Prospect theory, personality traits, cognitive reflection test and investor profile analysis: A behavioral finance study

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Abstract

This study investigates which of four paradigms best portrays the risk profile manifest by investors in their financial asset investment decisions. The paradigms used to explain this profile were: prospect theory, investor profile analysis (IPA), the Big Five Personality Test, and the Cognitive Reflection Test (CRT). The choice of proxy for the risk preferences (profile) of a typical investor was defined by simulating investments in a laboratory setting. The results are analyzed using ordered logistic regression and show that people who have greater risk tolerance according to IPA, who violate prospect theory, and who have a high degree of openness to experience have the greatest probability of taking higher levels of risk in their investment decisions. With regard to the CRT, higher numbers of correct responses in this test has an inverse relationship with risk taking.

Keywords: Investor profile analysis; Cognitive reflection test; Big Five personality test

1. Introduction

Modern financial theory is based on the concept of *homo economicus*, adopted from neoclassical economics. This ideal, self-interested, and perfectly rational agent maximizes his utility by choosing at each point in time the best options available. This perfect rationality, combined with the efficient markets hypothesis, was assumed by Markowitz [1] when he developed his portfolio selection theory, which is considered the starting point of modern finance theories. The market efficiency concept was formally set out by Fama [2] and modern financial theories are founded on the assumptions of rational investors and efficient markets.

In contrast, the *agent* of behavioral finance is not perfectly rational, but a normal human who acts and takes decisions under the influence of emotions and cognitive errors [3]. Starting with a study by Kahneman and Tversky [4], interdisciplinary elements (in particular from psychology) began to be incorporated into behavioral theories of finance, in attempts to understand the process of decision-making under risk. Against this background, this study considers that manifestations of investors' risk preferences are influenced by behavioral biases.

Thus, the principal objective of this paper is to investigate which paradigm or model best portrays the risk profile manifest by investors in their financial asset investment decisions. The four paradigms used to explain this profile were: prospect theory, investor profile analysis (IPA), which is related to financial institutions' obligation to assess an investor's risk profile before they invest, the Big Five Personality Test, and the Cognitive Reflection Test (CRT), which measure's people's cognitive capacity. The choice of proxy for the investor's risk preferences (profile) was defined by simulating investments in a laboratory setting.

Working from this starting point, the specific objectives are to: (i) assess whether people's personalities influence their investment decisions and risk preferences; (ii) identify whether performance in the CRT might provide evidence on people's risk behavior; and (iii) classify individuals into risk profiles according to the IPA approved by the Brazilian Association of Financial and Capital Market Entities (ANBIMA) and the International Organization of Securities Commissions (IOSCO) and administered by financial institutions, evaluating the influence of these characteristic on decision-making under risk.

This study employs the experimental method to achieve these objectives, with application of structured questionnaires, and computer simulation of investments with *Expecon* software utilizing data on real financial instruments that are available on the market [5; 6]. This makes it possible to identify respondents' behavior in terms of their preferences for financial instruments and their risk profiles. The results are analyzed using an ordered logistic regression model.

These considerations stated, it should also be mentioned that the motivation for this study primarily comes from the importance of understanding the many different aspects that can alter risk behavior, since risk taking is a key factor that molds investments, consumption, health, and other important choices [7]. Additionally, this study is further justified by the need to better understand how behavioral and personality variables can impact on risk decisions related to investments, contributing not only to behavioral finance theory, but also to economic analyses and formulation of public policies [8].

In addition to the introduction, this paper presents a literature review, describes the methodology used for data collection, the experimental method, and statistical analysis of the data, before presenting the research results and closing with some final comments.

2. Theoretical Framework

2.1 Behavioral finance and prospect theory

For many decades, studies of people's decision-making under uncertainty were guided by the expected utility theory [9]. According to this theory, economic behavior is seen as rational behavior. This hypothesis has been questioned and was challenged by Kahneman and Tversky [4], who proposed an alternative theory that they called prospect theory. This theory has become one of the most important tools used in behavioral finance to explain a series of biases affecting decision-making under conditions of risk.

