Higher Order Risk Attitudes of Financial Experts

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Abstract

The risk attitudes of market participants have an important influence on market behavior. We measure risk aversion, prudence and temperance in a sample of 173 financial experts. These experts are traders, analysts, or work in support or commercial functions in the financial industry, which routinely deals with risk. To assess their risk attitudes relative to the broader population, we compare their decisions with those of a demographically representative sample and of university students that are reported in the study of Noussair et al. (2014). The experts were more risk-seeking and intemperate than individuals in the other two groups. They were also more imprudent than students, though similarly prudent to the general population.

JEL codes: D83, G11, G41
Keywords: Risk aversion, Prudence, Temperance, Experiment

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1 Introduction

Risk attitudes are a key determinant of economic decisions, affecting investment, savings, employment, educational, leisure, and other choices. To quantify the relationships between risk attitudes and economic outcomes, the risk attitudes of decision makers must be measured or estimated. This measurement of risk attitudes has primarily focused on risk aversion, which is the most basic dimension of risk attitude. However, there is also recognition that a full characterization of an individual's attitude toward risk is more complex than pure aversion or attraction. In particular, the higher order risk attitudes of prudence and temperance have been drawing increasing attention (see Trautmann and van de Kuilen, 2018, for a review).

Prudence is defined as the convexity of the first derivative of the utility function, or equivalently as a positive third derivative ($u^{'''} > 0$; Kimball, 1990). A prudent attitude implies high negative weight given to downside risks (Eeckhoudt et al. 1995), or a preference for positive skew in a payoff distribution (Ebert, 2013), a pattern strongly observed in investment decisions (Harvey and Siddique, 2000; de Roon and Karehnke, 2017). A prudent attitude is also equivalent to a demand for precautionary saving (Leland, 1968; Kimball, 1992), since a convex marginal utility function implies that the expected marginal utility of wealth is increasing in background risk. A consequence of prudence that is especially useful for the design of measurement tasks is that a prudent (imprudent) individual, when forced to accept an unavoidable risk, prefers to do so in relatively high (low) wealth states (Eeckhoudt and Schlesinger, 2006).

Temperance is defined as the concavity of the second derivative, or equivalently as a negative fourth derivative ($u^{''''} < 0$; Kimball, 1993), of the utility function. Temperance implies a dislike of kurtosis in payoff distributions (Ebert, 2013). Thus, temperance can influence the valuation of assets (Corrado and Su, 1996; Harvey and Siddique, 2000). Temperate (intemperate) individuals take on less (more) risk in the presence of greater unavoidable background risk. If faced with multiple unavoidable independent risks, a temperate person prefers to disaggregate them across different states (Eeckhoudt and Schlesinger, 2006), while an intemperate individual prefers to concentrate them in the same states.

To understand the potential of risk attitudes to affect the behavior of financial markets, it is important to measure the preferences of market participants. The study that we report in this paper measures the higher order risk attitudes of a sample of financial experts. The sample consists of individuals who work as traders, financial analysts, or in support and commercial functions in the financial industry. These experts tend to make more numerous, higher-stake, and more important decisions than the population at large, and even those who are not traders themselves influence traders through advice or example.

It is already well-known that lower risk assets trade at relatively high prices and that there is a premium in the return on riskier assets, the effects stemming from the risk aversion of investors. Less understood, however, is how the higher order risk attitudes of market participants can influence the behavior of financial markets. For example, if market players are prudent, they seek to minimize downside risk and avoid negative skew, and the consequence would be that positively skewed assets would trade at a premium and those with negative skew at a discount, thus yielding higher returns. If market participants are imprudent, the opposite pattern would be observed. Higher-order risk attitudes also affect how one responds to background risk, such as asset value variability resulting from uncertainty in the broader economy. If the riskiness of the environment increases, prudent individuals will save more for the future, drawing money out of the financial markets when conditions are risky. When background risk increases, temperate individuals will take on less risk, increasing the market value for relatively safe assets and lowering prices for riskier assets. Thus, higher order risk attitudes on the part of market participants can exert an impact on market outcomes, with the nature of responses to background risk crucially depending on these attitudes. To know the direction in which the market can be expected to react to changes in background risk, we must establish whether participants are prudent or imprudent and whether they are temperate or intemperate. As we discuss in section two, there is some evidence on the extent of prudence and temperance present in some population groups, students in particular. However, our study is the first to document the incidence of prudence and temperance among a sample of expert market participants.

Our procedures follow those of Noussair et al. (2014), who have studied the correlates of prudence and temperance in a demographically representative sample of the Dutch population as well as university students. They found that their measurements of prudence and temperance exhibited a number of strong correlations with financial decisions outside the experiment. To gauge how different our sample is from other segments of the population, we compare our results with the two samples that Noussair et al. (2014) consider. The fact that behavior in the particular experimental task we implemented correlates so strongly with other life decisions means that the behavior we observe in our task is likely to be informative of other decisions that our participants make outside the experiment.[1]

We find that the financial experts participating in our experiments are significantly more risk-seeking and intemperate than both students and the demographically representative participants in Noussair et al. (2014). The experts are significantly less prudent than students but their level of prudence does not differ from members of the general population. Regression analyses are conducted to study the effect of personal characteristics such as gender, age, education, occupation and experience, that are usually found to be correlated with risk attitudes (Brunette and Jacob, 2019). We find a weak relationship between risk aversion and gender, with women less risk averse than men, and a negative relation between age and both prudence and temperance. Specific job characteristics are not significantly correlated with higher order risk attitudes. Finally, the data show a significant negative relationship between cognitive ability, as measured with the Cognitive Reflection Test (Frederick, 2005), and risk aversion, as observed in prior studies (Lilleholt, 2019).

In the next section, we discuss some relevant literature. Section 3 describes the experiment and Section 4 reports the results. We provide some concluding remarks in Section 5.

[1] We are aware that the temporal distance between the collection of the samples is an issue for comparative studies. We compare our newly collected sample of financial experts (2017) with a unique large sample of the general Dutch population (2010) and a further sample of university students. Our design is concerned by a potential exogenous shock occurring during the time window elapsing between the two experimental moments. This shock could shift the average level of risk or higher-order risk in the population (Schildberg-Hörisch, 2018) and provide a source of bias for proper estimation. Both samples have been collected within a time window comprised after the subprime crisis of 2007 and also before the COVID-19 pandemic.

