institutions interested in expanding financial education and have several implications for policy. By acknowledging the complementarity among inputs, it is possible to establish how each latent factor affects specific households differently. When designing programs to foster financial literacy the best intervention may depend on household characteristics. For example, risk attitudes can vary independently of income, initial wealth and education, and we show that heterogeneity in early life risk tolerance can result in significant differences in later life. Dynamic complementarities in financial competencies call for interventions at younger ages that can trigger a virtuous cycle in which individuals who make smarter financial decisions also increase their resources and progressively improve their financial knowledge. This process appears to be associated with reductions in wealth inequality, which is unusual for policies that result in higher wealth growth on average.

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A Data selection

We use the following criteria to select our sample

1. The household is part of the three waves of the PHF
2. FKP is the same across waves
3. The observation is part of the third implicate. The PHF consists of five different imputed data sets (implicates). Creating more than one dataset is a generally accepted norm. The Survey of Consumer Finances (SCF) also has five implicates

To preserve anonymity the Bundesbank classifies four broad regions:

- North: Bremen, Hamburg, Lower Saxony and Schleswig-Holstein
- South: Baden-Württemberg, Bavaria and Hesse
- West: North Rhine-Westphalia, Rhineland-Palatinate and Saarland
- East: Berlin, Brandenburg, Mecklenburg-West Pomerania, Saxony, Saxony-Anhalt and Thuringia

We impute years of education using the highest level of education completed as follows

- Lower secondary school is nine years
- Higher secondary school and East German standard school up to 10th grade is ten years
- University of applied sciences diploma, technical school or entrance diploma is 12 years
- Those who are studying in a professional education institution have 14 years of education
- University degree is 16 years
- Doctorate is 20 years

B Financial literacy questions

1. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?

(a) More than today
(b) Exactly the same
(c) **Less than today**
(d) Don't know
(e) Prefer not to say

2. Buying a single company's stock usually provides a safer return than a stock mutual fund.

    (a) True
    (b) **False**
    (c) Don't know
    (d) Prefer not to say

3. Suppose you had \$100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

    (a) **More than \$102**
    (b) Exactly \$102
    (c) Less than \$102
    (d) Don't know
    (e) Prefer not to say

4. Let's assume you've taken out a loan of \$1,000 on which you're paying interest of 20% per annum. If you do not pay down any of the loan and interest is also charged on the accrued interest the following year, how many years would it take for the debt to double?

    (a) Less than two years
    (b) **At least two years but less than 5 years**
    (c) At least 5 years but less than 10 years
    (d) At least 10 years
    (e) Don't know
    (f) Prefer not to say

C Questions on risk

The following questions are the measurements to estimate the risk preference latent variable:

1. **SELF-ASSESSMENT: RISK**
   Question: How do you assess yourself: Are you generally a person who is willing to take risks or do you try to avoid taking risks?
   Give your answer on a scale from "0" and "10", with "0" being "highly risk averse" and "10" being "very happy to take risks".

2. **RISK PREFERENCES**
   Question: Which of the statements in list 32 comes closest to describing the attitude to risk when your household makes savings or investment decisions? Please try and characterise the household as a whole, even if this is not always easy.

   (a) We take substantial financial risks expecting to earn substantial returns

   (b) We take above-average financial risks expecting to earn above-average returns

   (c) We take average financial risks expecting to earn average returns

   (d) We are not willing to take any financial risk

3. **SELF-ASSESSMENT: PATIENCE**
   How do you assess yourself: Are you generally a patient person or an impatient person? Assess yourself on a scale from "0" to "10", with "0" being "very patient" and "10" being "very impatient".

D Complete estimation results

Table 14: Production function. 90% confidence intervals based on 100 replications in square brackets

Financial knowledge			
Finlit	0.258	education	-0.117
	[0.084,0.579]		[-0.155,-0.064]
Resources	0.516	single	0.008
	[0.273,0.756]		[-0.034,7.516]
Constant	-0.039	divorced	0.018
	[-0.064,-0.01]		[-0.023,7.061]
age	0.012	widowed	0.003
	[-0.017,0.042]		[-0.032,6.499]
age^2	-0.001	married	-0.059
	[-0.001,0.001]		[-0.118,10.895]
female	0.028	separated	-0.003
	[-0.001,0.057]		[-0.026,3.426]
children	0.003	ρ	0.003
	[-0.02,0.022]		[-0.107,0.018]
elasticity	1.003		
	[0.903,1.018]		
resid. resources	-0.518		
	[-0.745,-0.258]		

