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'O Sole Mio: An Experimental Analysis of Weather and Risk Attitudes in Financial Decisions

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Although weather has been shown to affect financial markets and financial decision making, a still open question is the channel through which such influence is exerted. By employing a multiple price list method, this paper provides direct experimental evidence that sunshine and good weather promote risk-taking behavior. This effect is present whether relying on objective measures of meteorological conditions or subjective weather assessments. Finally, employing a psychological test, we find evidence that weather may affect individual risk tolerance through its effect on mood. (*JEL* C91, D03, G02)

The impact of sunlight and, more generally, weather conditions on economic activity and the stock market has been documented by several studies (see, e.g., Saunders 1993; Hirshleifer and Shumway 2003; Kamstra, Kramer, and Levi 2003; Lo and Wu 2010). These findings are of interest to financial economists because they are perceived as challenging the classic notion of market efficiency and rational stock market pricing, and they "support the view that security markets are systematically influenced by investor psychology" (Saunders 1993).

Although it can be expected that mood has an effect on human behavior, less clear is the process by which mood exerts such influence.[1] For example,

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[1] In the clinical psychology literature, good mood has been associated with low levels of humidity (Sanders and Brizzolara 1982), high levels of sunlight (Cunnigham 1979; Parrot and Sabini 1990; Schwarz and Clore 1983),

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investors in a good mood may just be characterized by a positive and upbeat bias and thus more inclined to hold stocks in their portfolios. In addition, mood may affect risk preferences and the level of individual risk aversion. Thus, people in a good mood would be more risk tolerant and more willing to hold stocks in their portfolio, and for lower expected returns.

This paper provides experimental evidence of the link between weather, mood, and risk-taking behavior in financial decisions. Specifically, we identify the existence of an effect of weather on individual risk tolerance. We find that sunlight and good weather have a positive impact on risk-taking behavior: Individuals are more risk tolerant in sunny days. This result holds for both objective and subjective measures of weather conditions. Finally, we assess the impact of weather on risk aversion by estimating the preference parameters of a power-expo utility function. We find that bad weather significantly increases our relative-risk aversion estimates.

We conduct a series of experiments in which subjects are presented with sets of lottery pairs and are required to choose one lottery out of each pair in all sets of lotteries. In our main treatment, we adopt the multiple price-list method of Holt and Laury (2002, 2005), which has become the standard approach in experimental economics to measure individuals' risk attitudes. Lottery pairs differ only by their expected returns and standard deviations; thus, our framework can be cast in terms of a standard mean-variance trade-off. Payoffs are determined as a function of the subjects' choices and the outcome of the randomization. At the end of the experiment, we ask the subjects to complete a psychological questionnaire to assess their mood and a biographical questionnaire to gather background information and their subjective assessment of the weather conditions.

Our paper sheds light on the economic importance of a risk-tolerance channel by which weather affects risk aversion. We are able to identify the risk-tolerance channel by controlling for confounding variables that might otherwise affect subjects' behavior. For instance, in our experiments the actual probabilities and payoffs of lotteries are fully transparent to subjects. In this way, the results of our study are suited to isolate the effect of weather on individual choices that happen through changes in the level of risk aversion rather than through their impact on cognitive biases (such as the perception of the objective probabilities involved in risky situations). We further control for a possible cognitive bias relative to the specific tasks involved in the experiments (specifically, the assessment of the first and second moments of the payoff distributions) by asking our subjects to complete an arithmetic quiz, aimed at assessing individuals' ability of computing means, variances, and performing basic calculations. We find that an overwhelming majority of our subjects have the mathematical skills needed to perform the simple tasks of our experimental treatments. More importantly,

high barometric pressure (Goldstein 1972), and high temperature (Cunnigham 1979; Howarth and Hoffman 1984).

we do not find any significant performance differences in good and bad weather conditions, suggesting that weather does not affect our subjects' assessment of means and variances.