An essential characteristic of this theory is that people taking decisions take into account changes to their wealth or wellbeing, rather than considering the final position. In other words, they evaluate changes or differences to their position considering a reference point, rather than evaluating absolute magnitudes. Thus, the context of the experience determines a reference point, and the stimuli are perceived in relation to this reference. This implies that the same level of wealth may seem to be a great deal to one person, but very little to another, depending on their current assets [4]. The value is therefore attributed to gains and losses and not to the final assets position.

Prospect theory suggests that people are risk averse in relation to gains and risk seeking in relation to losses. This means that the value function is S-shaped, being concave above the reference point and convex below it [4]. In general, the value function has the following characteristics: (i) it is defined in terms of displacements from a reference point; (ii) it is concave for gains and convex for losses; (iii) it is steeper for losses than for gains.

The concept of loss aversion emerges from this value function. According to this concept, people suffer more pain from loss than the pleasure they reap from an equivalent gain. Thus, the agent of behavioral finance judges gains and losses with relation to a reference point and so people exhibit risk-averse behavior with relation to gains and risk seeking with relation to losses. Agents are therefore loss-averse, since when faced with the possibility of a loss, they will accept risk in order not to realize the loss [10].

Kahneman and Tversky [4] contested the expected utility theory, showing evidence of patterns of behavior incompatible with the theory's axioms. In other words, there is a pattern of behavior in which there is no evidence to support the expected utility theory, showing that errors are systematic and non-random. The expected utility theory is therefore inadequate in the majority of models of economic behavior [9; 6].

2.2 Theories of the personality

Economists are starting to consider aspects of the personality as relevant to economic studies. Borghans et al. [11] demonstrate the relevance of personality to the economy. Currently, the most accepted taxonomy for definition of personality is centered on the "Big five personality traits".

The Big Five Personality Traits is the personality model that has been most widely researched and adopted [12]. This model groups personality traits under five major factors, in order to represent personality on a wide level of abstraction. It therefore suggests that differences between individuals can be classified within these five dimensions: openness to experience, conscientiousness, extraversion, agreeableness, and neuroticism [11, p.983]:

Many different instruments containing measurement items have been developed to capture personality differences. For example, the BFI-10 comprises just 10 short sentences, each of which should be assessed by the respondent against a scale ranging from "completely disagree" to "strongly agree". The responses can be used to compute a profile in each of the five major dimensions of personality.

Each individual’s personality corresponds to a combination of the five personality traits. Thus, each person can be placed on a scale in which one personality trait will be more evident than the others. This does not imply that the other traits are not also present. Thus, participants in a sample can be classified according to the predominance of characteristics as high, moderate, or low for each major dimension of personality.

2.2.1 Empirical studies of the five personality traits

A wide range of studies have been conducted to identify the influence that personality characteristics have on investment decisions, on risk taking, on decisions relating to debt, on economic preferences, and on other factors. This subsection presents some of the studies that have investigated how the big five personality traits are related to different variables, with particular attention to individuals’ risk-taking profiles.

A study by Sreedevi and Chitra [13] based on the Big Five Personality Model analyzed the influence on investments choices of emotional stability, extraversion, risk, return, agreeableness, conscientiousness, and reasoning. Their results showed that personality has an impact on decision-making and influences choice of investment method [13].

Brown and Taylor [14] analyzed influences of personality traits on debt and on decisions about maintenance of financial instruments by families. High levels of the characteristics extraversion and openness to experience had a significant influence on total debt and financial instruments held, although extraversion has an inverse effect on financial asset holding. The authors therefore concluded that there is strong evidence that personality influences aspects of people’s economic and financial decision-making [14].