2 Related Literature

Most experimental studies attempting to directly measure risk attitudes with incentivized tasks have focused on undergraduate students. This has the scientific advantage that students are a segment of the population that is readily available to most researchers. Employing student participants facilitates the gathering of data and the replication of prior studies. However, undergraduate students are not demographically representative of the general population in terms of age, educational level, or income, and what can be inferred from them about the preference parameters of the general population or other specific groups of interest is limited. As a consequence, laboratory protocols to measure risk attitudes that were originally developed for students have been administered, sometimes in modified form, to other populations in artefactual field experiments (Harrison and List, 2004). These studies have almost all been focused on the measurement of *risk aversion*, the concavity of the utility function, and its' demographic and behavioral correlates. This research agenda has been very productive and risk aversion has been shown to vary systematically by age, gender, income, religion, and nationality (Donkers et al., 2001; Dohmen et al., 2017; Harrison et al., 2007; Noussair et al., 2012; Falk et al., 2018).

The incidence of prudence and temperance in student populations have been evaluated in a number of studies. Ebert and Wiesen (2011, 2014), Deck and Schlesinger (2010, 2014) and Noussair et al. (2014) all observe that a majority of student participants are prudent. Ebert and Wiesen (2014), Deck and Schlesinger (2014) and Noussair et al. (2014) also report that a majority of individuals are temperate, while Deck and Schlesinger (2010) find that a majority are intemperate. Deck and Schlesinger (2014) report two common general patterns of risk attitude. The first type of individual, the *mixed risk averter*, prefers to combine unavoidable adverse events with favorable ones, or in the words of Deck and Schlesinger, they seek to "combine good with bad". Under the assumption of expected utility, mixed risk averters exhibit alternating signs in the derivatives of their utility function. They are risk averse ($u'' < 0$), prudent ($u''' > 0$), and temperate ($u'''' < 0$). The other profile, the *mixed risk seeker*, prefers to "combine good with good and bad with bad", that is, concentrating favorable (unfavorable) events together. Individuals with this profile are risk seeking ($u'' > 0$), prudent ($u''' > 0$), and intemperate ($u'''' > 0$). Thus, both types are prudent, while the two types differ in whether or not they are risk averse and temperate.

Noussair et al. (2014) are the only authors, to our knowledge, who measure prudence and temperance among a non-student population. Their sample consists of 3566 subjects: 3457 demographically representative Dutch residents, drawn from a participant pool called the *LISS panel*, maintained by Tilburg University in the Netherlands, and 109 students currently enrolled at the University. They measure higher-order risk attitudes, study their correlations with risk aversion, link them to demographic characteristics, and analyze their relationship with savings and portfolio choices. They observe that majorities of individuals are prudent and temperate. Prudence correlates positively with educational level, savings, and owning one's own home, and correlates negatively with credit card debt. Temperance correlates with a lower probability of holding risky investments and with a lower share of risky assets in one's investment portfolio. On average, women are more temperate than men. There have been, to our knowledge, no attempts to measure the levels of prudence and temperance among individuals who specialize in analyzing and working with risk.

A number of studies have considered the risk-taking behavior of financial professionals, and contrasted their behavior with students. Gilad and Kliger (2008) find that the investment decisions of professionals are more susceptible to priming intended to influence risk taking than are those of undergraduate students.[2] Abdellaoui et al. (2013) observe that financial professionals are risk averse in the domain of gains and risk seeking in the losses, with similar preference parameter estimates to those for students. In contrast, Razen et al. (2020) find that financial professionals take more risk than those in other professions when decisions are taken in the loss domain, but there is no difference in the gain domain.

Kirchler et al. (2018) investigate the impact of ranking and risk-taking on a very large sample of professionals in the financial industry, as well as on students. They show that (i) an anonymous ranking of participants among their peers (without any financial rewards linked to the ranking), or (ii) a tournament (where remuneration depends in part

[2] Thoma et al. (2015), using survey evidence rather than incentivized tasks, report that financial professionals take more risk than non-expert decision makers.

on the ranking), increases the risk taking of professional traders who are underperformers, while students are only affected by the tournament structure.

Cohn et al. (2015) report that risk aversion is countercyclical, in that financial professionals primed with time series of declining market prices take less risk than those primed with a rising market. This pattern does not extend to students (Alempaki et al. (2019), König-Kersting and Trautmann (2018)).

Holzmeister et al. (2020) observe that the perception of risk among financial professionals, in nine different countries, depends on the skew of the return distribution rather than its variance. Participants in their study were shown return distributions and asked to indicate how risky they thought the distributions were. Variance and kurtosis did not influence the risk perception of either professionals or laypeople. Assets with negatively-skewed returns were viewed as less risky than those with symmetric returns, which in turn were perceived as less risky than those with positively-skewed returns. The level actually invested depended on both variance and skew.[3]

We aim to contribute to this literature by measuring the levels of prudence and temperance among individuals who specialize in analyzing and working with risk, and by comparing them with those of students and the general population.

3 Experimental design

To facilitate a comparison between our expert participants and the other subject pools, we utilize the same protocol as Noussair et al. (2014). In the experiment, participants face

[3]There have also been a number of recent experimental studies that have compared the decisions made by financial professionals with those of university students in areas other than risk taking. Haigh and List (2005) showed that professional traders of futures and options at the Chicago Board of Trade exhibited behaviors that were more consistent with myopic loss aversion (MLA) than did undergraduate students. In another experiment, professionals were slightly less inclined to fall prey to the Allais paradox than students (List and Haigh, 2005). In an option pricing experiment, Abbink and Rockenbach (2006) found that traders from a German bank performed worse than students. Glaeser et al. (2007) found that financial professionals exhibited more overconfidence in their forecasts and skills than students. Kaustia et al. (2008) showed that professionals were less prone to anchoring bias than students. While Cipriani and Guarino (2009) found that professionals exhibited herding behavior that was close to that of students, Alevy et al. (2007) reported that professional traders, in an information cascade game, were better able to analyze, discern and use information than students were. Cohn et al. (2014) showed that banking professionals tended to cheat more than students. Weitzel et al. (2020) found, in a bubble-prone experimental asset market setup, that professional traders generated price bubbles, albeit significantly smaller ones than students. In a forecasting experiment, Schwaiger et al. (2020) observed that professional traders made more optimistic price forecasts than students, both when the stock whose price was to be predicted declined and then recovered, and when the asset generated a positive final return.

