Journal of the Economic Science Association (2026), 1–13
doi:10.1017/esa.2026.10034

ORIGINAL PAPER

Matching risk attitude to investment behaviour: insights from self-reported responses

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(Received 11 March 2025; revised 10 March 2026; accepted 26 March 2026)

Abstract

Using data from the 2004–2022 waves of the Italian Survey of Household Income and Wealth (SHIW), this paper evaluates the reliability of self-assessed financial risk attitude *among investors* by comparing it with their reported investment choices. The survey allows respondents to self-assess their risk tolerance, specify the types of investments they hold (categorised as more or less risky), and report the corresponding amounts. The consistency observed between stated risk attitude and the composition of reported portfolio holdings supports the reliability of the risk-aversion measure. The findings contribute to the ongoing methodological debate, providing evidence that self-reported measures are robust and reliable instruments for validating behaviour in financial markets.

Keywords: Financial risk; incentive mechanisms; investment decisions; risk attitude; survey data

JEL Codes: D14; G11; G51

1. Introduction

In experimental settings, providing real incentives has long been considered fundamental to ensuring the reliability of results. These incentives are believed to more accurately reflect participants' actual behaviour (Bardsley et al., 2010, and references therein). The most popular methods for eliciting risk-attitude in laboratory experiments are binary lottery choice tasks (Hey, 2001) and the Multiple Price Lists (Holt and Laury, 2002), although other approaches have been introduced in recent years (see Crosetto and Filippin, 2013, among others).

Several studies demonstrate the validity and robustness of responses obtained through self-assessment without monetary incentives, highlighting their relevance for understanding decision-making. A comprehensive review of this literature lies beyond the scope of the present study; however, a few illustrative contributions are noteworthy. In the context of pro-social behaviour, Gneezy and Rustichini (2000) demonstrate that monetary incentives can reduce task performance by crowding out intrinsic motivations. Building on this, Asulin et al. (2024) confirm the crowding-out effect of low monetary incentives and show that well-designed non-monetary incentives can substantially enhance performance in prosocial tasks.

Luccasen III and Thomas (2014) compare participants' choices in experiments where incentives consist of extra class credit points rather than cash payments, showing that non-monetary incentives can effectively motivate participants in economic experiments. Similarly, Vinogradov and

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Shadrina (2013) find that non-monetary incentives in online experiments yield results comparable to those obtained in laboratory settings when participants, driven by curiosity and altruism, voluntarily engage in and complete the experiments, despite knowing they will receive no remuneration or prizes upon completion. In their meta-analysis on individual intertemporal preferences, Matousek et al. (2022) show that the reported discount rate is not systematically influenced by whether individuals receive real or hypothetical rewards.

Although experimental protocols serve as a valuable benchmark by replicating decision contexts under controlled conditions, such protocols can be costly and not always feasible to implement, particularly on a large scale. Survey-based measures, by contrast, offer a scalable and cost-efficient alternative, making them especially useful for empirical research. Falk et al. (2018) introduce a large-scale, experimentally validated dataset measuring key economic preferences, time preference, risk preference, positive and negative reciprocity, altruism, and trust, across diverse populations worldwide. Their analysis examines the determinants of these preferences demonstrating the importance of preferences for understanding economic outcomes. Self-assessed risk measures have proven to be reliable predictors of actual risk-taking behaviours (Dohmen et al., 2011; Einav et al., 2012; Vieider et al., 2015). The validity of the generic risk measure is further supported by its ability to explain actual behaviour in applied settings. For instance, Bonin et al. (2007) demonstrate this in the context of occupational earnings risk, while Jaeger et al. (2010) report similar findings in the context of migration.

As the collection of self-reported measures becomes increasingly prevalent, particularly in large-scale surveys, assessing their accuracy and reliability is critical for informing decisions. This paper focuses on financial risk attitude, which plays a crucial role in understanding investment decisions and the relationship between perceived and actual risk-taking behaviour. Financial risk tolerance is defined as the highest level of uncertainty an individual is willing to accept when making financial decisions (Grable, 2000). In efficient markets, investors anticipate higher returns for taking on greater risk. Consequently, individuals with higher risk tolerance are more inclined to invest in riskier assets in pursuit of higher long-term returns (Yao et al., 2001), thereby seeking to accumulate wealth (Neelakantan, 2010).

We use self-reported measures concerning financial risk behaviour from the Italian Survey on Household Income and Wealth (SHIW), a highly regarded and widely used survey conducted by the Bank of Italy, providing a representative snapshot of the Italian population. The SHIW has been extensively employed in numerous studies to examine various aspects of household behaviour, which underscores its reliability and significance as a data source.[1] Its widespread academic and institutional recognition further strengthens its credibility as a data source. Moreover, the prestige and authority of the Bank of Italy as the institution conducting the survey likely encourage respondents to take the questionnaire seriously and provide thoughtful, accurate answers. In addition interviewers provide a brief assessment of response reliability at the end of each interview, comparing reported information with observable indicators (e.g., neighbourhood, dwelling type, or quality of furnishings) and with national accounts, while accounting for definitional differences.

