ERASMUS UNIVERSITY ROTTERDAM

Erasmus School of Economics

Master Thesis Behavioural Economics

An empirical study on differences in measuring risk attitudes

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Abstract

This research is aimed at finding if there is a correlational relationship between the psychometric scale for risk propensity (GRiPS - General Risk Propensity Scale), the risk attitude measured in the context of Prospect Theory - using the Unfolding Brackets method of utility elicitation, and financial risk tolerance - using plausibility judgements and proxies for measures of actual financial and health risk behaviours. Other variables were used to control for confounding effects. At best, we would find strong correlations between the three types of assessments of risk, at worst, there would be no correlation between them, suggesting that they define different constructs. Correlation and regression analysis done on a sample of 174 respondents reveals that there is significant correlation between risk attitudes measured with the Unfolding Brackets method and risk attitude measured by a General Risk Propensity scale.

Keywords: risk attitude, preferences, prospect theory

1. Brief history of risk in economic thinking

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1.1. Risk as hazard

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Although the notion of risk has been around forever, as we can read from old epic poems like the one on Gilgamesh, a hero who displays courage and risk-taking behaviour against monsters which are more likely to win, the earliest mentioning of the word can be traced back to the 17th century. The meaning attributed to it was "a source of unwanted consequences", it was related to the term "hazard" (Blount, 1661) and it is similar to our present-day meaning of the phrase "the possibility of something bad happening". Not incidentally, the notion appeared at the same time with the sea explorations, which implied a lot of risk. The hero Gilgamesh seeked to mitigate the risk he was facing by calling his friend Enkidu to help. Just like him, we also sought to find ways to avoid, reduce, or share the risks we are facing. In 1688 Lloyd's Coffee House became a well-known establishment dedicated to meeting and discussing maritime insurance and shipbroking (Sakai, 2015). In 1706 the first company which offered life insurance was founded, to mitigate life and health risks.

Later, in 1738 in a famous article, mathematician Daniel Bernoulli showed a calculation on whether one should adopt an insurance against transportation risk, depending on the level of previous wealth. With that calculation he showed that as wealth increases so the extra utility that one derives from a good or service, decreases - the idea of diminishing marginal utility of wealth. In the same article, he also wrote "This is the rule that it is advisable to divide goods which are exposed to some danger into several portions rather than to risk them all together." (Bernoulli, 1738) - which is the idea of hedging. Another important contribution that he made was that he showed that two people facing the same lottery may value it differently because of a difference in their psychology. Half a century later, the professor of moral science, Adam Smith wrote in his book about the perception a person has when risk interferes with his economic gains: "The chance of gain is by every man more or less overvalued, and the chance of loss by most men undervalued." (Smith, 1776). This is at odds with another famous phrase that we are going to discuss later: "Losses loom larger than gains".

1.2. Risk as probability

At the beginning of the 20th century, in the context of two unforeseeable situations arising, the First World War and the Great Depression, the notion of risk expanded to allow also positive connotation. For economist F. H. Knight, it was the chance of something occurring, or a "measurable uncertainty". For him, uncertainty must be taken in a sense radically distinct from the familiar notion of risk, from which it had never been properly separated (Sakai, 2015).

A further somewhat common view of the distinction between risk and uncertainty was made by John Maynard Keynes. For him it was important to make the distinction between instability due to speculation and the instability due to human nature (or the nature of spontaneous optimism) (Sakai, 2015). Keynes acknowledged the role of human nature in economic decision, in other words that economics 'deals with introspection and values with motives, expectations, psychological uncertainties' (Keynes, 1936). This instability is what we refer to now as risk and uncertainty. These two notions have different interpretations. While risk refers to a numerical probability that something would happen and can be mathematically formulated, the second instability is a sort of true uncertainty that is neither measurable nor comparable (Sakai, 2015). However, nowadays the field is developing and there are results in the study of uncertainty. Our focus is on the risk or measurable uncertainty which is inextricably related to the degree of belief that something would happen. Since then, the fundamental question has been how to best conceptualise and operationalize risk since it is an indisputable part of human economic behaviour.

Nowadays we are in a paradigm that could be called risk as the consequence times the likelihood. We want to assess the risks as accurately and meticulously as possible, yet we all have different perceptions on it. Studying risk at an individual level has applications in dilemmas concerning everyday choices like making financial decisions, choosing to go pursue higher education, labour market choices, adoption of social norms and health outcomes.

2. Theoretical background

In this section we are going to discuss the concept of risk perception from the two perspectives that shaped our understanding: one from economics, in particular behavioural economics and one from psychology, in particular psychometrics. These two domains have not been evolving isolated from each other and exchanges have been made, in this chapter we will attempt to overview the theories, their assumptions, the methods they employ and their shortcomings.

2.1.1.1. The psychometric approach

Experimental measurements happened in the natural sciences long before they were employed in the social sciences. The birth of psychology is sometimes considered to have taken place when they incorporated experimental measures as methodology. The emergence of psychology as a field in the sciences is considered to have taken place during the time when the first experimental measurements took place. In the early days, works of Gustav Fechner and Ernst Weber explained how people perceive stimuli and how sensation and perception work. The field expanded to trying to objectively measure latent mental states that cannot be directly observed. Examples of such constructs are intelligence, skills, values, beliefs, attitudes, and they represent a departure from the well-known physical scales that we use to measure things in the physical world. A distinction needs to be made here. We developed different ways to measure these concepts, such as intelligence and to mathematically model them but this does not mean that such measurements adhere to the rules of rigorous mathematical measurements which need monotonicity, additivity, and the existence of a zero point. In psychometrics people make quantitative judgements about the levels of different risks which are analysed using factor analysis, conjoint analysis, and multivariate analysis methods to determine the components that are most important.

Risk preference is commonly defined in psychology as the propensity to engage in behaviours or activities that are rewarding yet involve some potential for loss. Risk attitude is oftentimes viewed as a trait and studied in relation with personality traits. Sensation-seeking as a trait has been investigated intensely in relation with risk-taking, across several domains of risk behaviour (Zuckermann, Bell, Black, 1990). Sharma et al. (2014) studied another trait theoretically connected to risk taking: impulsivity; however, they showed through factor analysis that only two of the underlying factors of impulsivity (as a personality trait) may influence risky decision making: response inhibition and impulsive decision making.

Personality researchers have developed other traits for the five-factor model to find out what makes people take more or less risk. Paunonen and Jackson (2000) propose a model of personality in which they add risk-seeking behaviour as a dimension and show that it accounts for more variance. Intermediary constructs of temperament such as disinhibition (versus constraint) and positive (versus) negative emotionality show correlations with problematic, risky behaviours (Roberts & Bogg, 2004). Departing from the personality dimensions, research such as Vollrath & Torgersen (2002) shows that people who exhibit high negative emotionality and high disinhibition have a higher preference for health risk taking.

A common approach to assess the validity of risk perception as a valid trait is to measure the correlation between it and complex traits which have been validated previously. Frey et. al. (2017) contributes to this view by showing a result on the correlation between risk perception and intelligence, as well as taking into consideration whether it is a domain specific or a general trait, concluding that it is both to some extent.

Related to our cognition processes, studies of traditional dual modes of information processing show that for situations of high risk, we do not want to substitute account of that situation with careful thought (Evans and Stanovich, 2013). Looking at how we process information, two branches emerged: risk as feeling (Loewenstein et al., 2001) and risk as analysis (Kahneman, 2003). Also related to how we interpret information, Reyna et al. (2014) show that experienced subjects tended to respond using the gist representation of information. Intelligent agents were willing to take more risks with human lives when outcomes were framed to losses, even more than inexperienced subjects. Other factors from fuzzy trace theory have also been shown to influence risk-taking: motivational/affective factors and metacognitive factors such as reflection and inhibition.

