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Risk-Taking and Skewness-Seeking Behavior in a Demographically Diverse Population*

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Abstract: We study the interaction between risk-taking and skewness-seeking behavior among a demographically diverse sample of French adults using an experiment that elicits certainty equivalent over lotteries that vary the second and third moments orthogonally. We find that the most common behavior is risk avoidance and skewness seeking. On average, we find no interaction between the two, and a weakly significant interaction only in some segments of the population. That is, in most cases, skewness seeking is not affected by the variance of the lotteries involved, nor is risk taking affected by the skewness of the lotteries. We also find a significant positive correlation between risk-avoiding and skewness-seeking behavior. Older and female participants make more risk-avoiding and more skewness-seeking choices, while less educated people and those not in executive occupations are more skewness seeking. Estimated decision models show that utility curvature, likelihood sensitivity, and optimism can explain the observed behaviors.

Keywords: Risk; Skewness; Certainty Equivalent; Experiment

JEL classification: C93; D81

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1. Introduction

While studying higher order risk preferences has become increasingly common in recent years, the interaction between risk-taking and skewness-seeking behavior remains understudied. Understanding the tradeoffs that people make when choosing among options that vary in both risk and skewness has important economic implications. To begin with, the well-known “favorite - long shot bias” in horse race betting is attributed to a preference for skewness that is sufficiently strong to overcome aversion to risk and lower expected returns (Golec and Tamarkin, 1998). More importantly, the skewness of future earning distributions is shown to significantly influence labor market choices. For example, Flyer (1997) shows how the higher order moments of the earnings distribution influences the initial career decisions of college graduates, while both Grove et al. (2021) and Choi et al. (2021) demonstrate the influence of highly skewed earnings distributions on entry into superstar markets. The latter also show that the costs (in lower wages) of these choices can be substantial and long lasting. Tradeoffs between risk taking and skewness seeking also influence whether farmers adopt new agricultural technologies, which generally change both the skewness and variance of crop yields (Chavas and Shi, 2015; Emerick et al., 2016), and their purchases of crop insurance.

By using a carefully designed experiment, we can vary the risk and skewness of lottery options in a controlled orthogonal way. The main novelty of our study is to investigate the interaction between risk-taking and skewness-seeking behavior among a diverse population, specifically a sample of French adults who are demographically diverse in terms of age, education, and occupation. We find that the most common behavior is risk avoidance and skewness seeking but on average the two do not interact with each other. That is, the risk-taking behavior of our sample is mostly unaffected by the skewness of the options, and similarly, skewness-seeking behavior is unaffected by the variance of the options. We find a weakly significant positive interaction effect only in some segments of the population. This segment containing the most risk-avoiding subjects, takes more risk as the skewness of the options increases and vice versa. We also find a significantly positive correlation between risk-avoiding and skewness-seeking behavior, that older and female participants make more risk-avoiding and skewness-seeking choices, and that less educated people and those not in executive occupations are more skewness seeking. We also estimate decision models and find that utility curvature, likelihood sensitivity, and optimism can explain behaviors observed in the experiment.

Our finding of no interaction effect on average among a diverse population contrasts with results found in lab studies using student subjects, where the most common finding is of greater risk taking when facing options with greater skewness; that is, a positive interaction effect (Grossman and Eckel, 2015; Astebro et al., 2015; Ebert, 2015; Dertwinkel-Kalt and Köster, 2020). Among these lab studies only Astebro et al. (2015) considers a non-standard subject pool, executives, in addition to student subjects, finding no difference in how skewness affects risk-taking behavior between students and executives, which might be explained by the similarity in education levels. We therefore contribute to this literature by studying how risk taking is affected by skewness, as well as how skewness-seeking behavior is affected by the risk of the lottery, and the interaction of both, in a demographically diverse population.[1]

While our study is novel in investigating the interaction between skewness seeking and risk taking in the general population, several studies investigate prudence and risk preference separately among the general population.[2] While prudence is the most common finding among adults (Noussair et al., 2014), adolescents (Fairley and Sanfey, 2020) and children (Heinrich

[1] Apart from Bougherara et al. (2021), we know of only one other study that asks this reverse question although this is not isolated in the experimental design but revealed in regression results. Specifically, Brünner et al. (2011) finds that higher variance generates more skewness-seeking choices in their experiment using binary lotteries.
[2] Prudence is a stricter feature of preferences, implying skewness-seeking behavior that is robust to different levels of kurtosis. Trautmann and van de Kuilen (2018) survey the growing number of experimental studies that study prudence. Ebert and Wiesen (2011) find evidence of prudence, with most prudent subjects also being skewness seeking but not necessarily vice versa.

and Shachat, 2020), few demographic factors seem to explain the heterogeneity observed. Highly educated participants are more prudent (Noussair et al., 2014) as are those with a higher IQ (Fairley and Sanfev, 2020) but other factors are uncorrelated. Risk aversion is the modal outcome observed in studies that measure risk preferences using incentivized methods among the general population (Harrison et al., 2007, Dohmen et al., 2010, 2011; von Gaudecker et al., 2011). These studies identify that gender, age, education, and income can affect risk-taking behavior although the effects vary considerably with the methods employed.[3]

In summary, while it is hard to reach general conclusions, demographic differences matter for risk-taking behavior, which reinforces the need to study the interaction between risk-taking and skewness-seeking behavior among a broader population than the standard lab sample. While our primary contribution is to study the interaction between risk taking and skewness seeking among a diverse sample, we are also novel in measuring skewness seeking (rather than prudence) in a broader sample. Finally, we also contribute further evidence to the small literature on risk taking in diverse populations.

To study the interaction between risk-taking and skewness-seeking behavior, our experiment employs a design that varies the variance and skewness of lotteries in an orthogonal fashion. By eliciting certainty equivalents for each lottery, we measure the intensity of preferences and therefore can examine the tradeoffs we are interested in. To examine if our results are robust to different directions of skewness, we include lotteries that are both negatively, positively, and zero skewed. All our lotteries involve only gains to avoid any confound from loss aversion.

Our basic experimental design follows the first part of Bougherara et al. (2021), however the lottery stakes are substantially increased and involve only gains (rather than mixed lotteries), the subject pool is more diverse with that experiment conducted using university

[3] We discuss these findings in more detail in the next section.

students, and a zero-skew lottery is included. In addition, that paper focused on explaining individual decisions and so involved a second lottery task used for that purpose.

Finally, note that we study skewness-seeking behavior rather than prudence.[4] We define skewness seeking as preferring a lottery with a larger skewness over another lottery with a smaller skewness but the same expected value, variance, and kurtosis (Ebert and Wiesen, 2011). Since we consider both right- and left-skewed lotteries, a larger skewness can therefore mean either a more right-skewed lottery or a less left-skewed lottery. Similarly, we study "risk taking" rather than risk preference, with the former referring to preferences over changes in variance holding the other moments constant.

Our results validate the importance of verifying lab findings in more diverse populations as our average result of a zero interaction effect has very different implications than the typical lab finding of a positive interaction effect. In particular, a zero interaction effect implies that people are no more likely to buy insurance as the skewness of the options either increases or decreases. In contrast, a positive interaction effect implies that people are more likely to buy insurance as outcomes become more left-skewed (i.e., less skewed). Many important risks faced by individuals are left-skewed such as health and employment outcomes, and investments in financial markets, where there is a small chance of a very poor outcome occurring. The threat of climate change, as well as greater global connectivity increases the importance of these left-skewed risks.

Our results further highlight how a positive interaction effect may be present only among certain segments of the population - in our experiment, these were the most risk avoiding who also tended to be the most skewness seeking. Such people are more likely to take on risks that they like more, which in their case are more right-skewed. Demographically this

[4] As noted earlier, prudence is a stricter feature of preferences, implying skewness seeking behavior that is robust to different levels of kurtosis.

segment of the population tends to be older and female. In addition, less educated segments tend to be more skewness seeking. Since education matters, then the labor market studies that focus on college graduates and superstars (Flyer, 1997; Grove et al., 2021; Choi et al., 2021) might not tell the whole story compared to a broader range of participants. Also, demographic differences in skewness seeking itself might become more important due to climate change and financial market linkages revealing vulnerabilities and potentially exacerbating inequities. Finally, the implications of the tradeoff between variance and skewness are particularly important in agriculture where crop yields from adopting new technologies and from climate risk typically affect all the moments of the distribution (Chavas and Shi, 2015; Emerick et al., 2016). Our results demonstrate the importance of extrapolating from population-specific findings when applying these results to specific settings.

2. Related Literature

In this section, we discuss in greater detail three types of related literature. First, lab-based studies of the interaction between risk taking and skewness seeking. Second, studies of prudence in the broader population. Third, studies of risk preference in the broader population.

Several lab studies using student subjects find a positive interaction effect between risk taking and skewness; that is, they observe greater risk taking when subjects face options with greater skewness. In particular, Grossman and Eckel (2015) find a positive interaction effect using a variation of their Eckel and Grossman (2002, 2008) risk elicitation task, Astebro et al. (2015) instead use a variation of the Holt and Laury (2002) risk elicitation task, and Ebert (2015) has subjects choosing among binary lotteries. These three studies all consider only right-skewed lotteries. Dertwinkel-Kalt and Köster (2020) also find evidence of what they call "skewness-dependent risk attitudes" in their Experiment 1, with subjects more willing to choose the lottery over the safe option yielding the lottery's expected value as the skewness of the lottery increases. Their experiment involves negative, zero, and positive skewness lotteries. On the other hand, Taylor (2020) shows that after controlling for the order effects in the Grossman and Eckel (2015) design, the impact of skewness on risk taking becomes mixed with changes observed in both directions, and Bougherara et al. (2021) find that subjects were more willing to take risks when facing more left-skewed lotteries.[5] Except for Astebro et al. (2015), these papers use only student subjects. Astebro et al. (2015) find no difference in how skewness affects risk-taking behavior comparing students and executives, which might be explained by the similarity in education levels.

Noussair et al. (2014) study prudence among a large sample of Dutch adults finding that most respondents are risk averse and prudent. However, compared to a lab sample of student subjects, the panel was less prudent, which the authors attribute to the effect of education as regressions reveal that more highly educated participants are more prudent, with other demographics not significant. Haering et al. (2020) study the effect of culture, using student subjects in lab experiments conducted across three countries: China, US, and Germany. They find no significant differences in prudence across cultures. Heinrich and Shachat (2020) find that Chinese children and adolescents are mostly prudent, while Fairley and Sanfey (2020) have a similar finding among Dutch adolescents. The latter also find a positive correlation between IQ score and prudence. In summary, while considerable heterogeneity is observed in prudence across the population, other than education and cognitive ability, demographic factors such as gender and age do not seem to be correlated with prudence.[6]

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[5] Some of these differences in results might be attributable to loss aversion as Grossman and Eckel (2015) and Bougherara et al. (2021) use mixed lotteries, while Astebro et al. (2015) uses only lotteries involving gains. Bleichrodt and van Bruggen (2022) find the standard result of risk aversion and prudence over lotteries involving only gains but find that risk loving and imprudence is common for lotteries involving only losses.

[6] Within a student subject pool, Breaban et al. (2016) also find that higher cognitive ability is correlated with greater prudence. Noussair et al. (2014) have the same finding among their student sample.

Several studies measure risk preferences using incentivized methods among the general population (Harrison et al., 2007, Dohmen et al., 2010, 2011; von Gaudecker et al., 2011).[7] Like the prudence results, considerable heterogeneity is observed although risk aversion is the modal outcome. Although demographic factors seem to matter more here than for prudence, it is hard to reach firm conclusions because results vary considerably with the methods employed. For example, with regard to gender, von Gaudecker et al. (2011), Dohmen et al. (2011) and Noussair et al. (2014) find that women take less risk, while Harrison et al. (2007) finds no effect.[8] Effects regarding age are also mixed with von Gaudecker et al. (2011) finding that risk taking decreases with age, while Harrison et al. (2007), Dohmen et al. (2010), and Noussair et al. (2014) find that older people are less risk averse.[9] Similarly, greater education can increase risk aversion (Harrison et al., 2007) or the opposite (von Gaudecker et al., 2011) or have no effect (Dohmen et al., 2010; Noussair et al, 2014). Only Dohmen et al. (2010) study the role of cognitive ability, finding a positive correlation between risk taking and cognitive ability. The impact of income or wealth is similarly mixed with von Gaudecker et al. (2011) finding no significant effects, while Dohmen et al. (2010, 2011) and Noussair et al. (2014) find a positive correlation between higher wealth or income and risk taking.