Table 1: List of choice tasks

Name of task	Left lottery	Right lottery
Riskav 1	20	[65_5]
Riskav 2	25	[65_5]
Riskav 3	30	[65_5]
Riskav 4	35	[65_5]
Riskav 5	40	[65_5]
Prud 1	[(90 + [20_-20])_60]	[90_(60 + [20_-20])]
Prud 2	[(90 + [10_-10])_60]	[90_(60 + [10_-10])]
Prud 3	[(90 + [40_-40])_60]	[90_(60 + [40_-40])]
Prud 4	[(135 + [30_-30])_90]	[135_(90 + [30_-30])]
Prud 5	[(65 + [20_-20])_35]	[65_(35 + [20_-20])]
Temp 1	[(90 + [30_-30])_(90 + [30_-30])]	[90_(90 + [30_-30] + [30_-30])]
Temp 2	[(90 + [30_-30])_(90 + [10_-10])]	[90_(90 + [30_-30] + [10_-10])]
Temp 3	[(90 + [30_-30])_(90 + [50_-50])]	[90_(90 + [30_-30] + [50_-50])]
Temp 4	[(30 + [10_-10])_(30 + [10_-10])]	[30_(30 + [10_-10] + [10_-10])]
Temp 5	[(70 + [30_-30])_(70 + [30_-30])]	[70_(70 + [30_-30] + [30_-30])]
RA_EU1	[40_30]	[50_24]
Prud_EU2	[(50 + [25_-25])_30]	[50_(30 + [15_-15])]

[a_b] indicates an equiprobable lottery in which either a or b is received; choice of the left lottery indicates risk aversion, prudence and temperance respectively.

17 binary choices between lotteries, presented sequentially. Table 1 summarizes the 17 choice tasks. Each of the 17 rows corresponds to one decision to be taken between the Left lottery and the Right lottery. The notation [a_b] indicates an equiprobable gamble in which either a or b is added to the previous total, each with probability .5. For example, in the choice entitled Riskav 1, shown in the first row in Table 1), the Right lottery has the values $a = 65$ and $b = 5$. This means that if the Right lottery is chosen, the outcome will be either 65 Experimental Currency Units (ECU) or 5 ECU with equal probability.

The elicitation procedure consists of four parts. The first part, which measures the degree of risk aversion, is composed of five choices between a sure payoff and a lottery with two possible payoffs, each occurring with equal probability. Parts two and three each include five binary choices between two different lotteries to measure prudence and temperance, respectively. Part four, consisting of the last two decisions (RA_EU1 and Prud_EU2), assesses the strength of relative risk aversion and relative prudence, respectively. RA_EU1 tests whether the coefficient of relative risk aversion, $RR(x) = -xu''(x)/u'(x)$, is greater than one under the assumption of the CRRA functional form,

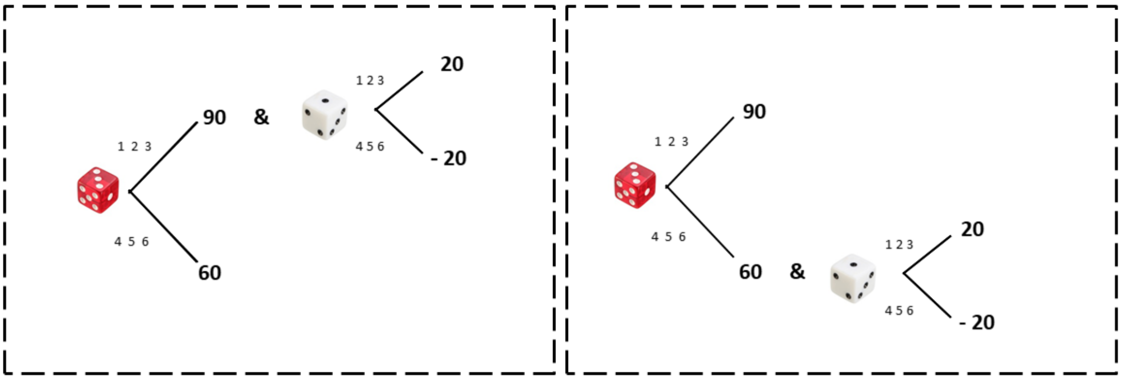


Figure 1: Prud 1 choice task, display shown to participants (subject chooses between compound lotteries on the left and on the right)

$u(x) = \frac{x^{1-r}}{1-r}$. In other words, it reveals whether an individual is more or less risk averse than logarithmic utility $u(x) = ln(x)$. Prud_EU2 measures whether the coefficient of relative prudence, $RP(x) = -xu'''(x)/u''(x)$, is greater than 2, under the assumptions of expected utility and CRRA. If the decision maker is sufficiently risk averse and prudent, she would select the Left lotteries in the last two rows of Table 1.[4]

The tasks that assess prudence in Part 2, listed in Table 1 as Prud 1 - Prud 5, have the following functional form:

$$[(a + [c_1\_ - c_1])\_b] \quad vs. \quad [a\_(b + [c_1\_ - c_1])] \tag{1}$$

where a, b, and c_1 are strictly positive monetary outcomes. For example, consider the lottery shown in Figure 1, termed Prud 1 in Table 1. The parameters are $a = 90$, $b = 60$, and $c_1 = 20$. a and b are the wealth levels in the good and bad states respectively. In both lotteries, there is an unavoidable risk, under which the individual gains or loses c_1 with equal probability. If the agent chooses the Left lottery, there is an initial random draw, visualized in the figure and on participants' computer screens as a die roll, which results in 90 or 60 ECU, each with probability .5. If the result is a 1, 2, or 3, resulting in 90 ECU, another virtual die is rolled, and 20 ECU is either added to or subtracted from the 90 ECU,

[4] As in Noussair et al. (2014), the sequence of parts 2 and 3 was counterbalanced. Half of the subjects completed Part 3 before Part 2. For these two parts, the positioning of the lotteries on the left and the right were reversed for one half of participants. In the first part of the session measuring risk aversion, one half of the participants received the lotteries in increasing order of the fixed payment, and the other in decreasing order. The instructions for the experiment are provided in Appendix **??**.