Specifically in relation to risk preference, Mayfield, Perdue, and Wooten [15], Rustichini *et al.* [16] and Nichelson *et al.* [17] all explored the impact of personality traits. Mayfield, Perdue, and Wooten [15] tried to identify the ways in which personal characteristics influence investors’ risk perceptions. Their results showed that people who are more extrovert tend to be especially involved in short-term investments, whereas long-term investments are preferred by those who score high for openness to experience. People who have a high score for the characteristic neuroticism were averse to short-term investments. The results revealed a significant negative correlation between the openness to experience personality trait and risk aversion. The extraversion trait was negatively related to prevention of investment risk. The characteristics extraversion and conscientiousness were positively related to short-term investment [15]. Similar results were observed by Nichelson et al. [17], who found that risk propensity was linked with high scores for extraversion and openness to experience and low scores for neuroticism, agreeableness, and conscientiousness.

Similarly, Rustichini et al. [16] examined the relationship between people's personality traits and their economic preferences. Their results showed that the characteristic neuroticism is negatively related to risk taking in the domain of gains, but that the effect of neuroticism is reduced in the domain of losses. The characteristic conscientiousness affected attitude to risk-taking. Intelligence was also a determinant of preference for more risky options.

2.3 Cognitive reflection test (CRT)

Countless phenomena can be associated with greater or lesser cognitive capacity, such as preference for risk, intertemporal preference, aversion to ambiguity, etc. However, the influence of people's different cognitive capacities on their decisions has been studied little.

According to Frederick [18], possible effects of cognitive abilities (or cognitive traits) are generally part of unexplained variance in studies that specifically analyze average behavior. However, as shown by Lubinski and Humphreys [19], intelligence, or specific cognitive abilities, are important determinants of decision-making and should not therefore be ignored.

The Big Five model captures the majority of specific personality traits. In this paper we have operationalized intellect as a separate concept to openness to experience, which is one of the components of the Big Five. This justifies combining the cognitive reflection test (CRT) with the Big Five [20]. The CRT was presented in a study by Frederick [18] and it attempts to measure people's cognitive capacity. It is designed to assess the capacity to substitute an impulsive, and incorrect, response with reflection that leads to the correct response. The metric used to assess the relationship between CRT results and risk preferences was based on choices between a certain gain/loss and the probability of a larger gain/loss.

2.4 Investor profile analysis

A procedure that has been adopted internationally to match investors' investments to their risk profiles is designed to set formal standards to determine how appropriate an investment is for a customer's risk profile. An individual's risk profile is constructed by considering several different characteristics including their financial situation, experience with investments, risk tolerance, investment time horizon, and investment objectives, among other factors [21].

The International Organization of Securities Commissions (IOSCO) is recognized as the global organization responsible for stock market regulation, with more than 95% of the world's stock markets affiliated, and it publishes the major guidelines for investment matching policies. The requirements are intended to afford consumers with protection, since these products have terms, resources, and investment risks that may make them difficult to understand [22].

ANBIMA (*Associação Brasileira das Entidades dos Mercados Financeiro e de Capitais*) is the principal representative organization for institutions that do business in the financial and stock markets of Brazil and, in consideration of the international guidelines, has made it obligatory for institutions that sign up to its Regulatory and Best Practices Code to analyze investors' profiles before they invest, through adoption of an Investor Profile Analysis (IPA) process. For this study, it was decided to employ the Bank of Brazil investor profile analysis questionnaire, in view of the bank's significant role in the country's financial sector.

3. Methodological Procedures

This study employs the experimental method, a methodology that is relevant to the field of behavioral finance [23]. According to Friedman and Cassar [24], experimental studies attempt to represent, in a simplified form, the collection of agents and institutions that make up the economy. A selection of different data collection instruments were used in the present study: several structured online questionnaires, designed to provide an understanding of risk profiles and personality, and a software package for simulating investments, used to track participants' decisions when managing an investment portfolio.

3.1 Data collection

The experiment was conducted with undergraduate students from the economics and electrical engineering courses at the Universidade Federal de Santa Catarina, during modules related to finance studies. A total of 140 students took part. Thirty-four participants were women and 106 were men. However, some of them were excluded from the study because of operational problems, leaving 137 people, and the final study sample comprised the results from 124 people, since participants who stated they already knew the answers to the CRT questionnaire were also excluded.