The identification of the specific pathway through which weather affects risk-taking behavior is important. In this respect, we are particularly interested in investigating the effect of weather on mood. We achieve this goal by using the responses that our subjects provided to a psychological questionnaire called PANAS-X (Watson and Clark 1994). The PANAS-X methodology is widely employed in the psychology literature and it uses two main scales to measure *positive and negative affect*, the dominant dimensions of emotional experience. Positive affect is defined as feelings that reflect a level of pleasurable engagement with the environment, such as happiness, joy, excitement, enthusiasm, and contentment (Clark, Watson, and Leeka 1989). Negative affect measures feelings such as anger, anxiety, and depression. We find that feelings of joviality, self-assurance, and attentiveness display a statistically significant increase in good weather conditions, and are associated with greater risk tolerance. We interpret these findings as offering evidence of the impact of mood on risk aversion: Our subjects are more willing to accept the risks at stake in the experimental treatment when they are in a better mood. Our results are thus consistent with the analysis of Kuhnen and Knutson (2011), who find that "positive emotional states such as excitement induce people to take risks and to be confident in their ability to evaluate investment options."

We assess the robustness of our findings by administering a control group of our subjects with four additional treatments involving lists of paired decisions: a choice between (1) a risk-free and a risky lottery; (2) two fifty/fifty lotteries; (3) lotteries with equal variance, but different degrees of asymmetry (skewness); and (4) lotteries with different degrees of variance and asymmetry. Furthermore, we control for the sensitivity of our results to the dollar amounts at stake by repeating all our baseline setups in an environment in which cash prizes are multiplied by a factor of ten. All our results confirm the finding that good weather increases individuals' risk-taking behavior.

The risk-tolerance channel that we establish in this paper is not mutually exclusive with decision-making biases, such as overoptimism or other cognitive biases. In our laboratory experiment we isolate (as much as possible) the risk-tolerance channel by offering well-defined risky choice, and by controlling that subjects understand the risk-return trade-offs involved in the experiments. More generally, our analysis is a necessary starting point to assess the relevance of other behavioral biases. By using the results of the experiment of this paper as a control, it would be possible to identify the incremental effect of weather on other cognitive biases, such as "feeling lucky" or overoptimistic, and their possible interactions with the degree of risk tolerance. For example, an ambiguity aversion framework, such as the ones proposed by Halevy (2007) and Bossaerts et al. (2012), may provide an ideal setup to study the effect of weather on the cognitive evaluation process when the probability distribution of outcomes is not fully specified.

Mood-based explanations of investors' behavior and asset returns have become increasingly popular in the finance literature (see, e.g., Mehra and Sah 2002; Dougal et al. 2012; Bodoh-Creed 2012), and weather is often invoked as a possible mechanism through which changes in mood could take place. This paper is the first systematic study that offers direct evidence of the effect of weather on risk aversion in which mood is the likely transmission mechanism. As such, it allows us to assess the plausibility of a channel whose importance had only been postulated at a qualitative level in previous studies. Our results are also of particular interest for the construction of finance and economics models because we provide specific guidance on how these models should be specified to accurately describe the changes in investors' preferences in the face of weather fluctuations.

Our paper is related to several strands of literature. The first one is the emerging literature documenting the impact of alternative measures of weather conditions on financial market performance, such as bid-ask spreads (Goetzmann and Zhu 2005), the VIX (Kaplanski and Levy 2008), and the extent of economic recessions (Chhaochharia, Korniotis, and Kumar 2012). A second stream of research is the literature aimed at measuring risk aversion and, more specifically, at identifying factors that affect individual risk aversion. We refer to Cox and Harrison (2008) for a comprehensive collection of works aimed at eliciting and measuring risk aversion in laboratory experiments. More closely related to our work is the research studying the impact of mood and mood disorders, such as seasonal affective disorders (SAD), on risk aversion. The contributions of Loewenstein et al. (2001), who argue that individual response to risky situations (including risk taking) is affected by emotional influences, such as fear and anxiety, and of Kramer and Weber (2012), who find that individuals more prone to SAD are more risk averse in the winter time, fall in this category. Our analysis is also related to the psychology literature that investigates the link between mood and the tendency to take risks. For example, Isen and Patrick (1983) and Isen (2000) show that the inducement of a positive affect (such as giving the subjects an unexpected gift certificate) promotes risk taking. We show that weather can induce such a positive affect in a natural way, and we provide a framework for assessing the impact of positive affect on the willingness to take risks in financial decisions.