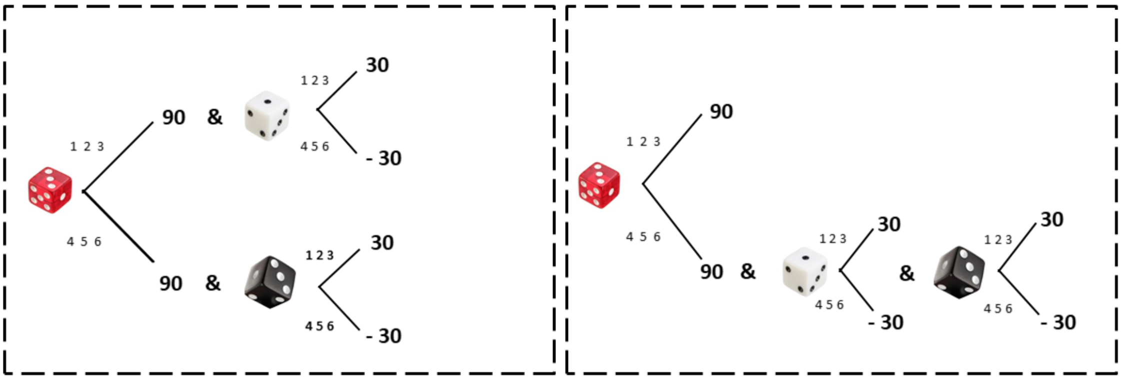


Figure 2: Temp 1 choice task (subject chooses between compound lotteries on the left and on the right)

each with probability .5. If the outcome of the initial die roll is 4, 5, or 6, the result is 60 ECU. The Right lottery differs in that the second die roll occurs if and only if the first roll results in 60 ECU. By making the choice on the left, the individual is choosing to take on the risk in the high-wealth state, and by choosing the option on the right, she is electing to put the risk in the low-wealth state. A choice of Left indicates prudence, one of Right shows imprudence.

In Table 1, we also describe the five temperance tasks constituting Part 3 of the experiment. Adhering to the notation introduced earlier, the choice tasks are listed in Table 1 in the form:

$$[(a + [c_2\_ - c_2])\_a + [c_1\_ - c_1])] \quad vs. \quad [a\_(a + [c_2\_ - c_2] + [c_1\_ - c_1])] \tag{2}$$

As an example, consider the Temp 1 task, displayed in Figure 2. The values of the parameters are $a = 90$, $c_1 = c_2 = 30$. a is the (here certain) payoff of the first die roll, c_1 or $-c_1$, and c_2 or $-c_2$, are the possible payoffs of a second and third equiprobable draw, respectively. A temperate decision maker has a preference for disaggregating the two risks by choosing the lottery on the left, while an intemperate individual prefers to assign both risks to the same state, as in the alternative on the right. The prospect of receiving an additional c_2 or $-c_2$ can be interpreted as a background risk. A temperate (intemperate) decision maker prefers to assign an additional unavoidable risk to a state with less (greater) background risk.

The decisions to measure prudence and temperance have the structure of risk apportionment tasks. Consider, for example, the task Prud 1, shown in Figure 1. The decision maker chooses whether to place the risk represented by the white die roll in the high or low wealth state. In the task Temp 1, shown in Figure 2, the individual chooses whether to apportion the risk represented by the black die to a state with no risk, or to one in which there is already the risk embodied in the white die roll. The notion of using risk apportionment tasks to distinguish higher-order risk attitudes is due to Eeckhoudt and Schlesinger (2006). The ability to frame the measurement tasks in such simple terms, moving a die roll to another location, makes it easier to implement such tasks with individuals who are not accustomed to experimental decision situations.

We replicated two treatments of Noussair et al. (2014), which they called "Real" and "Real lowvar". Here, for greater clarity, we term the two treatments "High Var" and "Low Var", respectively. The only difference between the two treatments is that the magnitude of the risk c_1 in Low Var is always equal to one-tenth of its value in the High Var treatment. The values for High Var are shown in Table 1. Noussair et al. (2014) included the Low Var treatment to evaluate a possibility raised by Eeckhoudt and Schlesinger (2006) that if one of the two risks that may be combined is small, individuals would become more intemperate. That is, individuals might be more likely to aggregate risks than to disaggregate them, if one of the risks is relatively small. We investigate this possibility in our experiment with financial experts. However, as reported in Section 5, we do not observe any difference between High Var and Low Var with regard to temperance. On the other hand, we do observe that the experts are less prudent under Low Var, where one of the risks is small.

After making the 17 binary choices listed in Table 1, subjects had to answer a seven-question version of the Cognitive Reflection Test (Frederick, 2005; Finucane and Gullion, 2010; Toplak et al, 2014).[5] The test is presented in Appendix **??**. At the end of the experiment, subjects also completed a final questionnaire, which is given in Appendix **??**, about their professional status and job description. The questions concerned the particu-

[5]Studying professional traders, Thoma et al. (2015) observe that higher CRT scores are associated with more years of experience and greater salaries. In general, laboratory asset-market experiments show that better cognitive abilities are associated with higher earnings (Corgnet et al., 2015; Breaban and Noussair, 2015; Noussair et al., 2016, Akiyama et al., 2017). Kirchler et al. (2018) find, in a large-sample study including professionals, that the average amount invested in a risky asset is not correlated with CRT score.

lar job they have, the trading strategies they use, the types of assets they invest in, their employer, and several personal characteristics.

The payment scheme is similar to the one used for the other samples (LISS and students). Each subject had a 10% chance of being selected by the computer to be paid. The computer then randomly selected one of the 17 options the subject had chosen and rolled virtual dice to determine the monetary reward. The currency used was called ECU. The exchange rate was 1 ECU equal to 4 Euros. If a subject was selected by the computer, the expected payoff was approximately 70 ECU, which equals 280 Euros, and could vary between 40 and 600 Euros, depending on the participant's choices and the lottery outcomes. The expected earnings for financial experts is four times larger than that for the other two samples (LISS and student), where the average payment, conditional on an individual being selected, was roughly 70 Euros and the actual payoff ranged from 10 to 150 Euros. In addition, each expert received a backpack worth 20 Euros at the end of this experiment as a reward for her participation. This corresponds to four times the show-up fee that was offered to the students, namely 5 Euros. The payoffs to the financial professionals were set to be comparable other experiments conducted around 2017 with similar participants. Cohn et al. (2015) paid 20% of their 162 participants, who could earn between 0 and 546 dollars. Kirchler et al. (2018) paid 20% of their professionals with an average (maximum) payment of 52 Euros (600 euros) for a 45-minute experiment, while Haigh and List (2005) paid 40 dollars for a 25-minute task. In the study of Weitzel et al. (2020), the average payment was 76.5 Euros for a 70-minute experiment. Using the calculations of Kirchler et al. (2018), who estimated that their professional participants earned an hourly net wage of 26 Euros in their job, the average (maximum) per-hour remuneration in effect in our experiment was 270% (2,308%) of hourly wage, which represents a substantial monetary incentive.[6]

The experiment was followed by a second, unrelated experiment on portfolio choices with the same subjects participating. The second experiment, which occurred after ours,

[6] Noussair et al (2014) paid both their LISS and student at typical levels employed in the literature in 2010. Hence, we argue that the reward scaling in our participant samples adjusts for price changes the time interval between the experiments. It is worth noting that during the time interval between the 2010 (LISS and student) and 2017 (financial expert) experiments, the average inflation rate in Europe has been well below 2%, thus barely affecting the real value of the nominal subject payments.

cannot influence our data, is to be reported in another paper.[7] The two experiments together lasted a total of one hour.