The questionnaire was completed online at the same time by all respondents, during an experimental session. The questionnaire comprised 5 blocks of questions. The first covered aspects relative to investor profile. Next, there were 10 questions about investment scenarios, adapted from Kahneman and Tversky [4], to evaluate violation of the expected utility theory, and the results were used to create a dummy variable where 1 indicates that a participant predominantly (at least 6 out of 10 questions were answered in a manner compatible with prospect theory) behaved in accordance with prospect theory, while the value 0 indicates that the participant behaved in a manner compatible with expected utility theory. The third block was made up of 10 questions from the Big Five Inventory [25]. Next were a further 8 questions from the Bank of Brazil IPA questionnaire, and, finally, 3 questions from the CRT [18].

The CRT was administered separately from the other questionnaires and all participants started to answer it at the same time, because it has a time limit of 5 minutes. Once they had completed the questionnaire, all participants started the computational investment simulation at the same time. The investigator stressed that participation was voluntary and did not offer any type of material incentive to the participants.

3.2 Computational investment simulation (ExpEcon)

In order to identify the respondents' "real" behavior with relation to their preferences for assets and their appetite for risk, computational investment simulation was conducted with the aid of ExpEcon (Experimental Economics) software. This software is used to identify participants' behavior and decisions in situations of risk [5-6].

The assets used in the simulation were defined as those available as investment options through Bank of Brazil. Among other factors, this bank was chosen because of information contained in a classification released by ANBIMA. Their results show that Bank of Brazil tops the ranking of institutions that manage investment funds in terms of assets invested in funds. In December 2015, BB DTVM S.A had a total of R$ 591,995.8 million in assets under management in different funds, which is the largest net assets of any of the Brazilian fund managers [26]. This result illustrates the bank's significant role in Brazil's financial sector, justifying choosing it. Bank of Brazil investment funds were chosen with special attention to risk levels and for each risk level the fund chosen was that which had the largest net assets on the definition date, in this case, in May 2015.

The data used for simulations are real financial data from the 2006 to 2014. The participants were not informed what period in time the data were from, they were only told that the data were real historic data on the assets involved. The deposit account profitability used was the six-monthly mean interest rate and was taken from the Central bank's information system (Sisbacen), while profitability figures for Bank of Brazil investment funds were taken from the six-monthly variation per unit for each fund, taken from the Brazilian securities commission database (Comissão de Valores Mobiliários - CVM). Six-months' real-world profitability data are used to model 1 year of trading in the investment simulator.

This approach to operationalization of the experiment was intended to make the simulation realistic, using historical profitability and interest data for the investment funds and deposit account. The objective of the simulation is to observe whether each participant chooses higher or lower risk assets to invest in, in order to approximate their "real" investor profile.

The participants were instructed to manage a financial investment portfolio over 18 periods. Price variations for the first 3 periods were displayed and used to provide a basis for initial investment decisions. Participants were not informed about the future performance of the assets.

The characteristics of each of the assets used in the simulation are shown in Table 1:

Table 1. Characteristics of assets used in the investment simulation.

Asset	**Risk**	**Risk scale**	**Objective**
Deposit account	Very low	0	Daily liquidity and tax free
BB Short term 50 thousand	Very low	1	Tracks CDI interbank deposit rate and is short term.
BB Fixed Income 500	Low	2	Tracks interest rate variations.
BB Fixed Income LP 50 thousand	Medium	3	Tracks interest rate variations.

BB Fixed Income LP Price Index 5 thousand	High	4	To achieve a return compatible with fixed rate investments.
BB Vale Shares	Very High	5	Made up of Vale S/A shares

Source: Bank of Brazil.

The results of portfolios were analyzed in order to capture participants' risk profiles and thus identify their asset preferences. In this study, it was decided to employ the weighted mean of assets held in the portfolio in the last three periods during which the agent bought or sold assets. This was used to classify agents into one of three risk profiles. These risk profiles resulting from the investment simulation using ExpEcon were used to populate a variable, termed Simulator_Profile, which would be used as the dependent variable for the logistic regression model. According to the portfolio they are holding at the end of the simulation, each participant is allocated a risk profile and a number to represent it, which is the dependent variable in the model (Dummy). The low risk profile is coded with the value 1, the moderate risk profile with value 2, and the daring risk profile is coded as 3.