Table 15: Production function and anchor equation. 90% confidence intervals based on 100 replications in square brackets

Finlit	0.17	education	-0.12
	[0,0.97]		[-0.154,-0.005]
Resources	0.674	single	0.064
	[0.018,0.827]		[-0.038,7.35]
Constant	-0.046	divorced	0.052
	[-0.065,0.046]		[-0.034,6.907]
age	0.026	widowed	0.026
	[-0.016,0.065]		[-0.033,6.354]
age^2	-0.001	married	-0.022
	[-0.002,0.001]		[-0.117,10.655]
female	0.028	separated	0.038
	[-0.012,0.051]		[-0.024,3.354]
children	-0.008	ρ	0
	[-0.03,0.02]		[-0.127,0.021]
γ_0	-0.013	elasticity	1
	[-0.024,0.087]		[0.888,1.022]
γ_1	1.145	resid. resources	-0.677
	[0.051,2.797]		[-0.802,-0.018]

Table 16: Production function and anchor equation by age. 90% confidence intervals based on 100 replications in square brackets

	Young	Old		Young	Old
Finlit	0.134	0.206	single	0.093	0.058
	[-0.037,0.896]	[0.053,0.918]		[-0.026,1.121]	[-0.032,6.727]
Resources	0.714	0.653	divorced	0.076	0.05
	[0.065,0.864]	[0.045,0.841]		[-0.031,1.056]	[-0.034,6.325]
Constant	-0.052	-0.053	widowed	0.035	0.034
	[-0.123,0.154]	[-0.093,0.063]		[-0.029,0.972]	[-0.034,5.821]
female	0.031	0.024	married	-0.011	-0.011
	[-0.006,0.07]	[-0.019,0.045]		[-0.114,1.622]	[-0.112,9.76]
children	-0.008	-0.015	separated	0.064	0.026
	[-0.036,0.017]	[-0.027,0.014]		[-0.027,0.518]	[-0.036,3.065]
education	-0.122	-0.117	ρ	0.001	-0.001
	[-0.146,-0.016]	[-0.158,-0.013]		[-0.129,0.034]	[-0.145,0.039]
γ_0	0.031	-0.031	elasticity	1.001	0.999
	[-0.059,0.205]	[-0.076,0.085]		[0.886,1.035]	[0.874,1.041]
γ_1	1.446	1.013	resid. resources	-0.721	-0.654
	[0.074,3.377]	[-0.114,2.754]		[-0.852,-0.064]	[-0.808,-0.044]

Table 17: Production function and anchor equation by risk level for young. 90% confidence intervals based on 100 replications in square brackets

	High risk aversion	Low risk aversion		High risk aversion	Low risk aversion
Finlit	0.242	0.063	single	0.074	0.075
	[-0.004,0.948]	[-0.039,0.806]		[-0.049,1.4]	[-0.056,5.072]
Resources	0.639	0.767	divorced	0.072	0.051
	[0.034,0.828]	[0.188,0.944]		[-0.031,1.317]	[-0.074,4.792]
Constant	0.172	-0.346	widowed	0.07	-0.038
	[-0.142,0.481]	[-0.535,0.187]		[-0.03,1.214]	[-0.118,4.4]
female	0.034	0.021	married	0.017	-0.086
	[-0.016,0.07]	[-0.024,0.073]		[-0.082,2.036]	[-0.246,7.318]
children	0.008	-0.02	separated	0.029	0.092
	[-0.024,0.032]	[-0.037,0.037]		[-0.092,0.644]	[0.002,2.365]
education	-0.139	-0.092	ρ	-0.028	0.033
	[-0.166,-0.007]	[-0.179,-0.029]		[-0.274,0.042]	[-0.123,0.062]
γ_0	0.263	-0.203	elasticity	0.973	1.034
	[-0.077,0.576]	[-0.521,0.237]		[0.785,1.043]	[0.891,1.066]
γ_1	1.222	2.116	resid. resources	-0.641	-0.777
	[-0.103,3.449]	[0.19,3.311]		[-0.821,-0.034]	[-0.919,-0.178]

Table 18: Production function and anchor equation by marital status. 90% confidence intervals based on 100 replications in square brackets