3. Experimental Design

Our experiment consists of three parts. In the first and main part, we elicit participants' certainty equivalents (CEs) for six different lotteries with changing variance and skewness. Second, we elicit participants' self-assessed risk attitudes over different domains. Third, we elicit basic socio-demographic information. Our experiment is carried out as a web survey with

[7] While Charness et al., (2020) elicit risk preferences among a sample of Dutch adults they focus on linking with financial decisions and do not report the link with socio-demographic factors.
[8] According to Filippin and Crosetto (2016) this null effect could be due to Harrison et al. (2007) using the Holt and Laury (2002) risk elicitation task. In contrast, Dohmen et al. (2010) elicit certainty equivalents, while von Gaudecker et al. (2011) and Noussair et al. (2014) use lottery choices.
[9] Dohmen et al. (2017) also find that risk taking decreases with age based on self-reported measures.

the instructions shown on a video. Experimental instructions for all parts (translated from French) are provided in Appendix A.

We designed six lotteries, shown in Table 1, that vary in skewness and variance but have the same expected value (€75) and kurtosis (2). Each lottery is defined as {(X1, 0.5), (X2, 0.25), (X3, 0.25)}, with X1, X2, X3 representing the outcomes and 0.5, 0.25 and 0.25 their respective probabilities. All amounts are in Euros (€).[10] Note that lotteries with three possible outcomes are required to vary the skewness while keeping the kurtosis, mean, and variance the same. We keep the probabilities fixed while varying the outcomes, and all lotteries involve only gains to avoid potential confounds with loss aversion.

Half of the lotteries (A, B, C) are less risky and have a lower variance than the other three lotteries (D, E, F). Within each set of lotteries with the same variance, we vary the skewness over three levels: negative, zero and positive, where the negative and positive skewness is of the same absolute magnitude (0.8). This orthogonal design enables us to study how participants trade off variance and skewness in a controlled manner.

For each lottery, we elicited the certainty equivalent, following standard methods used in the risk preference literature (Etchart-Vincent and L'Haridon, 2011; Cubitt et al., 2015; Diecidue et al., 2015). In particular, subjects are asked to repeatedly choose between a sure amount and the particular lottery, where the sure amount varies from the lowest lottery outcome to the highest in €5 steps.[11] To reduce the noise in the data we constrain subjects to switch from the sure amount to the lottery only once.[12] To help participants understand the chances we included a graphical representation as illustrated in Figure A-1 in Appendix A. Subjects see

[10] For ease of presentation and to avoid confusion, we rounded the amounts to whole Euros.

[11] Our design, which follows the approach of Diecidue et al., (2015), ensures that CEs are elicited with the same precision across all lotteries. Consequently, the number of decision rows varies between the low and high variance lotteries. In particular, subjects face either 12 or 13 decision rows for the low variance lotteries (A, B, and C), and either 18 or 19 decision rows for the high variance lotteries (D, E, and F).

[12] As stated, our aim in constraining subjects to switch only once was to reduce noise in the data especially given the online nature of the experiment where we have less control over subject's attention. Nevertheless, we acknowledge that a drawback of this approach is that we cannot capture indifference or confused preferences.

each lottery one at a time, but to control for potential order effects, we created six sequences that were randomized across subjects (ABCDEF, FABCDE, EFABCD, DEFABC, CDEFAB, BCDEFA).

Table 1. Lottery characteristics

Lottery	X1 (p=0.5)	X2 (p=0.25)	X3 (p=0.25)	Expected Value	Variance	Skewness	Kurtosis
A	75	104	46	75	400	0.0	2.0
B	58	108	75	75	400	0.8	2.0
C	92	75	42	75	400	-0.8	2.0
D	75	30	120	75	1,024	0.0	2.0
E	49	127	75	75	1,024	0.8	2.0
F	101	23	75	75	1,024	-0.8	2.0

Note: Only the information contained in columns 2 to 4 is provided to the subjects.

In the second part of the experiment, we collected a self-assessment of risk attitudes using two approaches that were easy to implement and less demanding for subjects than using another set of lottery choices. First, we used the generalized risk question from Dohmen et al. (2011) who found a strong correlation between this measure and an incentivized experimental measure of risk taking. Subjects are asked to rate their attitude towards risk taking in general on a scale from 0 (not at all willing to take risks) to 10 (very willing to take risks). Second, we also collected a self-assessment of risk attitudes in different domains using the French version of the 30-item domain-specific risk-taking (DOSPERT) scale of Blais and Weber (2006). Subjects indicated the likelihood that they would engage in a particular activity or behavior on a scale from 1 (Extremely unlikely) to 7 (Extremely likely) for 30 items, which are made up of six questions in each of five domains (social, recreation, ethical, financial, and health). The financial domain is further divided into gambling and investment questions (three items each). We also construct an overall (global) measure which is the sum of all items. All these variables are proxies for risk attitude, a key variable to explain lottery choices. Finally, participants answered a short demographic questionnaire collecting information on age, gender, income, education, and occupation.

A French crowdsourcing company (*Foule Factory*) conducted the experiment using their existing panel of participants.[13] Participants undertook the online survey at their own convenience on their own devices. In total, the survey took around 15 minutes to complete. There were 308 participants. Fifteen randomly chosen subjects (approximately 5% of the participants) were paid for one randomly selected lottery decision. In particular, one row for this decision task was drawn randomly. If for the selected row the subject preferred the sure amount to the lottery, then the payment was equal to this sure amount. If for the selected row the subject chose the lottery instead of the sure amount, then the lottery was played, and the payment was equal to the outcome of the lottery. Such selective payment methods are commonly used in field experiments measuring risk preferences (Harrison et al., 2007; Dohmen et al., 2010; von Gaudecker et al., 2011; Noussair et al., 2014). Average earnings of the 15 randomly chosen subjects were €74.53. This was in addition to the standard Foule factory payment of €0.14 per minute paid to all subjects (equivalent to around €2 for a 15-minute experiment).

The major advantage of conducting our experiment online is the ability to readily access a large pool of demographically diverse subjects in a short time.[14] By using Foule Factory to reach our sample we received only complete responses and avoided multiple submissions, thereby mitigating several of the potential disadvantages of online experiments. The online survey can also be taken in a more natural and comfortable environment than the artificial lab

[13] Like Amazon Mechanical Turk, Foule Factory is a crowdsourcing company (for further discussions, see e.g., Barraud de Lagerie and Sigalo Santos, 2018; Renault, 2018). It was created in 2014 and claims 50,000 workers exclusively residing in France. This platform allows clients to offer tasks to registered workers, microtasks or more demanding tasks, sometimes requiring qualifications. A very active worker will earn a monthly average of around €40. Earnings (capped at €3,000 per year) are additional income for the workers.

[14] This paragraph draws on Reips (2000) who provides a comprehensive comparison of the advantages and disadvantages of online experiments. We discuss the aspects most relevant to our experiment.

environment. On the other hand, online experiments may suffer loss of control as subjects might be more easily distracted than in the lab, potentially leading to lower data quality (e.g., Anderhub et al., 2001). Online experiments are also typically much shorter in duration, thereby collecting less data per subject. Self-selection is a concern with both online and lab experiments, although dropouts are more common with online experiments. Fortunately, comparisons of findings between online studies and lab studies typically find little difference (e.g., Anderhub et al., 2001; Berinsky et al., 2012) and ensure quality even in interactive experiments (Arechar et al., 2018). Arcehar et al. (2018) also show that attrition in their online experiment is unrelated to demographic characteristics.

4. Descriptive analysis of the experiment results

4.1 Average behavior with respect to variance and skewness

In all that follows, the certainty equivalent (CE) is the value of the sure amount on the next row after the player has switched from the lottery to the sure amount. It is measured in Euros (€). Table 2 shows summary statistics on CEs for each of the six lotteries, ordered from the highest to the lowest mean CE.[15] The mean elicited CE varies from €62.4 for lottery F to €74.4 for lottery B. Mean and median CEs are at their lowest for lotteries C and F, which are the two lotteries exhibiting negative skewness. On the contrary, the mean and median CEs are at their highest for the two lotteries characterized by positive skewness (B and E). Standard deviation of CEs (and thus heterogeneity in CEs) is higher for lotteries E, F and D, which are the lotteries exhibiting the highest variance.

[15] Since sure amounts are proposed in €5 steps, subjects may choose a CE that is less than the minimum amount that could have been won in the lottery. For example, for lottery A the lowest CE range starts at €45 while the minimum amount they can win is €46. Choosing the minimum CE might indicate that the subject's actual CE lies in the range between the minimum lottery value and the next CE step, and therefore be a legitimate choice albeit a very risk averse one. However, such choices may instead reflect confusion or lack of attention. We present results in Appendix F that demonstrate robustness to excluding subjects who chose the lowest CE across all six lotteries.

Table 2. Summary statistics on elicited CE for each lottery (amounts in €)

Lottery characteristics			Statistics on elicited CEs						
Lottery	Variance	Skew.	Mean CE	Std. Dev.	Min CE	Max CE	1st Quart.	Me -dian	3rd Quart.
B	400	0.8	74.4	15.0	55	110	60	75	80
E	1,024	0.8	72.5	21.7	45	130	55	70	80
A	400	0.0	70.1	16.6	45	105	55	75	80
D	1,024	0.0	67.9	24.5	30	120	50	75	80
C	400	-0.8	65.4	17.5	40	95	50	65	80
F	1,024	-0.8	62.4	25.8	20	105	45	65	80

Figure 1 below locates the six lotteries on a space featuring skewness on the horizontal axis (from negative on the left to positive skewness on the right) and variance on the vertical axis (from small at the bottom to large variance at the top). For example, lottery C is characterized by a small variance and a negative skewness while lottery E has a large variance and positive skewness. The figures close to the circles around lottery names are the mean CEs expressed in Euros. We run one-sided paired t-tests on mean CEs and report the sign and significance of the mean comparison next to each arrow. Interpretation of the Figure is as follows: the arrow originating at lottery F and pointing to lottery D features a (+ ***), which indicates that the difference between the mean CE for lottery D (€67.9) and the mean CE for lottery F (€62.4) is positive and statistically different from zero at the 1% level. Similarly, the arrow originating at lottery C and pointing to lottery F shows a (-**), indicating that the difference between the mean CE for lottery F (€62.4) and the mean CE for lottery C (€65.4) is negative and statistically different from zero at the 5% level.

The six horizontal comparisons (F versus D, D versus E, F versus E, C versus A, A versus B, and C versus B) show that the respondents are consistently skewness seeking since more skewed (right) lotteries are always preferred to lower skewed (left) lotteries with the same expected value, variance, and kurtosis (t-tests outcomes for only four differences are shown on

Figure 1 to avoid overloading the graph). The pattern is the same whether the variance is low (C versus A, A versus B, and C versus B) or high (F versus D, D versus E, and F versus E).