4 Subject pool

We compare three subject pools from different experiments. The general population and student data were collected in 2010, while the data from experts were collected in October 2017 at the 30th International Federation of Technical Analysts (IFTA) Conference. The conference was held in Milan (Italy), at the Excelsior Hotel Gallia. For the occasion, and in collaboration with the leaders of the trading federation, an experimental laboratory was prepared in a room next to the conference hall. The experiment was conducted in compliance with the ethical rules of the LEEN (experimental economics laboratory of Nice) and implemented using O-Tree (Chen et al.,2016). The 3457 LISS panel members who participated in the experiment was stratified to reflect the Dutch population.[8] Several demographic variables are available for the LISS panel. In particular, 52% are women, the average age is 48.6 years and 30% of the participants have completed higher education. In addition, 109 undergraduate students participated in the same experiment, at the CentER laboratory, located at Tilburg University.

Among the 178 financial market experts that participated to the experiment, 80 were Italians, and the other most represented countries were Malaysia (24), Switzerland (11), United Kingdom (10), United States (7), Australia (6) and Germany (5). Five subjects did not finish the experiment because they did not complete the questionnaire. Removing them, our final sample is made up of 173 experts of whom 27 are women (16% of the sample). The average and standard deviation of their ages is 44.04 and 12.25 years, respectively. We also collected information about their academic background. 6% of the participants (11) declared that they held a PhD and the great majority (108, 63%) have a post-graduate degree. The sample distributions of gender, age and academic background are reported in Appendix **??**. The sample of experts differs from the LISS sample in terms

[7] At the beginning of the experiment, participants knew that two successive experiments would be run. Introductory instructions, shown at the beginning of the experiment, are given in Appendix **??**.

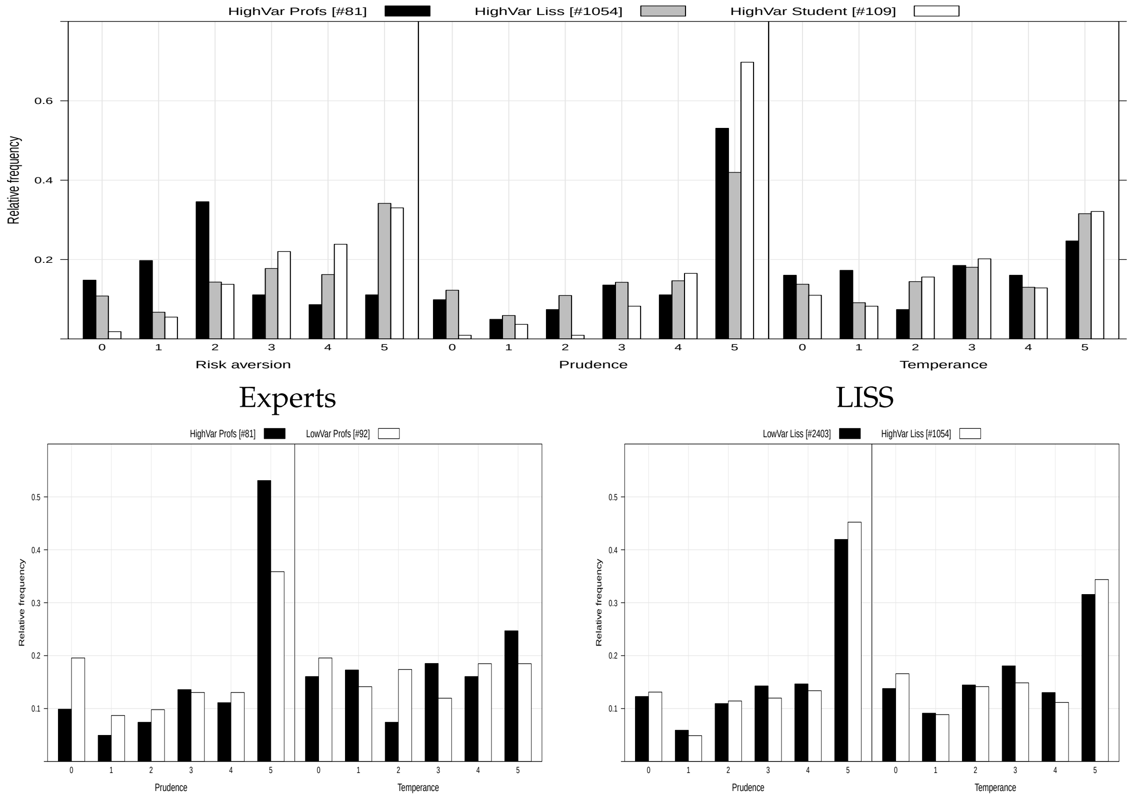
[8] The LISS panel is an internet panel of 9000 individuals managed by CentERdata, an organization affiliated with Tilburg University.

of participants' gender and percentage with higher education, while the average age is similar. Such differences reflect typical characteristics of the employees at the financial sector.

The average score on the seven-item CRT questionnaire (CRT7) was 2.83 with a standard deviation of 1.74. Considering only the first three questions (CRT3), corresponding to the standard three-item version of the test, the average score was 0.9 with a standard deviation of 0.98. Other studies on financial professionals typically report higher average CRT scores. Kirchler et al. (2018) document an average CRT score of 1.81 in their sample and Thoma et al. (2015) observe an average of 1.62. Such differences might be associated with different experimental settings; e.g. Kirchler et al. (2018) administer the CRT test with online surveys and do not put time limits for answering, while we impose a two-minute time constraint during an experiment in a laboratory setting conducted in the context of a conference of financial experts. Only 13% of subjects hit the two-minute limit on at least one out of the seven questions. This suggests that the time limit was not a relevant issue. Moreover, those subjects who answered all of the three questions in CRT3 correctly never ran out of time. The percentage of individuals who ran out of time at least once in CRT7 among those that fail to answer 1 or 2 questions correctly in the CRT3 are 11% and 13% respectively. Among those who have failed to answer all the three questions correctly, 23% have run out of the time in at least one question in CRT7. These data suggest that subjects generally took the time they needed to answer the questions correctly.[9]

Participants reported several different job specializations. 75 of them can be classified as working in the area of trading (prop trader, sales trader, sales, asset/portfolio manager), while 21 work as analysts (financial analyst, strategist/economist, risk analyst). The remaining 77 respondents did not provide a precise answerand usually worked in support or sales functions in finance and asset management. With regard to their operating strategies, the large majority of subjects (132) indicated that they mainly applied technical analysis and very often used other trading strategies in addition. In terms of the type of market they work with, 44 subjects operate exclusively in spot markets, 32 in

[9]The distribution of correct responses is reported in Appendix **??** along with the list of questions. The distributions of responses for most of the items in the questionnaire about job experience are given in Appendix **??**, along with the text of the survey form.