	Not married	Married		Not married	Married
Finlit	0.118	0.284	female	0.022	0.031
	[-0.051,0.569]	[0.045,1.02]		[-0.001,0.057]	[-0.009,0.059]
Resources	0.51	0.727	children	0.006	-0.031
	[0.215,0.633]	[-0.026,0.98]		[-0.018,0.04]	[-0.045,0.013]
Constant	0.203	-0.189	education	-0.091	-0.125
	[0.091,0.351]	[-0.224,-0.012]		[-0.133,-0.046]	[-0.171,0.005]
age	0.028	-0.001	ρ	0.001	-0.028
	[-0.012,0.084]	[-0.026,0.046]		[-0.084,0.058]	[-0.339,0.009]
age^2	-0.003	0			
	[-0.003,0.003]	[-0.001,0.001]			
γ_0	0.182	-0.108	elasticity	1.001	0.973
	[0.058,0.356]	[-0.157,0.016]		[0.922,1.062]	[0.747,1.009]
γ_1	1.829	0.894	resid. resources	-0.522	-0.717
	[0.185,3.418]	[-0.043,2.793]		[-0.63,-0.208]	[-0.958,0.025]

Table 19: Production function and anchor equation by marital status for young (younger than 55). 90% confidence intervals based on 100 replications in square brackets

	Not married	Married		Not married	Married
Finlit	0.156	0.127	children	0.001	-0.036
	[-0.054,0.545]	[0.063,0.993]		[-0.028,0.032]	[-0.071,0.008]
Resources	0.486	0.917	education	-0.091	-0.146
	[0.232,0.686]	[0,0.976]		[-0.135,-0.044]	[-0.165,-0.002]
Constant	0.174	-0.232	ρ	-0.003	-0.099
	[-0.011,0.508]	[-0.32,0.111]		[-0.106,0.098]	[-0.545,0.017]
female	0	0.058			
	[-0.023,0.055]	[-0.008,0.084]			
γ_0	0.188	-0.123	elasticity	0.997	0.91
	[0.007,0.507]	[-0.236,0.202]		[0.904,1.108]	[0.647,1.017]
γ_1	2.047	1.145	resid. resources	-0.509	-0.903
	[0.557,3.643]	[-0.066,2.872]		[-0.647,-0.22]	[-0.935,0.009]

Table 20: Production function and anchor equation by number of children. 90% confidence intervals based on 100 replications in square brackets

	No children	Children		No children	Children
Finlit	0.125	0.249	single	0.049	0.07
	[-0.009,0.933]	[-0.009,1.064]		[-0.025,8.582]	[-0.056,6.861]
Resources	0.722	0.541	divorced	0.044	0.048
	[0.032,0.847]	[-0.044,0.879]		[-0.021,8.06]	[-0.063,6.45]
Constant	0.043	-0.203	widowed	0.024	0.026
	[-0.028,0.164]	[-0.261,-0.028]		[-0.029,7.412]	[-0.06,5.935]
age	0.031	0.027	married	-0.037	-0.008
	[-0.011,0.063]	[-0.013,0.07]		[-0.085,12.443]	[-0.171,9.954]
age^2	-0.001	0	separated	0.018	0.056
	[-0.003,0.002]	[-0.003,0.002]		[-0.052,3.914]	[-0.028,3.129]
female	0.018	0.039	ρ	0	-0.006
	[-0.004,0.049]	[-0.015,0.054]		[-0.115,0.032]	[-0.23,0.016]
education	-0.12	-0.113			
	[-0.144,-0.009]	[-0.159,0.012]			
γ_0	0.075	-0.167	elasticity	1	0.994
	[0.02,0.197]	[-0.24,0.011]		[0.897,1.033]	[0.813,1.016]
γ_1	1.341	0.959	resid. resources	-0.723	-0.543
	[-0.202,2.925]	[-0.39,2.621]		[-0.803,-0.033]	[-0.838,0.042]

Table 21: Production function and anchor equation by gender. 90% confidence intervals based on 100 replications in square brackets