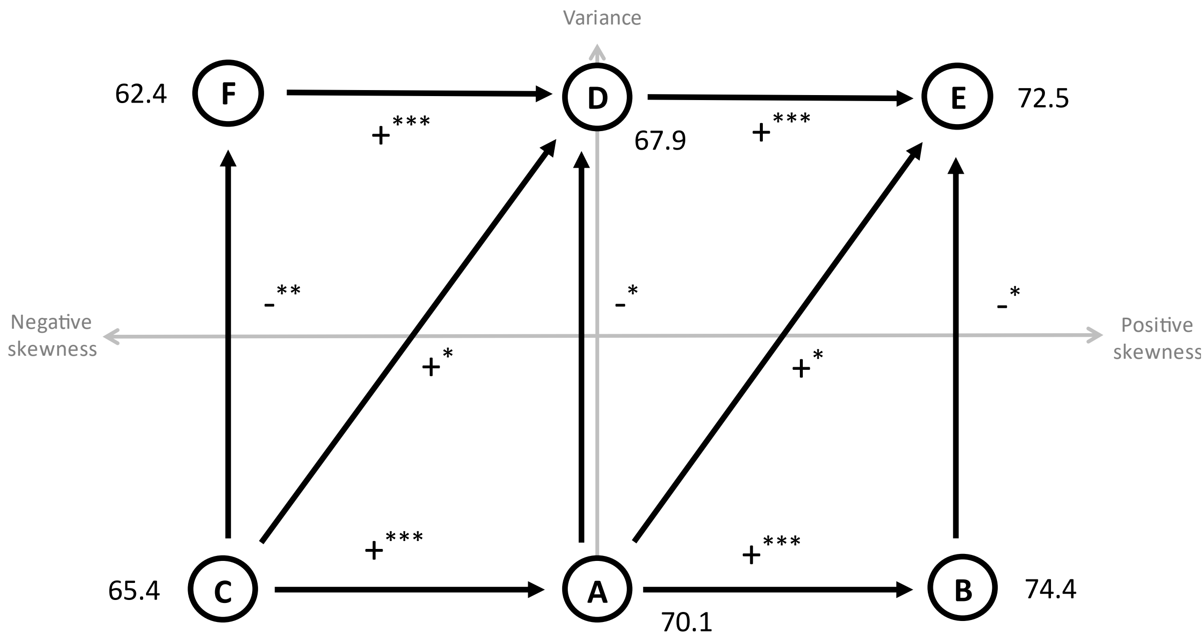


Fig. 1. Mean certainty equivalent for each lottery

Notes: all values in €; the arrows show the direction and significance of one-sided paired t-tests of CEs; *** p<0.01, ** p<0.05, * p<0.10.

We also ran the Jonckheere-Terpstra test of ascending ordered alternatives separately for the three lotteries with low variance (A, B and C) and for the three lotteries with high variance (D, E and F). More precisely, we tested the following two null hypotheses of skewness-seeking behavior: i) $CE_B > CE_A > CE_C$ and, ii) $CE_E > CE_D > CE_F$. The two Jonckheere-Terpstra tests of ascending ordered alternatives produce significant p-values at the 1% level and confirm preferences for lotteries with higher skewness, whatever the level of the variance.

The three vertical comparisons based on independent paired t-tests show that, whatever the level of skewness (negative, zero or positive), lotteries with a higher variance are valued less. The difference in average CEs is significant at the 5 or 10% level. To check for a possible interaction effect between variance and skewness, we compare the difference between the average CEs for each of the three vertical comparisons ($CE_F - CE_C$ vs $CE_D - CE_A$ vs $CE_E - CE_B$). While this difference decreases as skewness increases, paired t-tests between the three differences are not statistically different from zero. Hence, we do not observe any change in risk taking (i.e., any change in the valuation of risk) when the level of skewness increases. Finally, the diagonal comparisons indicate that the (positive) skewness effect dominates the (negative) variance effect: the average CE is significantly higher (at the 10% level) in lotteries with both a higher variance and which are more right-skewed (C versus D, and A versus E).[16]

We also conducted a detailed descriptive analysis of individual-level behavior with respect to skewness and variance, by comparing CEs of the six lotteries for each individual. Overall, the findings are consistent with the average results reported in this section, but they also show that subjects are not always consistent in their choices. Appendix B contains full details.

4.2 Socio-demographic statistics and self-assessment of risk attitudes

Table 3 summarizes the socio-demographic characteristics of our sample. Among the 308 subjects, 56% are male with an average age of 40. The education level is coded from 0 (no training beyond the first four years of secondary education) to 7 (Master's degree or beyond).[17] The average education level of our sample is between level 4 and 5, where 5 stands for achievement of a Bachelor's degree and 4 corresponds to one or two extra years after the French *baccalaureat* (equivalent to US high-school diploma). This corresponds to 75% of the subjects

[16] All the above discussion was based on independent paired t-tests. We checked the robustness of our findings by applying Bonferroni's correction to account for multiple hypothesis testing. For the six horizontal comparisons, the p-values still indicate significance at the 10% level except for the comparison between the CEs in lotteries A and B (the difference is only significant at the 15% level). For the three vertical comparisons for which paired t-tests were weakly significant, differences in CEs are no longer significant at the 10% level when considering Bonferroni-corrected p-values.

[17] See Appendix A for details of each code.

having a higher education, defined as one year of education or more after the *baccalauréat*. Our pool of subjects is younger and more educated than the general French population (see Appendix C for national statistics on gender, age, and education level). Close to 20% of our subjects occupy an executive or senior intellectual job (referred to as executives from here on).[18] We created a continuous (individual) income variable from the seven categories in our questionnaire. For each interval, the continuous measure was set equal to the interval mid-point.[19] The average monthly income of our sample is €1,777.

Each subject was asked to assess his/her own willingness to take risk from a scale varying from 0 (highly cautious, not willing to take risks) to 10 (fully prepared to take risks). The distribution (see Figure E-1 in Appendix E) shows heterogeneity in risk attitudes. It is characterized by an average risk-taking score of 4.3 and a mode around 5 and 6, in line with results presented in Dohmen et al. (2011) for a large representative sample of German adults.

Table 3. Socio-demographic characteristics of our pool of subjects (N = 308)

Variable	Mean	Std. Dev.	Min	Max
Age (years)	40.2	13.0	18	76
Male (0/1)	56.2%	49.7%	0%	100%
Education level (0 to 7)	4.6	1.6	0	7
Higher education (0/1)	74.7%	43.6%	0%	100%
Executive or senior intellectual job (0/1)	18.5%	38.9%	0%	100%
Monthly income (continuous measure, in €), N = 295	1,777	1,019	550	6,500

[18] Due to technical problems when implementing the web survey, some intermediate occupations did not appear on the screen and therefore could not be chosen by the subjects. However, from the answers that have been recorded, we believe that those subjects who could not select the intermediate occupation category selected a category that was below their current level, since the percentage of subjects in lower occupation seems to be high compared to the general population. On the contrary, we are confident that the measurement of the executive and senior intellectual jobs is fairly accurate, hence our choice of this measure.

[19] A total of 13 subjects out of 308 (4%) did not provide their income category. For the only subject who reported an income above €6,500, we set the continuous income measure at €6,500. The distribution of monthly income for the 295 subjects who responded to the question is shown in Figure D-1 in Appendix D.

Each subject also answered a typical DOSPERT questionnaire (see Appendix A). Statistics on the global score from DOSPERT questionnaire and the five DOSPERT domain scores are shown in Table E-1 in Appendix E. Subjects are less willing to take risks in the Ethical, Financial, Health, and Recreation domains compared to the Social domain. Within the Financial domain, they are more willing to take risks with investing compared to gambling. Given the strong correlation across the domains (as reported in Table E-2), in the analysis that follows we only consider the global score from the DOSPERT questionnaire.[20]

5. Regression analysis of the experimental results

We first study how subject's choices as measured by the elicited CE depend on lottery characteristics (here, their second and third moments). Regression analysis is used to confirm results from the descriptive analysis showing higher CEs for positively skewed lotteries and for lotteries with smaller variances. The benchmark model features the individual CE for subject *i* and lottery *t* (*t* = A, B, C, D, E, F) as the dependent variable. Explanatory factors include the variance and skewness of the lottery (the two direct effects and their interaction) along with individual-specific effects assumed to be random. Each subject makes six choices. The intercept of the model is individual specific but the slope is assumed constant over individuals and lotteries. The model is as follows with u_{it} the error term assumed to be independent and identically distributed:

$$CE_{it} = \alpha_i + \beta_{var}.var_t + \beta_{sk}.skew_t + \beta_{var\,\mathrm{x}\,sk}.var_t.skew_t + u_{it} \tag{1}$$

[20] Unless noted otherwise results are unchanged if we alternatively use the DOSPERT score in the recreational and financial domains, which are the most relevant for our purpose. Even if lottery games involving possible gains can be seen as financial decisions, the (relatively low) level of stakes may also make our experiment more comparable to risk-taking in the recreational domain (like scratch games people may play from time to time for fun).

The estimation is run on a total of 1,848 observations, corresponding to 308 subjects each making six choices. We estimate two versions of the model in Eq. (1). First, in model (1), we consider only the direct effects of variance and skewness (i.e., we assume $\beta_{var \times sk} = 0$). Second, we add the interaction term between the two moments (models (2) to (5)) with and without control variables (risk preferences and socio-demographics). Due to missing observations, the models including income are run on a total of 1,770 observations, corresponding to 295 subjects each making six choices. Each random-effect model is estimated using Generalized Least Squares (GLS).[21] Results are shown in Table 4.

The two models produce comparable estimates for the direct effect of variance and skewness, confirming that subjects value lotteries that have a smaller variance or a larger skewness more. The interaction term between variance and skewness is not found statistically significant. The expected change in CE following a change in lottery variance and skewness is rather moderate and in line with what was shown on Figure 1: considering two lotteries with identical skewness, the estimated coefficients in the model without interaction imply that moving from a small variance to a high variance lottery leads to a decrease in CE by around €2.50 (around 4% of the average elicited CE).[22] Similarly, when considering two lotteries with identical variance, a 0.8 increase in skewness (from -0.8 to 0 or from 0 to 0.8) induces an average increase in CE estimated at €4.72 (around 7% of the average CE).[23]

[21] We also controlled for the order of presentation of the six lotteries. Results remained unchanged.
[22] The expected change in CE moving from a lottery with variance equal to 400 to a lottery with variance equal to 1024 is computed as follows: -0.004*(1024 – 400) = -2.496.
[23] We checked if these relatively small changes in CE might have resulted from subjects not paying much attention. We ran the analysis excluding those subjects whose decision time fell in the lowest or in the highest quartile, and results remain unchanged. We also did not observe any specific tendency to select the middle row when subjects had to choose between the lottery and the sure amount.

Table 4. GLS estimation of CE as a function of lottery characteristics

	Model w/o interaction term	Models w/ interaction term					
	(1)	(2)	(3)		(4)	(5)	
			(a)	(b)		(a)	(b)
	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)
Variance	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Skewness	5.902***	5.237***	5.237***	5.237***	5.474***	5.474***	5.474***
	(0.428)	(1.117)	(1.117)	(1.117)	(1.134)	(1.134)	(1.134)
Var x Skewness	–	0.001	0.001	0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Risk preference	–	–	2.525***	2.259***	–	2.310***	1.651**
			(0.388)	(0.706)		(0.401)	(0.766)
Male (0/1)	–	–	–	–	4.659**	3.079	3.726**
					(2.037)	(1.952)	(2.070)
Age	–	–	–	–	-0.186**	-0.134*	-0.137
					(0.083)	(0.079)	(0.085)
Higher education (0/1)	–	–	–	–	-0.059	0.295	-0.052
					(2.453)	(2.328)	(2.438)
Executive occ. (0/1)	–	–	–	–	6.017**	6.082**	6.061**
					(2.853)	(2.706)	(2.835)
Log income	–	–	–	–	0.847	-0.227	0.807
					(1.821)	(1.737)	(1.810)
Constant	71.625***	71.625***	60.765***	62.299***	69.003***	65.592***	61.004***
	(1.199)	(1.199)	(2.028)	(3.147)	(12.692)	(12.056)	(13.147)
# of obs.	1,848	1,848	1,848	1,848	1,770	1,770	1,770
# of subjects	308	308	308	308	295	295	295
R-sq. overall	0.0379	0.0380	0.1207	0.0600	0.0838	0.1500	0.0940

Notes: In models (a), the risk preference variable is the general risk-taking score while in models (b), it is the global DOSPERT score; *** p<0.01, ** p<0.05, * p<0.10.