What makes this survey particularly valuable for our study is its comprehensive approach: it captures not only self-assessed financial risk attitude but also detailed information on stated resource allocation across various financial instruments. This dual perspective enables a more precise and meaningful assessment of the real financial risks undertaken by respondents.

One of the main variable of interest is the self-assessed risk attitude towards financial risk, label "RISFIN" in the survey (which will be explained in more detail later). This variable has been introduced in 2004 and it has been already used in prior studies (Deidda, 2013; Conte et al., 2024a), but to answer different research questions. Deidda (2013) investigates the determinants of precautionary

[1]For a bibliography of works based on the SHIW survey, please refer to the Bank of Italy website: www.bancaditalia.it

https://doi.org/10.1017/esa.2026.10034 Published online by Cambridge University Press

saving, focusing on the role of financial risk and portfolio choices in household saving behaviour. Conte et al. (2024a) explore the mitigating role of financial literacy in intertemporal choices.

Throughout the paper, we refer to the survey answers on financial risk attitude as self-assessed financial risk attitude or similar. The SHIW survey collects information on the financial assets held by households and the corresponding amounts. Based on these survey responses, we construct measures of portfolio composition across asset classes. Accordingly, we refer to these variables as stated asset holdings or similar, from which portfolio shares are derived.

Along similar lines to our study, albeit using a different methodological approach, Kuzubaş and Saltoğlu (2024) recently examined the reliability and validity of a risk assessment questionnaire. Differently from our study, their research focuses specifically on pensioners in Turkey. Notably, the period under investigation coincides with elevated inflation and the COVID-19 pandemic, two exceptional circumstances likely to influence individuals' risk preferences, which are not inherently stable and may be influenced by broader economic and social conditions (Schildberg-Hörisch, 2018; Conte et al., 2025).

This paper contributes to the literature on the external validity of survey-based measures of risk attitude by linking self-assessed risk profiles to stated household investment behaviour. Drawing on multiple waves of the nationally representative SHIW, we present robust empirical evidence that self-assessed risk attitude reliably predicts portfolio allocation.

Unlike studies confined to specific settings or short observation windows, our approach explicitly considers stated investment decisions over an extended horizon. While related work has validated self-assessed measures in other contexts, such as labour markets or migration, we contribute evidence on household portfolio allocation, a key dimension of financial decision-making. Taken together, our findings support the predictive and external validity of self-assessed risk measures and contribute to the ongoing debate on the reliability of non-incentivised measures.

The reminder of the paper is organised as follows. Section 2 describes the data set and the variables of interest. Section 3 present the estimated results. Section 4 concludes.

2. Data and variables

Our data source is the Italian Survey of Households Income and Wealth (SHIW), a survey representative of the Italian population conducted by the Bank of Italy. The survey usually occurs biennially, employing a rotating panel approach where approximately half of the participants are re-interviewed in subsequent waves. It collects detailed information on demographics, incomes, savings, wealth, and other household economic and financial decisions. We employ data from all waves spanning 2004–2022, with an average of around 7,924 households surveyed per wave, distributed across all twenty Italian regions.

Our interest lies in financial investments and attitude towards financial risk. It is important to note that while investments concern the entire household, the attitude towards financial risk is only measured from the survey respondent. The person answering the survey questions is the household head, defined as the individual responsible for the household's economic and financial matters.[2] Therefore, there is no discrepancy between the person managing household investments and the individual from whom the attitude towards risk is measured.

Guiso and Zaccaria (2023) define participation in financial markets as the condition where a household holds wealth in at least one of the following asset classes: Italian government bonds, other fixed income, stocks, shares of funds, and other assets (e.g., derivatives or structured products).

[2]The definition of household head has evolved slightly over time. From 1991 to 2006, households identified the head as the person in charge of economic and financial matters. In the 2008 survey, this definition expanded to include the individual most knowledgeable about economic management, in addition to the previous criterion. Since 2012, the term "household head" has been replaced with "reference person", although the role's description remains unchanged.

https://doi.org/10.1017/esa.2026.10034 Published online by Cambridge University Press

Table 1 Investors per year

	2004	2006	2008	2010	2012	2014	2016	2020	2022
Full sample	8012	7768	7977	7951	8151	8156	7420	6239	9641
Investors' sample	1400	1662	1674	1797	1538	1607	1215	1638	2178

Note: The table shows the number of households in each wave (Full sample) and the number of households that invest at least in one of the financial assets considered (Investors' sample).

