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What Are Investors Afraid of? Finding the Big Bad Wolf

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Abstract: The aim of financial institutions and regulators is to find an effective way to measure the risk profile of different segments of investors. Both economists and psychologists developed several methodologies to elicit and assess individual risk attitude, but these are not perfect and show several drawbacks when used in practice. Thanks to a unique database of around 15,000 investors, this paper combines survey-based evidence with revealed preferences based upon observed asset allocation. This paper confirms some results known in the literature like the gender and age differences in risk-taking. Moreover, the behavioral clustering approach used for the analysis is useful in an inferential framework. The segments built starting from the questionnaire permit to "forecast" the individual risk attitude that is described by the individual choices in terms of asset allocation. Loss aversion per se is a relevant variable in explaining financial risk-taking.

Keywords: risk profile; behavioral finance; loss aversion; investors' clustering; investors' protection

JEL Classification: D14; D18; G11; G41

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1. Introduction

Segmentation is a way of organizing individuals into groups with similar traits, performance characteristics, or expectations, which can be obvious and simple at one extreme or complex at the other. Segmentation of investor groups consists of identifying homogeneous groups of customers who behave differently to different financial instruments. Private investors do not represent a homogeneous group but rather individuals with various financial practices combined with different levels of experience, anxiety, and interest in financial matters.

Traditionally, the industry segmented individuals en masse on a relatively simplified basis, firstly, by defining three points of reference: amount of wealth, source of wealth, and age of wealth, useful for industrial and organizational purposes. Secondly, within each commercial segment, individuals were clustered in terms of their supposed investment profile, and measured in terms of financial knowledge, investment objective, risk tolerance, and capacity. Both tiers of segmentation are under review because they fall short in the intent to create homogeneous groups of clients from a behavioral perspective.

In addition, the request to figure out a more precise segmentation of investors is also a regulatory requirement into the field of investor protection. The aim that is pursued with the introduction of product governance requirements is to ensure that financial intermediaries take into account the client's interests and needs during the entire life cycle of their products and services, and an adequate target market, i.e., segment of clients, is clearly identified. Central to the definition of different target markets is the investor risk profile. Despite the central role of risk profiling in current investor-servicing processes, what constitutes an adequate, accurate risk profile remains an open question and, consequently, a reliable classification of clients is still missing. To address this issue, financial intermediaries collect information such as income, age, level of financial literacy, investing experience, and tax status (see Yao and Curl (2011) and Mandal and Roe (2014) for age and risk preferences, Outreville (2015) for education, Dohmen et al. (2011) for cognitive ability, Charness and Gneezy (2012) for gender, and Guiso and Paiella (2008) for wealth). The problem is that, although socioeconomic variables can proxy for the willingness to take risk, they cannot fully capture it. Attempting to judge risk preferences more accurately, financial intermediaries can develop surveys aimed at measuring risk tolerance. In many countries, these surveys are part of the "know-your-client" process, a mandatory regulatory step. Psychometric measurement is the simplest risk attitude measurement method in terms of elicitation, analysis, and inference. While the use of psychometric techniques is long established in the fields of personality and cognitive psychology, it is relatively new to risk attitude measurement.

In addition to surveys, economists and psychologists developed several methodologies to elicit and assess individual risk attitude. A common method for eliciting preferences relevant for investment decision is the use of incentivized instruments in economic experiments (see Holt and Laury (2014) and Hey (2014) summarizing the literature). With these instruments, people make incentivized decisions that reveal their preferences and attitudes. Through the control of the laboratory environment, experiments make it possible to measure multiple dimensions of risk attitudes. However, experiments are costly, both in terms of time and resources, and they appear unfeasible in many contexts. A final approach to elicit risk attitude is via observed behaviors. The approach is to infer attitude to risk by observing individuals' actions, often in the natural environment in which they make them. This approach has a number of advantages, most regarding validity. Compared to questionnaire-based assessments, which are usually performed on a demographically restricted sample (i.e., college students), observed behaviors can be assessed in a wide variety of circumstances for more representative samples. Observed behavior studies also benefit from "natural validity", i.e., they measure the risk attitude being evidenced in its natural environment. A plethora of studies used investment holdings to estimate risk aversion coefficients (among others, Huberman and Dorn (2010) and Ferreira (2018)). The downside to observed behaviors is that the reduced control over sample, control variables, and environmental stimuli means that inferences regarding risk attitude may be significantly confounded. As a result, the number of assumptions in observed behavior studies is much larger, the fragility of data analysis is higher, and the ability to make causal inferences is limited.