Next, we investigate whether there is heterogeneity in the valuation of lottery variance and skewness with respect to subjects' self-assessment of risk attitudes (risk-taking score) and global DOSPERT score. We distinguish between subjects for which the risk-taking score is below the median (mostly risk-averse subjects), and those for which it is above (mostly risk takers). We also test if the coefficients vary between subjects depending on how their scores computed from the DOSPERT questionnaire compare to the sample median. Results are shown in Table 5.

Table 5. GLS estimation of CE as a function of lottery characteristics for different groups of subjects

	Risk-taking score < = median	**Risk-taking score > median**	**Global DOSPERT < = median**	**Global DOSPERT > median**
	(1)	(2)	(3)	(4)
	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)
Variance	-0.007***	-0.001	-0.005***	-0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Skewness	4.263***	6.212***	5.500***	4.978***
	(1.450)	(1.689)	(1.527)	(1.630)
Var X Skewness	0.003*	-0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	69.101***	74.149***	70.360***	72.873***
	(1.782)	(1.521)	(1.808)	(1.566)
# of obs.	924	924	918	930
# of subjects	154	154	153	155
R-sq. overall	0.0478	0.0347	0.0387	0.0388

Notes: *** p<0.01, ** p<0.05, * p<0.10.

We observe some heterogeneity in subjects' valuation of variance and skewness depending on their self-assessed risk attitudes. Subjects who are characterized by a risk-taking score which is lower than the median, value lotteries with a higher variance significantly less (model (1)). On the contrary, the lottery variance does not matter for subjects who are characterized by a risk-taking score which is higher than the median (model (2)). For both groups, lotteries with a larger skewness are valued more. The coefficient of the skewness component is not statistically different between the two groups. The interaction between variance and skewness is significant (at the 10% level) only for those individuals who are willing to take less risk than the median subject. The coefficient of the interaction term is positive indicating that the valuation of a lottery with positive skewness is higher for lotteries having high variance. When subjects are classified based on their global DOSPERT measure, the variance component remains significant at the 5% level for those exhibiting a global DOSPERT which is higher than the median subject. The interaction term is not found significant in either model (3) or (4). These findings show significant heterogeneity in behavior and valuation of second and third moments of the lotteries as well as some differences in variance and skewness significance depending on which self-assessed risk attitude measure is used.[24] In Appendix F we present and discuss some robustness checks with respect to those subjects who selected the lowest CE across all six lotteries (as discussed in footnote 15).

Result 1: (a) On average, subjects value lotteries with lower variance or greater skewness more and there is no interaction between the two. (b) The most risk averse subjects exhibit a weakly significant positive interaction effect (based on the general risk-taking score, only).

To investigate further the heterogeneity in risk-taking and skewness-seeking behavior, we run regressions on the number of risk-avoiding choices and the number of skewness-seeking choices made by each subject, on subjects' characteristics. As explained in Appendix B, for each horizontal pairwise comparison of CE (F vs. D, D vs. E, F vs. E, C vs. A, A vs. B, and C vs.B; cf. Figure 1), we define a subject as a skewness seeker if they gave the more skewed lottery a higher CE. The number of skewness-seeking choices for each subject varies from 0 to 6. Similarly, for each vertical comparison (F vs.C, D vs. A, and E vs. B; cf. Figure 1), we define

[24] Replacing the DOSPERT global score with either the DOSPERT recreational or financial score generates estimated coefficients that are not statistically different from those shown in columns (3) and (4) of Table 5. However, the coefficient on the lottery variance is no longer significant for subjects taking more risk (in both domains) than the median subject.

a subject as a risk avoider if the higher variance lottery has a lower CE. The number of risk-avoiding choices for each individual varies from 0 to 3. We control for self-assessed risk attitudes and socio-demographic characteristics. To avoid multicollinearity problems, we include in separate models the risk-taking score and the DOSPERT global measure. OLS estimation results are shown in Table 6.

Table 6. OLS estimation of the number of risk-avoiding and skewness-seeking choices on subjects' characteristics

	#Risk-avoiding choices			**#Skewness-seeking choices**		
	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
	(1)	(2)	(3)	(4)	(5)	(6)
Age	0.011**	0.008	0.008	0.034***	0.030***	0.031***
Male (0/1)	-0.302**	-0.228*	-0.238*	-0.387*	-0.280	-0.328
Higher educ (0/1)	-0.239	-0.256*	-0.240	-0.593**	-0.617**	-0.593**
Log income	-0.136	-0.085	-0.133	-0.263	-0.191	-0.261
Executive occ. (0/1)	-0.240	-0.243	-0.243	-0.664**	-0.669**	-0.667**
Risk-taking score	-	-0.108***	-	-	-0.156***	-
Global DOSPERT	-	-	-0.006*	-	-	-0.005
Constant	2.435***	2.595***	3.093***	4.971***	5.202***	5.578***
Number of obs.	295	295	295	295	295	295
Adjusted R-sq	0.0586	0.1070	0.0722	0.1200	0.1519	0.1216

*** $p<0.01$, ** $p<0.05$, * $p<0.10$

The number of risk-avoiding choices is primarily explained by subjects' gender and self-assessed risk measures. In model (1) where self-assessed risk measures are not included, age and gender are the only characteristics that are statistically significant, indicating that older subjects and female subjects make more risk-avoiding choices. In models (2) and (3), male subjects and subjects who consider themselves as taking more risk, make fewer risk-avoiding choices, although the effect of gender is only weakly significant. The risk-taking score has a stronger significance than the DOSPERT measure. Results from models (2) and (3) suggest that the impact of age is captured by the risk measures (see later for further discussion and evidence).

On the contrary, gender is not a significant determinant of skewness-seeking choices (it is found weakly significant only in model (4)), but age, education, and occupation are significant. Older, less educated subjects, and those who are not executives make more skewness-seeking choices on average. Subjects who exhibit a higher risk-taking score also make fewer skewness-seeking choices. The DOSPERT measure is not found to be significant.

Result 2: (a) Risk avoiders tend to be older and female and exhibit lower risk-taking scores on average and lower DOSPERT measures. (b) Skewness seekers are older, less educated, less likely to have an executive occupation and are less willing to take risk (based on the general risk-taking score).

We also ran additional regressions along the lines of Dohmen et al. (2011) to assess the relationship between self-assessed risk attitudes and subjects' socio-demographic characteristics. We ran regressions featuring the following dependent variables: the risk-taking score, and the global, recreational, and financial DOSPERT scores. Results are shown in Table E-3 in Appendix E. The willingness to take risks as measured by the four self-assessed scores is found to be higher for males and to decrease with age, as in Dohmen et al. (2011, Table 1). Whether the respondent has reached a higher education level and is working as an executive are not found significant in any of the four models. Subjects' income is found significant (at the 10% level) only in the first model, indicating that wealthier subjects are willing to take more risks in general, as measured by the self-assessed risk-taking score.

These results further our interpretation of the results in Table 6. Specifically, while gender does not directly impact on skewness-seeking behavior, male subjects have a higher risk-taking score, and correspondingly make fewer skewness-seeking choices. Age, however, seems to operate through two channels. First, older subjects take fewer risks leading to more skewness seeking. However, there is also a direct effect of age. Finally, education and occupation do not impact risk-avoiding behavior only skewness-seeking behavior, with both more educated people and executives less likely to exhibit skewness-seeking behavior. Older and female subjects therefore are more likely to exhibit both risk-avoiding and skewness-seeking behavior.

6. Structural estimation of risk preferences

So far, we have avoided the need to make structural assumptions. In this section, we follow Astebro et al. (2015) in estimating preference parameters associated with a decision model seeking to explain behavior in our experiment. In particular, we use a rank-dependent utility (RDU) model (Quiggin, 1982), which extends expected utility theory by considering probability distortion. The utility function is as follows:

$U(x) = x^{1-\alpha}/(1-\alpha)$ when $\alpha \neq 1$, and

$U(x) = \log(x)$ when $\alpha = 1$,

where α is the shape parameter of the utility function ($\alpha > 0$ for risk aversion, $\alpha < 0$ for risk loving) and x is the lottery prize plus the endowment. Under RDU, probabilities p are transformed by a probability weighting function, which we specify according to Prelec (1998)'s two-parameter function:

$$\Gamma(p) = \exp\left(-\left(-\beta ln(p)\right)^{\eta}\right)$$

where p is the probability associated with a lottery outcome ($0 < p < 1$), $\eta > 0$ is a measure of likelihood sensitivity, that is the shape of the probability weighting function, S-shaped (>1) or inverse S-shaped (<1), and $\beta > 0$ is the elevation parameter and measures the degree of optimism (<1) or pessimism (>1). We follow the empirical modelling strategy of Harrison and Rutström (2008) to estimate individual structural parameters in our sample using maximum likelihood estimation. Table 7 reports results from two models, with and without covariates.[25]

Table 7. ML estimation of risk preference parameters

	(1)		(2)	
	Coef.	(SE)	Coef.	(SE)
Utility curvature (α)				
Constant	0.761***	(0.011)	0.694***	(0.052)
Subject is male (0/1)	–	–	-0.042*	(0.022)
Subject's age	–	–	0.004***	(0.001)
Higher education (0/1)	–	–	-0.068**	(0.027)
Executive occ. (0/1)	–	–	-0.037	(0.029)
Likelihood sensitivity (η)				
Constant	1.190***	(0.036)	1.052***	(0.138)
Subject is male (0/1)	–	–	-0.075	(0.070)
Subject's age	–	–	0.008***	(0.003)
Higher education (0/1)	–	–	-0.087	(0.095)
Executive occ. (0/1)	–	–	-0.238***	(0.077)
Optimism/Pessimism (β)				
Constant	0.837***	(0.016)	0.933***	(0.068)
Subject is male (0/1)	–	–	-0.010	(0.034)
Subject's age	–	–	-0.002*	(0.001)
Higher education (0/1)	–	–	0.005	(0.039)
Executive occ. (0/1)	–	–	0.039	(0.057)
# of obs.	28,336		28,336	
# of subjects	308		308	
Log likelihood and test	-14,113		-13,696***	

Note: *** p<0.01, ** p<0.05, * p<0.10; Standard errors are clustered at the individual level.

Results in model (1) indicate that on average subjects are risk averse ($\alpha = 0.761 \neq 0$, p-value<0.001), have an S-shaped probability weighting function ($\eta = 1.190 \neq 1$, p-

[25] These two models are also estimated for a sample where we exclude the individuals who chose the lowest CE for the six lotteries (see Table F-3 in Appendix F). Results are similar except that education and gender no longer significantly affect utility curvature.

value<0.001) and exhibit optimism ($\beta = 0.837 \neq 1$, p-value<0.001). Using model (2), we find similar results when computing the three parameters at the sample mean.[26] Results from model (2) show that older subjects, females, and less educated respondents have a higher utility curvature parameter, that is a higher risk aversion. The likelihood sensitivity parameter increases with age and is lower for executives. In particular, while on average 18-year old subjects do not distort probabilities ($\eta = 1.037$), 76-year old subjects are oversensitive ($\eta = 1.474$). Similarly, on average executive do not distort probabilities ($\eta = 1.010$), while non-executives do ($\eta = 1.248$). Optimism increases with age, the only significant socio-demographic variable, though weakly, and both 18-year olds ($\beta = 0.894$) and 76-year olds ($\beta = 0.752$) exhibit optimism.[27]

The fact that older subjects and females are more risk averse might explain why they make more risk-avoiding choices (see Result 2a). Less educated subjects are found more risk averse in the structural estimation. These subjects were also found taking more risk-avoiding choices only in one of the three models in Table 6 (model (2) only). Age has an impact on likelihood sensitivity (more S-shaped) as well as on the elevation parameter (greater optimism). When we use these estimates to compute the decision weights associated with each outcome for each lottery, we find that, at the sample mean, older subjects tend to overweight probabilities associated with high and middle outcomes of lotteries much more than younger subjects. These decision weights tend to favor preference for higher skewness (see Result 2b). Similarly, greater likelihood sensitivity among non-executives might explain why they make more skewness-seeking choices (see Result 2b).