Note: In the top panel: percentages of individuals' making different numbers of safe choices in both the High Var and Low Var treatments, prudent and temperate choices in the High Var treatment only; LISS panel participants shown in gray, university students in white, and experts in black. In the bottom panel: histograms of individuals' number of prudent (left within a panel) and temperate (right within a panel) choices in the HighVar (white bars) and LowVar (dark bars) treatments; for experts (left) and LISS respondents (right).

Figure 3: Distribution of choices

derivatives markets, and 65 in both. The remaining 32 participants did not specify the markets in which they were active. The average and standard deviations of their years of experience in the financial sector are 14.01 and 8.61 years, respectively. The survey responses indicate that the participants have daily and extensive exposure to working with monetary risk, and thus can be considered as experts in finance.

5 Results

5.1 Comparing experts to LISS and student samples

We measure, as in Noussair et al. (2014), individual risk aversion as the number of safe choices in decisions 1 to 5 in Table 1, Part 1 of the experiment. It can be seen from the payoff structure of these decisions that making from 2 to 5 choices is consistent with risk aversion. Zero or 1 safe choices is consistent with risk seeking preferences, and either 1 or 2 safe choices would be made by a risk-neutral individual. Making zero safe choices is consistent only with risk seeking and 3 - 5 only with risk aversion. Following Noussair et al. (2014), we measure prudence (temperance) by the number of prudent (temperate) choices made in decisions 6 to 10 (11 to 15) in Table 1, Parts 2 and 3 of the experiment. We classify an individual as prudent if a majority of her five decisions were prudent in Part 2. Similarly, a participant is classified as temperate if a majority of her decisions in Part 3 were temperate.

In order to have a first glance at the distributions of higher-order risk attitudes for all samples and treatments, we provide a graphical representation of our main results. Figure 3 is composed of two panels. The top panel contains histograms of the risk aversion (left panel) levels in the three samples from Part 1 of both the High Var and Low Var treatments, as measured by the number of safe choices made. The figure also reports the distribution of the number of prudent (middle panel), and temperate (right panel) choices made in the three samples, from Parts 2 and 3 of the High Var treatment, where there is data available from all three samples. The gray and white bars show the data for the LISS panel participants and the student sample of Noussair et al. (2014), respectively, and our sample of experts is displayed with black bars. In the figure, each individual constitutes one observation. The bottom panel contrasts the behavior of both experts and LISS participants between the High Var and Low Var treatments, in terms of prudence and temperance. The Low Var treatment was not administered to students. In what follows, we present a statistical analysis comparing the different samples for each of the three measures of risk attitudes. We supplement Figure 3 with Tables 2, 3 and 4.

Risk aversion: The data reported in Table 2 highlight that the experts are significantly more risk loving than students ($p < 0.0001$, MW two-sided test) and LISS panel respondents ($p < 0.0001$, MW two-sided test), whereas LISS respondents are slightly, though significantly, less risk-averse than students ($p = 0.09$, MW two-sided test).

The average number of safe choices is 2.439 for financial experts, 3.596 for students, and 3.378 for Liss panel participants. Almost 29% of the experts can be classified as risk-seekers, as they make $\{0, 1\}$ safe choices, while almost 18% and 7% of LISS participants and students, respectively, are risk-seeking by the same criterion. This percentage

Table 2: Risk Aversion

# Safe ch.	Experts	LISS♠	Students♠
0	0.104	0.108	0.018
1	0.185	0.067	0.055
2	0.312	0.143	0.138
3	0.133	0.177	0.220
4	0.098	0.162	0.239
5	0.168	0.342	0.330

Percentages of individuals' making safe choices.♠ highlights a rejection (at 5%) of the null that the distribution is identical to the Expert one.

of risk seekers rises to approximately 60% for the experts if we also include those who make two safe choices, thereby creating a category for risk-seekers plus risk-neutral individuals. The percentages in this category are 32% and 21% for LISS participants and students, respectively. The results from the RA_EU1 task also show lower risk aversion among experts than LISS participants. 36% of experts choose the relatively safe option, in comparison with 49% of LISS Panel respondents and 37% of students. A Mann-Whitney rank sum test is statistically significant when comparing the experts with LISS participants (p = 0.002, MW two-sided test), but not with the student sample (p = 0.962, MW two-sided test). The experts are significantly less risk averse than members of the other groups.

Prudence: Table 3 shows that a large majority of decisions made by the experts reflects a prudent attitude. The average number of prudent choices is 3.70 for financial experts in the High Var treatment, 2.99 in Low Var, and 3.32 in the pooled data from the two treatments. For LISS panel participants, the average is 3.39 in High Var, 3.34 in Low Var and 3.38 overall. The average is 4.45 for students in High Var. More than 22% (38%) of the experts make two or fewer prudent choices, and thus are classified as imprudent, in the High (Low) Var treatment. This corresponds to the 31% of experts (pooled across treatments) being imprudent. Among LISS participants, 29% are imprudent under High Var, 32% in Low Var and 30% overall. Finally, 6% of the students are imprudent.

The experts are significantly less prudent than students in the High Var treatment (p = 0.003, MW two-sided test). When we compare experts' prudence attitude with respect to LISS sample, we find that there is not consistency across treatments. While they are more imprudent (p = 0.03, MW two-sided test) than LISS in LowVar treatment, they are not different in the HighVar one. Moreover, if we compare experts' and LISS

Table 3: Prudence

# Prudent ch.	HighVar Experts	LowVar Experts	HighVar LISS♠	LowVar LISS	HighVar Student♠
0	0.099	0.196	0.123	0.131	0.009
1	0.049	0.087	0.059	0.049	0.037
2	0.074	0.098	0.109	0.114	0.009
3	0.136	0.130	0.143	0.120	0.083
4	0.111	0.130	0.147	0.134	0.165
5	0.531	0.359	0.420	0.452	0.697

Percentages of individual's making prudent choices in HighVar and LowVar treatments. ♠ highlights a rejection (at 5%) of the null that the distribution is identical to the HighVar Experts one.

prudent choices pooled across treatments we do not find any significant difference in prudence attitudes.

Furthermore, in the PRUD_EU2 task, 62% of the experts chose the relatively prudent option. This is a similar percentage with respect to the LISS respondents (59%), but lower than the students (83%). Again, experts are significantly less prudent than students (p = 0.0002, MW two-sided test), but not different from the LISS participants (p = 0.572, p = 0.519, MW two-sided test). Thus, the experts are not systematically more or less prudent than the general population.