The present study aims to investigate more effective ways to deal with the definition of investor risk profile, combining an extensive survey based psychometric measurement with observed behaviors (i.e., pension saving asset allocation). In such a way, the drawbacks of the two approaches are limited and a more robust evidence can be obtained. We use a unique database of almost 15,000 investors, with rather homogeneous income and cultural characteristics—the managing directors of the Italian manufacturing and services firms—and characterized by equivalent financial needs and time horizons, as well as their retirement saving asset allocation, and who eventually differ in terms of their risk profile. We believe that the homogeneity of our dataset in terms of individual income and possibly wealth bracket (ISTAT/Banca d'Italia 2019) permits to isolate the risk attitude independently from these socio-economic variables.

Our study's contributions are several. Firstly, we explore the association between the results of the survey and the observed behaviors of real investors. While other papers researched the determinants of risk attitudes (Dohmen et al. 2011; Ding et al. 2010), the association between different experimental measures of risk aversion (Menkhoff et al. 2006), and the empirical association between different dimensions of risk preferences (Deck and Schlesinger 2014), none examined a questionnaire designed for the financial industry. Secondly, we contribute to a small but dynamic literature investigating the interaction among different psychological traits and their impact on risk attitude (Mishra and Lalumière 2011; Young et al. 2012). Finally, thanks to the extension and the depth of our database, we provide useful and original insights for a behavioral segmentation of investors' profiles.

The paper is organized as follows: Section 2 deals with risk profiling; Section 3 illustrates the empirical analysis and the resulting main findings; Section 4 concludes with some final remarks.

2. Profiling Investors in Terms of Risk Attitude

A definition of risk profile in the practitioner community (Davies 2017) encompasses the understanding of two characteristics of a client: his ability and his willingness to take risk. The first aspect, ability to take risk, goes by many loosely defined labels, such as risk capacity, capacity for loss, and ability to bear loss. Since risk capacity concerns the investor's ability to meet any future liabilities, it depends on a number of elements of the investor's holistic financial position, and can be considered a more objective measure of how much risk an investor can afford to take.

The second aspect, willingness to take risk, is often variously and ambiguously referred to as risk attitude, risk tolerance, risk aversion, or risk appetite. This aspect deals with more subjective characteristics of the client, and it is the variable we aim to focus on in this paper.

Such willingness to take risk, or financial risk attitude (FRA), requires a distinction between risk tolerance and behavioral risk attitude. The former has to do with the trade-off an investor is willing to make between the perceived risk and expected return of different investment choices (Grable 2017). This definition derives from a psychological interpretation of the risk–return framework of classical portfolio theory (Markowitz 1952). It treats risk tolerance as an attitude toward risk and decouples this pure attitudinal variable from the perceptions of risks and returns—psychological variables in their own right and distinct from the expected value and variance of the distribution of possible outcomes (Weber and Milliman 1997). This second set may in fact contain a whole range of different influences on risk attitude, including loss aversion, ambiguity aversion, regret aversion, risk perceptions, and probability distortion.

Risk tolerance, in this sense, is the mediator that translates perceptions of risk and situational needs and constraints into decision and action. It may differ among investors as a function of socioeconomic and biological differences as mentioned in the introduction.

In addition to the attitudinal difference (toward risk and time delay) granted by economics, psychology allows for individual and situational differences in the perception of a situation. Weber et al. (2013) demonstrated the importance of changes in the subjective perception of risk during the 2008–2009 financial crisis. Investors use a wide variety of information and mental processes to make financial decisions. These mental processes include emotions, and moral and professional rules of conduct, as well as other social norms. The same set of external circumstances might elicit very different emotions depending on the way these circumstances are "experienced" or processed by the individual. Furthermore, individual decisions are dramatically susceptible to the frame in which decision-making problems are described. Loss aversion reflects a prevalent avoidance behavior involving choices that could result in losses (De Martino et al. 2010; Lee and Veld-Merkoulova 2016). Several researchers noted that an individual's distaste for losses is a separate attitude from dislike of volatility, and that risk-taking behavior could be characterized by an aversion to losses (Kahneman and Tversky 1979; Tversky and Kahneman 1992; Kahneman and Riepe 1998; Shefrin 2000). Other types of aversion, namely ambiguity (Ellsberg 1961; Slovic and Tversky 1974; Curley et al. 1986; Dimmock et al. 2016) and regret (Mellers et al. 1999; Zeelenberg et al. 1996; and more recently Somasundaram and Diecidue 2017), also impact on investors' risk-taking.