	Male	Female		Male	Female
Finlit	0.183	0.155	single	0.084	0.02
	[0.044,1.015]	[-0.037,0.95]		[-0.034,6.838]	[-0.04,9.094]
Resources	0.776	0.562	divorced	0.067	0.022
	[-0.015,0.884]	[0.032,0.747]		[-0.034,6.435]	[-0.046,8.543]
Constant	0.003	-0.087	widowed	0.028	0.011
	[-0.059,0.146]	[-0.215,0.095]		[-0.06,5.921]	[-0.036,7.857]
age	0.013	0.035	married	-0.031	-0.042
	[-0.025,0.072]	[-0.014,0.065]		[-0.13,9.921]	[-0.124,13.192]
age^2	0	-0.002	separated	0.036	0.031
	[-0.002,0.001]	[-0.003,0.003]		[-0.027,3.125]	[-0.052,4.143]
children	-0.018	0.002	ρ	0	-0.014
	[-0.032,0.025]	[-0.025,0.028]		[-0.117,0.021]	[-0.199,0.024]
education	-0.146	-0.095			
	[-0.181,0.004]	[-0.123,-0.007]			
γ_0	0.043	-0.073	elasticity	1	0.986
	[0,0.179]	[-0.206,0.1]		[0.895,1.021]	[0.834,1.025]
γ_1	0.739	1.513	resid. resources	-0.776	-0.57
	[-0.284,2.619]	[-0.144,3.105]		[-0.832,0.015]	[-0.765,-0.033]

Table 22: Estimate of effect of financial literacy on wealth accumulation by tercile of θ^1. 90% confidence intervals based on 100 replications in square brackets

	Tercile 1	Tercile 2	Tercile 3		Tercile 1	Tercile 2	Tercile 3
Finlit	-0.073	-0.056	0.908	education	-0.157	-0.182	-0.016
	[-0.221,0.826]	[-0.108,1.283]	[-0.253,1.199]		[-0.175,-0.031]	[-0.18,0.052]	[-0.241,0.032]
Resources	0.875	1.157	0.063	single	0.125	0.153	0.01
	[0.136,1.014]	[-0.235,1.071]	[-0.156,0.988]		[-0.009,12.045]	[-0.037,0.756]	[-0.058,4.305]
Constant	-0.248	-0.046	0.188	divorced	0.108	0.11	0.007
	[-0.656,0.234]	[-0.104,0.132]	[-0.228,0.56]		[0,11.324]	[-0.036,0.719]	[-0.062,4.051]
age	0.041	0.024	0.001	widowed	0.061	0.051	0.009
	[-0.012,0.057]	[-0.021,0.047]	[-0.032,0.041]		[-0.02,10.425]	[-0.035,0.671]	[-0.045,3.731]
age^2	-0.003	0	0	married	0.028	-0.028	0.001
	[-0.004,0.002]	[-0.002,0.001]	[-0.001,0.002]		[-0.094,17.49]	[-0.086,1.016]	[-0.141,6.247]
female	0.028	0.051	0.005	separated	-0.041	0.059	0.004
	[0,0.066]	[-0.012,0.063]	[-0.012,0.1]		[-0.026,5.495]	[-0.079,0.419]	[-0.03,1.974]
children	-0.018	-0.053	0	ρ	-0.02	0.021	-0.018
	[-0.033,0.026]	[-0.03,0.023]	[-0.044,0.034]		[-0.218,0.142]	[-0.137,0.046]	[-0.136,0.058]
γ_0	0.037	-0.016	0.193	elasticity	0.981	1.021	0.983
	[-0.36,0.452]	[-0.092,0.183]	[-0.216,0.567]		[0.821,1.166]	[0.88,1.048]	[0.88,1.061]
γ_1	1.905	1.753	-0.087	resid. resources	-0.883	-1.151	-0.062
	[0.214,3.854]	[-2.537,4.237]	[-1.16,2.281]		[-1.015,-0.132]	[-1.057,0.234]	[-0.985,0.156]

E Mixtures and loadings in measurement system

Table 23: Mixtures: means (μA, μB) and probabilities (τ, $1-\tau$). Point estimates and 90% confidence intervals (θ^1: financial knowledge, θ^2: resources, θ^3: risk aversion)

	A	B
	Probabilities	
	0.877	0.123
	[0.864,0.892]	[0.108,0.136]
	Means	
θ_3^1	-0.016	-0.006
	[-0.032,0.003]	[-0.025,0.014]
θ_2^1	-0.023	0.01
	[-0.039,-0.004]	[-0.014,0.02]
θ_1^1	0.001	-0.007
	[0,0.002]	[-0.012,0.002]
θ_3^2	0.023	0.622
	[-0.084,0.124]	[0.403,0.9]
θ_2^2	-0.067	0.767
	[-0.202,0.072]	[0.464,1.119]
θ_1^2	-0.083	0.589
	[-0.134,-0.052]	[0.388,0.942]
θ_3^3	0.058	0.306
	[-0.026,0.143]	[0.229,0.384]
θ_2^3	0.1	0.321
	[0.018,0.177]	[0.248,0.424]
θ_1^3	-0.027	0.193
	[-0.041,-0.014]	[0.095,0.287]

