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RESEARCH ARTICLE

Investment in risky assets and participation in the financial market: does financial literacy matter?

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Abstract
Our study contributes to a better understanding of the relationship between financial literacy and households' investments in risky assets. We estimate a structural equation model with data from the Panel on Household Finances of the German central bank. Our results show that although households' net wealth is the dominant driver of investments in risky assets, financial literacy plays a remarkable role. Financial literacy has an indirectly positive influence on participation in the financial market. The higher the financial literacy, the lower is the risk aversion. The lower the risk aversion, the higher is the participation in the financial market.

Keywords Financial markets participation · Risky investments · Personal finance · Household finance

JEL Classification D14 · D81 · D91 · G11 · G41 · G51

1 Introduction

The participation of private households in financial markets is one of the key issues in the literature on empirical financial markets in general and in the emerging field of household finance in particular (see Cocco et al. 2005; Campbell 2006; Halko et al. 2012; Guiso and Sodini 2013; Kaustia et al. 2019; Oehler and Horn 2020). Studies have postulated theoretically and empirically that financial literacy, or the lack thereof, is a key driver of whether and to what extent people participate in financial markets (see Lusardi and Mitchell 2008, 2014; Van Rooij et al. 2011; von Gaudecker 2015; Chatterjee et al. 2017; Oehler et al. 2018b).

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In this study, we examine the relationship between financial literacy and households' investments in risky assets. To do so, we first use a structural equation model (SEM) that applies the extensive database on the third wave of data from the Panel on Household Finances (PHF) in 2017 compiled by the German central bank. We also introduce a set of risky assets as proxies for participation in the financial market, such as mutual funds, bonds, publicly traded shares, value of non-self-employment private business, and other financial assets (e.g., total value of shares in cooperatives, precious metals, options, futures) that are unique to the literature.

Our results indicate that households' net wealth is the dominant factor in driving the investment in risky assets and participation in the financial market. With a regression weight of 0.84, which is significant at the one per-mill level, net wealth is the crucial variable in explaining the extent of participation in financial markets. These results correspond to other studies on a decreasing relative risk aversion (DRRA; see, e.g. Cohn et al. 1975; Oehler 1998; Guiso and Sodini 2013; Calvet and Sodini 2014), the Behavioural Portfolio Theory (BPT; see, e.g., Shefrin and Statman 2000; Das et al. 2010; Statman 2017; Oehler and Horn 2020), and a portfolio hierarchy of financial needs (Kaustia and Luotonen 2016; Oehler et al. 2018a; Kaustia et al. 2019).

Furthermore, higher financial literacy does not directly trigger investments in risky assets but through its influence on risk aversion. The higher the financial literacy, the lower the risk aversion is. Literacy has a regression weight of −0.41 which is significant at the one-per-mill level.

A household's risk aversion has a moderate effect on the investments in risky assets with a regression weight of −0.11 which is significant at the 1% level. Hence, lower risk aversion triggers higher investments in risk assets. This result is consistent with the literature.

Our study is organized as follows: In the next section, we describe the dataset with the independent and dependent variables used in the model, including a brief summary of the related literature and first descriptive evidence. In Sect. 3, we present our method for estimating the SEM. In Sect. 4, we present the empirical results. We discuss our findings and conclude in Sect. 5.

2 Data

2.1 PHF survey data

We use data from the third wave of the Panel on Household Finances (PHF) by the German central bank (Deutsche Bundesbank). The dataset covers a variety of financial and behavioral variables at the household level, such as questions about a household's wealth as invested in different asset classes and personal data on all household members. Each household is represented by a financially knowledgeable person (FKP) who can provide the necessary information about the household and is assumed to be mainly responsible for the household's financial decisions (see von Kalckreuth et al. 2012; PHF Survey Team 2019a, 2019b; Altmann et al. 2020).

Information about the FKP comprises age, gender, graduation, professional qualification, and financial literacy.

The PHF Survey data can be considered as a dataset with only a small measurement error. First, trained interviewers conduct the interviews. These interviews are face-to-face and computer-aided which should almost eliminate the possibility of errors during data collection. Second, Deutsche Bundesbank's comparisons with external statistics show that the PHF dataset does not suffer from selectivity problems. Hence, the dataset is representative of German households.

The third wave of the PHF started in March 2017, and the collection process ended in November 2017. The total number of households that participated was 4962. For the structural equation model (SEM), we divided the variables into two categories: independent or exogenous variables and dependent or endogenous variables. An overview of the variables used in the empirical analysis and how they were measured are presented in Table 1.

Table 2 displays the descriptive statistics.

2.2 Dependent or endogenous variables

We use *RiskyAssets* (households' amount of wealth invested in risky assets), *FinLit1* and *FinLit2* (Financial Literacy), and *RiskFin* and *RiskGen* (Risk Aversion) as the dependent variables.

2.2.1 Participation in the financial market

Following the literature the variable *RiskyAssets* is measured in Euros and is used as a proxy for participation in the financial market (Calvet et al. 2007; Halko et al. 2012; Calvet and Sodini 2014; Bucciol et al. 2019). *RiskyAssets* comprises the following wealth positions of a household (2019b, 4–5): mutual funds, bonds, publicly traded shares, value of non-self-employment private business, and other financial assets (survey definition: total value of shares in cooperatives; precious metals; options; futures; effective pieces of securities which are not held in a securities account; claims arising from legal proceedings or from an estate extraction rights, for example, for oil and gas; claims arising from patents and licenses; other securities in securities account; and market value of certificates in total). Following von Gaudecker (2015), we exclude households with less than 1000 Euros in risky assets, which also means that we exclude households that do not invest in risky assets at all. This restriction decreases the sample from 4962 to 1963 households. There are three main reasons for this restriction. First, since the majority of households does not invest in risky assets at all, including these households would skew the results toward differences between non-investing households and investing households. We, however, aim to explain differences in the invested wealth among households that invest in asset markets. Second, including households that invest only tiny fractions of their wealth in risky assets may contribute to noisy results. Third, by using the same cut-off value as previous studies, we ensure a better comparability with previous results (see also, e.g., Oehler and Horn 2019).