3. Empirical Investigation

3.1. Preface

The assessment of risk profile via survey is usually conducted by asking consumers several questions about their attitudes and reaction toward uncertain prospects and, depending on the scores achieved, respondents are classified in different brackets of risk attitude. Rarely, survey data are used in connection with the actual investment decision and, consequently, the consistency of declaration and action cannot be measured. The analysis conducted in this paper makes a highly valuable exception: survey data are connected with actual pension saving asset allocation and some socio-demographic features of the respondents. Behavioral segmentation of respondents is then feasible, making clear how different dimensions of financial risk attitude impact on observed risk taking.

3.2. Questionnaire and Sample Relevant Data

We produced a 21-item multivariate questionnaire aimed at measuring the financial risk attitude (FRA) of respondents. It differentiates from a mere financial risk tolerance (FRT) questionnaire since it includes questions on risk, regret, and loss aversion. Following Grable and Lytton (1999), three different dimensions such as investment risk, comfort with risk, and finally knowledge of risk are investigated to produce a comprehensive measure of risk aversion. Questions on regret and loss aversion are consistent with Pann and Statman (2012) and Grable and Lytton (2003), respectively. Since the investigation was aimed at measuring FRA in pension saving allocation decisions, some questions were asked making specific references to investment for retirement as in Goldstein et al. (2008).

The survey was submitted to the whole population of members of Previndai, the pension fund for the managing directors of the Italian corporations belonging to the association representing manufacturing and services companies in Italy (Confindustria). The Italian pension system is rather complicated; together with the mandatory social security pension contribution, managing directors of Confindustria companies benefit from, as a part of their welfare package, the automatic enrolment into the Previndai pension fund. The employer contributes to the fund and the members can voluntarily top up with further contribution. Members cannot opt out, but they must choose the investment line their direct and indirect contribution is addressed to.

The survey was submitted online and each member received a link via email to the questionnaire webpage. Respondents could fill out the questionnaire anonymously; however, as explained to members in the accompanying email, the link allowed to draw from the pension fund internal database several socio-demographic, behavioral and financial information of the participating member (a full list is provided in Table A1, Appendix A). Age and gender were the most relevant socio-demographic variables employed. A dummy (0, 1) measure of dynamism computed on specific actions, such as fund switches over the last five years and voluntary contribution above the default rate, was an additional interesting behavioral variable. Finally, the asset allocation, both stocks and previous year flows, among the different three investment lines available: a guarantee investment product and two financial plans (a middle-low risk fixed-income based investment line and a more aggressive equity-based investment fund), was the financial variable of investigation.

The questionnaire was live for the whole month of May 2015; late April 2015, members received an email with a call to action explaining the aim of the survey and, one week before the expiration, all members received a generic email thanking those who participated and, leveraging on social norms, stimulating others to complete it.

Eventually, almost 15,000 members, representing around 19% of the Previndai population, answered the survey. Respondents' socio-demographic characteristics did not deviate substantially from the Previndai population, except for gender, with female respondents underrepresented. On the contrary, behaviorally and financially, the sample appeared more active and dynamic and more prone to financial investments than the entire Previndai population (see Table A2 in Appendix A for a full comparison).

The answers to the questionnaire could range from a minimum of 3 (lowest risk-taking attitude) to a maximum of 80 points (highest risk-taking attitude). Respondents showed heterogeneous financial risk attitude, as presented in Table 1. The average score was 34; however, two respondents, one female aged 46 and a male aged 54 scored a minimum of 3, while one respondent, a male aged 46, scored a maximum of 79. Only 10% of respondents exhibited an extremely low or high financial risk attitude. However, almost 30% demonstrated a medium–high risk attitude. This seems at odds with proxy numbers for the entire Italian population (Linciano et al. 2015); nevertheless, it appears consistent with literature relating wealth/income and risk tolerance (see, e.g., Guiso and Paiella 2008).

Table 1. Classification of respondents into financial risk attitude (FRA) classes.