Slovic (1994) showed that affect has a role to play in how people assess risk: if they feel good about a hazard, they overweigh the benefits and under weigh the risk. Slovic (1987) describes the psychometric approach of studying risk preference (of cognitive nature and heuristics), which takes a different path than the cultural approach, only to reunite later in the cultural cognition domain (Kahan et al, 2006). However, whether these scattered constructs all contribute to a broad risk-taking disposition is still debatable.

A large study of risk has been conducted by Frey, Pedroni, Mata, Rieskamp, and Hertwig (2017). They use a large number of scales which measure the risk propensity, measures of actual risk behaviour and measures of frequency of risk behaviour. In what follows we will review the most commonly used scales.

The domain-specific risk-taking scale (DOSPERT) was published in 2002 and it assesses risk taking in 5 different domains: financial, health and safety, recreational ethical and social. These domains were chosen from a literature review of risk-taking behaviours (e.g., Byrnes et al., 1999). Their motivation comes from previous literature like Schoemaker (1990) who showed that if we consider separate domains for gains and losses, and mixed domain, the tendency of subjects is to be risk averse for gains, and mixed domain and risk seeking for losses. Individuals do not consistently seek or avoid risk in diverse areas and contexts, according to MacCrimmon and Wehrung (1986) and Schoemaker (1990). Research by Weber (2002), which is the basis for developing the scale, measures not only conventional risk attitudes in the content domains but also the perceived-risk attitudes. In fact, this is a theme that is found earlier in another scale developed by Weber and Luce (1986), the conjoint expected risk model which decomposes perceived risk into a probability side and an expected outcome side.

According to the authors, the scale is developed taking into consideration two criteria related to the perception of risk. On one hand, risk perception is measured in the classical sense, as a degree or amount that describes how much an individual appears to avoid or pursue risky options or activities to which he is presented. The second method involves situational variations which permit rating perceived riskiness of the behaviour before, without implying its riskiness for the respondent.

The simplified conjoint expected risk model (SCER) measures risk aversion using dimensions such as probability and expectation of harm, probability, and expectation of benefit. In the same paper, they compare SCER with a psychometric scale developed by Slovic (1987). They find that augmenting the two models together provides a better fitting model for explaining risk attitude (Holtgrave and Weber, 1993). The model developed by Slovic (1987) includes psychological risk dimensions such as voluntariness, dread, control, knowledge, catastrophic potential, novelty, and equity.

Another largely used scale is included in the German Socio-Economic Panel study (SOEP), a wide-ranging representative longitudinal study of private households. As opposed to the DOSPERT scale, developing the risk aversion scale in the SOEP survey was supplemented by a field experiment in which the risk attitude is measured using revealed preferences methods. Their findings show that the questionnaire is a meaningful measure of risk attitudes, which maps into actual choices in lotteries with real monetary consequences (Dohmen et al, 2011). SOEP is included in the Cross-National Equivalent File (CNEF) survey which is a great tool to control for cultural differences. Similar questions about risk attitudes are included in a series of large sample surveys such as Luxembourg Income Studies (LIS), LISS data (part of the Measurement and Experimentation in the Social Sciences project). In the DOSPERT scale they refer to domains such as financial decisions, health/safety, recreational, ethical and social while in SOEP they refer to contexts such as car driving financial matters, sports and leisure, health and career, but we see no conceptual distinction between them. These questions are shown to not perform well with the general risk-taking question but provide strong correlations with domain specific risk measures. We do not choose this scale because for prediction purposes, the context of the choice is not very relevant. When we want to assess the behaviour with the goal of influencing it, a general measure becomes important (Weber, 1999).

A third psychometric scale of measuring is the General Risk Propensity Scale (GRiPS). Its main attribute is that it is non-contextual and non-domain specific. In developing it, they define *a person's cross-situational tendency to engage in behaviours with a prospect of negative consequences such as loss, harm, or failure* (Zhang et al, 2019). This definition includes one important aspect that differentiate it from other scales, namely not being constrained to a person-situation duality.

The limitation of using a psychometric scale for assessing risk attitudes is that unrealistic perceptions of self, inattention and strategic motives may cause biased responses.

2.1.1.2. The behavioural approach

The revealed-preference tradition developed at the same time with the stated-preference tradition that we saw earlier, but it originates in the work of economists, starting with Samuelson. As the name indicates, it is a method to discern preferences by observing behaviour. Observed behaviour can take the form of an abstract representation of a behaviour, like a choice task (Hertwig, Wulff and Mata, 2019). This way of measuring preferences has an important stake because by observing a particular set of choices, we can find a model that could have predicted these particular choices and we can use this model to predict other choices.

In the early days (of classical utilitarianism) it was believed that people's preferences are towards the option which will produce the highest outcome. One problem with this approach is that sometimes choices must be made between outcomes that are intangible or not comparable. Supposedly we fix this problem, and we refer to monetary outcomes which have the same value for an individual. It is still hard to generalise that the same monetary outcome will have the same value for different individuals. This problem is known as St. Petersburg Paradox[1]. One of the proposed resolutions of the problem at the time, was the hypothesis under which people determine the value of an option through the utility they derive from it, which depends on factors such as their previous wealth. For Nicolas Bernoulli, the explanation on why a person would choose not to engage in the game is purely depending on the fact that the utility one derives from engaging in decreasing marginally, not from a perception of the riskiness of the gamble (Smidts, 1997).

This hypothesis was proven in 1947 when von Neumann and Morgenstern presented their theorem that if certain axioms are fulfilled, an individual's preferences can be modelled under a utility function. This is done by presenting individuals with multiple gambles and observing their choices. This way, the expected utility can be specified in terms of outcomes and the probabilities associated with those outcomes. Since its inception, the Expected Utility Theory has been employed in a lot of empirical research and its normative capabilities have been used extensively in finance and game theory but at the same time questions about its descriptive capacities arose.

One of the problems raised by Matthew Rabin in 2000 regarding Expected Utility was the fact that risk aversion in low stakes situations imply a huge amount of risk aversion in high-stakes lotteries (Abdellaoui, 2007).

In 1979, Prospect Theory was published which was a generalisation of the Expected Utility Theory which lessens the assumptions that need to be satisfied. The difference between the Expected Utility Theory and Prospect Theory is that the latter incorporates distorted probabilities (different probability weighting functions for gains and for losses) and that its reference point in terms of wealth is not fixed. An important contribution of PT is that it introduced the concept of loss aversion which states that people behave differently when they must choose between potential losses and potential gains. In its revised 1992 form, Cumulative Prospect Theory can be defined as follows: In decisions under risk, we have a set $\mathbb{R}$ of possible monetary outcomes (positive or negative; gains or losses) and a reference point (or a wealth level). A prospect can offer outcome x_i with a probability p_i. Prospect Theory entails that the value of the prospect will be given by the formula:

$$\sum_{i=1}^{k} \pi^-(p_i) \times v(x_i) + \sum_{j=k+1}^{n} \pi^+(p_j) \times v(x_j)$$

Here π^- and π^+ are the decision weights for gains and losses which can be calculated by:

$\pi_i^- = w^-(p_1+\ldots+p_i) - w^-(p_1+\ldots+p_{i-1})$, for i between 1 and k, and

$\pi_j^+ = w^+(p_1+\ldots+p_j) - w^+(p_{j+1}+\ldots+p_n)$, for j between k and n.

[1] Peterson, Martin, "The St. Petersburg Paradox", The Stanford Encyclopedia of Philosophy (Fall 2020 Edition), Edward N. Zalta (ed.), https://plato.stanford.edu/archives/fall2020/entries/paradox-stpetersburg

Here, w^+ is the probability weighting function for gains and w^- for losses, which are both strictly monotone with, and w^+, w^- are 0 when $p = 0$ and 1 when $p = 1$, defined as $w^+, w^- : [0, 1] \rightarrow [0, 1]$ while $v : \mathbb{R} \rightarrow \mathbb{R}$ is a continuous and strictly increasing utility function satisfying $v(0) = 0$. From the utility function we can further derive the risk a person is willing to take. k is the reference point or the inflexion point of the utility where the individual changes its state from risk averse to risk seeking.