These demographic differences with respect to age are similar to those of Astebro et al. (2015) who also found that older people are more risk averse and more optimistic. On the other

[26] In particular, the sample means [95% confidence interval] using model (2) are α=0.756 [0.735,0.776], η=1.204 [1.131,1.277], and β=0.840 [0.807,0.872].

[27] The average parameter values reported in this paragraph are computed with all other socio-demographic variables set at the sample mean.

hand, they found no impact of age on likelihood sensitivity. Astebro et al. (2015) also found that any observed differences between students and executives disappeared once age differences were controlled for. In contrast, our wider pool of subjects detects additional differences through occupation and education.

Result 3: (a) Subjects are on average risk averse, tend to underweight small probabilities and to overweight large probabilities, and exhibit optimism; (b) Older subjects, females and less educated subjects are more risk averse. (c) Older subjects and non-executives exhibit greater likelihood sensitivity. (d) Older subjects are more optimistic.

7. Discussion

Our main contribution is to measure risk-taking and skewness-seeking behavior and the interaction between them in a diverse population. We find that the most common behavior is risk avoidance and skewness seeking, but on average there is no interaction between the two. That is, skewness seeking is not affected by the variance of the lotteries involved, nor is risk taking affected by the skewness of the lotteries. While risk avoidance has been documented in diverse populations, skewness seeking (as compared to prudence) has not. Further, our average finding of no interaction effect contrasts with the common finding of a positive interaction effect in lab experiments and reinforces the need to study broader populations.

Despite consistent aggregate level findings, we also observe considerable heterogeneity in both skewness-seeking and risk-avoiding behavior, some of which is correlated with individual characteristics. In particular, we observe that skewness seekers are older, less educated, and less likely to have an executive occupation than non-skewness-seekers. Those with a lower risk-taking score also make more skewness-seeking choices. That is, we observe a significant positive correlation between risk-avoidance and skewness-seeking behavior.

Further, we find a weakly significant positive interaction effect among those who were more risk avoiding (as measured by those whose general risk-taking score is below the median). This segment of our sample values skewed lotteries more when the variance is higher, and higher variance lotteries higher when the skewness is higher. The estimated decision models show that older, females, and less educated respondents are more risk averse, while occupation explains likelihood sensitivity and age optimism.

Our results also contribute to evidence regarding risk-taking behavior among a broader population. First, based on experimental choices, we found that risk avoiders are more likely to be older, female, less educated, and less likely to be in an executive role than non-risk avoiders. Second, based on our survey measures, we found that both females and older subjects are less willing to take risk, while no other characteristics were correlated. This finding is consistent for both the risk-taking score and the DOSPERT measures, and the same as reported by Dohmen et al. (2011).

Finally, our results also add to the literature on the correlation between survey-based and experimental measures of risk preferences. We find that the general risk-taking score measure was very informative, with the DOSPERT measures less so. The regressions in Table 6 confirm that these measures remain useful even after controlling for socio-demographics, with the general risk-taking score strongly significant. The risk-taking score is also strongly associated with the number of skewness-seeking choices, as seen in Table 6, whereas none of the DOSPERT measures were. Thus, similar to Dohmen et al. (2011), who also elicit CEs, we show the validity of these survey measures, particularly the simple risk-taking measure, in predicting behavior in an incentivized lottery task.[28]

[28] While Dohmen et al. (2011) found domain specific measures (although much simpler than DOSPERT) predictive, Deck et al. (2013) instead found that domain specific risk attitudes didn’t explain variation in experimental measures of risk preferences. Crosetto and Filippin (2016) also find weak connection to actual tasks noting low explanatory power (R-squared).

8. Conclusion

Our results validate the importance of verifying lab findings in more diverse populations as our average result of a zero interaction effect has very different implications than the typical lab finding of a positive interaction effect. On the other hand, although our sample is more diverse than a standard lab sample, we acknowledge that it is not representative of the French population as our subjects are younger and more educated than the general French population. Similarly, while the outcomes in our lotteries were considerably higher than in many lab-based studies, the magnitudes are still smaller than in many real-world scenarios. This might explain why our estimated effect sizes for variance and skewness were small even if strongly significant. On the other hand, Astebro et al. (2015) found that while increased stakes lead to less risk taking, it had no effect on how skewness affected risk taking for either students or executives. Similarly, Haering et al. (2020) found that a ten-fold increase in stakes did not affect prudence in their lab experiment with Chinese subjects.

Even if the design of the six lotteries, particularly the expected monetary gain, was constrained by the available budget, the chosen skewness (of magnitude 0.8) is in the range of what is observed in the real world. In their study of firm returns in the US industry, Choi et al. (2021) report a median annual skewness of 0.86. In the agricultural sector, crop yield distributions described in Babcock (2015) are characterized by a skewness that varies between 0.05 and 0.62 in magnitude.[29]

Finally, for a clean design, we focused only on lotteries involving gains, yet many important real-world examples, such insurance, climate risk, and health decisions involve losses, often of a substantial magnitude. Bleichrodt and van Bruggen (2022) find very different preferences over lotteries involving only losses compared to only gains. Specifically, while risk

[29] In Babcock (2015), crop yields are assumed to follow a Beta distribution. The skewness of the three crop yield distributions is not reported by the author, but it can be computed from the shape parameters shown at the bottom of Table 1.

aversion and prudence are the modal preferences for lotteries involving only gains, this switches to risk loving and imprudent choices for lotteries involving only losses. Relatedly, studies that use mixed lotteries (Grossman and Eckel, 2015; Bougherara et al., 2021) find varying results. Bougherara et al., (2021), for example, find the most common behavior is skewness avoidance and risk taking, while Taylor (2021) shows how loss aversion accounts for at least some of the positive interaction effect found in Grossman and Eckel (2015). Given the importance of losses in real-world examples, it is crucial to understand examples such as these in future work.

Further work should also seek to explain the heterogeneity in behavior and link it to underlying theoretical models. Several recent papers provide different explanations. We demonstrate, along with Astebro et al. (2015), the role of optimism and likelihood sensitivity. A similar perspective is given by Bougherara et al. (2021) who find a link between skewness-avoiding behavior and probability weighting at the individual level. Dertwinkel-Kalt and Koster (2020) provide experimental evidence that salience (in particular, the contrast effect) can explain skewness preferences. On the other hand, Bayrak and Hey (2020) develop an alternative model of risky choices, where the skewness of the outcomes, lottery dispersion, and individual optimism all explicitly enter the decision-making process. They provide experimental evidence that their new model outperforms other common models including salience theory. Unifying these disparate findings and models should be a top priority for future work.

References

Anderhub, V., Muller, R., Schmidt, C., 2001. Design and evaluation of an economic experiment via the internet. Journal of Economic Behavior & Organization 46(2), 227-247.

Arechar, A.A., Gächter, S., Molleman, L., 2018. Conducting interactive experiments online. Experimental Economics 21(1), 99-131.

Astebro, T., Mata, J., Santos-Pinto, L., 2015. Skewness seeking: Risk loving, optimism or overweighting of small probabilities? Theory and Decision 78, 189-208.

Babcock, B.A., 2015. Using cumulative prospect theory to explain anomalous crop insurance coverage choice. American Journal of Agricultural Economics 97(5), 1371-1384.

Barraud de Lagerie, P., Sigalo Santos, L., 2018. For a few euros more. Microwork crowdsourcing and the commodification of time. Réseaux 212(6), 51-84.

Bayrak, O.K., Hey, J.D., 2020. Decisions under risk: Dispersion and skewness. Journal of Risk and Uncertainty 61, 1-24.

Berinsky, A.J., Huber, G.A., Lenz, G.S., 2012. Evaluating online labor markets for experimental research: Amazon.com's Mechanical Turk. Political Analysis 20(3), 351-368.

Blais, A.R., Weber, E.U., 2006. A Domain-Specific Risk-Taking (DOSPERT) scale for adult populations. Judgment and Decision Making 1(1), 33-47.

Bleichrodt, H., van Bruggen, P., 2022. The reflection effect for higher order risk preferences, The Review of Economics and Statistics 104(4), 1-13.

Bougherara, D., Friesen, L., Nauges, C., 2021. Risk taking with left- and right-skewed lotteries. Journal of Risk and Uncertainty 62(1), 89-112.

Breaban, A., van de Kuilen, G. Noussair, C.N., 2016. Prudence, emotional state, personality, and cognitive ability. Frontiers in Psychology 7, 1688.

Brünner, T., Levínský, R., Qiu, J., 2011. Preferences for skewness: Evidence from a binary choice experiment. The European Journal of Finance 17(7), 525-538.

Charness, G., Garcia, T., Offerman, T., Villeval, M.C., 2020. Do measures of risk attitude in the laboratory predict behavior under risk in and outside of the laboratory? Journal of Risk and Uncertainty 60, 99-123.

Chavas, J.P., Shi, G., 2015. An economic analysis of risk, management and agricultural technology. Journal of Agricultural and Resource Economics 40(1), 63-79.

Choi, D., Lou, D. Mukherjee, A., 2021. Superstar firms and college major choice. Working Paper, London School of Economics, UK.

Crosetto, P., Filippin, A., 2016. A theoretical and experimental appraisal of four risk elicitation methods. Experimental Economics 19(3), 613-641.

Cubitt, R.P., Navarro-Martinez, D., Starmer, C., 2015. On preference imprecision. Journal of Risk and Uncertainty 50(1), 1-34.

Deck, C., Lee, J., Reyes, J.A., Rosen, C.C., 2013. A failed attempt to explain within subject variation in risk taking behavior using domain specific risk attitudes. Journal of Economic Behavior & Organization 87, 1-24.

Dertwinkel-Kalt, M., Köster, M., 2020. Salience and skewness preferences. Journal of the European Economic Association 18(5), 2057-2107.

Diecidue, E., Levy, M., van de Ven, J., 2015. No aspiration to win? An experimental test of the aspiration level model. Journal of Risk and Uncertainty 51(3), 245-266.

Dohmen, T., Falk, A., Huffman, D.B., Sunde, U., 2010. Are risk aversion and impatience related to cognitive ability? American Economic Review 100 (3), 1238-1260.

Dohmen, T., Falk, A., Huffman, D.B., Sunde, U., Schupp J., Wagner, G.G., 2011. Individual risk attitudes: Measurement, determinants, and behavioral consequences. Journal of the European Economic Association 9(3), 522-550.

Dohmen, T., Falk, A., Golsteyn, B.H.H, Huffman, D.B., Sunde, U., 2017. Risk attitudes across the life course. The Economic Journal 127, F95-F116.

Ebert, S., Wiesen, D., 2011. Testing for prudence and skewness seeking. Management Science 57(7), 1334-1349.

Ebert, S., 2015. On skewed risks in economic models and experiments. Journal of Economic Behavior & Organization 112, 85-97.

Eckel, C.C., Grossman, P.J., 2002. Sex differences and statistical stereotyping in attitudes toward financial risk. Evolution and Human Behavior 23, 281-295.

Eckel, C.C., Grossman, P.J., 2008. Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. Journal of Economic Behavior & Organization 68(1), 1-17.

Emerick, K., de Janvry, A., Sadoulet, E., Dar, M.H., 2016. Technological innovations, downside risk, and the modernization of agriculture. American Economic Review 106(6), 1537-1561.

Etchart-Vincent, N., l'Haridon, O., 2011. Monetary incentives in the loss domain and behavior toward risk: An experimental comparison of three reward schemes including real losses. Journal of Risk and Uncertainty 42(1), 61-83.

Fairley, K., Sanfey, A.G., 2020. The role of demographics on adolescents' preferences for risk, ambiguity, and prudence. Journal of Economic Behavior & Organization 179, 784-796.