3.3 Data analysis

An ordered logistic regression model was used to achieve the study objective. Table 2 contains a description of each of the variables used in this stage of the study:

Table 2. Descriptions of study variables

Variables	**Measurement**	**Description**
Simulator_Profile (dependent variable)	Profile categorized on a scale from 1 to 3, based on mean risk	Classified in three risk profiles: Risk-averse agents are coded as 1, when the participant has a weighted mean risk from 0 to 2 points, agents who accept moderate risk are coded as 2, when the final weighted risk of the assets in their portfolio is 2.1 to 4.0, and the risk-seeking profile is coded as 3, when the participant is tolerant of a high level of risk, with a weighted mean from 4.1 to 6.0.
CRT Profile	Number of correct responses, on scale of 0 to 3	For each participant, this variable is equal to the number of correct answers on the Cognitive reflection test.
Mean IPA	Mean risk score	This is the participant's mean weighted risk calculated from answers to the IPA questionnaire and the respective weightings for each response.
Mean prospect	Dummy	This dummy variable takes the value 1 when the participant predominantly behaves in a manner compatible with prospect theory, i.e., if the majority of the questionnaire items were answered according to that theory. The variable takes the value 0 if the participant predominantly behaves in a manner compatible with the alternative theory – expected utility.
Mean Personality	Mean personality profile	This variable is obtained by taking the arithmetic means of the result obtained after scoring each response to the BFI-10 questions.

Extraversion Dummy	Scale from 1 to 3	Personality profiles that that take the value 1 if the participant scores low for that dimension, 2 if the participant has a moderate score, and 3 for participants with a high score.
Agreeableness Dummy		
Conscientiousness Dummy		
Neuroticism Dummy		
Openness to experience Dummy		

Source: Data collected during study.

The logistic regression model assumes that the response variable exhibits a natural order of options. The model employs an index, with a single multinomial variable that is inherently ordered [27-28].

According to Greene [28], the model is constructed by starting from the same form as a multinomial logit model:

$$y^* = x'\beta + \varepsilon. \tag{1}$$

In which, y^* is not observed. What is observed is

$$\begin{aligned} y &= 0, && \text{if } y^* \leq 0. \\ y &= 1, && \text{if } 0 < y^* \leq \mu_1 . \\ y &= 2, && \text{if } \mu_1 < y^* \leq \mu_2 . \\ &\vdots \\ y &= J, && \text{if } \mu_{J-1} \leq y^*. \end{aligned}$$

Where μ_s is an unknown parameter, to be estimated from β. The probabilities are therefore as follows:

$$\text{Prob}(y = 0|x) = \Phi(-x'\beta). \tag{2}$$

$$\text{Prob}(y = 1|x) = \Phi(\mu_1 - x'\beta) - \Phi(-x'\beta). \tag{3}$$

$$\text{Prob}(y = 2|x) = \Phi(\mu_2 - x'\beta) - \Phi(\mu_1 - x'\beta). \vdots \tag{4}$$

$$\text{Prob}(y = J|x) = 1 - \Phi\left(\mu_{J-1} - x'\beta\right). \tag{5}$$

For probabilities to take positive values, necessarily

$$0 < \mu_1 < \mu_2 < \cdots \mu_{J-1}$$

The function $\Phi(.)$ is a notation used for the standard normal distribution. As with other logistic regression models, the regressors' marginal effects on the probabilities are not equal to the coefficients. However, the sign of the regression parameter can be interpreted as an increase or not of the ordered variable. Thus, if β_j is positive, then an increase in x_{ij} necessarily reduces its probability of being in the lowest category (y_i=1) and increases the probability of being in the highest category [27].