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There are a number of methods to elicit utility functions through the revealed preferences, in accordance with the assumptions from Prospect Theory. A more informed overview on the different methods can be found in Charness et al. (2012). There has been much preceding literature not cited by these authors, for instance in the survey paper Farquhar (1984). However, I will focus on Charness et al. (2012). We are going to describe them briefly: the multiple lottery choice from Eckel and Grossman 2002; the choice list with only risky prospects from Holt and Laury 2002 and the Unfolding Brackets method from Dohmen et al 2016. The common denominator of these methods is that they all can be used under the gain domain (Eckel and Grossman, 2002), which is the purpose of this research as well.

In Eckel and Grossman (2002) they present the participants with five gambles with 2 payoffs and ask which one of them they want to play. One of the payoffs is sure while the other presents a risk. The variation between the gambles comes from increasing the risk and the payoff.

In Holt and Laury (2002) participants are given a choice list with ten rows and two options: A and B. Lottery A is less risky while lottery B is riskier. The payoffs are held the same while the probability of the options change so that option B becomes less risky. The point where the person changes between the two options determines his certainty equivalent. Earlier switching points indicate a lower certainty equivalent than later switching points.

Unfolding brackets (or iterative choice sequence) elicit the risk preference with the purpose of finding the Certainty Equivalent. It employs a choice between varying sure payments and a constant lottery. In this study we are going to use an alternative to the unfolding brackets method, a shorter, streamlined version developed by Dohmen et al in 2016 which narrows down the risk preference in 5 questions. Their aim was to find survey items that would best predict choices in incentivized preference elicitation tasks (Dohmen, 2016). The final version is slightly weaker explanatory power (the loss of explanatory power between the full version and the shortened one in terms of R^2 is 0.02), but it makes up with time efficiency, simplicity, and cultural neutrality (Dohmen, 2016).

Participants made 5 choices between two lotteries which are adapted depending on their previous choice. This allowed us to determine the point where they switched from the safe choice, which was always the same, to the risky choice. With the help of the information, we were able to determine an approximation of their indifference point or Certainty Equivalent (further shortened to CE). Given the fact that the risky choices were incremental of 20 euros, we calculated the Certainty equivalent to be an average of the two end points of the interval.

3. Methodology

The method used in the research is empirical and its aim is to see whether there is a correlation between the different ways to measure risk aversion. In order to gather data, we developed a questionnaire which has 5 sections: Demographic, GRiPS for risk attitudes, the Unfolding Brackets method for risk preferences, Financial risk taking propensity and health risk taking behaviour (see Appendix 1).

3.1. Research questions

The present study aims to examine the possibility of a correlation between the different measures of risk aversion. Additionally, a subsequent aim is to check whether a combined measure of risk yields a better explanatory power for certain risk-taking behaviour in the health and financial domains.

3.2. Data sampling and participants

The data set was collected through an online questionnaire on the Qualtrics platform, between 8 and 22 February 2022. The questionnaire contains 62 items: 9 items for demographic information, 8 items for the General Risk Propensity Scale, 31 items are included for the basis of the Unfolding brackets method, 8 items assess the financial risk-taking behaviours, and 6 items assess the health risk behaviour. The duration of the questionnaire is approximately 12.4 minutes

The sampling method used for gathering the data is snowball sampling. We chose a probability type of sampling because our population of interest has no restrictions in terms of socio-demographic characteristics and exclusion based on other considerations is not required.

In total, 223 people answered the questionnaire. After checking for missing data, 40 observations were eliminated for missing more than half of the answers. The final dataset contains 173 observations. Two variables have missing values: birth and consequently age has 6 missing values and wealth has 3 missing values due to item non-response.

4. Analysis

4.1. Eliciting the risk attitude using GRiPS scale.

GRiPS scale treats risk attitudes as a general propensity towards risk taking. As described in the literature review, GRiPS scale consists of 8 items which are statements to which the participants are asked to indicate the degree to which they agree with, on a 5-point Likert scale. The answers are coded 1 for “Strongly disagree” and 5 for “Strongly agree”. Because there are no inversely coded statements, we are able to add together the answers and determine a composite score from the 8 items relatively easily. The scale reliability coefficient of the GRiPS questions, using Cronbach’s alpha coefficient is 0.8795.

4.2. Financial domain

Measuring risk aversion for the financial domain is inspired by the RAND Corporation’s panel American life. Module 3 of this survey is concerned with financial decision making. Questions include stock literacy, financial literacy, financial education participation, savings plan, retirement plans, investment plans and risk-taking attitudes. In the survey we use a composite of three questions. Two of the questions refer to attitudes toward a risk that is perceived as profitable: “If I think an investment will be profitable, I am prepared to borrow money to make this investment.” and “I think I should take greater financial risks to improve my financial position.”. A third question about how much a reward counts in risk decision making: “I am prepared to take the risk to lose money, when there is also a chance to gain money.”. The emphasis here is on the risk-return trade-off. The scale reliability coefficient of the three questions, using Cronbach’s alpha is 0.6098.

During the 2008-2009 financial crisis, Hoffmann, Post, and Pennings (2012) investigated investor risk perceptions and behaviours. They found that different investor perspectives have brought about significant fluctuations in trading and risk behaviour during the crisis.

Three other measures were introduced to describe financial decisions: the distributions of savings, tangible assets, stocks, ETFs, and bonds in the total financial portfolio.

4.3. Health domain

As a sub-research question, besides the measure of financial risk, another measure of risk behaviour was introduced, from the health domain. COVID-19 risk perception is integrated in a question where respondents are asked to evaluate the chances that they will get infected with coronavirus, from ‘Almost 0’ to ‘Large’. We also included a control measure of attitude towards vaccination, actual health risk behaviour and whether they contracted the disease in the past.

4.4. Eliciting the probabilistic risk attitude.

Methods such as the certainty equivalent and the probability equivalent are non-parametric methods and they allow for modelling the utility function freely, without implying a specific form to it (Blavatskyy, 2004). The iterative multiple price list method (or unfolding brackets) is a modified version of certainty equivalent which uses fewer questions and allows the researcher to approximate the certainty equivalent (Holzmeister, 2017).

We use the unfolding brackets method with 5 questions. In the first question, all participants are asked to make a choice between a lottery that would grant them a safe payment of €160 and a lottery which offers with 50% chance €300 otherwise nothing. In the second and subsequent questions the safe payment was modified: every time they would choose the safe option it would decrease while every time, they chose the lottery the safe option would increase. We used values between €30 and €310 as research showed that best values for Prospect Theory formulas parameters are between 0 and $400. The answers to these 5 questions allow us to zoom in on the indifference point and enable us to approximate the amount that makes the individual indifferent by averaging the upper and lower bounds. This result already tells us a lot about the individual. The expected value of the lottery is €150, which means that an individual who is willing to accept less is risk averse while an individual who is only willing to accept more is risk seeking. However, using the certainty equivalents that we obtained, we can also estimate the parameters corresponding to the functional forms in Cumulative Prospect Theory (Kahneman and Tversky, 1992). In accordance with the elicitation method chosen, we are going to focus only on the gain domain of the theory.

In the revised version of Prospect Theory, Tversky and Kahneman (1992) obtain the parameters of the probability weighting function and of the utility function by assuming the utility of the certainty equivalent is equal to the utility of the value times the probability weighting function, or:

$$v(CE) = w(p) \times v(x)$$

I give this functional form for completeness. In fact, a joint power of the weighting and utility function is non-identifiable in our data set, and I will not use it. My analysis will be directly targeted towards certainty equivalents. Tversky and Kahneman use the following specific forms of the functions:

$v(x) = x^{\alpha}$, where α is the risk aversion parameter

$w(p) = \frac{p^{\gamma}}{(p^{\gamma} + (1-p)^{\gamma})^{1/\gamma}}$, where γ is the probability weighting parameter.