Filippin, A., Crosetto, P., 2016. A reconsideration of gender differences in risk attitudes. Management Science 62, 3085-3391.

Flyer, F.A., 1997. The influence of higher moments of earnings distributions on career decisions. Journal of Labor Economics 15, 689-713.

Golec, J., Tamarkin, M., 1998. Bettors love skewness, not risk, at the horse track. Journal of Political Economy 106(1), 205-225.

Grossman, P.J., Eckel, C.C., 2015. Loving the long shot: Risk taking with skewed lotteries. Journal of Risk and Uncertainty 51(3), 195-217.

Grove, W.A., Jetter, M., Papps, K.L., 2021. Career lotto? Labor supply in a superstar market. Journal of Economic Behavior & Organization 183, 362-376.

Haering, A., Heinrich, T., Mayrhofer, T., 2020. Exploring the consistency of higher-order risk preferences. International Economic Review 61(1), 283-320.

Harrison, G.W., Lau, M.I., Rustrom, E.E., 2007. Estimating risk attitudes in Denmark: A field experiment. Scandinavian Journal of Economics 109, 341-368.

Harrison, G., Rutström, E., 2008. Risk Aversion in the Laboratory. (R. M. Isaac & D. A. Norton, Eds.), Risk Aversion in Experiments (Vol. Research i). Bingley: Emerald.

Heinrich, T., Shachat, J., 2020. The development of risk aversion and prudence in Chinese children and adolescents. Journal of Risk and Uncertainty 61, 263-287.

Holt, C.A., Laury, S.K., 2002. Risk aversion and incentive effects. American Economic Review 92(5), 1644-1655.

Noussair, C.N., Trautmann, S.T., van de Kuilen, G., 2014. Higher order risk attitudes, demographics, and financial decisions. Review of Economic Studies 81, 325-355.

Prelec, D., 1998. The probability weighting function. Econometrica 66(3), 497-527.

Quiggin, J., 1982. A theory of anticipated utility. Journal of Economic Behavior & Organization 3(4), 323-343.

Reips, U.D., 2000. Chapter 4 - The Web Experiment Method: Advantages, Disadvantages, and Solutions. In Psychological Experiments on the Internet. Birnbaum (Ed.) (pp. 89–117). San Diego: Academic Press.

Renault, S., 2018. Le « crowdsourcing » de micro-tâches : contours et enjeux d’une nouvelle figure du travail. Le cas de la plateforme Foule Factory. Recherches en Sciences de Gestion 127(4), 81-105. [In French]

Reynaud, A., Couture, S., 2012. Stability of risk preference measures: Results from a field experiment on French farmers. Theory and Decision 73(2), 203-221.

Taylor, M.P., 2020. Liking the long-shot … but just as a friend. Journal of Risk and Uncertainty 61(3), 245-261.

Trautmann, S.T., van de Kuilen, G., 2018. Higher order risk attitudes: A review of experimental evidence. European Economic Review 103, 108-124.

von Gaudecker, H., van Soest, A., Wengstrom, E., 2011. Heterogeneity in risky choice behavior in a broad population. American Economic Review 101, 664-694.

Appendix A: Experimental Instructions (Translated from French)

This survey is part of a public research project supported by INRAE, the French National Research Institute for Agriculture, Food and Environment (www.inrae.fr/en).

The main purpose of this survey is to better understand how individuals make their decisions when facing uncertainty. The outcome of this survey will only be used for public research purposes.

At the end of the survey, 15 persons (among the 308 participants) will be selected at random and will receive a payment which depends on their decisions in the survey.

It is important that you be careful to: i) not be disturbed when answering the survey; ii) not do other things while answering the survey (such as navigating on the internet) and, iii) answer the survey on your own, without the help of anyone.

The survey will be anonymous. The scientists involved in this research project will not be able to make any link between your identity and your responses. The other survey participants will not be able to identify you and you won’t be able to identify them.

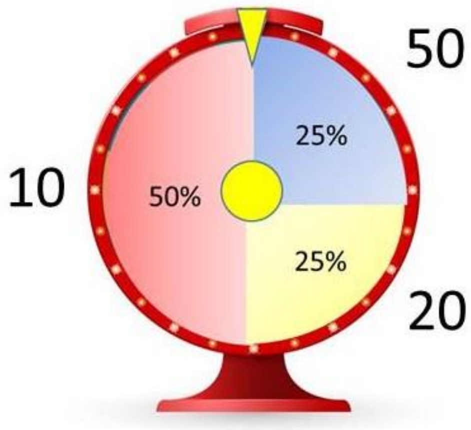
The survey will be divided in two parts. In Part I, you will be able to win some amount of money depending on your decisions. In Part II, you will be asked to fill a short questionnaire.

Part I

In this part, you will be asked to choose repeatedly between a fixed amount of money and a lottery. The lottery will always give you a chance to win one of three amounts of money (a first given amount with 50% chance of winning, a second given amount with 25% chance, and a third given amount with 25% chance).

Figure A-1 shows a typical choice task.

Figure A-1: Example of a typical decision task

<table>
<tr><th>Lottery (amounts and % chance)</th><th>Sure amount</th><th>I prefer:</th></tr>
<tr><td rowspan="9"></td><td>10</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>15</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>20</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>25</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>30</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>35</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>40</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>45</td><td>□ The lottery □ The sure amount</td></tr>
<tr><td>50</td><td>□ The lottery □ The sure amount</td></tr>
</table>

Let’s comment on this EXAMPLE. In this lottery, you have 50% chance of receiving 10, 25% chance of receiving 50 and 25% chance of receiving 20. For each row, you are asked to indicate whether you would prefer to play the lottery or to obtain the sure amount of money by ticking the preferred option.

We are interested in the amount for which you will switch from preferring the lottery to preferring the sure amount. Most likely, you will begin by choosing the lottery for small sure amounts, and at a certain point switch to the sure amount as the latter increases. If you do not want the lottery at all, you can choose to get the sure amount in the first row and then continue with the sure amount for all choices (if you prefer receiving 10 with certainty over the lottery you should also prefer getting 15 over the lottery, etc.). Where you will switch from the lottery to the sure amount depends entirely on your preferences—there are no right or wrong answers. You are allowed to switch only once.

THE ABOVE WAS JUST AN EXAMPLE. The decision tasks that you will face in Part I will be based on different values for the lottery outcomes and the sure amounts. You will be asked to undertake 6 decision tasks as the one shown in the example.

At the end of Part I and if you are among the 15 persons randomly selected for receiving a payment, then one of the 6 decision tasks will be chosen at random. Then for this decision task one row, corresponding to one of your decisions to choose between the sure amount and the lottery, will be drawn randomly. If for the selected row you had preferred the sure amount to the lottery, then your payment will be equal to this sure amount. If for the selected row you had chosen the lottery instead of the sure amount, then the lottery will be played and your payment will be equal to the outcome of the lottery.

Part II - Questionnaire

a. Self-assessment of risk attitudes

Some people like to take risks while others are more reluctant. How would you rate your attitude towards risk taking in general? Choose a number on a scale from 0 (not at all willing to take risks) to 10 (very willing to take risks).

b. DOSPERT questionnaire - Domain-specific risk-taking scale

For each of the following statements, please indicate the likelihood that you would engage in the described activity or behaviour if you were to find yourself in that situation. Provide a rating from Extremely Unlikely to Extremely Likely, using the following scale:

1	2	3	4	5	6	7
Extremely Unlikely	Moderately Unlikely	Somewhat Unlikely	Not Sure	Somewhat Likely	Moderately Likely	Extremely Likely

1. Admitting that your tastes are different from those of a friend. (S)
2. Going camping in the wilderness. (R)
3. Betting a day's income at the horse races. (F/G)
4. Investing 10% of your annual income in a moderate growth diversified fund. (F/I)
5. Drinking heavily at a social function. (H/S)
6. Taking some questionable deductions on your income tax return. (E)
7. Disagreeing with an authority figure on a major issue. (S)
8. Betting a day's income at a high-stake poker game. (F/G)
9. Having an affair with a married man/woman. (E)
10. Passing off somebody else's work as your own. (E)
11. Going down a ski run that is beyond your ability. (R)
12. Investing 5% of your annual income in a very speculative stock. (F/I)
13. Going whitewater rafting at high water in the spring. (R)
14. Betting a day's income on the outcome of a sporting event (F/G)
15. Engaging in unprotected sex. (H/S)
16. Revealing a friend's secret to someone else. (E)
17. Driving a car without wearing a seat belt. (H/S)
18. Investing 10% of your annual income in a new business venture. (F/I)
19. Taking a skydiving class. (R)
20. Riding a motorcycle without a helmet. (H/S)
21. Choosing a career that you truly enjoy over a more secure one. (S)
22. Speaking your mind about an unpopular issue in a meeting at work. (S)
23. Sunbathing without sunscreen. (H/S)
24. Bungee jumping off a tall bridge. (R)
25. Piloting a small plane. (R)
26. Walking home alone at night in an unsafe area of town. (H/S)

27. Moving to a city far away from your extended family. (S)
28. Starting a new career in your mid-thirties. (S)
29. Leaving your young children alone at home while running an errand. (E)
30. Not returning a wallet you found that contains $200. (E)

Note. E = Ethical, F = Financial, H/S = Health/Safety, R = Recreational, and S = Social.

c. Socio-demographic questionnaire

Age:

Gender: □ male □ female

What is your highest education level? [coded from 7 to 0]
□ *Bac +5 ou plus* [Master's degree or beyond]
□ *Bac +4* [Intermediate degree between bachelor's and master's degree]
□ *Bac +3 (Licence ou équivalent)* [Bachelor's degree]
□ *Bac +1/+2* [Baccalaureate + 1 or 2 years]
□ *Baccalauréat (général, technologique ou professionnel)* [General, technological or vocational baccalaureate; equivalent to US high-school diploma]
□ BEP, CAP or equivalent [BEP: Diploma of Occupational Studies, CAP: Certificate of Professional Aptitude]
□ *BEPC (brevet des collèges)* [certificate granted after completing the first four years of secondary education]
□ No training beyond *collèges* [*collèges*: first four years of secondary education from the ages of 11 to 15]

Individual monthly income before income tax:
□ Less than €1,100
□ Between €1,100 and €1,899
□ Between €1,900 and €2,299
□ Between €2,300 and €3,099
□ Between €3,100 and €3,999
□ Between €4,000 and €6,499
□ More than €6,500

What is your socio-professional category?
□ Farmers
□ Craftsmen, traders, company managers
□ Executives and higher intellectual occupations
□ Employees
□ Retired
□ Students
□ Unemployed

Appendix B: Individual behavior with respect to variance and skewness

We infer individual-level behavior with respect to skewness by considering the six horizontal pairwise comparisons of CE *for each subject*. For *each* horizontal comparison, we define a subject as a skewness seeker if they gave the more skewed lottery a higher CE (e.g., $CE_B > CE_A$), skewness neutral if both lotteries have the same CE (e.g., $CE_B = CE_A$), and a skewness avoider if the more skewed lottery has a lower CE (e.g., $CE_B < CE_A$).

Figure B-1 shows the proportion of subjects classified in each of the three groups. The pattern is similar for the first four (horizontal) pairwise comparisons with, in each case, 56 to 58% of subjects classified as skewness seekers, 20 to 23% as skewness neutral, and 20 to 23% as skewness avoiders. For the last two comparisons (E versus F and B versus C), we observe a larger proportion of skewness seekers (62% and 68%, respectively). These two comparisons are between lotteries for which the difference in skewness is at its maximum (1.6 instead of 0.8 for the first four comparisons).

While these comparisons reveal that the most common behavior is skewness seeking (consistent with the average results reported in the previous section), they also reveal a large minority of behavior that is not skewness seeking (as high as 44% of lottery comparisons). We checked the consistency of individual subjects' choices by counting the number of times that each subject exhibited skewness-seeking behavior out of the six lottery comparisons above, with the results shown in Figure B-2.