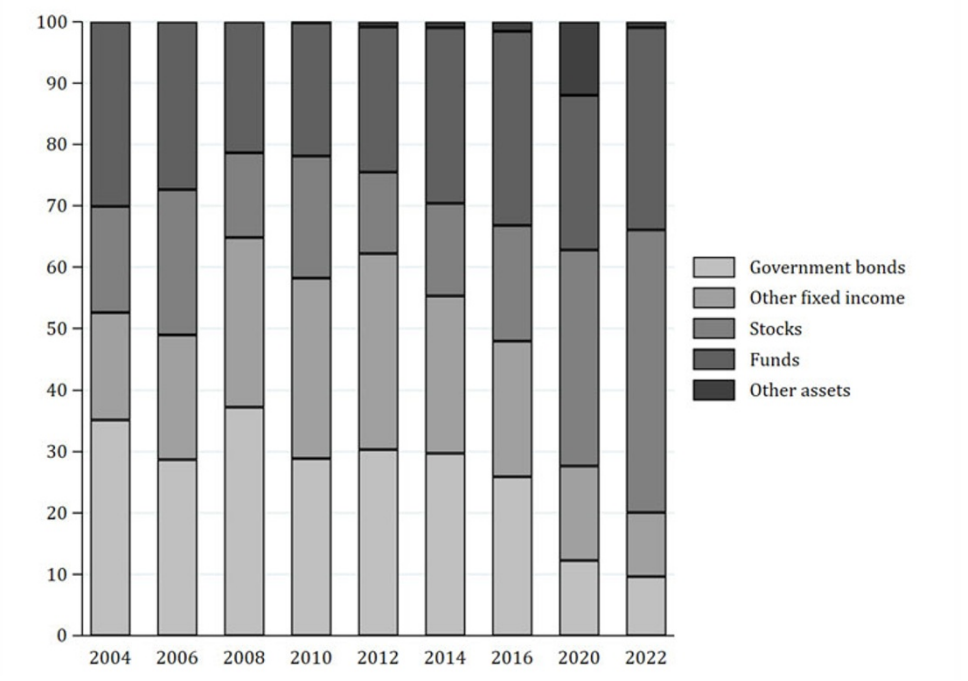


Fig. 1 Participation to financial markets by stated investments type and year
Note: The figure shows the percentage of stated investments held for each asset class per year, between 2004 and 2022.

Each investment option carries unique attributes, advantages, and potential risks tailored to various financial objectives and risk tolerance levels.

In the subsequent analyses, we focus on the subsamples of respondents who have reported having invested in at least one of these asset classes (investors' samples). This restriction is imposed to establish a direct link between the risk level of the stated investments and their self-assessed measure of risk attitude. Table 1 displays the relative dimensions of the subsamples considered in relation to the entire sample.[3]

Figure 1 shows the distribution of the stated investments across different asset classes. *Government bonds* refers to the total amount invested in Italian government securities. *Other fixed income* indicates investments in bonds issued by Italian firms or banks. *Stocks* represents the amounts invested in shares of both listed and unlisted companies. *Funds* captures the value of investments in any type of fund. *Other assets* includes the amounts allocated to alternative instruments such as derivatives or structured products. A detailed description of the investment categories, along with the other

[3]In all the waves, the question on the type of assets held is asked first, whereas the question on financial risk attitude is posed irrespective of respondents' investment behaviour.

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variables employed in the analysis and their corresponding survey codes, is provided in Table A.1 in Appendix A.

Between 2004 and 2010, the portfolio structure remained relatively stable, with a substantial share allocated to government bonds and fixed-income instruments. From 2012 to 2016, however, the share of government bonds declined sharply, likely reflecting the impact of the sovereign debt crisis, accompanied by a gradual diversification towards stocks and funds. In 2020, amid the COVID-19 pandemic, investments in funds reached their highest level in the entire period, while the share of government bonds continued to decrease. By 2022, the composition shows a clear shift towards more diversified portfolios, with a diminishing role of government bonds and an increasing weight of funds and other assets (Banca d'Italia, 2021).

3. Estimation and results

We classify respondents' attitude towards risk into four categories according to their answers to the following question in which they are asked to self-report their level of financial risk-aversion:

In managing your financial investments, would you say you have a preference for investments that offer:

1) [*Highly risk-loving*] **very high returns**, but with a **high risk** of losing part of the capital;
2) [*Fairly risk-loving*] a **good return**, but also a **fair degree of protection** for the invested capital;
3) [*Fairly risk-averse*] a **fair return**, with a **good degree of protection** for the invested capital;
4) [*Highly risk-averse*] **low returns**, with **no risk** of losing the invested capital.

In the upcoming discussion, we will refer to the financial risk profiles identified in the question above using the labels in square brackets (added by the authors), categorised along a spectrum of increasing risk aversion. The distributions of the financial risk profiles are shown in Figure 2 for the investors' samples and in Figure B.1 in Appendix B for the full samples.