However, according to Greene [28], the marginal effects of the variables can be obtained from, for example, the following probabilities:

$$\frac{\partial \text{Prob}(y = 0|x)}{\partial x} = -\Phi(-x'\beta)\beta. \tag{6}$$

$$\frac{\partial \text{Prob}(y = 1|x)}{\partial x} = [\ \Phi(-x'\beta) - \Phi(\mu_1\ - x'\beta)]\beta. \tag{7}$$

$$\frac{\partial \text{Prob}(y = 2|x)}{\partial x} = \ \Phi(\mu - x'\beta)\beta \tag{8}$$

Since the model does not illustrate a linear relationship between variables, the coefficients obtained from ordered logistic regression should not be interpreted as a direct increase of the probability. According to Greene [28] and Cameron and Trivedi [27], the signs of the coefficients are unequivocal. However, it is necessary to interpret the coefficients with caution. They should be interpreted considering their marginal effects.

4. Analysis of the Results

The profile of the participants showed that the sample was balanced in terms of the proportion of students from each of the two undergraduate courses, with around 50.4% from the economics degree and 49.6% from the electrical engineering degree. The majority (94.2%) of the participants were single. Married students accounted for just 2.9% of the sample and those with other types of marital status also accounted for 2.9% of the sample. The majority were male (75.2%) and aged less than 25 years, since they were university students.

Of the variables investigated, the first result observed was the risk profile captured using the investment simulator, i.e. decision-making when faced with “real” decisions. Thus, based on their investment decision choices, 11 people (8.87%) were defined as risk averse on the system, 68 (54.84%) were identified as having moderate risk behavior, and 45 (36.29%) as having a daring risk profile. However, according to the IPA investor profile questionnaire, the sample predominantly exhibited a moderate risk tolerance profile (52.5%). The timid profile accounted for 35.7% of the sample and the daring risk profile for 11.7%.

Evaluating respondents’ behavior with respect to prospect theory, it was found that 113 participants (92%) violated expected utility theory, corroborating the assumptions of prospect theory and confirming that in situations of risk people do not take decisions compatible with expected utility theory [9]. With relation to personality traits, the findings revealed that the participants predominantly had “High” scores for personality characteristics in all dimensions and the characteristics possessed by the greatest numbers of participants were openness to experience (85%) and conscientiousness (74%). Finally, assessing cognitive capacity, it was found that just 14% of the sample answered all questions correctly, indicating elevated cognitive capacity, and 32% did not answer any of the three questions correctly.

4.1 Ordered logistic regression Model

An ordered logit model was used to evaluate behavioral and personality variables that possibly have an impact on the risk profile in "real" environments. The dependent ordered variable, the Simulator_Profile, corresponds to the 3 risk levels extracted from the investment simulation: Low, Moderate, and High risk. Analyses of the results are conducted by comparing these different categories. Thus, the coefficient is calculated maintaining other categories constant. The initial results are shown in Table 3.

Table 3. Ordered logistic regression model.

Models	1	2	3	4	5
Explanatory variables	**Ordered dependent variable Simulator_Profile**				
Mean IPA	4.286*** (0.737)	14.06*** (2.156)	32.96*** (5.629)	33.04*** (5.653)	35.98*** (6.400)
CRT Profile		-2.875*** (0.504)	-5.626*** (0.961)	-5.648*** (0.967)	-6.161*** (1.103)
Mean_Prospect			-6.729*** (1.457)	-6.735*** (1.463)	-7.096*** (1.537)
Mean personality				-0.0979 (0.343)	-0.0175 (0.457)
Extraversion Dummy					0.0371 (0.353)
Agreeableness Dummy					-0.0202 (0.339)
Conscientiousness Dummy					-0.727 (0.473)
Neuroticism Dummy					-0.0825 (0.329)
OpennessExpDummy					1.343** (0.654)
Constant cut1	1.744** (0.712)	7.597*** (1.449)	6.309*** (1.849)	5.705** (2.799)	9.017*** (3.459)
Constant cut2	5.591*** (0.910)	13.21*** (1.981)	14.71*** (2.816)	14.14*** (3.428)	18.41*** (4.406)
R^2	**0.1981**	**0.4351**	**0.5907**	**0.5910**	**0.6227**
Observations	124	124	124	124	124

Source: Data collected during study.

(1) The table lists the coefficient for the variable with the standard deviation in parentheses.