Then they estimate the parameters γ and α.

There are however other functional forms of the aforementioned functions. An overview of the many specifications can be found in Bernheim and Sprenger (2019, 2020), Booji, van Praag and de Kuilen (2010), Baláž et. al. (2013), Charpin (2019), Harrison and Swarthout (2016), Stott (2006), Fox and Poldrack (2014). For the value function and the probability weighting function, most widely used formats are included in the tables below.

Table 1

Types of value functions as found in the literature

Equation	Name
$v(x) = \frac{x^{1-r} - 1}{1 - r}$	Power
$v(x) = x - \alpha x^2$	Quadratic
$v(x) = 1 - e^{-\alpha x}$	Exponential
$v(x) = -\frac{ln(1 + \alpha x)}{1.0001 - \alpha}$	Logarithmic

Note. Adapted from *Cumulative prospect theory's functional menagerie.*
Stott, H.P., J Risk Uncertainty 32, 101–130 (2006). https://doi.org/10.1007/s11166-006-8289-6

Table 2

Forms of the probability weighting function found in the literature

Equation	Name
$w(p) = \frac{p^\gamma}{p^\gamma + (1 - p)^\gamma}$	Karmarkar (1978)
$w(p) = \frac{p^\gamma}{(p^\gamma + (1 - p)^\gamma)^{1/\gamma}}$	Kahneman & Tversky (1992)
$w(p) = e^{(-(-ln(p))^\gamma}$	Prelec (1998)
$w\ (p) = \frac{\delta p^\gamma}{\delta p^\gamma + (1 - p)^\gamma}$	Goldstein and Einhorn (1987)

Note. Adapted from *Cumulative prospect theory's functional menagerie.*
Stott, H.P., J Risk Uncertainty 32, 101–130 (2006). https://doi.org/10.1007/s11166-006-8289-6

4.5. Control variables

Based on the literature, a series of control variables were also included: age, gender, education level, employment status, residence type, income, total wealth, marital status, occupation.

4.6. Data description

Table 3 describes the participants in the questionnaire. As mentioned before, the sample size is 184. In terms of gender, 45.66% of the respondents are female, 53.76 are male and half a percentage belong to ‘other’.

The range for age is between 19 and 64, the mean age of the sample is 35 years while the median is 34 years. 42.51% of the sample are under 30 years, 25.75% under 40, 16.17% under 50 while 15.57% under 64.

In terms of education, 16.18% have graduated from high school, 81.50% are university graduates while 2.31% have finished a form of vocational or professional training.

The vast majority of respondents (65.90%) are earning a gross yearly income lower than €20.000, 23.70% are earning between €20.000 and €39.999, 7.51% earn between €40.000 and €70.000 while 2.89% earn more than €70.000.

Wealth distribution is highly concentrated below €100.000 with 75.88% of the respondents belonging to that category, 12.94% between €100.000 and €200.000, 7.06% between €200.000 and €300.000, and 1.76% between €300.000 and €400.000, and 2.35% more than €500.000.

In terms of civil status, 30.64% are single, 34.68% are in a relationship, 27.17% are married, 6.94% are divorced or separated and 0.58% are widowed.

In terms of residence, 44.51% own a house, 18.50% rent an apartment of a house, 17.92% rent a room in a shared apartment or house, 3.47% live in a dormitory, and 15.61% live with their parents.

In terms of employment, 52.60% are working full time, 2.89% are working part time, 28.32% are unemployed or looking for work, 4.05% were students and 12.14 were retired.

To analyse the data and check the correlations we performed regression analysis. We are not interested in causal effects because the assumptions necessary are unlikely to be met. We allow for other factors to be included into the analysis, through variables such as age, gender, education level, income, and wealth. A complete description of these variables can be found in Table 1 from Appendix A.

5. Results

We started interpreting the data results by performing a Cronbach alpha test on the two psychometric scales to check for their internal consistency. The General Risk Propensity scale consists of 8 items ($\alpha = .88$), highly reliable, similar to the results from the original paper ($\alpha = .87$). Financial Risk attitude scale consists of 3 items ($\alpha = .61$), acceptably reliable.

Further we check for correlations between our 3 scales of risk propensity (GRiPS, Financial Risk and CE), answering the research questions about the relationship between them. We do so by testing for Spearman's correlation, despite the fact that the CE variable is measured continuously, the FR variable and the GRiPS are not. In order to be able to use the Spearman's correlation test, two assumptions must be met. The first assumption refers to the fact that the two variables must be measured on a continuous or ordinal scale. This assumption is satisfied. The second assumption refers to the fact that there needs to be a monotonic relationship between the two variables. This is not straightforward so to check the sign of their correlation, we plotted the variables against each other, two by two. The scatter plots can be visualised in Appendix B. Based on them, we concluded that the 3 variables are co-monotonic. Further we ran a Spearman's correlation test which showed that there is a weak positive correlation between CE and FR (statistically significant, rs = .1320, p = .0835), CE and GRiPS are weakly correlated (statistically significant, rs=.2603, p=0.0005), FR and GRiPS are also weakly correlated (statistically significant, rs = .2905, p = .0001).

Before creating specific models, we check for the normality of the variables that we want to use as dependent (Appendix C). As it can be seen, the distributions of the GRiPS, FR and CE in the population, reveal heterogeneity in risk attitudes across the population. Given the gaussian distributions, we can apply Bayesian regression analyses with CE, GRiPS and FR measures as dependent variables.

Results are reported in Appendix D. Next, the most significant results will be interpreted.

The first model includes Certainty Equivalent (CE) coefficient as a dependent variable: Model (1).

$$\begin{aligned} CE = \beta_0 + \ & \beta_1 \times age + \beta_2 \times education + \beta_3 \times gender + \beta_4 \times residence \\ & + \beta_5 \times employment + \beta_6 \times occupation + \beta_7 \times income + \beta_8 \times wealth \\ & + \beta_9 \times marital\ status \end{aligned}$$

Its results show that on average, being a female, compared to being a male, determines a decrease in the certainty equivalent of 24.15 euros, keeping all other variables fixed. This effect is significant at a 10% level. This means that females have an average higher risk aversion. Being in a relationship, compared to being widowed, determines an increase in the value of the certainty equivalent of 138.3 euros, ceteris paribus, ($p<0.1$). On average, having a total wealth lower than 100.000 euros, compared to having a total wealth higher than 500.000 euros determines an increase in the certainty equivalent by 65.71 euros, keeping all the other variables fixed. This effect is significant at a 5% confidence level. At the same time, having a total wealth between 100.000 euros and 200.000 euros, compared with a total wealth higher than 500.000 euros determines an increase in the certainty equivalent by 70.60 euros, keeping all the other variables the same. This means that people with a lower total wealth have a lower risk aversion, thus a higher propensity to take risks. This result refers to risk aversion in an absolute sense, as opposed to risk aversion in a proportionate sense.

Commented [Wakker6]: OK.

The second model includes the Financial Risk-taking propensity as dependent variable: Model (2).

$$\begin{aligned} FR = \beta_0 + \beta_1 \times age + \beta_2 \times education + \beta_3 \times gender + \beta_4 \times residence \\ + \beta_5 \times employment + \beta_6 \times occupation + \beta_7 \times income + \beta_8 \times wealth \\ + \beta_9 \times marital\ status \end{aligned}$$

Unlike the Certainty Equivalent coefficient, taking financial risks seems to be more correlated with education and total wealth. Having graduated high school, compared with vocational or professional training, determines a decrease in the propensity to take financial risks. This effect is statistically significant at a 5% level ($p<0.05$). Having graduated from a university, compared to vocational or professional training, determines a decrease in the propensity to take financial risks. This effect is statistically significant at 5% level ($p<0.05$). Being a female, compared to being a male, determines a decrease in the propensity to take financial risks ($p<0.1$). Having a total wealth lower than 100.000 euros and larger than 300.000 euros, compared to having a total wealth larger than 500.000 euros determine a decrease in the propensity of taking financial risks ($p<0.1$ and $p<0.1$).