We aim to map an individual's stated risk aversion to their reported investment behaviour. We hypothesise that if individuals accurately assess and act according to their risk profile, the following trends will be consistently observed across different year:

H1: *The proportion of financial investments in assets characterised by high risk is lower the higher the level of risk aversion.*

H2: *The proportion of financial investments in assets characterised by low risk is higher the higher the level of risk aversion.*

To test our hypotheses, we select the savings and investment activities identified by Guiso and Zaccaria (2023) from the list included in the SHIW survey, as described in the previous section. We classify the selected assets into three categories based on their risk profiles: *High-risk assets*, *Medium-risk assets*, and *Low-risk assets*. The *High-risk assets* includes shares in listed and unlisted companies as well as other instruments, such as derivatives. The *Medium-risk assets* includes bonds issued by Italian firms and banks, and shares of investment funds. The *Low-risk assets* category consists of various Italian government bonds with different maturities.

To formally test our hypotheses, we employ Tobit regression models of the shares invested in *High-risk assets* and *Low-risk assets*. We use a Tobit model since there are several zero-investment observations but also all-in-one asset cases, which are likely to arise from corner solutions when the constraint on the invested share (≥ 0 and ≤ 1) becomes binding.[4]

To test for the existence of a linear trend in the relationship between "RISFIN" and investment shares, we re-run the aforementioned regressions, treating "RISFIN" as a *linear trend* rather than

[4]This model is rather standard, so we do not expand on it. For more details, see Moffatt (2016).

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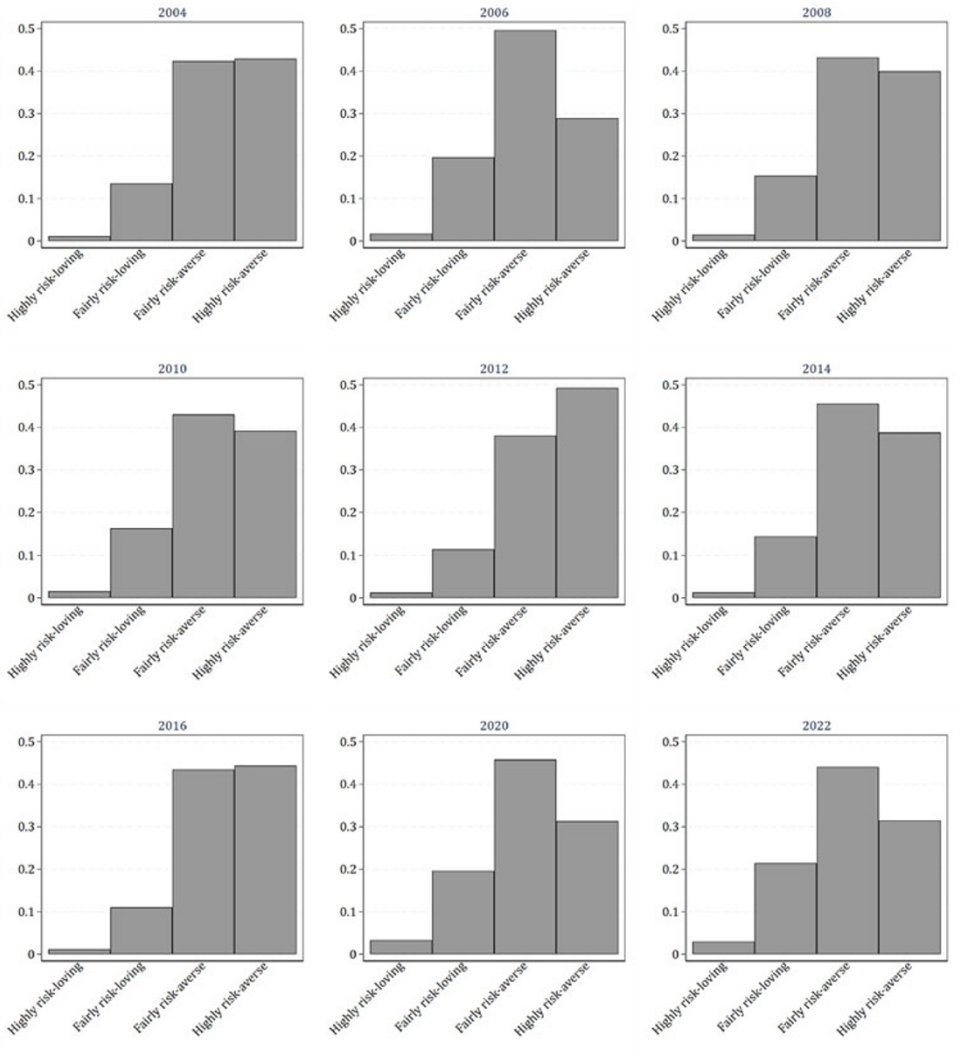


Fig. 2 Distribution of self-assessed risk attitude (investors' sample), by year
Note: Distributions of responses to the question on financial risk attitude. The samples include investors only. On the vertical axes, proportions are measured.

a categorical-ordered variable.[5] The coefficient estimates on this variable provide evidence for the following:

- A *positive linear trend* if the coefficient is positive and statistically significant;
- A *negative linear trend* if the coefficient is negative and statistically significant;
- *No linear relationship* if the coefficient is not statistically different from zero.