Around one-third of the subjects are fully consistent in either always exhibiting skewness-seeking behavior (22% of the sample) or never showing such behavior (11%). When looking at skewness-avoiding behavior (figure not shown here), we find that 139 subjects

(45%) never exhibit skewness-avoiding behavior while three subjects always exhibit such behavior.[30]

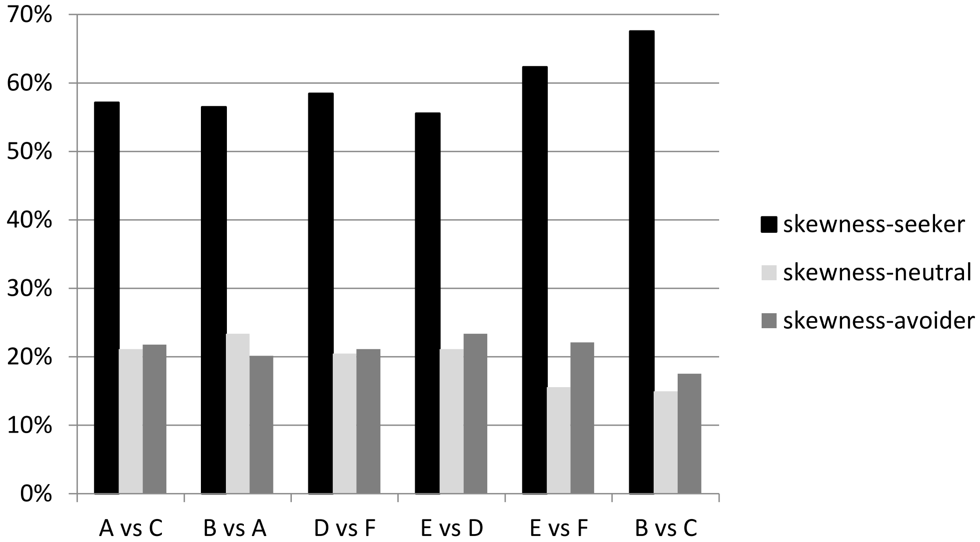


Fig. B-1. Behavior with respect to skewness inferred from pairwise lottery comparisons

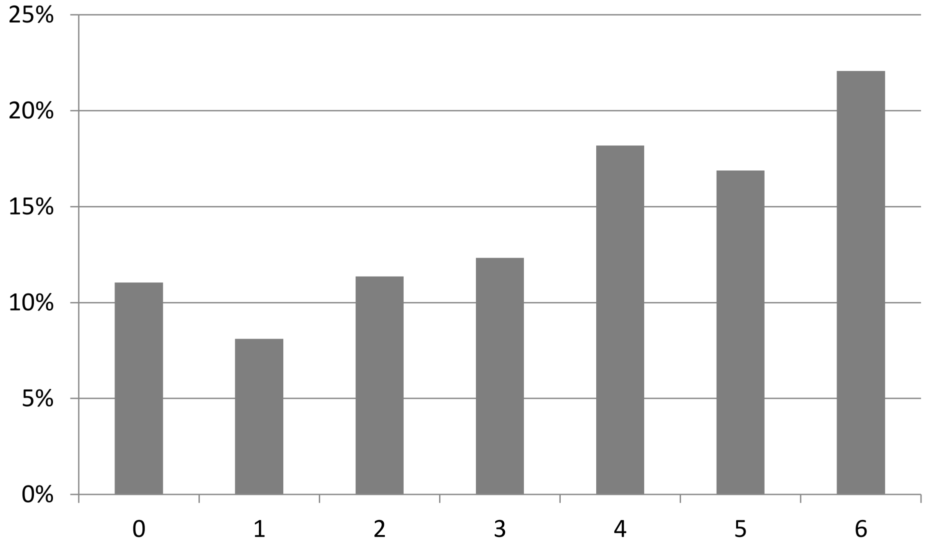


Fig. B-2. Number of times subjects exhibit skewness-seeking behavior

[30] Separate analyses of the three lotteries with low variance (A, B and C) and the three lotteries with high variance (D, E, and F) indicate the following: i) for the low-variance lotteries: 99 subjects (32%) exhibit skewness seeking for all three comparisons and 57 (19%) never show any skewness-seeking behavior; ii) for the high-variance lotteries: 113 subjects (37%) are skewness seekers for all three comparisons and 70 subjects (23%) do not exhibit skewness-seeking behavior in any of the three comparisons.

Individual behavior with respect to variance can be inferred through the three vertical pairwise comparisons. For *each* vertical comparison, we define a subject as a risk taker if they gave the higher variance lottery a higher CE (e.g., $CE_F > CE_C$), risk neutral if both lotteries have the same CE (e.g., $CE_F = CE_C$), and a risk avoider if the higher variance lottery has a lower CE (e.g., $CE_F < CE_C$). As for the case of skewness, Figure B-3 shows significant heterogeneity in the population with 45 to 51% of the subjects being classified as risk avoiders, 19 to 24% as risk neutral, and 26 to 31% as risk takers (this corresponds to the weaker differences in CEs we found in the vertical lottery comparisons).

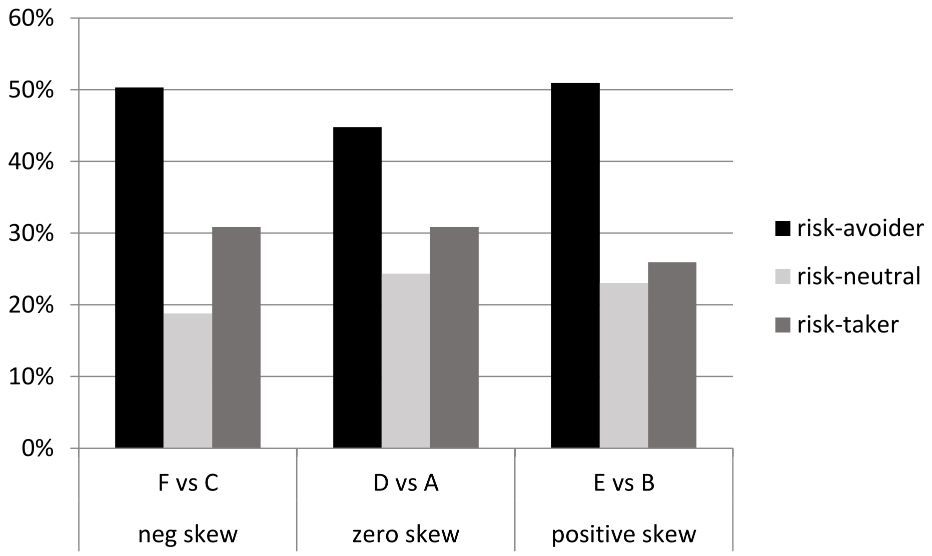


Fig. B-3. Behavior with respect to risk inferred from pairwise lottery comparisons

In Figure B-4 we check for the consistency of choices in relation to risk-avoiding behavior by counting the number of times each subject exhibits risk-avoiding behavior among the three lottery comparisons. Around half of our subjects make consistent choices by either always being risk avoiding (25%) or never being risk avoiding (25%). The remainder change their behavior depending on the skewness of the lotteries being considered.

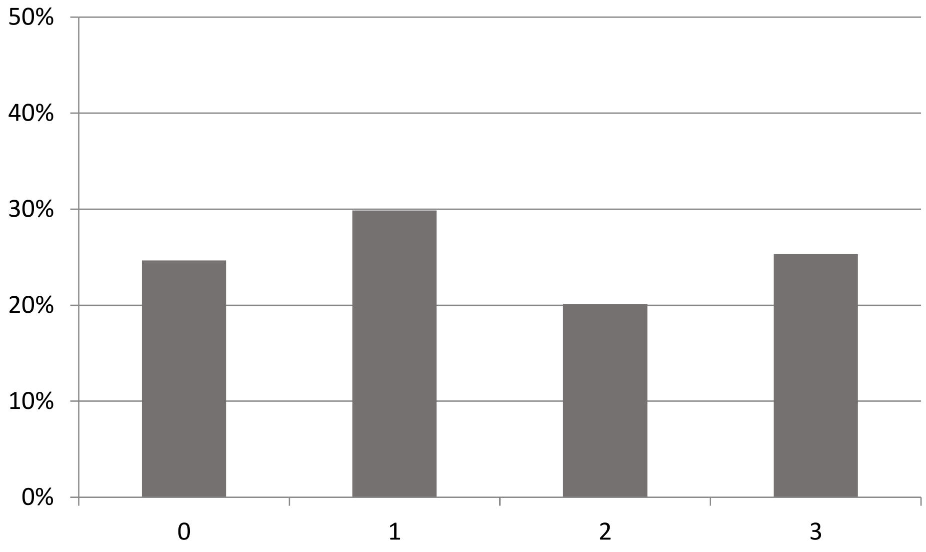


Fig. B-4. Number of times subjects exhibit risk-avoiding behavior

Finally, we computed the Spearman rank correlation coefficient between the number of risk-avoiding choices and the number of skewness-seeking choices, finding a strongly significant positive correlation of 0.51 (p-value = 0.000).[31] Thus, more skewness-seeking subjects are also more likely to make risk-avoiding choices.

[31] Noussair et al. (2014) also report a significant positive correlation between risk aversion and prudence among their panel although from actual lottery choices rather than inferred from CEs.

Appendix C: Representativeness of the sample

All national statistics were obtained from the website of INSEE (https://www.insee.fr/), the national statistics bureau of France. All the figures reported below are for the year 2020.

Structure by sex and age

As shown in Table C-1, in France in 2020, women represented 53% of the population of 20+ and men 47%. In the sample we have 44% women and 56% men. Our sample is also younger than the general French population. In our sample 77% of our subjects are aged between 20 and 50 while the corresponding proportion in France is 48%.

Table C-1. Population structure by sex and age

Age group	**France (2020)**		**Sample**	
	Female	Male	Female	Male
20-29	7.3%	7.4%	8.8%	14.6%
30-39	8.3%	7.8%	12.3%	16.9%
40-49	8.5%	8.2%	13.0%	11.7%
50-59	8.8%	8.4%	7.8%	6.8%
60-69	8.2%	7.4%	1.6%	4.2%
70 +	11.5%	8.2%	0.3%	1.9%
Total	**52.6%**	**47.4%**	**43.8%**	**56.2%**

Education level by sex and age groups

Table C-2. Percentage of population (by sex and age group) with *Baccalauréat* or higher diploma

Age group & gender	25-34		35-44		45-54		55-64	
	Female	Male	Female	Male	Female	Male	Female	Male
France	72.6	66.2	70.0	62.4	54.3	47.0	40.1	35.6
Our sample	90.9	96.4	88.9	90.9	85.3	87.5	86.7	83.3

As shown in Table C-2, our sample is more educated than the French population, on average.