Table 24: Loadings (Λ). Point estimates and 90% confidence intervals

	θ_3^1	θ_2^1	θ_1^1	θ_3^2	θ_2^2	θ_1^2	θ_3^3	θ_2^3	θ_1^3
Period 3. Q. inflation	1	0	0	0	0	0	0	0	0
	[1,1]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Q. diversification	2.44	0	0	0	0	0	0	0	0
	[0.751,4.429]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Q. compound interest 1	0.909	0	0	0	0	0	0	0	0
	[-0.088,1.732]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Q. compound interest 2	3.026	0	0	0	0	0	0	0	0
	[1.552,7.765]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Discretionary savings	0.012	0	0	0	0	0	0	0	0
	[-0.014,0.045]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Q. inflation	0	1	0	0	0	0	0	0	0
	[0,0]	[1,1]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Q. diversification	0	2.121	0	0	0	0	0	0	0
	[0,0]	[1.079,5.211]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Q. compound interest 1	0	1.31	0	0	0	0	0	0	0
	[0,0]	[0.328,1.771]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Discretionary savings	0	-0.289	0	0	0	0	0	0	0
	[0,0]	[-0.668,0.352]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 1. Q. inflation	0	0	1	0	0	0	0	0	0
	[0,0]	[0,0]	[1,1]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 1. Q. diversification	0	0	-4.746	0	0	0	0	0	0
	[0,0]	[0,0]	[-8.912,-0.057]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 1. Q. compound interest 1	0	0	0.599	0	0	0	0	0	0
	[0,0]	[0,0]	[-6.283,2.038]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 1. Discretionary savings	0	0	-0.779	0	0	0	0	0	0
	[0,0]	[0,0]	[-20.086,0.832]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Income	0	0	0	1	0	0	0	0	0
	[0,0]	[0,0]	[0,0]	[1,1]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Net wealth	0	0	0	1.752	0	0	0	0	0
	[0,0]	[0,0]	[0,0]	[1.034,2.447]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 3. Make ends meet	0	0	0	0.152	0	0	0	0	0
	[0,0]	[0,0]	[0,0]	[0.092,0.33]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Income	0	0	0	0	1	0	0	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[1,1]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Net wealth	0	0	0	0	1.327	0	0	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0.61,2.477]	[0,0]	[0,0]	[0,0]	[0,0]
Period 2. Make ends meet	0	0	0	0	0.12	0	0	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0.062,0.322]	[0,0]	[0,0]	[0,0]	[0,0]
Period 1. Income	0	0	0	0	0	1	0	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[1,1]	[0,0]	[0,0]	[0,0]
Period 1. Net wealth	0	0	0	0	0	1.112	0	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0.277,1.864]	[0,0]	[0,0]	[0,0]
Period 1. Make ends meet	0	0	0	0	0	0.118	0	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0.076,0.314]	[0,0]	[0,0]	[0,0]
Period 3. Self-assessed risk	0	0	0	0	0	0	1	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[1,1]	[0,0]	[0,0]
Period 3. Risk preference	0	0	0	0	0	0	2.744	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[1.766,4.434]	[0,0]	[0,0]
Period 3. Self-assessed patience	0	0	0	0	0	0	0.017	0	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[-0.326,0.379]	[0,0]	[0,0]
Period 2. Self-assessed risk	0	0	0	0	0	0	0	1	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[1,1]	[0,0]
Period 2. Risk preference	0	0	0	0	0	0	0	6.102	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[4.381,8.765]	[0,0]
Period 2. Self-assessed patience	0	0	0	0	0	0	0	-0.038	0
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[-0.447,0.307]	[0,0]
Period 1. Self-assessed risk	0	0	0	0	0	0	0	0	1
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[1,1]
Period 1. Risk preference	0	0	0	0	0	0	0	0	6.724
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[4.418,11.433]
Period 1. Self-assessed patience	0	0	0	0	0	0	0	0	-0.244
	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[0,0]	[-0.88,0.044]