Table 1 Overview and descriptions of variables used in the empirical analysis

Variable	Description
Exogenous (independent) Variables	
Wealth Status NetW_calc	
ddn3001	*ddn3001*, the calculated net-wealth position, is calculated in Euros: "Total household assets excluding public and occupational pension wealth minus household's total outstanding liabilities." (PHF Survey Team 2019b, 11)
Level of Education LevEduc	
School	*School* is the highest level of school education completed and is determined by the answer to the question, "What is the highest school degree that you have?" 1—Lower level secondary school (Hauptschule); 2—Mid-level secondary school (Realschule); 3—Degree in vocational school, 10th grade; 4—Secondary school (Fachoberschule) with diploma permitting admission to university of applied sciences; 5—General or specific upper level secondary school permitting admission to university (Gymnasium or EOS and EOS with training)" (PHF Survey Team 2019b, 30) and 0 otherwise
Profession	*Profession* is the highest level of professional education completed and is determined by the answer to the question, "Do you have a completed vocational degree or a university degree? If there are multiple degrees, please list only the highest one. 1—Currently in vocational training or degree program; 2—Yes, completed work-company training program (apprenticeship); 3—Yes, completed professional-school vocational training (vocational school, higher business school); 4—Yes, completed training at a vocational college, master or technical college, vocational or specialist academy (with up to 880 h); 5—Yes, bachelor's degree, degree from University of Applied Science, engineering college completed; 6—Yes, diploma—or master's degree, graduated with training as teacher or—Yes, completed specialist academy with a long preparation time of more than 880 h; 7—Yes, received PhD/second dissertation" (PHF Survey Team 2019b, 31) and 0 otherwise
Financial Satisfaction Status SatFin	
dhi0750	*dhi0750* is the variable to measure the satisfaction with financial status (subjective) and is determined by the answer to the question on the estimate of the wealth distribution position of the household, "Looking at this net worth, what section of Germany's wealth distribution do you think the household is in?" on a scale from 1 to 10. One is the bottom 10%, 10 is the top 10% of net worth in Germany. (PHF Survey Team 2019a, 42)
Life-Cycle Status Age	
2017-year of birth	*2017-year of birth* is calculated for the variable age (calculated as the difference between the year of the third wave of the survey (2017; PHF Survey Team 2019a, 168) and the year of birth)

Table 1 (continued)

Variable	Description
Patience	
zi105	Following the literature (Fey et al 2020, 8), a possible reason why individuals invest less in risky assets may be a lack of patience because these investments require a degree of tenacity in order to endure the ups and downs in the capital market. *Zi105* is the variable to measure *patience* and is determined by the answer to the question, "How do you view yourself personally? Are you in general a person who is patient or do you tend to be impatient? Please use the numbers from 0 to 10: Zero means "very patient" and 10 means "very impatient". With the values in between you can graduate your rating." (PHF Survey Team 2019a, 121)
Endogenous (dependent) Variables	
Financial Market Participation FinMaPar	
RiskyAssets	Following the literature, the variable *RiskyAssets* is measured in Euros and is used as a proxy for participation in the financial market (Calvet et al. 2007; Halko et al. 2012; Calvet and Sodini 2014; Bucciol et al. 2019). The variable includes the following wealth positions of a household as recalculated by the PHF Survey Team (2019b, 4–5): mutual funds, bonds, publicly traded shares, value of non-self-employment private business, and other financial assets (survey definition: Total value of shares in cooperatives; precious metals; options; futures; effective pieces of securities which are not held in a securities account; claims arising from legal proceedings or from an estate extraction rights, for example, for oil and gas, claims arising from patents and licenses; other securities in securities account; and market value of certificates in total). Following von Gaudecker (2015), we exclude households with less than 1000 Euros in risky assets
Financial Literacy FinLit	
FinLit1	*FinLit1* is determined by the answers to four questions which have been broadly used in the literature and cover knowledge about the effects of compound interest, inflation, and diversification (the so-called Big Three, e.g., Lusardi and Mitchell 2008, 2011, and 2014, Bucher-Koenen et al. 2017, Bucher-Koenen and Knebel 2021, Bucher-Koenen et al. 2021), plus a fourth question on compound interest and debt (PHF Survey Team 2019a, 164–165) The literature often codes these variables as indicators (e.g., Van Rooij et al. 2011). For our analysis we create the variable FinLit1 which equals four if all answers are correct, three if three out of four answers are true, two if two out of four questions are answered correctly, one if only one answer is correct, and zero otherwise
FinLit2	*FinLit2* is determined by the answer to the question about economic education in school, "During your schooling or vocational training did you attend any talks, courses or training sessions on household finances or asset management?" (PHF Survey Team 2019a, 32). The variable FinLit2 equals one if one participated and zero otherwise

Table 1 (continued)

Variable	Description
Risk Aversion RiskAv	
RiskFin	*RiskFin* is the self-assessment of risk preferences in the financial domain and is determined by the answer to the question, "If savings or investment decisions are made in your household, which of the statements best describes the attitude toward risk?" (PHF Survey Team 2019a, 153) on a scale from 1 to 4. One means "We take significant risks and want to generate high returns", 2 means "We take above-average risks and want to generate above-average returns", 3 means "We take average risks and want to generate average returns", and 4 means "We are not ready to take any financial risks"
RiskGen	*RiskGen* is the self-assessment of general risk-taking and is determined by the answer to the question, "How do you view yourself: Are you in general a risk-taking person or do you try to avoid risks?" on a scale from 0 to 10. 0 means that you are "very willing to take risks", 10 means that you are "not at all ready to take risks" (the original scale is recoded to align in the same direction as in the question on risk aversion in the financial domain)

Table provides an overview of the variables used in the empirical analysis and variable descriptions from the PHF

2.2.2 Financial literacy

For the definition of financial literacy, we follow the growing strand of literature that uses the concept of financial capability with the key element of practical skills (see Bernheim et al. 2001; Dixon 2006; Oehler and Werner 2008; Deepak et al. 2015; Aubram et al. 2016; Xiao and O'Neill 2016; Oehler et al. 2018b) and the related concept of financial competencies by the OECD (OECD/INFE 2016).

To measure financial literacy empirically, Lusardi and Mitchell developed three questions that they used to elicit a survey-based and empirically narrow definition of financial literacy (see Lusardi and Mitchell 2011, 2014; Bucher-Koenen and Knebel 2021; Bucher-Koenen et al. 2021).