<20—Low	20–39—Medium	40–59—Medium–High	≥60—High
9%	62%	28%	1%

Consistently with the literature (see, e.g., Dohmen et al. 2011, 2012), gender was a significant source of variation, and females showed a lower financial risk attitude than males; in addition, a negative correlation existed between age and score.

The respondents' observed asset allocation and resulting risk-taking are presented in Table 2. Around two-thirds of the respondents allocated their retirement saving to the lowest risk guaranteed investment product (insurance-based), and only a small minority concentrated on the most volatile equity-based financial plan. The correlation between FRA questionnaire scores and a normalized actual risk-taking score was positive and statistically significant but rather low (0.27). At first sight, this result is dissimilar from existing evidence (Guiso and Sodini 2012; Guillemette et al. 2012), and it requires further investigation. We introduced a different methodology aimed at understanding if and how the different components of FRA interact and their relationship with the revealed risk-taking.

Table 2. Classification of respondents into asset allocation categories.

Min Risk	Low Risk	Medium Risk	High Risk	Max Risk
67.5%	7.5%	9.0%	12.8%	3.2%

3.3. Clustering Methodology

We wanted to explore the different determinants of financial risk attitude by using our survey data in order to define a more precise relationship between attitude and behavior. To perform the task, we conducted a cluster analysis by gathering together respondents sharing similar features in terms of the multidimensional financial risk-taking attitude, and we inferred the actual risk-taking behavior. Our clustering exercise followed two subsequent steps. The first step was a principal component analysis (PCA) to define the number of relevant factors, and the second step was a k-means clustering algorithm to define the proper clusters. Both steps, together with the whole elaboration, were implemented by using MatLab.

We performed a standard principal component analysis (PCA) on the entire questionnaire in order to determine the effective size of the linear space defined by the 21 questions. As a first result, we obtained that the first five principal components were chosen among the others according to Kaiser's criterion, i.e., with corresponding eigenvalues greater than 1. Furthermore, we noticed that the percentage of the total variance explained by the first five principal components was approximately equal to 55%, confirming that five dimensions were enough to describe the financial attitudes and behavioral tendencies contained in the questionnaire.

What makes principal component analysis difficult to interpret is that each component is a linear combination of the original variables, leading to the creation of new variables with no trivial and immediate interpretation. To avoid this shortcoming, we propose to use the PCA analysis exclusively to determine the number of factors needed to explain the total variability of our sample. Following this intuition, we decided to group the 21 original questions into five factors, where the single question belonged to a specific factor on the basis of its intrinsic content. The resulting five factors were named comfort with risk, investment risk, knowledge of risk, regret, and loss attitude. For a detailed description of the factors, see Box 1.

The multi-dimension of FRA found confirmation in the preliminary correlation analysis shown in Table 3. It appears that the three risk aversion items (comfort with risk, investment risk, and knowledge of risk all constructed to measure at higher scores with lower aversion) were positively correlated, but they still maintained specific traits as in Grable and Lytton (1999). In general, correlations up to 0.5 were even regarded as "independent" in these circumstances (Cohen 1988). Quite surprisingly, regret attitude (the higher the score, the lower the regret aversion), expected to be fully independent from risk aversion, correlated similarly with the three risk aversion dimensions. On the contrary, attitude about losses (here again, the higher the score, the lower the loss aversion), showed the lowest correlation with the other dimensions of risk attitude. This result suggests that we faced a trait somehow different from the other variables under investigation.

Table 3. Correlation among different dimensions of the FRA.

	Comfort	Investment	Knowledge	Regret	Loss
Comfort	1				
Investment	0.50	1			
Knowledge	0.41	0.48	1		
Regret	0.41	0.45	0.50	1	
Loss	0.30	0.31	0.28	0.31	1

Furthermore, the goodness of the five proposed factors was empirically proven ex-post by calculating the respective Cronbach's alpha. Cronbach's alpha measures the inter-item reliability of a scale generated from a number of items. An alpha value greater than 0.6 is considered to be acceptable for internal consistency (Robinson et al. 1991). In our case, the alpha for the factors ranged from a minimum of 0.75 to a maximum of 0.82. The final constructs and their internal reliability are summarized in Box 1.