The model which takes the General Risk-Taking Propensity as a dependent variable is Model (3).

$$\begin{aligned} GRiPS = \beta_0 + \beta_1 \times age + \beta_2 \times education + \beta_3 \times gender + \beta_4 \times residence \\ + \beta_5 \times employment + \beta_6 \times occupation + \beta_7 \times income + \beta_8 \times wealth \\ + \beta_9 \times marital\ status \end{aligned}$$

Being a female, compared to being a male, determines a decrease in the risk-taking propensity ($p<0.01$). Living with parents, compared to living in a dormitory, determines a decrease in the general risk-taking propensity ($p<0.1$). Being divorced, and being married, compared to being widowed, both determine a decrease in the risk-taking propensity ($p<0.1$ and $p<0.1$).

Models (1) to (3) were used to check the relationships between different types of measuring risk attitudes and our data. For the Certainty equivalent method, the potentially important variables are gender, marital status, and total wealth. For the Financial Risk scale, the relevant variables are gender, education, and total wealth. For the General Risk-Taking Propensity scale, the explanatory variables with highest significance are the residence and the marital status. What we did not check is the endogeneity of these variables, for example a greater propensity to take risks may determine larger wealth levels.

Another model that we used to explore the data is referring to the financial risk: Model (A).

$$FR = \beta_0 + \beta_1 \times GRiPS + \beta_2 \times CE + \beta_3 \times age + \beta_4 \times gender + \beta_5 \times residence + \beta_6 \times employment + \beta_7 \times occupation + \beta_8 \times income + \beta_9 \times wealth + \beta_{10} \times marital\ status + \beta_{11} \times education$$

How does the GRiPS and the CE influence the financial risk-taking propensity? A simple regression was used to predict the financial risk-taking propensity depending on the GRiPS score and the CE measure. The general risk-taking propensity explained a good portion of variance in the financial risk-taking propensity ($p<0.001$). The regression coefficient $\beta_1 = .38$ indicates that an increase with one unit on the GRiPS scale corresponds, on average, to an increase in financial risk-taking propensity of 0.38 points, keeping all the other variables the same. Further, being university educated, compared with having a vocational or professional education determines an increase in the propensity to take financial risks ($p<0.01$). At the same time, having graduated highschool, compared to a vocational or professional education, determines an increase in the propensity to take risks ($p<0.05$). Another significant result is that of total wealth. Having a total wealth between 300.000 euros and 500.000 euros determines a decrease in the financial risk-taking propensity ($p<0.05$). The model is $F(32, 134) = 1.69$, $p = .02$, $R^2 = .28$, $R^2_{adjusted} = .11$. Log likelihood value is -217. Akaike indicator tells us how much information is lost in the model: the lower the value, the better. For this model 2.664.

Another model we tried on is Model (B).

$$PR = \beta_0 + \beta_1 \times GRiPS + \beta_2 \times CE + \beta_3 \times FR + \beta_4 \times age + \beta_5 \times gender + \beta_6 \times residence + \beta_7 \times employment + \beta_8 \times occupation + \beta_9 \times income + \beta_{10} \times wealth + \beta_{11} \times marital\ status + \beta_{12} \times education$$

$F(14, 152) = 1.69$, $p = .0001$, $R^2 = .22$, $R^2_{adjusted} = .15$ This model shows that if the general risk propensity increases, a person is more willing to take financial risks. An increase of one unit on the GRiPS scale determines an increase by 0.36 on the financial risk-taking scale. This result is significant at a 1% confidence level. Having graduated high school determines a decrease in the financial risk-taking score by 1.34 ($p<0.01$), compared to a vocational or professional education. At the same time, having a university degree determines a decrease in the financial risk propensity score by 1.40, ($p<0.01$), compared to vocational or professional training. Belonging to a wealth category above 300.000 euros determines a decrease in the financial risk propensity score. These results are in line with the previous model, with the exception of education as a relevant factor: in the previous model the effects of education were not statistically significant.

Model (C).

$$FR = \beta_0 + \beta_1 \times GRiPS + \beta_2 \times CE + \beta_3 \times age + \beta_4 \times gender + \beta_5 \times residence + \beta_6 \times education$$

This model shows the same results as the previous one. General Risk-taking propensity is positively correlated with the financial risk-taking propensity ($p<0.001$). Having high school ($p<0.05$) or university degree ($p<0.01$) determines a decrease in the financial risk-taking propensity.

Models (A) to (C) were used to determine what are the determinants of Financial Risk taking. The difference between them consists of what control variables we included. Model (A) is the most complete, using all control variables, while Model (B) excludes marital status, occupation, employment status and income. Model (C) further excludes wealth. When we compare the three models, based on the R2 score, we prefer Model (A) - R2 = .28, which is the most complete and explains best the financial risk-taking propensity. The value is good, as any study that attempts to predict human behaviour will have an R2 lower than 50%. In essence, from the most basic models, the General Risk Propensity Score, and education predict the Financial Risk-taking propensity. When we add characteristics about economic resources, the occupation, income and total wealth appear to influence Financial risk taking attitude. The results that are not significant are personal characteristics such as gender, residence, marital status, and employment. The Certainty Equivalent score does not seem to explain any of the financial risk-taking decisions.

Further we sought for models that incorporate combinations of all three risk taking measures. Data analysis is done by running logistic regression, linear regression and probabilistic regression on different models and choosing the best in terms of explanatory power. Results are reported in Appendix E.

A logistic regression was calculated to predict the perceived risk (which assessed what the respondent believes are the chances to get infected with Covid), based on GRiPS, FR, as well as the risk measured with the CE: Model (X).

$$FR = \beta_0 + \beta_1 \times GRiPS + \beta_2 \times CE + \beta_3 \times age + \beta_4 \times gender + \beta_5 \times residence + \beta_6 \times wealth + \beta_7 \times education$$

From the latent dependent variable Perceived Risk, we generated a new binary variable which takes value of 0 if the perceived risk is smaller than 3 which means a lower risk and 1 otherwise which means a higher perceived risk of getting COVID-19. This would mean that we create a variable that denotes that they perceive the risk of getting the disease as real (1) or inexistent (0). The results are shown in Appendix D. For the interpretation of coefficients, we are going to use average marginal effects for the most significant results. They are reported in Appendix D. They show that an increase in the GRiPS score (which means a greater inclination to take risks) determines a decrease in the likelihood of perceiving the risk as real by 9 percentage points, keeping all the other variables fixed ($p<0.1$). At the same time, a larger value of the CE (which denotes a greater risk aversion), determines an increase of 0.1 percentage points in the probability of perceiving the risk as real ($p<0.05$). On average, being a female, compared to being a male decreases the probability of perceiving the risk as real by 17.12 percentage points ($p<0.05$). On average, being a house or apartment owner, determines a decrease in the probability of perceiving the risk of getting COVID-19 as real, by 26.89 points on the scale ($p<0.05$). At the same time, living with parents, determines a decrease in the probability of perceiving the risk as real of 30.65 percentage points, keeping all other variables fixed ($p<0.01$). Working in economics determines an increase in the probability of perceiving the risk as real by 24.86 percentage points, keeping all other variables fixed ($p<0.01$). On average, working in the arts, culture and entertainment determines an increase in the probability of perceiving the risk as real by 32.44 percentage points, ceteris paribus ($p<0.05$). Relationship status also shows to be an important factor determining an increase in the perceived risk of getting the disease ($p<0.001$). As opposed to being widowed, being single, in a relationship or married, determine on average an increase of approximately 20 percentage points on the probability of perceiving the risk to be real. Having had the vaccine in the past, compared with not having it, determines an increase in the likelihood of perceiving the risk as real, by 47.46 percentage points, keeping all other variables fixed ($p<0.001$). Another significant result is that a person who never uses hand sanitization after being in a public place, compared to one that does, is perceiving the risk as being non-existent ($p<0.1$). Overall, the model explains 0.94 AUC (area under the curve) and the data is a good fit for the model, according to the McFadden index (0.55).