The three questions were on compound interest, inflation, and risk diversification. The PHF Survey also follows this measurement of financial literacy. However, in its third wave, it added a fourth question on compound interest and debt (PHF Survey Team 2019a, 164–165).

We determine our first variable on financial literacy, *FinLit1*, with the answers to these four questions and code the answers as indicator variables (e.g., Van Rooij et al. 2011). For our analysis we create the variable *FinLit1* which equals four if all answers are correct, three if three out of four answers are correct, two if two out of four questions are correct, one if only one answer is correct, and zero otherwise.

Table 3 shows the frequency distribution for *FinLit1*. Of the households, 55.6% answered all four questions correctly. This percentage is a good value considering that the proportion of people in Germany that answer all of the original three questions correctly varies between 53 and 62% (Bucher-Koenen and Knebel 2021).

Table 2 Summary statistics on participants' characteristics ($N = 1963$)

	Mean	Median	SD	Min	Max
Wealth Status NetW_calc in Euros					
ddn3001	826,309	478,490	2439,326	0.00	92,691,570
Level of Education LevEduc					
School	4.58	5.00	1.61	0.00	6.00
Profession	4.16	5.00	1.99	0.00	7.00
Financial Satisfaction Status SatFin					
dhi0750	5.41	5.00	1.94	0.00	10.00
Life-Cycle Status Age					
2017-year of birth	59.83	61.00	14.95	19.00	90.00
Patience					
zi105	4.79	5.00	2.34	0.00	10.00
Financial Market Participation FinMaPar in Euros					
RiskyAssets	112,059	27,000	351,598	1000	6500,000
Financial Literacy FinLit					
FinLit1	3.38	4.00	0.84	0.00	4.00
FinLit2	0.35	0.00	0.48	0.00	1.00
Risk Aversion RiskAv					
RiskFin	3.43	3.00	.58	1.00	4.00
RiskGen	5.58	5.00	2.07	0.00	10.00

Table displays descriptive statistics of participants' characteristics. For each variable we provide mean value (Mean), median value (Median), standard deviation (SD), minimum value (Min), and maximum value (Max). Example: The mean value of *RiskyAssets* is 112,059 Euros with a range from 1000 Euros to 6,500,000 Euros (following von Gaudecker 2015, we exclude households with less than 1000 Euros in risky assets)

Table 3 Frequency distribution for *FinLit1*

	Frequency	Percent
0	27	1.4
1	42	2.1
2	176	9.0
3	627	31.9
4	1091	55.6
Total	1963	100.0

The PHF Survey enables us to add a second measure of financial literacy: *FinLit2*. This variable is determined by the answer to a specific question about economic education in school, that is, whether the respondent participated in courses or training sessions on household finances or asset management (PHF Survey Team 2019a, 32). The variable *FinLit2* equals one if a member of the respective household participated and zero otherwise. Over one-third of the households participated in such courses or training sessions (35.3%).

2.2.3 Risk aversion

The degree of risk aversion is one of the main determinants of investments in risky assets and participation in the financial market. Risk aversion is covered by two different concepts in the financial domain (see Schoemaker 1993; for an overview of these concepts in different domains and from different research perspectives). One strand of literature relies on the neo-classical assumption that the financial risk of an individual reflects their socioeconomic and sociodemographic characteristics that mirrors exactly their risk aversion (see, e.g., Pratt 1964; Arrow 1965). Hence, it can be measured by the self-selected level of financial risk that is considered objective risk aversion (see Nosic and Weber 2010). Other studies use the terms risk-taking (Schooley and Worden 1996), observed risk-taking (Schoemaker 1993), risk tolerance (Wang and Hanna 1997), or relative risk aversion (Riley and Chow 1992).

Another strand of literature assumes that investment decisions are the result of a process that is additionally influenced by individuals' subjective perception, heuristics, and bounded rationality (see, e.g., the survey of Hirshleifer (2015) on the behavioral aspects of the decision process). Therefore, the investment decisions, and likewise the measured objective risk aversion, are most likely driven by partially unobservable factors (see, e.g., Schoemaker 1993). In this framework, researchers consequently can only measure an individual's risk aversion by directly asking them to self-assess their willingness to take financial risk (see, e.g., Chaulk et al. 2003; Nosic and Weber 2010; Dohmen et al. 2011). Since individuals' self-assessment always includes subjective components, it is a subjective risk aversion. Other studies use the terms such as financial risk aversion (Kaustia and Luotonen 2016) or intrinsic attitude toward risk (Schoemaker 1993).

Both concepts undoubtedly have their merits. Since the concepts are not mutually exclusive, some studies combine both in one framework. For example, Nosic and Weber (2010) differentiate between subjective and objective risk aversion. To measure subjective risk aversion, subjects are asked to rate their willingness to take financial risks on a scale from 1 to 5. Nosic and Weber (2010) find that the answer to this question is a significant determinant of the objective risk aversion, i.e., the amount of money a subject invests in stocks (see also Schooley and Worden 1996; Chaulk et al. 2003; Halko et al. 2012; Kaustia and Luotonen 2016). Oehler et al. (2018a) conclude from a simultaneous analysis of both measures of risk aversion in an experimental setting that the subjective risk aversion is a better predictor for the objective risk aversion than a set of commonly used sociodemographic and economic factors such as age or income.

Dohmen et al. (2011) add to this discussion and use a question asking people about their willingness to take risks "in general". They find that an experiment that uses paid lottery choices confirms the behavioral validity of this measure as they conclude that this question is the best all-round predictor of risky behavior.

Following the main findings of the literature, we use both measures to determine a household's subjective risk aversion: the self-assessment of risk aversion in the financial domain, *RiskFin*; and the self-assessment of general risk-taking, *RiskGen*.

Table 4 Frequency distribution for *RiskFin*

RiskFin	Frequency	Percent
We take significant risks and want to generate high returns	5	0.3
We take above-average risks and want to generate above-average returns	80	4.1
We take average risks and want to generate average returns	951	48.4
We are not ready to take any financial risks	927	47.2
Total	1963	100.0

Table 5 Frequency distribution for *RiskGen*

RiskGen	Frequency	Percent
Very willing to take risks	13	0.7
1	21	1.1
2	93	4.7
3	196	10.0
4	279	14.2
5	405	20.6
6	264	13.4
7	323	16.5
8	223	11.4
9	78	4.0
Not at all ready to take risks	68	3.5
Total	1963	100.0

RiskFin is determined by the answer to the question, "If savings or investment decisions are made in your household, which of the statements best describes the attitude toward risk?" (PHF Survey Team 2019a, 153), on a scale from one to four. One means that "We take significant risks and want to generate high returns"; two means that "We take above-average risks and want to generate above-average returns"; Three means that "We take average risks and want to generate average returns"; and four means that "We are not ready to take any financial risks".