As a final step, we performed the cluster analysis for individual segmentation on the dataset using the k-means clustering algorithm. The clusters are defined on the base of six variables, the five factors from the questionnaire described above and the age of the individuals, representing the most important and objective socio-demographic variable impacting risk attitude (Dohmen et al. 2017). In addition, as our database deals with pension savings allocation, age of participants is a very relevant dimension in pension funds asset allocation choice (see, e.g., Agnew et al. 2003; Bikker et al. 2012).

All of the variables were normalized in a 0–1 range to avoid possible biases due to the different scales; in fact, each factor was composed of a different number of questions and needed to be compared to the age of respondents whose unit of measure was years.

Given a set of observations, k-means clustering divides the observations into k clusters minimizing the variance within-cluster. The algorithm uses the Euclidean distance as a metric, and each observation belongs to the specific cluster with the nearest mean, where the mean is the parameter that identifies the cluster. The k-means algorithm is well known in the literature, and its use is widespread in many applications because of its simplicity. Despite the positive aspects, the k-means algorithm presents well-known drawbacks. Firstly, the number of clusters (k) is an input parameter of the procedure such that a pre diagnostic on the number of clusters in the dataset is necessary to avoid poor results in the application. Secondly, the procedure can converge to local minimum solutions producing unstable results.

Box 1. Risk profiling construct of investors.

Comfort with risk—8 questions (Cronbach's alpha = 0.78)

Some individuals have psychological traits that allow them to accept taking risk. These individuals typically see risk as involving a "thrill" or "opportunity" rather than as a "danger" or a "loss". Questions addressing risk comfort levels often involve individuals choosing among alternative courses of action relating to saving decisions, or simply stating their comfort level with risk.

(1) People who know me would describe me as a cautious person.
(2) You have saved enough money for your ideal holiday, and if you lose your job 6 weeks before departure, how would you behave.
(3) I associate the word "risk" with the idea of "opportunity".
(4) You participate in a television (TV) show where you have to decide between a safe option and several risky options.
(5) You have to take an international flight early in the morning and the recommended check-in time is 90 min before departure. Which is your preferable attitude?
(6) I am concerned by the uncertainty of the stock market investment.
(7) If in six months' time your pension plan would register a remarkable drop in value, what would you do?
(8) I believe that the best long-term results can be achieved with an aggressive investment strategy and I am willing to accept a considerable and lasting drop in value during the investment period.

Investment choices—4 questions (Cronbach's alpha = 0.75)

Preferences for different kinds of investments can also help to gauge risk attitude, for example, the safety of a bank account versus the risk/return potential of the stock market.

(1) I generally look for the safest type of investment, even if that means lower returns.
(2) I feel comfortable about investing in the stock market.
(3) You have a friend who developed an app he is about to launch. There is a 15% chance to succeed and, in that case, the reward is 10 times the capital initially invested. How much would you put into this venture?
(4) I prefer the safety of keeping my money in the bank.

Knowledge—4 questions (Cronbach's alpha = 0.76)

Individuals with more financial and investment knowledge are generally more willing to accept investment risk. Knowledgeable individuals often know that they will need to take at least some risk to generate higher returns. Short-term fluctuations in the values of investments need not matter for investors with longer-term horizons.

(1) I feel comfortable about investing in the stock market.
(2) I find investment and other financial matters easy to understand.
(3) Did you happen to choose an investment with a strong, while temporary, capital loss? In which case?
(4) I have little experience of investing in stocks and shares.

Regret—3 questions (Cronbach's alpha = 0.75)

This negative emotion arises from making the wrong decision. Individuals who are particularly prone to regret tend to try to make decisions that are less likely to cause it. For example, they might engage in regret avoidance.

(1) Usually it takes me a long time to make up my mind on financial matters.
(2) You are given the possibility to choose among several pension plans. How would you behave?
(3) When it comes to investing, I would rather be safe than sorry.

Loss—2 questions (Cronbach's alpha = 0.82)

People feel losses more deeply than gains of the same value. In other words, it is more painful to lose something than to get that same thing.

(1) You have to renew your house insurance and you can choose among several mixes of premium and deductible.
(2) Choose among the following min and max returns you could achieve on your portfolio over a one-year investment horizon.