1. Experimental Design and Demographics

1.1 Experimental design

We conducted a controlled experiment in which subjects were exposed to different weather conditions (treatments). To operationalize the weather treatments and control the assignment of subjects, we scheduled twin pairs of experimental sessions per week in days with good and bad weather forecasts (where details of the definitions of good and bad weather conditions are provided below). Subjects could participate in the experiment only by registering for both twin sessions. Subjects were told that they would be selected for participating in one of the twin sessions, but that they could not choose which session they could attend (although they could give a preference). Subjects were randomly allocated by the experimenter to one of the two sessions, regardless of the subjects' preference. To minimize any possible cross-session influences on the outcomes of the experiments, the participants were allowed to participate only once in the experimental study.

The experiment was conducted by paper and pencil in a large classroom that allowed for exposure to the outside weather conditions. The same classroom was used in all experimental sessions. We recruited a total of 262 participants from March 2011 to September 2012, with 133 participants allocated to the bad weather treatment and 129 to the good weather treatments. Out of this pool, 208 subjects actually participated in the experiment with exactly 104 subjects in each weather treatment. The participation rate was virtually identical across weather treatments: 78.2% and 80.6% for the bad and good weather, respectively.

We used a within-subject design for the payoff and task treatments: Every subject participated in the payoff and task treatments sequentially. The first three rounds were lottery-choice tasks with low payoffs, in which subjects could win an average of about $2. The Holt and Laury (2002) risk-aversion treatment described in Section 3 was present in all the sessions, whereas the other two treatments were rotated among the following four lists of paired decisions between: (1) a risk-free and a risky lottery; (2) two fifty/fifty lotteries; (3) lotteries with equal variance but different degrees of asymmetry (skewness); and (4) lotteries with different degrees of variance and asymmetry. The details of these control treatments are described at length in Section 5. In the last three rounds, subjects were asked to complete the same tasks described above, but with lottery payoffs being ten times the lottery payoffs of the first three rounds. We observed a total of 13,620 decisions for the six payoff/task treatments.

At the end of the six rounds, and before payoffs were computed, subjects were asked to participate in three additional tasks: a questionnaire about their mood (PANAS-X), a questionnaire about socioeconomic characteristics, and an arithmetic test. The Appendix reports more details about the experimental procedures and the actual instructions that were distributed to the subjects.

1.2 Demographics

Table A.1 in the Appendix reports the demographics of the population on which the experiment was conducted. The population of the experiment presents low dispersion in age, racial group, marital status, area of birth, candidate voted in the 2008 Presidential election, and religious faith. However, the sample appears to be more evenly distributed when it comes to income, political leaning, religiousness, gender, and the extent to which the current status of

Table 1
Risk-aversion treatment

Panel A: Table of payoffs

	Option A	Option B
Decision 1 :	$2.00 w.p 10% , $1.60 w.p 90%	$3.85 w.p 10% , $0.10 w.p 90%
Decision 2 :	$2.00 w.p 20% , $1.60 w.p 80%	$3.85 w.p 20% , $0.10 w.p 80%
Decision 3 :	$2.00 w.p 30% , $1.60 w.p 70%	$3.85 w.p 30% , $0.10 w.p 70%
Decision 4 :	$2.00 w.p 40% , $1.60 w.p 60%	$3.85 w.p 40% , $0.10 w.p 60%
Decision 5 :	$2.00 w.p 50% , $1.60 w.p 50%	$3.85 w.p 50% , $0.10 w.p 50%
Decision 6 :	$2.00 w.p 60% , $1.60 w.p 40%	$3.85 w.p 60% , $0.10 w.p 40%
Decision 7 :	$2.00 w.p 70% , $1.60 w.p 30%	$3.85 w.p 70% , $0.10 w.p 30%
Decision 8 :	$2.00 w.p 80% , $1.60 w.p 20%	$3.85 w.p 80% , $0.10 w.p 20%
Decision 9 :	$2.00 w.p 90% , $1.60 w.p 10%	$3.85 w.p 90% , $0.10 w.p 10%
Decision 10 :	$2.00 w.p 100% , $1.60 w.p 0%	$3.85 w.p 100% , $0.10 w.p 0%