Model (X) was used to explore the probability that a person perceives the risk of getting infected with COVID-19 as real or non-existent. Here, importantly the Certainty Equivalent and the General Risk-taking propensity turned out to be significant. On top of that, gender, residence, marital status, occupation, and behaviours related to health proved to be significant.

In the next chapter we will return to a discussion of the economic significance of these results.

6. Discussion

Our main interest in this section is whether survey data can predict actual risk-taking behaviour hypotheses. What are the determinants of the Certainty Equivalent method? We found personal characteristics such as gender and civil status and economic characteristics to be determinant. Studies including Dohmen et al. (2011), Halek and Eisenhauer (2001) confirm the same effect. A study by Fehr-Duda (2006) shows that there are gender differences. They estimate Rank Dependent Utility models separately for each gender and they show that women tend to underweight higher probabilities. Due to the fact that all utility elicitation methods are biased due to the form of the non-linear probability weighting function, the result is still debatable. Our results could be interpreted as a tendency of men to calculate the expected value of the lottery and that amount acts like an anchor on the decision on the amount that they want to settle for (H. Fehr-Duda, 2006). A comprehensive overview on gender and risk aversion we found in Eckel (2008). An important result on this topic which uses the pricing tasks and choice menu methods is Holt and Laury (2002). In their research they show that gender does influence the risk attitude but that this disappears, however, when there are high-payoff lottery choices. According to Byrnes, Miller, Schaefer (1999), theories on gender differences can be split into 3 categories: theories such as sensation-seeking personality which assume that gender varies but not across contexts (the gap would remain the same), theories such as CPT which assume differences across situations (gender difference does not matter), and theories which explain individual differences in specific situations (so gender differences would also vary by context).

In terms of the influence of marital status on determining the risk attitude using a lottery type elicitation method, we found that its effect is significant. However, this effect is only present in approximating the coefficient of being in a relationship, compared to being widowed. This is contrary to what most studies find, an example being Hartog et al. (2002). Dohmen et al. (2011) show that marital status is a significant result only in a special case where the respondent is married, as opposed to divorced or widowed, or having children. Faff et al. (2006) show that, in a similar online lottery experiment, a dummy variable of being married or not is significant for the value for which one is ready to settle but only in a specific round of the lottery, when the gains are high. Being married determines a higher amount, thus a lower risk aversion.

The same study by Faff et al. finds that wealth (defined as net assets of the participant including the family home and other personal-use assets, minus any amounts owed adjusted for number of dependents) is relevant as well in high gains set-up, as opposed to loss rounds or low gains rounds. In our study, we found that people with lower total wealth have a higher propensity to take risks. In the literature, the common result is that wealth and income are determinants of the risk-taking propensity, however, the direction of these results is inverse with the direction of the result of this present study. A large number of research papers imply that a larger wealth level increases the willingness to take risks because it acts like a buffer for losses. These results have been theorised as Bernoullian expected utility theory (Bernoulli, 1783), and financial-cushioning hypothesis (cf.

Dohmen, Falk, Huffman, Sunde, Schupp, Wagner, 2011). As opposed, we found out that people from lower wealth levels are more likely to take risks, suggesting that they are more preoccupied with improving their wealth. This would imply that the very wealthy of society are more concerned with protecting their wealth rather than increasing it.

When we refer to the Financial Risk-taking propensity (FR), education, gender and wealth become important. The difference between FR and CE is that for the financial domain, education also plays an important role. In the Faff (2006) paper education does not play a critical role in financial risk-taking propensity. In the paper by Dohmen et al. (2011) education is positively correlated with the willingness to take risks in ‘financial matters’. A similar result comes from a paper (Moffatt et al., 2019) which uses SOEP survey to analyse risk taking through a question about willingness to take risks and a hypothetical lottery. Among age, gender and marital status, education is highly significant (and positive). In our model, financial risk is lower for both high school graduates and university graduates, compared to vocational or professional training. This is similar to a paper by Barsky et al. (1997) which shows that education behaves as a U-shaped function, where exactly 12 years of education are least risk tolerant while lower and higher education categories show greater risk tolerance.

The same study Halek and Eisenhouer (2001) notes that risk-taking is lower among high school and university graduates than among dropouts, but at the margin, risk-taking rises with years of education. Our model shows the same, only we did not calculate the marginal effects.

The General Risk-Taking Propensity (GRiPS) scale, which takes risk as a broad construct, was developed to be able to predict broad outcomes. As recommended by the authors of the scale, more large sample studies need to be done to assess its validity. So far, the present study found that gender, residence and marital status are determinants of risk-taking propensity. A study by Harris and Jenkins (2006) explores the reasons why women appear to be more risk averse. One of the causes is that they assume that the negative outcomes are less desirable. An alternative interpretation is that they assess the probabilities of negative outcomes as greater.

The determinants of Financial Risk-taking propensity we found are gender, education, total wealth and a general risk-taking propensity (GRiPS). Interestingly, none of the measures of the distribution of investments in their present portfolio is not correlated with Financial Risk-taking propensity. A study by Fisher, P. J., & Yao, R. (2017) suggests that gender differences result from income uncertainty and wealth and not from gender itself. Education is widely thought of as a determinant of financial risk-taking, high-risk takers are individuals with more education. However, our results show a counter position. People with high school education have lower financial risk appetite and people with university degrees even lower. This result may mean that individuals with a higher level of education are more sophisticated in their discerning of risks. Another result diverging from commonly held beliefs is that of wealth. The direction of our results show that wealthier people tend to be more risk averse. This may be explained by the fact that wealthier people are more inclined to preserve their wealth.

Further, we sought to find which of the three risk measures is best at predicting the perceived risk of getting COVID-19. As expected, GRiPS wes correlated. Surprisingly, the Certainty Equivalent also appeared as a significant result, however, the magnitude of the effect is very small. Gender, residence, occupation, marital status, and health factors also determine the perceived risk of getting Covid-19 this year. Being a female means you perceive the risk higher than men. Being a house owner means a lower perceived risk. This could be due to factors related to certainty and being in control of one's own behaviour more, not having to interact with other people. The same applied to living with parents. Working in the economics determines a rise in the perceived risk, as well as working in arts, culture or entertainment fields. This result could stem from the fact that the two fields have been taking most of the negative consequences of the lockdowns.

The results of this study have implications for how we assess risk attitudes. The psychometric scales and the Certainty Equivalent are only slightly correlated (FR and CE, or GRiPS and CE). This suggests that there is a crevice between them and that assessments should be made depending on the context in which they are used.