RiskGen is determined by the answer to the question, "How do you view yourself? Are you in general a risk-taking person or do you try to avoid risks?" on a scale from 0 to 10. Zero means that you are "very willing to take risks"; 10 means that you are "not at all ready to take risks" (the original scale is recoded to align in the same direction as in the question on risk aversion in the financial domain).

Table 4 shows the frequency distribution for *RiskFin*. About half of the households are absolutely risk averse (47.2%).

Table 5 shows the frequency distribution for *RiskGen*. The median value is five and indicates that the general risk aversion is not as high as the risk aversion in the financial domain.

2.3 Independent or exogenous variables

We use the variables *NetW_calc* (Wealth Status), *LevEduc* (Level of Education), *SatFin* (Financial Satisfaction Status), *Age* (Age), and *Patience* (Patience) as independent variables.

2.3.1 Wealth status

We use the calculated net wealth position that is measured in Euros and that is derived from the total household assets excluding public and occupational pension wealth and minus the household's total outstanding liabilities (variable "ddn3001", PHF Survey Team 2019b, 11). Following Calvet and Sodini (2014), Kaustia et al. (2019), Oehler and Horn (2020), and Fey et al. (2020), we predict that the households' net wealth position is a key driver for the extent of participation in risky assets, and we use it as a proxy for participation in the capital market: the higher the net wealth, then the higher the amount invested risky assets should be.

Table 6 presents the means of the volume invested in risky assets per quartile of the net wealth position.

2.3.2 Level of education

According to Guiso and Sodini (2013), Kaustia et al. (2019), Bucher-Koenen et al. (2021), and Bucher-Koenen and Knebel (2021), the basic and main drivers of financial literacy are the formal level of education in school and the formal level of professional education. Education can affect decision-making in several ways; for example, through increasing financial literacy and cognitive skills, or social networks, job opportunities, and beliefs and attitudes (Kaustia et al. 2019).

We combine the highest level of school education completed and the highest level of professional education completed in *LevEduc*. Specifically, we use "dpa0300" (PHF Survey Team 2019b, 30) for the formal first level of education and "dpa0400" (PHF Survey Team 2019b, 31) for the formal second level of education.

Table 7 shows the frequency distribution for the level of education in school.

Table 8 shows the frequency distribution for the level of professional education.

Table 6 Means of the volume invested in risky assets per quartile of the net wealth position

Net wealth_quart	Mean in Euros	*N*
RiskyAssets		
1	20,241	491
2	42,377	491
3	72,862	491
4	313,168	490
Overall	112,059	1963

Table 7 Frequency distribution for the level of education in school

School	Frequency	Percent
Lower level secondary school (Hauptschule)	279	14.2
Mid-level secondary school (Realschule)	452	23.0
Degree in vocational school, 10th years	44	2.2
Secondary school (Fachoberschule) with diploma permitting admission to university of applied sciences	211	10.7
General or specific upper level secondary school permitting admission to university (Gymnasium or EOS and EOS with training)	973	49.6
Other	4	0.2
Total	1963	100.0

2.3.3 Financial satisfaction status

Xiao and O'Neill (2016) finds that financial satisfaction or well-being rises if a household's financial situation is above the national average. The PHF Survey provides a subjective measure of financial satisfaction that captures the self-perceived overall financial status.

We use *SatFin* which is determined by the answer to the question, "Looking at this [your] net worth, what section of Germany's wealth distribution do you think the household is in?" on a scale from 1 to 10. One represents the bottom 10%, and 10 represents the top 10% of net worth in Germany (variable "dhi0750", PHF Survey Team 2019a, 42).

Following Xiao and O'Neill (2016), we predict that the subjective financial satisfaction, *SatFin* affects the risk aversion: the higher the satisfaction, then the lower the risk aversion.

Table 9 shows the mean values of risk aversion in the financial domain, *RiskFin*, across the different levels of *SatFin*. The lowest financial risk aversion is realized within the upper deciles of *SatFin*.

2.3.4 Age

Following Guiso and Sodini (2013), human capital is accumulated slowly through formal education or work experience. Over the life cycle, it reaches its highest level early in life and then declines as the number of earning years lowers and the flow of expected income declines. Therefore, we use the variable *Age* as a proxy for the life-cycle status.

Moreover, age is negatively related to the sophistication of a household's financial decisions (Calvet et al. 2009). Korniotis and Kumar (2011) state that although a household's experience regarding investment decisions increases with age, this positive effect is dominated by adverse effects of cognitive aging, which, overall, leads

Table 8 Frequency distribution for the level of professional education

Profession	Frequency	Percent
Currently in vocational training or degree program	10	0.5
Completed work-company training program (apprenticeship)	564	28.7
Completed professional-school vocational training (vocational school, higher business school)	98	5.0
Completed training at a vocational college, master or technical college, vocational or specialist academy (with up to 880 h)	205	10.4
Bachelor's degree, degree from University of Applied Science, engineering college completed	218	11.1
Diploma- or master's degree, graduated with training as teacher or completed specialist academy with a long preparation time of more than 880 h	653	33.3
PhD/second dissertation	130	6.6
Other	85	4.3
Total	1963	100.0

to worse investment decisions with increased age. Hence, we predict that financial literacy will be higher at a lower age.

Age is calculated as the difference between the year of the third wave of the survey (2017; PHF Survey Team 2019a, 168) and the year of the birth of the FKP. Some empirical studies have also used the squared age and higher moments of age (Poterba and Samwick 2001; Ameriks and Zeldes 2004; Cocco et al. 2005; Guiso and Sodini 2013; Fagereng et al. 2017; Kaustia et al. 2019; Fey et al. 2020). When we use the age squared, the results of our model differ only marginally. Hence, we only use *Age* for a more logical interpretation.

Table 10 shows the mean values of *FinLit1* in different age groups.