Panel B: Distribution of lotteries

	Option A				Option B			
	Exp	Var	Skew	Kurt	Exp	Var	Skew	Kurt
Decision 1 :	1.64	0.01	2.67	8.11	0.48	1.27	2.67	8.11
Decision 2 :	1.68	0.03	1.50	3.25	0.85	2.25	1.50	3.25
Decision 3 :	1.72	0.03	0.87	1.76	1.23	2.95	0.87	1.76
Decision 4 :	1.76	0.04	0.41	1.17	1.60	3.38	0.41	1.17
Decision 5 :	1.80	0.04	0.00	1.00	1.98	3.52	0.00	1.00
Decision 6 :	1.84	0.04	−0.41	1.17	2.35	3.38	−0.41	1.17
Decision 7 :	1.88	0.03	−0.87	1.76	2.73	2.95	−0.87	1.76
Decision 8 :	1.92	0.03	−1.50	3.25	3.10	2.25	−1.50	3.25
Decision 9 :	1.96	0.01	−2.67	8.11	3.48	1.27	−2.67	8.11
Decision 10 :	2.00	0.00	–	–	3.85	0.00	–	–

Panel A shows the table that the experimental subjects were offered in the risk-aversion treatment. Panel B reports Mean, Variance, Skewness, and Kurtosis for each of the lotteries.

the economy is a concern. Interestingly, this is also the same set of variables that other studies have already found to have a potential impact on individuals' risk attitudes (see, e.g., Benjamin, Choi, and Fisher 2010; Dohmen et al. 2011; Eckel and Grossman 2007; Guiso and Paiella 2008; Hibbert, Lawrence, and Prakash 2008; Hilary and Hui 2009; Renneboog and Spaenjers 2011; Shu, Sulaeman, and Yeung 2010). In this way, our experiment provides an ideal framework to test the hypothesis of the effect of weather on risk aversion, after controlling for other personal characteristics that can affect risk aversion.

2. Risk Aversion

2.1 Risk preference elicitation

We employed the standard experimental protocol to capture risk preference given by the lottery choice task from Holt and Laury (2002). In the Holt and Laury (2002) design, subjects are presented with a sequence of choices between two lotteries, which we call "Option A" and "Option B." Panel A of Table 1 illustrates the matrix presented to subjects in our experiments. Subjects are asked to make ten choices between ten pairs of lotteries. The amounts at stake are identical across the ten decisions, but the probabilities with which they may occur differ. For example, the first row shows that Option A offered a

10% chance of receiving \$2 and a 90% chance of receiving \$1.60. Similarly, Option B in the first row has a 10% chance of receiving a payoff of \$3.85 and a 90% chance of receiving a payoff of \$0.10, and so on.

Payoffs were decided as follows. First a six-sided die was thrown at the beginning to determine which one of the six treatments had been selected. Second, a ten-sided die was thrown to determine which one of the ten decisions had been selected. Finally, the payoffs were determined by a fair throw of 2 ten-sided dices (one with sides going from 0 to 9 and one from 00 to 90).[2] For Decision 1, the first payoff is paid if the throw of the two ten-sided dice sums to ten or less and the second payoff is paid for any other throw of the dice. Similarly, for Decision 2, the first payoff is paid if the sum of the two ten-sided dice is twenty or less, and the second payoff is paid if the sum of the two dices is more than twenty. As one proceeds down the matrix, the payoffs remain the same, but the probability of receiving the first payoff increases in both lotteries. Decision 10 is a choice between a certain amount in Option A and a certain amount in Option B.