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8. Appendices

Appendix A. Summary and Definition of the Variables in this Study

Table 1

Descriptive statistics of the variables

Variable	Value	Mean	Median	#	Percentage
Age (continuous)	years	35	34	167	
Gender (unordered, categorical)		1.54	2	184	
	Female=1			84	45.65%
	Male=2			99	53.80%
	other=3			1	0.54%
Education (unordered, categorical)		1.86	2	184	
	High School=1			30	16.30%
	University=2			150	81.52%
	Vocational or professional=3			4	2.17%
Residence (unordered, categorical)		2.27	2	184	
	Own an apartment or a house=1			81	44.02%
	Rent an apartment or a house=2			35	19.02%
	Rent a room=3			33	17.93%
	Dormitory=4			7	3.80%
	Live with parents=5			28	15.22%

Income (ordered, categorical)		1.48	1	184	
	Less than €20.000=1			122	66.30%
	€20.000 to €39.999=2			42	22.83%
	€40.000 to €69.999=3			13	7.07%
	More than €70.000=4			7	3.80%
Wealth (ordered, categorical)		1.41	1	181	
	Less than €100.000=1			138	76.24%
	€100.000 to €199.999=2			23	12.71%
	€200.000 to €299.999=3			14	6.63%
	€300.000 to €399.999=4			4	2.21%
	More than €400.000=5			4	2.21%
Civil status (unordered, categorical)		2.10	2	184	
	Single=1			57	30.98%
	In a relationship=2			65	35.33%
	Married=3			49	26.63%
	Divorced or separated=4			12	6.52%
	Widowed=5			1	0.54%
Employment (unordered, categorical)		2.18	1	184	
	Working full-time (paid employee / self-employee) =1			97	52.72%
	Working part-time=2			22	11.96%
	Unemployed or looking for			6	3.26%

	work=3				
	Student=4			52	28.26%
	Retired=5			7	3.80%
Occupation (unordered, categorical)		4.48	4	184	
	Economics, finance, or business professional=1			48	26.09%
	Health care and social assistance sector=2			21	11.41%
	Arts, culture and entertainment=3			15	8.15%
	Professional, scientific or technical services=4			14	7.61%
	Construction, infrastructure, transportation or warehousing=5			5	2.72%
	Retail and commerce=6			6	3.26%
	IT sector=7			26	14.13%
	Other=8			49	26.63%
GRiPS (continuous)		2.92	3	179	
	Composite index where: 1=less risk taking propensity 5=more risk taking propensity				
Financial risk (continuous)		2.89	3	173	
	Composite index where: 1=less financial risk taking 5=more financial risk taking				
Savings (ordered,	*How much of your assets are in savings?*	2.23	2	173	

categorical)					
	Less than 10% = 1			73	42.20%
	10 to 30% = 2			41	23.70%
	30 to 50% = 3			21	12.14%
	50 to 70% = 4			21	12.14%
	More than 70% = 5			17	9.83%
Gold (ordered, categorical)	*How much of your total assets are in gold, jewels, art and collectibles, and real estate?*	1.73	1	173	
	Less than 10% = 1			117	67.63%
	10 to 30% = 2			19	10.98%
	30 to 50% = 3			17	9.83%
	50 to 70% = 4			5	2.89%
	More than 70% = 5			15	8.67%
Stocks (ordered, categorical)	*How much of your total assets are in stocks?*	1.39	1	173	
	Less than 10% = 1			139	80.35%
	10 to 30% = 2			14	8.09%
	30 to 50% = 3			10	5.78%
	50 to 70% = 4			6	3.47%
	More than 70% = 5			4	2.31%
Etfs (ordered, categorical)	*How much of your total assets are in ETFs or mutual funds?*	1.20	1	173	
	Less than 10% = 1			154	89.02%
	10 to 30% = 2			8	4.62%
	30 to 50% = 3			7	4.05%

	50 to 70% = 4			2	1.16%
	More than 70% = 5			2	1.16%
Bonds (ordered, categorical)	*How much of your total assets are in corporate or government bonds?*	1.10	1	172	
	Less than 10% = 1			161	93.60%
	10 to 30% = 2			6	3.49%
	30 to 50% = 3			4	2.33%
	50 to 70% = 4			0	0%
	More than 70% = 5			1	0.58%
Past covid (binary)	*Did you get the COVID-19 disease in the past?*	0.45	0	173	
	Yes = 1			95	54.91%
	No =0			78	45.09%
Past Vaccine (binary)	*Did you get the COVID-19 vaccine?*	0.90	1	173	
	Yes = 1			157	90.75%
	No = 0			16	9.25%
Perceived Risk (ordered, categorical)	*If I don't get the booster, I think my chances of getting COVID-19 this year would be...*	4.08	4	172	
	Almost 0 = 1			18	10.47%
	Very small = 2			17	9.88%
	Small = 3			18	10.47%
	Moderate = 4			53	30.81%
	Large = 5			29	16.86%
	Very large = 6			20	11.63%
	Almost certain = 7			17	9.88%

Risk Norm (ordered, categorical)	*Besides the governmental recommendations, vaccinating against COVID-19 is a good idea.*	1.85	1	173	
	Strongly agree=1			99	57.23%
	Somewhat agree=2			35	20.23%
	Neither agree nor disagree=3			19	10.98%
	Somewhat disagree=4			5	2.89%
	Strongly disagree=5			15	8.67%
Actual behaviour (ordered, categorical)	*It happens very often that I sanitise my hands after going to a public place.*	2.36	1	173	
	Never=5				26.01%
	Sometimes=4				40.46%
	About half of the time=3				9.83%
	Most of the time=2				18.50%
	Always=1				5.20%
Switchrow (continuous, from 1 to 32)	Denotes the implied number when they switched from the risky option to the safe bet	12.26	12	175	
Cert (continuous, from 10 to320)	Denotes the Certainty Equivalent for which they switched	117.65	115	175	

Appendix B. Scatterplots

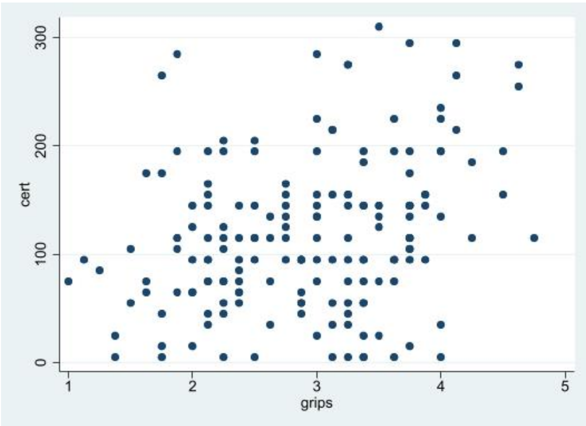

Figure 1. Scatterplot of the relationship between the Certainty equivalent measure and GRiPS scale.

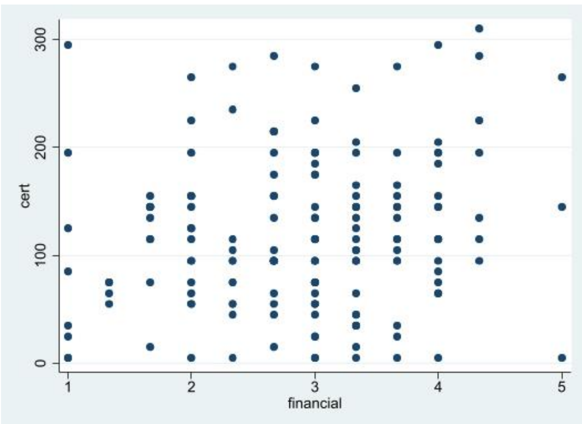

Figure 2. Scatterplot of the relationship between the Certainty equivalent measure and Financial Risk scale.

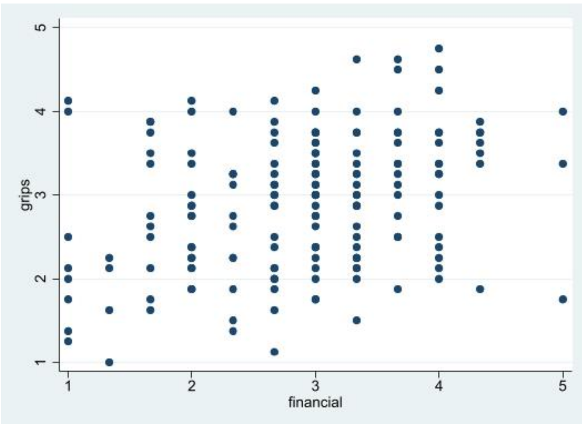

Figure 3. Scatterplot of the relationship between the GRiPS scale and the Financial Risk scale.

Appendix C. Distributions of the main dependent variables.