2.3.5 Patience

Following the literature (Fey et al. 2020), a possible reason why individuals invest less in risky assets may be a lack of patience because these investments require a degree of tenacity in order to endure the ups and downs in the capital market. In the PHF Survey, patience is measured by the answer to the question, "How do you view yourself personally: Are you, in general, a person who is patient, or do you tend to be impatient? Please use the numbers from 0 to 10: Zero means "very patient" and 10 means "very impatient" (variable "zi105", PHF Survey Team 2019a, 121).

Table 9 Mean values of risk aversion in the financial domain, *RiskFin*, across the different levels of *SatFin*

SatFin	Mean	N	% of Total
RiskFin			
0	3.6111	18	0.9
1	3.9032	31	1.6
2	3.6727	55	2.8
3	3.6193	218	11.1
4	3.6118	304	15.5
5	3.4961	406	20.7
6	3.3142	331	16.9
7	3.2674	344	17.5
8	3.2323	155	7.9
9	3.0877	57	2.9
10	3.0227	44	2.2
Total	3.4261	1963	100.0

3 Structural equation model

Structural equation modeling is a family of statistical models that seek to explain the relationships among multiple variables (Hair et al. 2010; Byrne 2016). It requires the construction of measurement models and structural models. Measurement models contain both latent variables (unobserved, not measured) and indicator variables (observed, measured). Structural models depict latent variables and the connections between them. When the measurement models and the structural model are considered together, the model is considered to be a structural equation model.

Structural equation modeling has been used in many disciplines and has become an important analysis method in academic research (e.g., Byrne 2001; Kline 2005; Savalei and Bentler 2006; Hair et al. 2010). Its multivariate statistical approach allows for the examination of both the measurement and structural components of a model by simultaneously testing the relationships among multiple independent and dependent constructs.

Figure 1 displays an overview of the hypothesized relationships and the expected effects of the level of education and age on financial literacy; the influences of

Table 10 Mean values of *FinLit1* in different age groups

Age_groups/year	Mean	N	% of Total
FinLit1			
≤ 25 years	3.5238	21	1.1
26 ≤ 50 years	3.4922	514	26.2
51 ≤ 75 years	3.3799	1087	55.4
≥ 76 years	3.2141	341	17.4
Total	3.3821	1963	100.0

financial satisfaction and financial literacy on the risk aversion; and the effects of patience, net wealth, and risk aversion on participation in the financial market. The directions of the arrows illustrate the expected influence of the unobserved variables.

Figure 1 displays an overview of the structural model and the hypothesized relationships and the expected effects of the level of education and age on financial literacy; the influence of financial satisfaction and financial literacy on the risk aversion; and the effects of patience, net wealth, and risk aversion on participation in the financial market. The directions of the arrows illustrate the expected influence of the unobserved variables.

According to our hypotheses, the signs at the arrows indicate whether the effects are positive ("+") or negative ("−"). Example: We predict a positive influence of net wealth on participation which means that households with higher net wealth hold a higher volume of risky assets as a proxy for that participation.

As discussed in Sect. 2, we predicted the net wealth position, *NetW_calc*, as the main driver for participation in the financial market, *FinMaPar*. *FinMaPar* is measured in Euros and includes the wealth invested in mutual funds, bonds, publicly traded shares, non-self-employment private business, and other financial assets. Following von Gaudecker (2015), we exclude households with *FinMaPar* < 1000 Euros. Consistent with the literature, we anticipate a moderate effect of *RiskAv* on *FinMaPar*. As key factors for *RiskAv*, we find that *FinLit* and *SatFin* both have negative signs. These signs mean that the more the households demonstrate financial literacy and the more they are financially satisfied, then the level of risk aversion is lower; therefore, they will participate more in financial markets. Furthermore, we predict that financial literacy is the highest in early years of the (adolescent) life cycle and that more patience leads to higher investments in risky assets.

We use AMOS 28 (Byrne 2016; Arbuckle 2019) to apply the structural equation model. As widely recommended in the literature, we apply the maximum-likelihood (ML) method (e.g., Weston and Gore 2006; Weiber and Mühlhaus 2014; Backhaus et al. 2015). Byrne (2001) notes that the ones assigned to the first of each set of factor loadings and to the regression coefficients associated with each error term are imposed automatically by AMOS. Accordingly, they do not estimate these values.

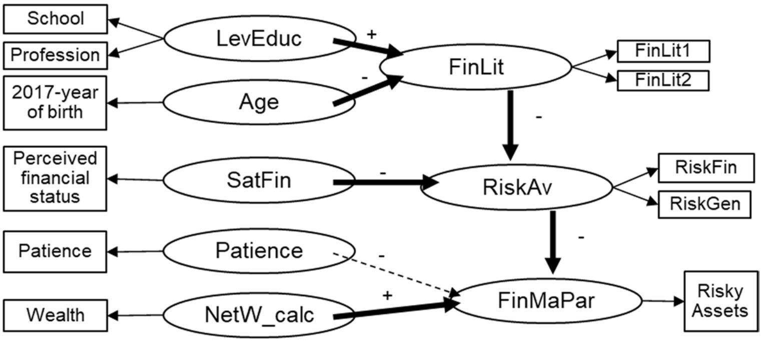

Fig. 1 Hypotheses in the structural model

Byrne (2001) explains that the ones associated with the factor loadings address the issues of model identification and the scaling of the unobserved factors, while those associated with the error terms represent values that are considered to be known (see also Weston and Gore 2006; Backhaus et al. 2015). As recommended in the literature, we examine the standardized estimates as they are considered most informative. Because different variables may have different scales, determining which variable has the greatest effect can only be done by comparing the standardized parameter estimates (Weston and Gore 2006; Backhaus et al. 2015).

Table 11 gives an overview of the full structural equation model that is divided in the measurement models by the unobserved variables and the structural model itself.

4 Results

We provide the results of the structural equation model in Table 12.

Figure 2 displays the results for the structural equation model. The exogenous and endogenous unobserved variables are depicted in ovals. The values presented at the arrows between the ovals represent the (standardized) path regression coefficients. The rectangles display the manifest (observed) variables with the respective factor loadings. The correlation coefficients between the exogenous variables are not shown for a better display of the structure of the model.