The results, displayed in Table 2, show that the coefficient on "RISFIN" for *High-risk assets* is consistently negative and statistically significant, whereas for *Low-risk assets* it is positive and significant, indicating opposite associations between risk attitude and asset allocation across the two categories.

[5]We thank Peter Moffatt for suggesting this approach.

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Table 2 Tobit regression estimates of risk aversion linear trends in investment shares (2004–2022)

	High-risk assets			*Low-risk assets*		
Year	Coeff.	Std. err.	*p*-value	Coeff.	Std. err.	*p*-value
2004	-0.607	0.075	0.000	0.820	0.142	0.000
2006	-0.575	0.062	0.000	0.446	0.087	0.000
2008	-0.541	0.061	0.000	0.618	0.081	0.000
2010	-0.571	0.060	0.000	0.438	0.080	0.000
2012	-0.426	0.060	0.000	0.344	0.083	0.000
2014	-0.419	0.066	0.000	0.534	0.088	0.000
2016	-0.316	0.090	0.000	0.247	0.141	0.079
2020	-0.209	0.039	0.000	0.095	0.056	0.093
2022	-0.262	0.034	0.000	0.139	0.042	0.001

Note: The table provides an extract from the results of the (unreported) Tobit regressions similar to those displayed in Tables C.3-C.9 in the Appendix, but using "RISFIN" unfactorised to estimate linear trends. It shows only the coefficients (Coeff.) on the linear trend "RISFIN", standard errors (St. err.), and *p*-values for the shares of investments in the riskiest (*High-risk assets*) and safest (*Low-risk assets*) activities. The *p*-values correspond to a t test of the null hypothesis that the coefficient on "RISFIN" equals 0, against the alternative that it is < 0 for *High-risk assets* and > 0 for *Low-risk assets*.

Table 3 Jonckheere-terpstra test for trends in risk aversion and investment shares (2004–2022)

	High-risk assets			*Low-risk assets*		
Year	Statistic	Std. err.	*p*-value	Statistic	Std. err.	*p*-value
2004	-133091	13105.05	0.000	107067	13987.51	0.000
2006	-189358	17001.80	0.000	118653	18593.82	0.000
2008	-175756	16676.16	0.000	170825	19379.83	0.000
2010	-213275	18146.71	0.000	107751	21098.86	0.000
2012	-121815	14254.72	0.000	74457	16212.05	0.000
2014	-131077	14886.78	0.000	127892	17723.63	0.000
2016	-47602	9351.393	0.000	49123	11274.12	0.000
2020	-167035	18644.21	0.000	34437	16876.57	0.041
2022	-297674	27459.80	0.000	97011	27356.44	0.000

Note: Let ms_1, ms_2, ms_3, and ms_4 represent the median investment shares for the four subpopulations identified by "RISFIN" $= 1, 2, 3,$ and 4, respectively. The null hypothesis states that $ms_1 = ms_2 = ms_3 = ms_4$, while the alternative hypothesis posits that $ms_1 \leq ms_2 \leq ms_3 \leq ms_4$ (with at least one strict inequality) for *High-risk assets*, and $ms_1 \geq ms_2 \geq ms_3 \geq ms_4$ (with at least one strict inequality) for *Low-risk assets*. ***, **, and * indicate significance at the 1%, 5%, and 10% level, respectively.

These findings are further supported by the results displayed in Table 3, which present the non-parametric Jonckheere-Terpstra (JT) test for detecting monotonic, generic trends (Terpstra, 1952; Jonckheere, 1954).

The results presented in Table 2 and Table 3 provide support for our hypotheses H1-H3. The following statements summarise these findings:

R1: *The portfolio share characterised by high risk is lower the higher the level of risk aversion. This result confirms our Hypothesis 1.*

R2: *The portfolio share characterised by low risk is higher the higher the level of risk aversion. This result confirms our Hypothesis 2.*

Figure 3 maps self-assessed risk profiles (x-axis, ordered from highly risk-loving to highly risk-averse) to portfolio holdings across asset classes pre-classified into risk tiers (y-axis: low, medium,