We now turn to the comparison between the High Var and Low Var treatments within each sample. Experts make more prudent choices in High Var (p=0.011, MW two-sided test). Indeed, nearly twice as many experts make zero prudent choices under Low Var, and the number of participants making five prudent choices is 17 percentage points higher under High Var. Noussair et al. (2014), on the other hand, found no difference between the treatments in the number of prudent choices for the LISS participants (p=0.274, MW two-sided test).

Temperance: Temperance choices are reported in Table 4. The average number of temperate choices is 2.753 for financial experts in the High Var treatment, 2.511 under Low Var, and 2.624 in the pooled data from the two treatments. The LISS panel participants made an average of 3.021 temperate decisions in the High Var treatment, 2.668 under Low Var, and 2.935 overall. Students made an average of 3.119 temperate choices under High Var. Almost 41% of the experts made two or fewer temperate choices in High Var, 51% in Low Var and 46% overall, and thus are classified as intemperate. For comparison, among LISS subjects, 37% and 40% were temperate in High Var, in Low Var respectively. 35% of students were intemperate.

Table 4: Temperance

# Temperate ch.	HighVar Experts	LowVar Experts	HighVar Liss	LowVar Liss♠	HighVar Student
0	0.160	0.196	0.138	0.166	0.110
1	0.173	0.141	0.091	0.089	0.083
2	0.074	0.174	0.144	0.141	0.156
3	0.185	0.120	0.181	0.149	0.202
4	0.160	0.185	0.130	0.112	0.128
5	0.247	0.185	0.316	0.344	0.321

Percentages of individuals' making temperate choices in HighVar and LowVar treatments.♠ highlights a rejection (at 5%) of the null that the distribution is identical to the LowVar Experts one.

In the High Var treatment, experts do not significantly differ from students in terms of temperance (p = 0.18, MW two-sided test). Conversely, experts are significantly less temperate than LISS participants, particularly in the Low Var treatment. (p = 0.028, MW two-sided test).

The difference between LISS panel members and students is not significant (p = 0.639, MW two-sided test). Thus, we find that experts are less temperate than the demographically representative sample.

We now turn to the comparison between the High Var and Low Var treatments shown in Figure 3. For temperance, however, neither experts (p=0.370, MW two-sided test) nor LISS respondents (p=0.846, MW two-sided test) show a statistically significant difference between High Var and Low Var.

5.2 Risk attitudes and demographic variables for the sample of experts

In this Subsection, we report the results of our investigation of the relationships between the experts' characteristics and their risk attitudes. Table 5 reports results of OLS regressions[10] of the risk aversion measure on age, CRT score, education and gender (female = 1).[11] Depending on the specification, the estimates include different groups of variables related to the preferred trading strategy, the nature of the employer, years of experience, and the type of job held by the participant.

The estimates suggest that a higher CRT score is associated with lower risk aversion and this result holds in all of our specifications. This is in agreement with most of the experimental evidence on non-student populations, which shows that more reflective

[10] All results are confirmed with an ordered logit.

[11] One subject declared an age of 0 and he/she has been discarded from the sample.

Table 5: Risk aversion scores and demographics/job correlates

VARIABLES	(1)	(2)	(3)	(4)	(5)
CRT	-0.190***	-0.183***	-0.184***	-0.191***	-0.187***
	(0.0613)	(0.0613)	(0.0630)	(0.0609)	(0.0615)
Female	-0.640*	-0.649*	-0.625*	-0.667*	-0.648*
	(0.361)	(0.365)	(0.373)	(0.361)	(0.370)
Age	0.0769	0.0833	0.0837	0.0985	0.0859
	(0.0647)	(0.0640)	(0.0644)	(0.0651)	(0.0662)
Age^2	-0.000843	-0.000887	-0.000896	-0.00108	-0.000916
	(0.000710)	(0.000720)	(0.000722)	(0.000728)	(0.000745)
Years of exp	0.00475				
	(0.0171)				
Postgraduate		-0.110			
		(0.245)			
Tech. analysis			0.0855		
			(0.300)		
Analyst				0.0503	
				(0.299)	
Other job				0.419	
				(0.255)	
Derivative					-0.0547
					(0.367)
Spot and Derivative					-0.0913
					(0.304)
Other markets					0.0130
					(0.377)
Constant	1.385	1.315	1.180	0.812	1.244
	(1.384)	(1.378)	(1.363)	(1.421)	(1.438)
Observations	172	172	172	172	172
R-squared	0.059	0.060	0.059	0.075	0.060

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Dependent variable is the Risk aversion score on a scale of 0 - 5. Higher scores indicate greater risk aversion.

subjects are, on average, less risk-averse (Frederick, 2005; Benjamin et al., 2013; Cueva et al., 2016).

We conducted the same regression, replacing the CRT score with an equivalent score variable based on the number of incorrect intuitive answers[12]. We find no statistically significant correlation between risk aversion and intuitive incorrect answers. As Frederick (2005 , p. 27) writes, "...the three items on the CRT are easy in the sense that their solution is easily understood when explained, yet reaching the correct answer often requires the suppression of an erroneous answer that springs impulsively to mind." Use of the intuitive incorrect (erroneous) answer is taken as a measure of impulsiveness. The estimates indicate that while more reflective individuals in our sample are less risk averse, there is no relation between impulsiveness and risk aversion.

Turning to gender issues, our estimates provide weak evidence (at the 10% level of significance) that females exhibit lower risk aversion than males. While this finding contrasts with much of the previous literature, we do not think that this result warrants emphasis since the number of females in our sample is small and the effect is not significant at conventional levels. We find no significant correlation between age and risk aversion. Some other studies have found a convex relationship (Barsky et al. (1997), Cohen and Einav (2007), Harrison et al. (2007), Noussair et al. (2014)). A positive correlation between risk aversion and age has also been reported in some studies (Donkers et al., 2001; Sahm, 2012; Dohmen et al., 2017). In particular, Dohmen et al. (2017) use data from two different large panel surveys from the Netherlands and Germany and find that the willingness to take risks decreases with age.[13] The absence of correlation between age and risk aversion in our sample might be a consequence of the fact that those who take more risk might attain more senior positions in their company. This result is thus consistent with the absence of any significant relationship between years of experience and risk aversion, if age and seniority level exert countervailing effects.

Regarding the other control variables, related to education (Postgraduate), trading

[12]Each question of the CRT has only one intuitive but incorrect response, and only one correct answer (see Noussair et al. (2016) for an analysis of different types of incorrect responses on the CRT test.). Please refer to the CRT questionnaire given in Appendix **??** for a full listing of the correct and incorrect intuitive answers for each question.