The squared multiple correlations (SMC) of the latent endogenous variables are shown on the right-hand side within the ovals (proportion of explained variance) and in Panel B of Table 12. Of the variance in *FinLit*, 46% is explained by the latent variables, 33% of *RiskAv*, and 48% of *FinMaPar*. According to the literature, this is a substantial value for participation in the financial market and financial literacy, and a moderate value for risk aversion. Most of the coefficients, i.e., the standardized regression weights (see also Panel C of Table 12) are above the benchmark of 0.20 and meaningful. For example, net wealth has a large effect on participation (0.84) and the level of education has a large effect on financial literacy (0.58). Both are significant at the one-per-mill level. The symbols ***, **, and * denote significance at the one per mill, 1%, and the 5% level, respectively. The bold arrows represent the significant regression weights.

The results give support to the hypothesized relationships.

4.1 Financial market participation

The squared multiple correlation (SMC) of *FinMaPar* is 0.48. This is the proportion of the variance in participation that the latent exogenous variables of *NetW_calc*, *Patience*, and *RiskAV* can explain. According to the example in Chin (1998b), these results show a substantial SMC.

Table 11 Variables in the structural equation model

Variable
Structural Model
Exogenous (unobserved) Variables
LevEduc
Age
SatFin
Patience
NetW_calc
Endogenous (unobserved) Variables
FinLit
RiskAv
FinMaPar
Measurement Models
Manifest (observed) variable i for an exogenous variable: School, Profession, 2017-year of birth, dhi0750 (perceived financial status), zi105 (patience), ddn3001 (wealth)
Manifest (observed) variable i for an endogenous variable: FinLit1, FinLit2, RiskFin, RiskGen, RiskyAssets

Table provides an overview and description of the variables used in the structural equation model

Within this part of the model, the household's net wealth position is the main driver for participation in the financial market with a regression weight of 0.84 that is significant at the one-per-mill level. The corresponding construct *NetW_calc* explains 28 percent ($0.53^2 = 0.28$) of the variance of the variable ddn3001. This suggests the presence of some measurement errors, such as inaccuracies in respondents' answers, and/or unconsidered variable effects, such as a nonlinearity of the relation in certain parts of the distribution. Nevertheless, the high regression weight and level of statistical significance show that the variable is very suitable to explain differences in the cross section of our sample. Consistent with the literature, the model estimation shows a moderate effect (−0.11; significant at the 1% level) of the level of risk aversion on participation in the financial market. Corresponding to the results in Fey et al. (2020), the regression weight of *Patience* has the hypothesized sign but is not significant.

4.2 Risk aversion

The proportions of the variance in *RiskAv* that are explained by *SatFin* and *FinLit* amounts to 0.33. According to the example in Chin (1998b), these results show a moderate SMC.

Within this part of the model, the financial literacy of households' FKP is the main driver of *RiskAv* with a regression weight of −0.41 that is significant at the one per mill level. With a regression weight of −0.32 that is significant at the one-per-mill level, *SatFin* plays a key role, too. These roles mean that the more the

Table 12 Results of the structural equation model (standardized estimates)

Panel A		
Model fit indices	Value	References
RMSEA	0.039; Benchmark: ≤ 0.06	Browne and Cudeck (1993), Hu and Bentler (1999), Byrne (1989), MacCallum et al. (1996), Schermelleh-Engel et al. (2003), Weston and Gore (2006), Hair et al. 2010, Weiber and Mühlhaus (2014), Backhaus et al. (2015), Byrne (2016)
SRMR	0.025; Benchmark: ≤ 0.08	
AGFI	0.976; Benchmark: ≥ 0.90	
TLI	0.929; Benchmark: ≥ 0.90	
IFI	0.962; Benchmark: ≥ 0.90	
CFI	0.961; Benchmark: ≥ 0.90	
Panel B		
Squared multiple correlations (SMC) of the endogenous (unobserved) variables	Value	Reference
Financial literacy *FinLit*	0.46	Chin (1998b), Benchmark (from his example): substantial
Risk aversion *RiskAv*	0.33	Moderate
Financial market participation *FinMaPar*	0.48	Substantial
Panel C		
Standardized regression weights	Variable	Value Benchmark: ≥ 0.2 OR ≤ -0.2 Ref.: Chin (1998a)
LevEduc	FinLit	0.58***
Age	FinLit	−0.24***
SatFin	RiskAv	−0.32***
Patience	FinMaPar	−0.32
NetW_calc	FinMaPar	0.84***
FinLit	RiskAv	−0.41***

Table 12 (continued)

Panel C		
Standardized regression weights	Variable	Value Benchmark: ≥ 0.2 OR ≤ -0.2 Ref.: Chin (1998a)
RiskAv	FinMaPar	−0.11**

We provide the fit indices for the full model in Panel A. Given the benchmark values from the literature referred to in the right column, our model has a very good fit. Panel B shows the squared multiple correlations (SMC) of the latent endogenous variables (proportion of explained variance) in which 48% of the variance is in participation in the financial market participation, 33% is in risk aversion, and 46% in financial literacy are explained by the latent variables. According to the reference in the right column (from an example of Chin 1998b), this is a substantial value for participation in the financial market participation and for financial literacy, and a moderate value for risk aversion. Panel C displays the standardized regression weights within the structural model. Most of the coefficients are above the benchmark and meaningful. For example, *NetW_calc* has a greater impact on *FinMaPar* (0.84) and *LevEduc* has a greater impact on *FinLit* (0.58). Both are significant at the one-per-mill level. The symbols ***, **, and * denote significance at the one per mill, 1%, and 5% levels, respectively.

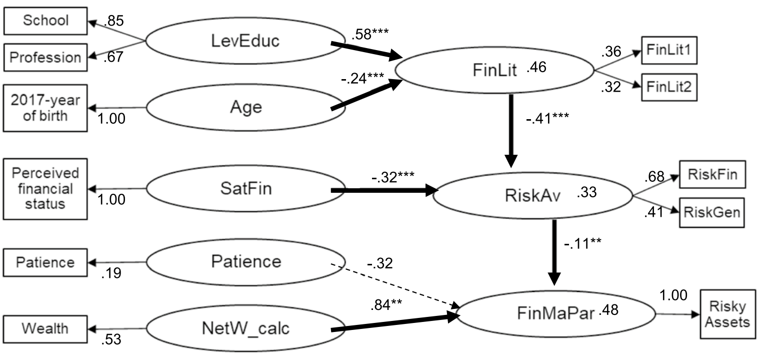

Fig. 2 Results for the structural equation model

households demonstrate financial literacy and the more they are financially satisfied, then their level of risk aversion is lower, and, therefore, they participate more in financial markets.