For these reasons, cluster solutions ranging from two to six clusters were tested. In order to determine the number of clusters (k), we applied Hartigan's approach (Hartigan 1975) and, comparing the explained sum of squares of the clusters when k varies, we discovered that, in our case, the minimum value where the criterion was verified was obtained for k = 4. Moreover, k = 4 was an optimal choice in our experiment considering that, in these settings, the k-means algorithm converged to a unique stable solution for the clusterization problem (while, for example, for k = 5, we found different local solutions rerunning the procedure). A further reason supporting the choice of k = 4 was that the population was divided in well-balanced groups in terms of size. The final four-cluster solution provided the greatest contrast between the groups; all six factors contributed significantly and were supported by their interpretability. The final cluster centers are displayed in Table 4.

Once we obtained the optimal clusterization of the individuals, we analyzed the cluster composition in terms of exogenous variables. In particular, the clusters were analyzed for the number of females, the size, the investment choices in terms of risk, and the degree of "dynamism".

For eachvariables used as input of the clusterization procedure, as well as for the exogenous ones, we performed a two-sample *t*-test to verify the null hypothesis that the entire population and the single cluster came from independent random samples from normal distributions with equal means and equal but unknown variances. The alternative hypothesis was that the clusters and the entire population had significantly unequal means. The significance level of the test was set to 5%.

Table 4. Risk profile characteristics of each segment.

Characteristic	All Respondents (n = 14,590)	Cluster I—The Alpha Males (n = 3155; 22%)	Cluster II—The Cautious (n = 3905; 27%)	Cluster III—The Static (n = 3537; 24%)	Cluster IV—The Loss Averse (n = 3993; 27%)
Age	53.94	51.74 *	56.13 *	52.38 *	54.91 *
Comfort with risk	0.3844	0.5356 *	0.2642 *	0.3695 *	0.3958 *
Investment risk	0.3691	0.553 *	0.2324 *	0.3484 *	0.3757
Knowledge of risk	0.473	0.701 *	0.2742 *	0.364 *	0.5838 *
Regret attitude	0.4871	0.7011 *	0.2887 *	0.422 *	0.5699 *
Loss attitude	0.3363	0.5789 *	0.142 *	0.4887 *	0.1997 *
Risk taking in asset allocation	0.2851	0.367 *	0.1896 *	0.2803	0.2632 *
Dynamism	0.1077	0.142 *	0.0855 *	0.078 *	0.1285 *
Gender (male)	92.19%	96.48% *	88.58% *	89.71% *	94.52% *

* 5% significance *t*-test.

3.4. Segmentation Profiles

The 14,590 respondents were classified into four clusters, whose sizes ranged from 3155 to 3993 individuals as presented in Table 4, also showing the percentage distribution.

From Table 4, we note that, within each cluster, almost all the values were significantly different from the average value of the total population. This fact supported the fact that the proposed clusters were able to capture specific peculiarities of the sub-groups. In particular, the values for risk-taking were significantly different from the average of the population for three of the four clusters, providing the evidence that the variables we proposed for the cluster analysis were useful for effective individual risk profiling. In other terms, we were able to prove when and how different financial risk attitude dimensions had an impact on risk-taking.

Results were comforting: respondents whose financial risk attitude was homogeneously high (cluster I) or low (cluster II) allocated their pension savings in high-risk and minimum-risk portfolios, respectively; respondents with similar risk and regret aversion scores but remarkably different loss aversion attitude results (clusters III and IV) invested in different portfolios, and loss aversion affected the willingness to take risk. Precisely, the different clusters can be described as follows:

Cluster I—The Alpha Male[1]

These respondents (around 22% of the sample) represented by far the group with the highest-risk attitude both in absolute and relative terms. These were investors with a high comfort with risk and who both knew and experienced risk-taking. Neither regret nor loss aversion appeared to represent a

[1] One of the two authors would like to disclose that he belongs to this group.

behavioral issue. Somehow consistently with an aggressive proactive attitude, they appeared very dynamic and active on their pension fund contribution decision. Investors in this group were mainly males, almost 97% of the cluster, and the youngest across the whole sample (less than 52 years old on average). They chose to invest predominantly in financial options, showing the most aggressive asset allocation.

Cluster II—The Cautious

This was the second largest group in the sample, representing more than one-quarter of the respondents. At the opposite end of "Alpha Male", these respondents fared the lowest scores in all dimensions of risk attitude. In particular, cautious investors showed high regret and loss aversion, and these could well be the major causes of this cluster's strong status quo attitude. The probability to make a mistake, caused by the low knowledge of risk, led these investors to a static attitude and a state of full inertia. Investors in this group were older than the average and the oldest among the different clusters, with the highest female presence (12% vs. sample average of less than 8%). These allocated their pension savings exclusively to the guaranteed investment line, showing the most conservative approach.