[13]Dohmen et al. (2017) have shown that self-reported subjective measures of risk attitudes are valid predictors of risk taking behavior.

strategies (technical analysis), jobs (analyst, other), market type (Derivative, Spot and Derivative, Other), we do not find any significant correlation with risk aversion. The results are robust to changing the econometric specifications to ordered probit regressions. While we do find that experts are less risk averse than the general population, we do not observe any effects of job-related variables within our sample of experts.

Turning to prudence, Table 6 reports results of regressions[14] with similar specifications as in the analysis of risk aversion, where the dependent variable is the number of prudent choices in the experimental task. The analysis also includes a treatment dummy, which is significant in all specifications. The estimates confirm that participants in the High Var treatment are more prudent than under Low Var. We do not find any correlation between prudence and CRT scores or education variables as well as any gender effect, and years of experience does not seem to affect prudence. There is a convex relationship between prudence and age. Those who answer "Other job", "Derivative" or "Other markets" are more prudent. It may be that experts working on markets with high leverage and risky positions such as some derivative markets, rather than the spot market, dislike downside risks and thus prefer associating an unavoidable risk with the high-wealth state. That is, they prefer assets with a positively-skewed payoff distribution. The differences across roles may be in part the result of self-selection.

We observe no statistically significant relationships between temperance, and job-related characteristics. The results of the analysis are reported in Appendix **??**. We also study the correlation between risk aversion, prudence, and temperance at the individual level. As shown in Appendix **??**, experts exhibit a positive correlation between prudence and temperance.

6 Conclusions

In this paper, we measured the higher order risk attitudes of a sample of financial experts. We compared the results with those from students and a demographically representative sample of the Dutch population reported in Noussair et al. (2014). We found that the experts who participated in our experiments were significantly less risk-averse

[14] All results are confirmed with an ordered logit.

Table 6: Prudence scores and demographics/job correlates

VARIABLES	(1)	(2)	(3)	(4)	(5)
Low Var Treat	-0.684**	-0.699**	-0.685**	-0.661**	-0.657**
	(0.285)	(0.286)	(0.284)	(0.285)	(0.279)
CRT	0.000256	-0.00647	-0.00716	-0.0116	0.0147
	(0.0894)	(0.0923)	(0.0910)	(0.0878)	(0.0831)
Female	-0.245	-0.239	-0.273	-0.234	-0.344
	(0.392)	(0.390)	(0.399)	(0.389)	(0.383)
Age	-0.121*	-0.121*	-0.122*	-0.101	-0.106*
	(0.0719)	(0.0635)	(0.0635)	(0.0623)	(0.0616)
Age^2	0.00135*	0.00135*	0.00137*	0.00110	0.00122*
	(0.000751)	(0.000700)	(0.000698)	(0.000680)	(0.000677)
Years of exp	-0.00108				
	(0.0179)				
Postgraduate		0.115			
		(0.295)			
Tech. analysis			-0.133		
			(0.375)		
Analyst				0.631	
				(0.487)	
Other job				0.590*	
				(0.306)	
Derivative					0.805*
					(0.436)
Spot and Derivative					0.618
					(0.385)
Other markets					1.319***
					(0.384)
Constant	6.242***	6.197***	6.370***	5.587***	5.194***
	(1.563)	(1.396)	(1.431)	(1.402)	(1.407)
Observations	172	172	172	172	172
R-squared	0.054	0.055	0.055	0.078	0.107

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Dependent variable is the number of prudent choices, ranging from 0 to 5. Higher scores indicate greater prudence.

than students and the general population. They were also less temperate than the general population and the students, as well as less prudent than the students.

Our data do not allow us to pin down the mechanism whereby the correlation between being an expert in financial risk and risk tolerance/ intemperance arises. It may be the case that those individuals who become experts in the domain are those who take risks in general and who concentrate their risks in a subset of the states. This pattern characterizes individuals who like to combine good with good in the taxonomy of Eeckhoudt et al. (2009). It may be that those who combine good with good are those who end up being in a position in which they can acquire the relevant expertise about risk. It could also be the case that risk-seeking and intemperate individuals are more likely to become experts in non-financial domains as well, though determining this would require further research. Furthermore, there may be the selection of risk tolerant individuals specifically into finance since employee compensation is relatively variable compared to other occupations (see, e.g., Deter and van Hoorn, 2021). There may be an additional selection for intemperate individuals, since income risks may be correlated leading income shocks to be concentrated into negative and positive clusters.

On the other hand, the causality might be in the other direction, that is, from expert to risk taker rather than from risk taker to expert. The reward structure in the financial industry may encourage individuals to take more risks (Cai et al., 2010; Sharma, 2012) and to behave in a less temperate manner. Dealing with risks frequently, and becoming familiar with them, may reduce one's fear of taking on risk (Cao et al., 2011) and of concentrating it in a small number of states. This behavior may then carry over to outside the workplace. The presence of a disproportionate percentage of such individuals in the financial industry specifically could contribute to the volatile market dynamics and excessive risk taking that affects the financial industry.

The financial industry also focuses on the management of downside risk, which is associated with prudent preferences. An emerging consensus is establishing that a strong majority of individuals in society is prudent (see, Noussair et al., 2014 and Deck and Schlesinger, 2014, as well as a review by Trautmann and van de Kuilen, 2018). Our experts are at least as prudent as typical individuals, though less than the university students that have been studied. Prudence is also strongly correlated with educational attainment

(Noussair et al., 2014), and our sample is very educated compared to the overall population. However, one might argue that imprudence might be a trait that is selected for in the financial industry, and this selection may offset the effect of educational attainment so that the average level of prudence among our experts is close to that of the general population.

In our data, we observe that our professionals are less risk averse and less temperate than the average person. How risk averse and temperate market participants are have implications for market behavior. Lower risk aversion on the part of market participants would lead to lower prices and higher returns on low risk assets than would otherwise be observed. It would also reduce the amount of diversification in investors' portfolios. Higher intemperance would lead to an overvaluation of assets with kurtotic return distributions. It would also lead to a weaker flight into safe assets when there is an increase in background risk than would occur if there was no relationship between temperance and participation in the market. We believe providing direct, possibly experimental, evidence of these relationships would be valuable future research.

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Declarations

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The experiment reported in this paper has not received IRB approval. Because when the experiment was conducted in 2018, IRB approval was not required for conducting non-intrusive experiments like ours at Université Côte d'Azur. The data and codes used to analyze the data are available from the authors upon request.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at ...

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