* 10% significance, ** 5% significance, *** 1% significance

Table 1 contains five different ordered logistic regression models. Each one shows the results of including additional variables and model 5 has the greatest explanatory power (R^2 is 62.2%) and will therefore be adopted for subsequent analyses. It was found that the statistically significant variables were Mean IPA, CRT Profile, Mean Prospect, and OpennessExpDummy. The β obtained in the regression reflects the impact of changes on the probability of X, but the results are best interpreted by calculating the exact values of the probabilities [28].

For example, it is possible that, for a unit increase (from 0 to 1) in mean participant risk, calculated from their responses to the IPA questionnaire, it is expected that the probability of the participant being on a higher risk tolerance level would increase, since the respective coefficient in the fifth model is positive. This is assuming that the other variables all remain constant. This result is coherent, since both measures assess individuals' risk tolerance.

The results for the impact that cognitive capacity has on the risk profile indicate that an increase in the number of correct answers to the CRT questionnaire (indicating greater cognitive capacity), triggers a reduction in the probability of greater risk taking. These results with relation to the CRT contradict findings reported by Frederick [18]. His study confirmed the hypothesis that participants with higher levels of education and intelligence exhibit higher risk tolerance, finding that in the domain of gains a group with High CRT was willing to risk more and to risk larger sums. Dohmen, et al. [29] also reported similar findings, indicating that people with greater cognitive capacity were significantly more willing to take risks in lottery experiments.

In contrast, when Frederick [18] evaluated risk taking in the domain of losses, he found that the group that scored high on the CRT sought less risk and were more willing to accept a guaranteed loss than a probability of a loss with lower expected value. In this case, in the domain of losses, the results observed by Frederick [18] are in agreement with those observed in the present study. Similarly, Mandal and Roe [7] revealed that the relationship between risk tolerance and cognitive capacity is non-linear. They state that people classified as at the two extremes of cognitive ability, i.e., those with low cognitive capacity and those with elevated cognitive capacity have greater risk tolerance.

The results for the variable Mean_Prospect, which represents violation or compliance with expected utility theory, revealed an inverse relationship. In other words, as an individual changes from 0 to 1 (compatible with prospect theory) there is a reduction in willingness to accept risk. This result is compatible with the certainty effect. According to Kahneman and Tversky [4], people tend to choose certain gains over probable results, indicating loss aversion.

The OpennessExpDummy variable reflects high, medium, or low scores for this characteristic in personality dimensions. A unit increase in this variable is expected to be related to an increase in the probability that the individual will accept higher levels of risk. These results for the dimension openness to experience are in line with results observed in a study by Mayfield, Perdue, and Wooten [15], who reported that this personality trait has an inverse relationship with risk aversion, indicating that people who have the characteristics creativity and novelty seeking are willing to take greater risks. These results also point in the same direction suggested by Nichelson et al. [17], that risk tolerance is directly related with the dimension openness to experience. Thus, high scores for openness to experience indicate greater risk propensity.

Starting from these initial results, since it is known that the estimations of logistic regression models do not directly reflect marginal responses, as in the traditional method of ordinary least squares, it is necessary to analyze the marginal coefficients of each explanatory variable on the basis of the mean values for the sample. This estimation method makes it possible to calculate the marginal effects separately for each alternative (Table 4).

Table 4. Marginal effects of the Ordered Logit Model for risk taking

Variables	**Alternatives**		
	Averse	**Moderate**	**Daring**
CRT Profile	0.002 ^{ns} [0.003]	**0.807 *** [0.193]**	**-0.810 *** [0.193]**
Mean IPA	-0.016 ^{ns} [0.020]	**-4.719 *** [1.081]**	**4.735 *** [1.082]**
Mean Prospect	0.003^{ns} [0.003]	**0.930*** [0.252]**	**-0.934*** [0.252]**
Mean personality	7.870^{ns} [0.003]	0.002^{ns} [0.060]	-0.002^{ns} [0.060]
Extraversion Dummy	-0.000^{ns} [0.003]	-0.005^{ns} [0.050]	0.005^{ns} [0.050]
Agreeableness Dummy	7.360^{ns} [0.003]	0.002^{ns} [0.046]	-0.002^{ns} [0.046]
Conscientiousness Dummy	0.000^{ns} [0.000]	0.094^{ns} [0.066]	-0.094^{ns} [0.066]
Neuroticism Dummy	0.000^{ns} [0.000]	0.101^{ns} [0.046]	-0.101^{ns} [0.046]
OpennessExp Dummy	-0.000^{ns} [0.000]	**-0.176** [0.085]**	**0.176** [0.086]**
LR Statistic	140.87		
Prob	0.000		
Pseudo R N.	0.662		
obs.	124		