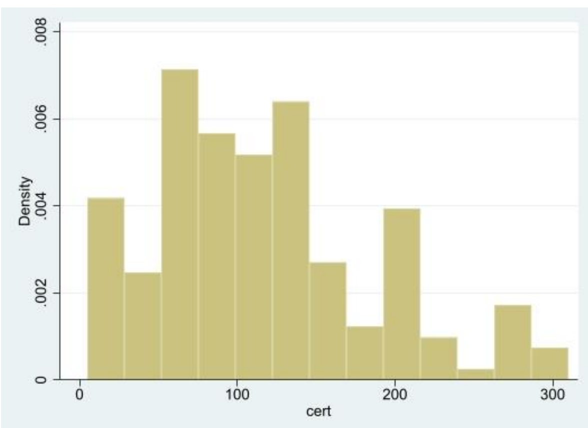

Figure 1. Distribution of the CE measure.

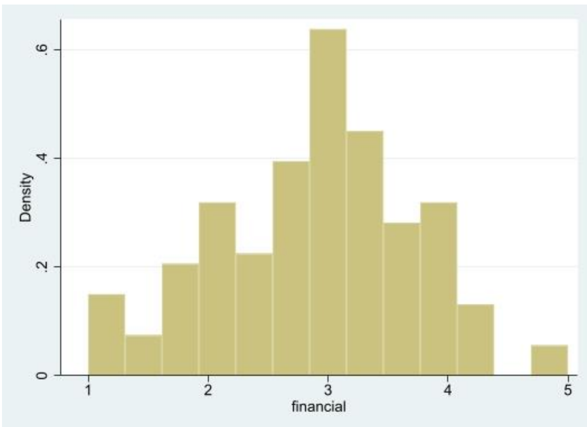

Figure 2. Distribution of the Financial Risk scores.

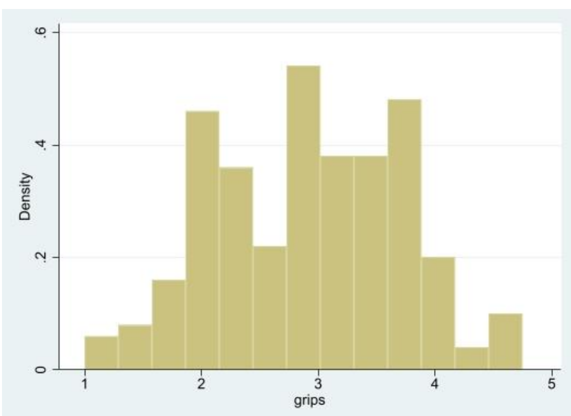

Figure 3. Distribution of the GRiPS scale measures.

Appendix D. Models (1) to (3).

	Model (1)	Model (2)	Model (3)
VARIABLES	CE	FR	GRiPS
age	0.934	-0.0133	0.0119
	(0.932)	(0.0118)	(0.00985)
highschool	-24.26	-1.051*	0.435
	(42.12)	(0.532)	(0.445)
university	-40.13	-1.198**	0.325
	(39.78)	(0.503)	(0.420)
female	-24.15*	-0.265*	-0.441***
	(12.41)	(0.157)	(0.131)
owner	8.978	0.296	-0.221
	(20.93)	(0.264)	(0.221)
rent	19.07	0.271	0.139
	(20.73)	(0.262)	(0.219)
dorm	-2.017	-0.000772	0.0227
	(36.69)	(0.464)	(0.388)
parents	-10.66	0.167	-0.378*

	(19.68)	(0.249)	(0.208)
single	124.8	-1.000	-0.909
	(82.47)	(1.042)	(0.871)
relationship	138.3*	-0.930	-0.826
	(82.52)	(1.043)	(0.872)
married	101.4	-1.019	-1.414*
	(80.48)	(1.017)	(0.850)
divorced	87.02	-1.241	-1.696*
	(84.02)	(1.062)	(0.888)
fulltime	-11.90	0.159	0.0862
	(34.56)	(0.437)	(0.365)
parttime	-7.605	-0.226	0.169
	(38.73)	(0.489)	(0.409)
unemployed	-28.45	-0.0655	0.00223
	(49.50)	(0.626)	(0.523)
student	-3.683	-0.181	-0.126
	(42.71)	(0.540)	(0.451)
economics	12.35	0.248	-0.0242
	(18.35)	(0.232)	(0.194)

healthcare	30.82	0.127	0.159
	(20.08)	(0.254)	(0.212)
arts	24.38	0.459	-0.0146
	(23.64)	(0.299)	(0.250)
science	8.075	0.202	-0.0315
	(24.59)	(0.311)	(0.260)
infrastructure	7.278	0.00118	-0.285
	(22.71)	(0.287)	(0.240)
retail	29.64	0.292	0.118
	(35.86)	(0.453)	(0.379)
it	8.773	0.397	-0.358
	(35.69)	(0.451)	(0.377)
less10k	-42.55	-0.454	-0.516
	(40.99)	(0.518)	(0.433)
less20k	-24.95	-0.471	-0.510
	(41.12)	(0.520)	(0.435)
less30k	-18.74	-0.773	-0.0930
	(42.96)	(0.543)	(0.454)
k1	65.71**	-0.268	0.332

	(30.31)	(0.383)	(0.320)
k2	70.60**	-0.136	0.162
	(32.72)	(0.414)	(0.346)
k3	52.52	-0.861*	0.0231
	(37.18)	(0.470)	(0.393)
k4	57.75	-1.242*	0.261
	(51.33)	(0.649)	(0.542)
Constant	-18.98	6.060***	3.806***
	(127.1)	(1.606)	(1.343)
Observations	167	167	167
R-squared	0.193	0.200	0.317

Appendix E. Model (X) and its marginal effects.

	(X)	(2)
VARIABLES	PR	Marginal Effects
financial	-0.221	-0.0247
	(0.341)	
grips	-0.868*	-0.0970
	(0.461)	
cert	0.00996**	0.00111
	(0.00491)	
age	-0.0607	-0.00679
	(0.0492)	
highschool	31.50	3.522
	(4,764)	
university	32.04	3.582
	(4,764)	
female	1.531**	0.171
	(0.659)	
owner	-2.406**	-0.269

	(1.135)	
rent	-0.383	-0.0428
	(1.044)	
dorm	-2.649	-0.296
	(2.110)	
parents	-1.837*	-0.205
	(1.038)	
single	18.75***	2.097
	(1.491)	
relationship	18.03***	2.016
	(1.537)	
married	19.59***	2.190
	(1.214)	
divorced	19.99	2.235
	(0)	
fulltime	-1.781	-0.199
	(1.483)	
parttime	-1.046	-0.117
	(1.710)	

o.unemployed	-	-
student	-2.178	-0.244
	(1.879)	
economics	2.742***	0.307
	(0.922)	
healthcare	1.250	0.140
	(0.835)	
arts	2.902**	0.324
	(1.253)	
science	20.12	2.249
	(3,369)	
infrastructure	1.631	0.182
	(1.033)	
retail	0.963	0.108
	(1.470)	
it	-0.545	-0.0610
	(1.629)	
less10k	-24.70	-2.762

	(2,454)	
less20k	-24.08	-2.692
	(2,454)	
less30k	-25.20	-2.817
	(2,454)	
k1	2.638	0.295
	(1.670)	
k2	2.671	0.299
	(1.709)	
k3	3.528*	0.394
	(1.891)	
k4	0.0676	0.00756
	(2.138)	
covid	-0.355	-0.0397
	(0.548)	
vaccine	4.246***	0.475
	(1.366)	
actual	-0.415*	-0.0464
	(0.250)	

savings	-0.0800	-0.00894
	(0.242)	
gold	0.167	0.0186
	(0.253)	
stocks	-0.379	-0.0424
	(0.321)	
etfs	0.595	0.0665
	(0.476)	
Constant	-25.66	
	(5,359)	
Observations	161	161

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1