Cluster III—The Static

Almost one-fourth of the sample belonged to this cluster. These respondents had a medium–low attitude to risk. Scoring particularly low on knowledge and experience of risk, they were the most static among the investors, confirming that a higher dynamism is a positive feature of more knowledgeable investors. Differently from Cautious investors, the Static investors appeared less affected by losses and this impacted directly on their risk-taking; therefore, they also allocated their pension contribution to medium-risk assets. Static investors were younger than the average, being only slightly older than the alpha male, but female respondents were over-represented (almost 11%).

Cluster IV—The Loss Averse

The Loss Averse, the most populous cluster of the sample, was the most interesting group from a behavioral perspective. They were mainly male and aged around 55 years old. They fared relatively high on all risk profile items, particularly knowledge of risk and lack of regret, other than loss aversion, where their scores were very low. The relevance of loss aversion attitude showed clearly on their asset allocation choices, as they invested mainly on guaranteed lines of investments. This finding was highly significant and proved the importance of our approach. By neglecting the loss aversion dimension, a more traditional clustering based upon total questionnaire scores would miss this perspective and infer a higher risk-taking attitude than real.

4. Concluding Remarks

In this paper, we examined the risk attitude of a large sample of investors by combining the results of a psychometric survey and their revealed preferences obtained by observing their pension saving asset allocation choices. Compared to similar researches, we had a very extensive sample composed of real investors. Standard research uses small samples, usually composed of students, and only occasionally can it combine the survey answers with real investment decisions. Our research put forward an individual segmentation in groups that differed in their attitude toward risk-taking. We confirmed some results known in the literature like the gender differences in risk-taking. Moreover, our approach was shown to be useful in an inferential framework. The clusters built starting from the questionnaire permitted to "forecast" the individual risk attitude that was described by the individual choices in terms of asset allocation. The findings in the paper could be used by financial service companies to better implement product governance, to target their financial products to suitable investor segments, and to distribute them more effectively. As our paper shows, questionnaires and fact finds used by financial institutions and financial advisers need to ask questions which enable them to distinguish the customer's degree of loss aversion, as well as their risk aversion. The results of this paper are important and illuminating as they indicate that this distinction is not an academic curiosity, but has real implications for individual investment behavior. The characteristics of our database were both a point of strength and the major limitation of our work. Its homogeneity in terms of income, possibly wealth, gender, and cultural background allowed to isolate the effect of financial risk attitude on risk-taking habits; however, we are fully aware that our sample was at best partially representative of the entire Italian population and it would be interesting to test our findings, especially those related to loss aversion implication, on a more heterogeneous and representative sample.

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Appendix A

Table A1. Socio-demographic and behavioral variables of the sample.

1.	Age
2.	Gender
3.	Enrolment year
4.	Class of manager
5.	District of residence
6.	District of work
7.	Stock of pension fund investment
8.	Flow to pension fund investment
9.	Active/not active
10.	Contractual contribution
11.	Employer contribution
12.	Voluntary contribution
13.	Full/partial Trattamento di Fine Rapporto (TFR) (sewage fund) contribution
14.	Other voluntary contribution
15.	Number of switches over the last five years

Table A2. Socio-demographic, behavioral, and financial features of respondents vs. entire population.

		Respondents (14,590)	**Population (76,207)**
Age	Mean	54	53
	Min	28	23
	Max	80	97
Gender	Male	92.00%	89.00%
	Female	8.00%	11.00%
Enrolment year	Ante 2005	54.00%	55.00%
	Post 2004	46.00%	45.00%
Active contributors	Active	71.00%	60.00%
	Not active	29.00%	40.00%
Degree of dynamism	Static	89.00%	94.00%
	Dynamic	11.00%	6.00%
Asset allocation (stocks)	Only guarantee	67.50%	74.20%
	Only financial	11.50%	8.80%
	Both	21.00%	14.50%
	None		2.50%
Asset allocation (2014 flows)	Only guarantee	69.00%	77.00%
	Only financial	14.00%	10.50%
	Both	17.00%	12.50%

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