4.3 Financial literacy

The proportion of the variance in *FinLit* that is explained by *LevEduc* and *Age* equals 0.46. According to Chin's (1998b) example, this result is a substantial SMC.

Within this part of the model, *LevEduc* is the main driver of their financial literacy with a regression weight of 0.58, which is significant at the one-per-mill level. With a regression weight of −0.24, which is significant at the one-per-mill level, *Age* plays a moderate role. Consistent with the theoretical and empirical literature, financial literacy is the highest in the early years of the (adolescent) life cycle and increases with the level of school education completed and the level of professional education completed.

4.4 Structural model

To evaluate the goodness-of-fit between the hypothesized model and the sample data, we calculate several fit indexes. As recommended in the literature, we use the root mean square error of approximation (RMSEA); the standardized root mean square residual (SRMR); the adjusted goodness-of-fit index (AGFI); and the Tucker-Lewis index (TLI), the incremental-fit index (IFI), and the comparative-fit index (CFI) for baseline comparisons between the default model and independence model (see Browne and Cudeck 1993; Haughton et al. 1997; Hu and Bentler 1999; Byrne 1989, 2016; MacCallum et al. 1996; Schermelleh-Engel et al. 2003; Weston and Gore 2006; Hair et al. 2010; Weiber and Mühlhaus 2014; Backhaus et al. 2015). According to the literature, the two main indexes are the RMSEA and the SRMR.

As an index of fit, RMSEA corrects for a model's complexity. As a result, when two models explain the observed data equally well, the simpler model will have the more favorable RMSEA value. A RMSEA value of zero indicates that the model fits the data exactly. Weston and Gore (2006) suggest using the 90% CI (confidence interval) for the RMSEA that incorporates the sampling error associated with the estimated RMSEA. The SRMR index is based on covariance residuals in which smaller values indicate a better fit. The SRMR is a summary of how much difference exists between the observed data and the model.

As presented in Panel A of Table 12 the RMSEA equals 0.039 (lower 90% confidence estimate: 0.032; upper 90% confidence estimate: 0.047; benchmark for all three mentioned values ≤ 0.06) and the SRMR equals 0.025 (benchmark ≤ 0.08), our model has a very good fit.

We use the software of Preacher and Coffmann (2006) to compute the minimum sample size required to achieve a statistical power of at least 0.80 (Inputs: $\alpha = 0.05$; degrees of freedom = 0.30; desired power = 0.80; null RMSEA = 0.05; Alt. RMSEA = 0.01). The respective minimum sample size is 366 and, hence, considerably smaller than our sample size of 1,936. A post hoc test for statistical power based on MacCallum et al. (1996; see also Cohen 1988) shows that our model in combination with our sample has a high power of less than 0.99 (Inputs: N = 1,936, degrees of freedom = 0.30, $\alpha = 0.05$; null RMSEA = 0.05; Alt. RMSEA = 0.01).

5 Discussion and conclusion

5.1 Overall discussion

We have applied a structural equation model to analyze to what extent financial literacy drives households' investments in risky assets. Our model analyzes the effects of the level of education and age on financial literacy; the influences of financial satisfaction and financial literacy on risk aversion; and the effects of patience, net wealth, and risk aversion on participation in the financial market.

The representation of these relations in a structural equation model is novel and improves the understanding of the relationship between financial literacy and participation in the financial market. We are the first to use the extensive dataset from the third wave of the PHF Survey for this purpose. This dataset is very suitable due to its detailed coverage of household characteristics and thorough data collection and preparation processes. The dataset enables us to interpret participation in the financial market in a broader sense than in other studies, that is, we not only focus on participation in the stock market but also on investments in mutual funds, bonds, publicly traded shares, value of non-self-employment private business, and other financial assets.

The limitations of our study are that we do not analyze the efficiency of the risky investments and that we cannot quantify the influence of financial advice. The findings of Oehler and Horn (2019) show that older households with a female FKP and a higher risk aversion have more efficient portfolios. In general, roughly 80% of German households rely on financial advice (Bluethgen et al. 2008) and almost all households have access to financial advice via their banks. Therefore, it is unlikely that mere access to financial advice explains the positive relationship

Table 13 Relationship between the investments in risky assets and the self-assessed risk preferences in the financial domain

RiskFin	Mean in Euros	*N*	% of Total
RiskyAssets			
We take significant risks and want to generate high returns	48,563	5	0.3
We take above-average risks and want to generate above-average returns	276,890	80	4.1
We take average risks and want to generate average returns	140,947	951	48.4
We are not ready to take any financial risks	68,542	927	47.2
Overall	112,059	1963	100.0

between households' net wealth and investments in risky assets. However, it is more likely that high-net-wealth households receive the advice to invest in risky assets. Hence, this financial advice might be a further reason for the dominant role of households' net wealth as a driver of investments in risky assets.

Although our results show that households' net wealth is the dominant driver of investments in risky assets, financial literacy plays a remarkable role. The positive relation between wealth and participation in the financial market is further support for a decreasing relative risk aversion (DRRA; see, e.g., Cohn et al. 1975; Oehler 1998; Guiso and Sodini 2013; Calvet and Sodini 2014), the Behavioural Portfolio Theory (BPT; see, e.g., Shefrin and Statman 2000; Das et al. 2010; Statman 2017; Oehler and Horn 2020), and a portfolio hierarchy of financial needs (Kaustia and Luotonen 2016; Oehler et al. 2018b; Kaustia et al. 2019).

Financial literacy has an indirectly positive influence on participation in the financial market through the households' risk aversion. The better the financial literacy, the lower the risk aversion is; and lower risk aversion is associated with higher investments in risky assets. Both findings logically make sense and are consistent with the literature. However, the influence of households' net wealth is substantially stronger than the influence of the risk aversion (and, therefore, financial literacy).

5.2 Additional robustness checks

Hence, an additional look at the weaker effect of risk aversion on the investments in risky assets is worthwhile. As shown in Tables 13 and 14, the relationship between the investments in risky assets and the self-assessed risk preferences in the financial domain and, in general, risk-taking looks hump-shaped. The households that are most risk-averse and are the most at risk in the financial domain invest a lower amount in risky assets. Thus, this situation may be an explanation for the quite weak relationship between risk aversion and the participation in the financial market.