Note: *** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.10$, ns. $p > 0.10$; [ ] standard error.

Observing the marginal results of ordered logit regression model 5, the first finding of note is that for the Low risk tolerance level from the investment simulation, none of the variables were significant. In other words they are not determinants of consolidation of the risk-averse profile. In contrast, for the moderate and daring profiles, the variables already discussed in relation to the results shown in Table 2 were significant.

Thus, taking the CRT profile first, it is understood that an increase in the number of correct answers on the cognitive reflection test reduced the probability of respondents exhibiting a daring risk profile on the simulator by 0.810 percentage points. However, an increase in the number of correct answers on the CRT increased the probability of participants exhibiting a moderate risk profile on the simulator by 0.807 percentage points. This confirms that, in the setting analyzed, individuals with high cognitive capacity tended not to take excessive risk in investment decisions, but were not conservative and rather had a moderate profile. This result is in line with descriptions by Mandal and Roe [7], who pointed out that the relationship between these two variables is non-linear.

With relation to IPA profiles, it was found that an increase in the level of risk allocated by the IPA increased the probability that respondents would exhibit a daring risk profile on the investment simulator by 4.745 percentage points, which is coherent, since both measures provide a risk profile. With regard to the variable representing violation or compliance with expected utility theory, it was observed that an increase in compliance with prospect theory reduced the probability that respondents would behave in a risk-seeking manner in their investment decisions on the simulator by 0.934 percentage points, confirming the existence of the certainty effect and risk aversion in unstable conditions [4]. Finally, it was also of note that of the five personality traits investigated, only openness to experience proved relevant to the risk profile, where an increase in this characteristic increased the probability that individuals would exhibit a daring risk profile by 0.176 percentage points, confirming the prevailing literature [15-17].

5. Conclusions

With the intention of contributing to finance studies, this article aimed to understand which of the following procedures is most relevant to understanding the true profile of an investor in situations involving decisions under risk: Investor profile analysis (IPA), prospect theory and personality theory, using the Big Five Personality Test, or the Cognitive Reflection Test (CRT).

This study employed Expecon software to attempt to understand the risk preferences of economic agents (in this case students). This program is designed to portray a simplified investment scenario in which participants manage an investment portfolio, buying and selling assets with different levels of risk, classified by the financial institution Bank of Brazil. The result of the simulation was used to classify participants into one of three risk profiles: risk averse, moderate risk, or bold risk (high risk tolerance).

The principal results reveal that the probability of participants exhibiting the moderate or daring risk profiles on the investment simulator changes in association with changes in the investor profile obtained on the IPA, cognitive ability, compliance with prospect theory, and the personality trait openness to experience. More specifically, it was found that people's classification according to the IPA is appropriate for understanding their risk profiles. With relation to the influence of personality on risk behavior, it was found that people who had higher scores for characteristics within this dimension (openness to experience) were more likely to take greater risk. These results are compatible with the findings of studies such as those by Mayfield, Perdue, and Wooten [15] and Nichelson et al [17].

With regard to prospect theory, the results confirmed that increased violation of utility theory led to reduced willingness to accept risk. Finally, the total number of correct answers on the CRT exhibited the inverse behavior to risk tolerance profile, indicated by its negative coefficient. Thus, the greater the participant's cognitive abilities, captured here by correct answers on the CRT questionnaire, the lower the probability of accepting high risk levels. This result confirms the instability in the relationship between these variables that has been identified by Mandal and Roe [7].

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