Appendix D: Distribution of individual monthly income in the sample

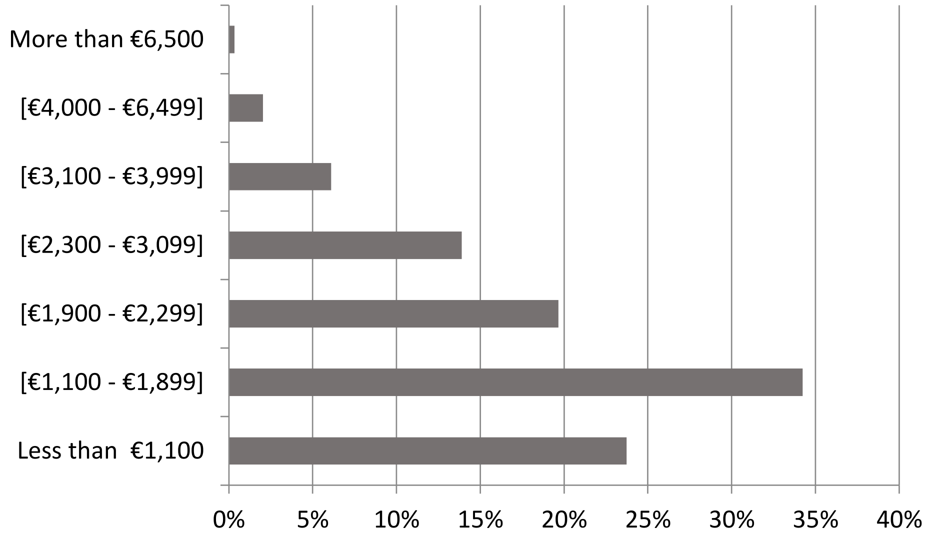


Fig. D-1. Distribution of individual monthly income in the sample (295 subjects)

Appendix E: Additional Analysis of Self-Assessed Risk Attitude Measures

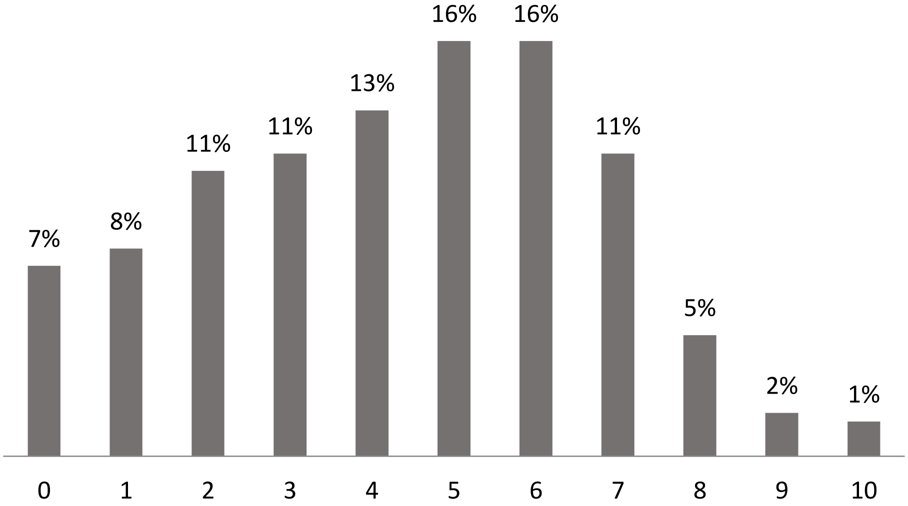


Fig. E-1. Distribution of the risk-taking score among the 308 subjects

Table E-1. Summary of answers to the DOSPERT questionnaire (N=308)

Index	Mean	Std. Dev.	Cronbach's alpha
Global	97.9	26.3	0.88
Social	30.1	6.7	0.71
Recreational	19.3	9.2	0.83
Health	17.4	7.5	0.72
Financial	16.3	7.9	0.80
Financial - Investing	9.9	4.8	0.74
Financial - Gambling	6.4	4.7	0.87
Ethical	14.8	6.2	0.63

For each of the DOSPERT domains we also compute Cronbach's alpha, a measure of consistency. Our results (the Cronbach's alpha varying from 0.63 to 0.88) are generally consistent with earlier findings from the literature (e.g., Blais and Weber, 2006; Dohmen et al., 2011, and Reynaud and Couture, 2012).

We report in Table E-2 below the mean and standard deviation (SD) of the risk-taking score and normalized DOSPERT measures for the 308 subjects. For comparison purposes, we standardize the DOSPERT variables on an 11-point scale: 0 (unwilling to take risks) to 10 (willing to take risks). The bottom of the table shows the correlation coefficients between the risk-taking score and DOSPERT items. All correlation coefficients are positive and statistically different from 0, as expected. The risk-taking score is moderately correlated with the global DOSPERT (correlation coefficient around 0.3) and has a slightly stronger correlation (around 0.4) with the DOSPERT score in social and financial-gambling domains. We note particularly high correlations between the DOSPERT scores in ethical and financial domains, in social and financial-investing domains, and in social and financial-gambling domains.

Table E-2. Correlation among the self-assessed risk attitude variables

	Risk-taking score	**Normalized DOSPERT measure**							
		Global	***Ethical***	***Health***	***Recreational***	***Social***	***Financial***	***Financial Investing***	**Financial Gambling**
Mean	4.30	4.13	2.88	3.56	4.05	6.88	3.28	4.20	2.36
SD	2.39	1.38	1.63	1.97	2.40	1.74	2.06	2.50	2.46
	Risk-taking score	***Global***	***Ethical***	***Health***	***Recreational***	***Social***	***Financial***	***Financial Investing***	**Financial Gambling**
Risk-taking score	1								
Global	0.3360***	1							
Ethical	0.1789***	0.6467***	1						
Health	0.2724**	0.7813***	0.3453***	1					
Recreational	0.1578***	0.5679***	0.1125***	0.3820***	1				
Social	0.4103***	0.7107***	0.3756***	0.4293***	0.2170***	1			
Financial	0.1278***	0.7692***	0.5242***	0.4462***	0.3184***	0.4163***	1		
Financial Investing	0.2999***	0.6041***	0.4174***	0.3172***	0.1056**	0.8292***	0.4222***	1	
Financial Gambling	0.3822***	0.5786***	0.2089***	0.3965***	0.2544***	0.8345***	0.2714***	0.3840***	1

Notes: *** p<0.01, ** p<0.05, * p<0.10.

Table E-3. OLS estimation of self-assessed risk scores as a function of socio-demographic characteristics (N = 295)

	Risk taking score		DOSPERT global		DOSPERT recreational		DOSPERT financial	
	Coef.	sig.	Coef.	sig.	Coef.	sig.	Coef.	sig.
Subject is a male (0/1)	0.684	**	0.565	***	1.008	***	0.879	***
	(0.283)		(0.155)		(0.268)		(0.234)	
Subject's age	-0.022	*	-0.029	***	-0.056	***	-0.032	***
	(0.012)		(0.006)		(0.011)		(0.010)	
Higher education (0/1)	-0.153	n.s.	-0.004	n.s.	-0.256	n.s.	-0.136	n.s.
	(0.341)		(0.187)		(0.323)		(0.282)	
Executive occ. (0/1)	-0.028	n.s.	-0.026	n.s.	0.235	n.s.	-0.005	n.s.
	(0.397)		(0.218)		(0.375)		(0.328)	
Log income	0.465	*	0.024	n.s.	0.036	n.s.	0.224	n.s.
	(0.253)		(0.139)		(0.240)		(0.209)	
Constant	1.477	n.s.	4.844	***	5.639	***	2.518	*
	(1.763)		(0.967)		(1.667)		(1.456)	
Adjusted R-squared	0.0311		0.1071		0.1246		0.0762	
Fisher-test p-value	0.0145		0.0000		0.0000		0.0000	

Note: Standardized DOSPERT scores have been used. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10. n.s. is for not significant.

Appendix F: Robustness checks, excluding subjects who have selected the lowest CE in all six lotteries

We observe that some subjects chose a CE that is less than the minimum amount that could have been earned playing the lottery. Since CEs were presented in €5 steps, these choices could still be legitimate if made by extremely risk averse subjects. However, we cannot exclude the case of subjects being confused or misunderstanding the game they had to play. We ran some robustness tests by re-estimating the regression models after excluding the 29 subjects who selected the lowest CE across all six lotteries.

Results of the GLS regression models shown in Table F-1 confirm findings obtained on the entire sample (Table 4) regarding lottery characteristics (variance and skewness) but the DOSPERT score in model (3b) and socio-demographic characteristics (male, age, and executive occupation in models 4, 5a and 5b) lose significance. Compared with results shown in Table 5, the coefficient of the variance x skewness interaction becomes non-significant when estimations are run on the reduced sample (Table F-2, column 1). The coefficient of variance also loses significance in the last two models (columns 3 and 4 in Table F-2).

Table F-1. GLS estimation of CE as a function of lottery characteristics, excluding those subjects who selected the lowest CE in all six lotteries

	Model w/o interaction term	Models w/ interaction term					
	(1)	(2)	(3)		(4)	(5)	
			(a)	(b)		(a)	(b)
	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)
Variance	-0.002*	-0.002*	-0.002*	-0.002*	-0.002*	-.0019*	-.0002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Skewness	5.230***	5.246***	5.246***	5.246***	5.509***	5.509***	5.509***
	(0.460)	(1.200)	(1.200)	(1.200)	(1.223)	(1.223)	(1.223)
Var x Skewness	–	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
		(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Risk preference	–	–	1.508***	0.982	–	1.341***	0.709
			(0.393)	(0.661)		(0.412)	(0.722)
Subject is male (0/1)	–	–	–	–	1.691	0.873	1.311
					(1.918)	(1.900)	(1.956)
Subject's age	–	–	–	–	-0.136*	-0.107	-0.116
					(0.079)	(0.078)	(0.081)
Higher education (0/1)	–	–	–	–	-4.017*	-3.344	-3.989*
					(2.372)	(2.339)	(2.373)
Executive occ. (0/1)	–	–	–	–	3.667	3.962	3.731
					(2.599)	(2.554)	(2.600)
Log income	–	–	–	–	2.176	1.370	2.175
					(1.691)	(1.679)	(1.692)
Constant	73.124***	73.124***	66.261***	68.985***	63.867***	62.445***	60.244***
	(1.166)	(1.167)	(2.125)	(3.020)	(11.806)	(11.603)	(12.369)
# of obs.	1,674	1,674	1,674	1,674	1,596	1,596	1,576
# of subjects	279	279	279	279	266	266	266
R-sq. overall	0.0330	0.0330	0.0644	0.0379	0.0581	0.0816	0.0603

Notes: In models (a), the risk preference variable is the general risk-taking score while in models (b), it is the global DOSPERT score; *** p<0.01, ** p<0.05, * p<0.10.

Table F-2. GLS estimation of CE as a function of lottery characteristics for different groups of subjects, excluding those subjects who selected the lowest CE in all six lotteries

	Risk-taking score < = median	**Risk-taking score > median**	**Global DOSPERT < = median**	**Global DOSPERT > median**
	(1)	(2)	(3)	(4)
	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)	Coef (Std Error)
Variance	-0.003*	-0.001	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Skewness	4.074**	6.226***	5.913***	4.593***
	(1.670)	(1.705)	(1.667)	(1.728)
Var X Skewness	0.002	-0.002	-0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Constant	71.632***	74.372***	72.432***	73.802***
	(1.808)	(1.505)	(1.729)	(1.572)
# of obs.	762	912	828	846
# of subjects	127	152	138	141
R-sq. overall	0.0333	0.0346	0.0278	0.0398

Notes: *** p<0.01, ** p<0.05, * p<0.10.

Table F-3. ML estimation of risk preference parameters, excluding those subjects who selected the lowest CE in all six lotteries

	(1) Coef. (SE)	(2) Coef. (SE)
Utility curvature (α)		
constant	0.716*** (0.010)	0.594*** (0.045)
Subject is male (0/1)	–	0.007 (0.019)
Subject's age	–	0.004*** (0.001)
Higher education (0/1)	–	-0.037 (0.024)
Executive occ. (0/1)	–	-0.015 (0.027)
Likelihood sensitivity (η)		
constant	1.125*** (0.033)	0.902*** (0.123)
Subject is male (0/1)	–	-0.020 (0.064)
Subject's age	–	0.007*** (0.003)
Higher education (0/1)	–	-0.012 (0.081)
Executive occ. (0/1)	–	-0.209*** (0.076)
Optimism/Pessimism (β)		
constant	0.837*** (0.017)	0.943*** (0.071)
Subject is male (0/1)	–	-0.016 (0.036)
Subject's age	–	-0.003* (0.001)
Higher education (0/1)	–	0.012 (0.041)
Executive occ. (0/1)	–	0.031 (0.058)
# of obs.	25,668	25,668
# of subjects	279	279
Log likelihood and test	-11,459	-11,216***
Tests of equality to one		
α=0	Rejected	Rejected
η=1	Rejected	Not rejected
β=1	Rejected	Not rejected