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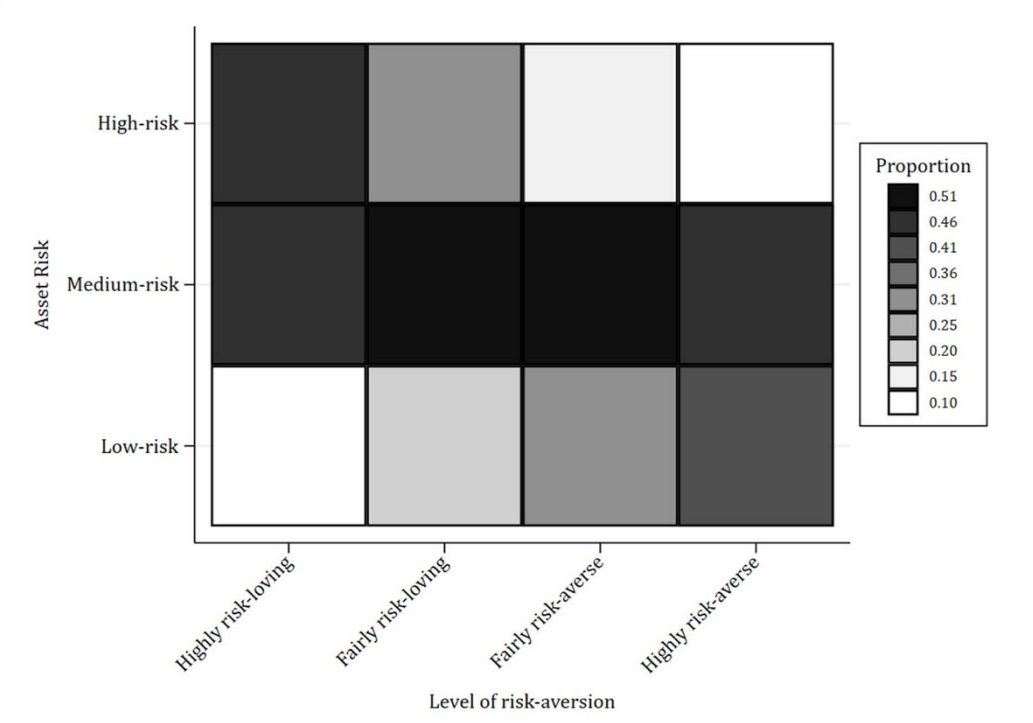


Fig. 3 Alignment between risk profiles and portfolio choices (2004-2020)
Note: The figure shows a heat map illustrating the relationship between individuals' self-assessed risk profiles and their participation in asset classes with varying levels of financial risk. The columns display the four categories of self-assessed risk propensity: *Highly risk-loving*, *Fairly risk-loving*, *Fairly risk-averse*, *Highly risk-averse*. The rows classify financial assets by risk level: *High-risk*, *Medium-risk*, and Low-risk. Each cell indicates the proportion of individuals within a given risk class, averaged through the years, who report holding at least one asset in the corresponding risk category. Darker shades indicate a higher share of investors within that group.

high) using all waves from 2004 to 2020. Cell intensity denotes the share of respondents holding at least one asset in the corresponding tier. A clear monotone gradient emerges: higher (lower) risk tolerance is associated with higher (lower) investment in high-risk assets. Holdings of medium-risk assets are comparatively stable across the risk-tolerance spectrum, with a slight concentration around intermediate profiles. This pattern supports the external validity of self-assessed risk measures, as the distribution of asset holdings aligns with theoretical expectations.[6]

We also run a panel Tobit analysis using data from all available years, the observational unit being the household. The dependent variable is, alternatively, the portfolio share invested by the hoursehold in a specific asset class. Shares equal to 0 and 1 are treated as censored observations. The model includes only those regressors that are consistently available across all survey waves considered. The results are displayed in Table 4.

In particular, the categorical-ordered variable of interest, "RISFIN", is factorised as explained above, and the factor corresponding to *Highly risk-averse* is used as the base case. *Female* is a dummy, which takes the value 1 if the respondent is female, 0 otherwise. *Age* is the age of the respondents. *Diploma* is a dummy taking the value 1 if the respondent holds an upper secondary school diploma, 0 otherwise. *University* is a dummy taking the value 1 if the respondent holds a university degree or a higher qualification, 0 otherwise. *Unemployed* takes the value 1 if the respondent is unemployed and 0 otherwise. *Employee* takes the value 1 if the respondent is a dependent employee, and 0 otherwise.

[6]Figure B.2 in Appendix B reports annual portfolio shares by risk tier.

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Table 4 Panel tobit 2004-2022 (High- and Low-risk assets)