Due to the small number of cases of a greater willingness to take risk ($N=5$ for significant risks in Table 13 and $N=13$ and 21 for 0 and 1 in Table 14), we check whether these few cases cause the quite weak relationship between risk aversion and the participation in the financial market. Following other studies which used

Table 14 Relationship between the investments in risky assets and the self-assessed risk preferences in general risk-taking

RiskGen	Mean in Euros	N	% of Total
RiskyAssets			
very willing to take risks	173,520	13	0.7
1	53,792	21	1.1
2	206,738	93	4.7
3	131,558	196	10.0
4	141,559	279	14.2
5	141,831	405	20.6
6	94,680	264	13.4
7	73,739	323	16.4
8	65,454	223	11.4
9	62,125	78	4.0
not at all ready to take risks	93,870	68	3.5
Overall	112,059	1963	100.0

the PHF Survey dataset and the risk aversion variables (e.g., Oehler and Horn 2019, 2020), we combined categories 1 and 2 for *RiskFin* and levels 0 to 2 for *RiskGen*. Reestimating the model with these two adjusted variables yields almost no changes in the results, so that an influence from the low occupation of the categories can be excluded. In a second robustness check, we checked if classifying households that answered, "don't know", "no answer", and "others" as fully risk averse had any effect on the results. Reestimating the model excluding these cases yields almost no or marginal changes in the results.

One of the so-called traditional variables used in the theoretical and empirical studies on participation in the financial market is the households' income which is often measured as net income (see, e.g., Kaustia et al. 2019; Fey et al. 2020). In most of these studies, income is used together with age within models of life-cycle patterns in households' portfolios to estimate their human wealth with the result that human capital declines and becomes a smaller component of households' total wealth. Additionally, measurement errors are claimed (Guiso and Sodini 2013; Calvet and Sodini 2014; Fagereng et al. 2017).

Moreover, the income variable is likely to be biased in the case of positive or negative wealth shocks. For example, households that have inherited a substantial amount of money or assets but tend to have lower incomes are more likely to behave like high-asset households than low-income households. On the other hand, households with high income and low wealth (e.g., shortly after starting a job or getting divorced) are more likely to behave like households with low wealth by first building up precautionary liquidity as insurance against income shocks (job loss or similar) and to be able to cover unexpected expenses.

For these reasons, we do not include income or net income in our structural equation model. Nevertheless, we consider net income in a robustness check and estimate our model again (with the quartiles of net income that are calculated from the total gross income minus total expenditures of the household). The main results differ only marginally. The explained variance for *FinMaPar* is two percentage points higher and for *RiskAv* one percentage point higher, while the regression weight of net income is close to zero (−0.12, not significant).

Another strand in the literature focuses on the question of whether there is a gender effect on participation in the financial market (see Fey et al. 2020 for an overview of the literature). Most of the studies conclude that the so-called gender gap disappears once risk aversion is considered (see, e.g., Halko et al. 2012). Fey et al. (2020) find from their analysis of the second wave of the PHF Survey that other factors rather than gender influence the participation in financial markets. They point out that a raw gender gap is mainly explained by different risk aversion and monetary endowments. As a robustness check, we control for gender effects. Therefore, we split the sample between female ($N=668$) and male ($N=1295$) participants and estimate separate SEMs. Although the structure of the effect in our model is largely unchanged for men and women, on principle and compared with the whole sample, the male (female) sample shows higher (lower) explained variance at 0.69 (0.39) for *FinLit* and 0.51 (0.43) for *FinMaPar*, and lower (higher) explained variance at 0.25 (0.38) for *RiskAv*. The influence of net wealth is a little bit more dominant for men (0.92) than women (0.82) compared to the whole sample.

Further, we analyze possible gender differences in financial literacy and risk aversion. Consistent with the literature (see, e.g., Fey et al. 2020; Bucher-Koenen et al. 2021; Bucher-Koenen and Knebel 2021), we find that women have a slightly lower score in *FinLit1* (women: 3.2, men: 3.5, mean: 3.4) and a slightly higher risk aversion in the financial domain (women: 3.6, men: 3.4, mean: 3.4).

5.3 Conclusion

Our main findings are as follows. First, households' net wealth is the dominant driver of their investments in risky assets. Second, financial literacy has an indirectly positive influence on participation in the financial market. The higher the financial literacy, the lower is a household's risk aversion. The lower the risk aversion, the higher are the households' investments in risky assets. Although the PHF Survey allows us to define participation in the financial market in a broader sense, there are still some possibilities for households to invest in risky assets such as mutual funds, bonds, publicly traded shares, and precious metals that are not covered by our approach. These possibilities are whole life insurances and voluntary retirement plans. The latter products are quite widespread among German households. Nevertheless, most households that invest in these products simultaneously invest in the risky assets that are covered by our approach (Oehler et al. 2018b). Hence, the effect of this blind spot should be negligible.

Our results provide implications for further research, policymakers, and practitioners. We provide further support for the idea that financial restrictions are the most important barrier to participation in the financial market. Greater financial literacy does not necessarily lead to more risky investments. Households' risky investments are in line with their risk aversion. The latter is related to financial literacy. However, households' net wealth is far more important for participation in the financial market than risk aversion. Hence, the (too) low engagement of households in risky financial markets is not driven by households' allegedly low financial literacy but rather by their tight budget (see also Campbell 2006; Vissing-Jorgensen 2002, 2004). When policymakers and academics elaborate on concepts to increase the engagement of households in risky financial markets, they should be aware of households' challenging economic situations as a determining factor. If policymakers and academics only focus on enhancing financial literacy without considering the households' financial restrictions, the interventions would most probably fail. Practitioners such as financial advisors should better point out to low-net wealth households that participation in the financial market is already possible and feasible with diversified investments as low as five Dollars/Euros per month, for example, via robo-advisors in exchange-traded funds (see D'Acunto and Rossi 2020; Horn and Oehler 2020; Rossi and Utkus 2020; Oehler et al. 2022).

Author contributions Andreas Oehler developed the idea, performed the statistical analyses, and drafted the manuscript. Matthias Horn and Stefan Wendt helped to prepare and interpret the data and added revisions to the first draft. All authors discussed the results and contributed to the final manuscript.

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Declarations

Conflict of interest The authors declare no competing interests.

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