	High-risk assets			*Low-risk assets*		
Variable	Coeff.	St. Error	*p*-value	Coeff.	St. Error	*p*-value
Highly risk-loving	0.859	0.082	0.000	-1.074	0.160	0.000
Fairly risk-loving	0.562	0.038	0.000	-0.488	0.055	0.000
Fairly risk-averse	0.262	0.030	0.000	-0.319	0.040	0.000
Female	-0.114	0.027	0.000	0.073	0.038	0.056
Age	-0.001	0.001	0.315	0.011	0.001	0.000
Diploma	0.080	0.034	0.020	-0.125	0.048	0.010
University	0.110	0.042	0.008	-0.091	0.060	0.126
Unemployed	0.200	0.054	0.000	-0.042	0.074	0.569
Employee	0.093	0.041	0.022	-0.209	0.058	0.000
Self-employed	0.080	0.046	0.080	-0.144	0.068	0.035
Parents' education	0.152	0.034	0.000	-0.175	0.052	0.001
IQ2	-0.076	0.119	0.519	-0.258	0.144	0.073
IQ3	0.029	0.112	0.795	-0.351	0.139	0.012
IQ4	0.099	0.111	0.375	-0.489	0.139	0.000
IQ5	0.314	0.112	0.005	-0.601	0.141	0.000
WQ2	-0.114	0.141	0.418	0.544	0.208	0.009
WQ3	-0.140	0.142	0.323	0.644	0.208	0.002
WQ4	-0.116	0.139	0.404	0.614	0.206	0.003
WQ5	0.042	0.140	0.762	0.410	0.207	0.048
Y_{2006}	-0.106	0.050	0.033	0.205	0.071	0.004
Y_{2008}	-0.170	0.051	0.001	0.379	0.071	0.000
Y_{2010}	-0.227	0.051	0.000	0.124	0.071	0.080
Y_{2012}	-0.257	0.053	0.000	0.003	0.074	0.965
Y_{2014}	-0.322	0.054	0.000	0.031	0.075	0.676
Y_{2016}	-0.327	0.059	0.000	-0.200	0.081	0.014
Y_{2020}	0.069	0.055	0.212	-0.530	0.082	0.000
Y_{2022}	-0.069	0.054	0.202	-0.411	0.078	0.000
Constant	-1.029	0.190	0.000	0.094	0.263	0.720
Regional Dummies		Yes			Yes	
σ_u	0.944	0.024	0.000	1.435	0.037	0.000
σ_e	0.799	0.017	0.000	1.172	0.026	0.000
Observations		14,709			14,709	
Uncensored		2,859			2,555	
Left-censored		10,209			8,619	
Right-censored		1,641			3,535	
Log-likelihood		-10348.318			-12520.122	

Note: The panel Tobit model is estimated using data from 2004 to 2022. The dependent variable is the portfolio share invested in the indicated assets. The observational unit is the household. Here, σ_u and σ_e represent the standard deviations of the random intercept and the normal error term, respectively.

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Self-employed is a dummy equal to 1 for self-employed people, 0 otherwise. *Parents' education* is a dummy equal to 1 if at least one of the parents hold a diploma or a higher degree. Following the previous literature on this survey (Conte et al., 2024a), we also control for household income (IQ) and wealth quantiles (WQ). Moreover, we include year dummies (Y) to account for period-specific effects on investments, such as the sovereign debt crisis and the COVID-19 pandemic, as well as regional dummies to control for socio-demographic factors not explicitly captured by the included variables but which may influence attitude towards risk.

Consistent with the formulated hypotheses, *Highly risk-loving* individuals allocate significantly larger shares of their portfolios to high-risk assets, while *Fairly risk-loving* individuals invest positively but to a lesser extent. In contrast, highly and fairly risk-averse individuals favour low-risk assets.

Regarding demographics and socioeconomic characteristics, females allocate less to high-risk assets but show no significant differences for medium- or low-risk assets. *Age* has a small but significant negative effect on medium-risk allocations and a positive effect on low-risk allocations, indicating a preference for safer investments among older individuals. Higher educational attainment and higher parental education are associated with increased holdings in high- and medium-risk assets, highlighting the role of both personal and family human capital in shaping portfolio choices. Self-employed and unemployed individuals tend to allocate more to high-risk assets compared with employees.

Higher income quintiles are strongly linked to increased allocations to high- and medium-risk assets and reduced allocations to low-risk assets, whereas lower-income individuals favour safer investments. Higher wealth quintiles are generally associated with larger low-risk allocations and reduced medium-risk allocations, implying a focus on capital preservation alongside selective high-risk exposure.

Temporal trends indicate declining high-risk allocations between 2006 and 2016, with a slight rebound in 2020. Medium-risk allocations generally increase over time, while low-risk allocations display heterogeneous patterns, with some years (e.g., 2020, 2022) showing significant reductions.

Overall, the results corroborate expected relationships between risk profiles, demographics, income, wealth, and portfolio choice: High-risk assets tend to attract more risk-tolerant and better-educated investors, whereas low-risk assets are preferred by more risk-averse or older individuals. Medium-risk assets are typically included in portfolios to achieve diversification. These patterns remain broadly stable over 2004–2022, with some variation attributable to macroeconomic and temporal factors.

For completeness, Table C.1 in Appendix C presents a panel Tobit model in which the two intermediate risk-tolerance groups, *Fairly risk-loving* and *Fairly risk-averse*, are pooled into a single category labelled Moderate risk profile. The results show that individuals with a moderate risk profile tend to allocate higher shares to medium-risk assets compared to those at the extremes. The resulting U-shaped pattern is consistent with a diversification role across the risk-tolerance spectrum.[7]

Finally, in Appendix B, Tables C.3–C.9 report Tobit regressions for each year separately for the *High-risk assets* and *Low-risk assets* only, which exhibit a clear pattern. We acknowledge that self-reported measures may be subject to biases stemming from prior experiences and unobserved heterogeneity, including differences in financial literacy. To address this concern, for the years in which these variables are available, we include financial literacy and other behavioural variables in addition to the other covariates described above.

[7]However, interpretation of the medium-risk tier warrants caution. Funds within the medium-risk tier span a wide range of underlying risk profiles. Because the Bank of Italy reports this category at varying levels of detail across waves, we cannot recover the precise riskiness of individual funds. As a result, both highly risk-tolerant and highly risk-averse respondents may hold medium-risk funds for diversification: the former tend to select relatively riskier funds within the tier (still safer than their main high-risk holdings), whereas the latter opt for relatively safer funds within the tier (still riskier than their main low-risk holdings). This composition attracts investors from both tails and attenuates the gradient in medium-risk holdings.

https://doi.org/10.1017/esa.2026.10034 Published online by Cambridge University Press

For the 2016 and 2020 waves, we include *Financial literacy*, defined as an indicator taking the value 1 if the participant answers all three questions correctly or at least two correctly. A "don't know" response is recorded if the participant selects this option for all three or at least two questions. Otherwise, an incorrect response is logged if at least two answers are provided and one or more are incorrect (Conte et al., 2024b; Conte et al., 2025). The results are consistent with the literature, showing that individuals with higher financial literacy tend to invest more in high-risk, high-return assets, whereas those with lower financial literacy allocate more to safer but less remunerative assets.

From the 2012 wave onward, we include the variable *Emergency*, a dummy equal to 1 if the respondent answers "yes" to the question: "In an emergency, do you think your household could temporarily borrow the sum of €5,000 from friends and relatives who do not live with you?", and 0 otherwise. This variable captures respondents' financial resilience (Conte et al., 2024b). The coefficient for high-risk assets is negative and significant in only one year, suggesting that investors in these assets exhibit lower financial resilience. Conversely, for low-risk assets, the coefficient is inconclusive, showing an increase in one year and a decrease in another.

4. Conclusions

In this work, we have examined the relationship between individuals' self-assessed financial risk attitudes and their portfolio allocations. Exploiting survey data, we found a consistent alignment between stated risk profiles and the declared composition of financial portfolios across different risk categories.

Our findings primarily contribute methodologically to the ongoing debate on eliciting preferences by validating self-assessed risk measures as reliable predictors of portfolio choices.

While experimental protocols provide a valuable benchmark by replicating decision contexts under controlled conditions, they are often costly and difficult to implement at scale. Survey-based measures, by contrast, offer a more practical and cost-efficient alternative for empirical research. The robustness of self-assessed measures, even without monetary incentives, suggests that such survey-based tools can be a credible and efficient resource for future studies investigating financial risk attitude. This opens the way for further research to refine these instruments and to explore how they interact with other behavioural and socioeconomic determinants of financial decision-making.

While we do not directly observe risk perception or risk management processes, the evidence that subjective risk attitudes are systematically reflected in (reported) investment behaviour has broader implications. For regulators, these results support the continued use of self-assessment tools as a cost – effective and informative proxy for risk tolerance. For financial intermediaries, the findings reinforce the relevance of incorporating self-assessed measures into advisory practices, ensuring that suggested products remain consistent with clients' expressed attitudes. Finally, at the individual level, our results highlight the potential value of reflecting on and explicitly articulating one's own risk preferences when making financial decisions.

Regarding the use of non-monetary incentives to elicit accurate responses, our findings confirm the robustness of self-reported measures when compared to reported investment behaviour, validating the reliability of such measures in assessing financial risk attitude. This consistency suggests that non-incentivised, self-assessed behavioural data can serve as a reliable tool for understanding the risk attitude of Italian households.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/esa.2026.10034.

CRediT author statement. **Anna Conte:** Conceptualization, Methodology, Software, Formal analysis, Data Curation, Writing - Review & Editing, Visualization

https://doi.org/10.1017/esa.2026.10034 Published online by Cambridge University Press

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Jacopo Temperini: Conceptualization, Writing - Review & Editing, Visualization

Data availability statement. Data is publicly available at: https://www.bancaditalia.it/statistiche/tematiche/indagini-famiglie-imprese/bilanci-famiglie/index.html?com.dotmarketing.htmlpage.language=1

Funding statement. The authors gratefully acknowledge support from the Sapienza Ateneo 2021 Project n. 1798/2022: "Athena vs Lyssa: the role of financial literacy and emotions in financial decisions", coordinated by Prof. Anna Conte.

Competing interests. The authors have no competing interests to declare that are relevant to the content of this article.

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Cite this article: Conte, A., Paiardini, P., & Temperini, J. (2026). Matching risk attitude to investment behaviour: insights from self-reported responses. *Journal of the Economic Science Association*, 1–13. https://doi.org/10.1017/esa.2026.10034

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