In this experiment design, in the first nine rows Option A represents the "safer" lottery and Option B the "riskier" as the lottery in Option A displays always a lower variance than Option B, but the expected value of Option B becomes greater relative to the expected value of Option A. In the tenth row, both options yield a sure amount. The expected value, variance, and higher order moments for both lotteries are shown in Panel B of Table 1.

The matrix of ten decisions is designed in a way that only extremely risk-seeking subjects choose Option B in the first row, and only extremely risk-averse subjects choose Option A in the ninth row. A risk-neutral subject would choose A as long as the expected value of Option A is higher than the expected value of Option B (which is the case in the first four rows), and B otherwise (which is the case in the last six rows). A moderately risk-averse subject is expected to select Option A in Decision 1 and then, depending on the subject's degree of risk-aversion, switch to Option B in a later decision. A subject characterized by greater risk aversion is expected to switch later from Option A to Option B. Notice that the tenth decision does not involve any risk. Thus, this decision is used as a control that the subject has understood the instructions and he/she is paying attention to the task, but it does not have any relevance for risk aversion.

Each subject was also exposed to an additional risk-aversion task, with prizes ten times the ones described by the above table. In this way, we can estimate the effect of weather on risk aversion for greater lottery payoffs. We also conducted additional treatments aimed at checking the robustness of our findings concerning the effect of weather on risk aversion. We discuss these additional treatments in detail in Section 4.

[2] Note that an additional six-sided die was thrown at the beginning to determine which one of the six treatments had been selected to determine the payoffs.

2.2 Definitions of good and bad weather

We use three main definitions of weather quality on the date of the experiment. The amount of sunlight is our primary measure of the weather condition. Following the methodology of Hirshleifer and Shumway (2003), we collected data on how many minutes the sky was clear, partly cloudy, and overcast for the ZIP code of the city in which the experiment was conducted. The Web site of Weather Underground (www.wunderground.com) offers detailed historical data on intradaily weather conditions for most ZIP codes in the United States. Accordingly, we defined a good weather day as one in which the sky was clear for the majority of the time, that is for more than 50% of the time between 7 a.m. and the time of the end of the experiment. We called this the *objective weather* condition measure, or alternatively the *clear/overcast* measure.

Because the subjective component plays a key role in assessing the perceived quality of weather, we used the answers to the question "How do you feel about the weather?" provided in the questionnaire, as our subjective measures of good/bad weather. Specifically, subjects were asked to answer this question on a scale from 1 to 7, where 1 is "Terrible" and 7 is "Awesome." In this way, we attempted to capture individual differences in the perception of weather conditions. We pooled subjects roughly into three terciles and focused on the differences between the two extreme ones: the bottom third, which included subjects that provided an assessment of weather between 1 and 3, and the top third, which included subjects that provided a weather assessment of 6 or 7. We denoted this measure as the *subjective weather* assessment.

Finally, precipitation provides another indicator of the quality of weather in any given day. Accordingly, we define a rainy day as one in which the amount of rainfall exceeds the daily average amount in the area in which the experiment was conducted (which is 0.12 inches per day). According to this measure a rainy day is a bad weather day. We denoted this assessment of the weather condition as the objective *precipitation* measure.

2.3 Risk aversion and weather

Figure 1 reports the raw results of our analysis. In this figure, we present the experimental distribution of the safer choice, that is, the proportion of Option A choices, in each of the ten decisions. Observations are pooled according to our three measure of weather assessment: the clear/overcast in Panel A, the subjective measure in Panel B, and the precipitation measure in Panel C. Good weather is represented by a "sun" and bad weather by "rain." Note that in this figure greater risk aversion leads to a rightward shift of the frequency line. The results of our experiments are strikingly clear: Good weather promotes greater risk-taking behavior.

The impact of weather on risk-taking is particularly pronounced for Decisions 4 to 7, the marginal decisions, where the majority of subjects start switching from the safer to the riskier lottery. Instead, only a negligible fraction of subjects switch from Option A to Option B between Decision 1 and 3

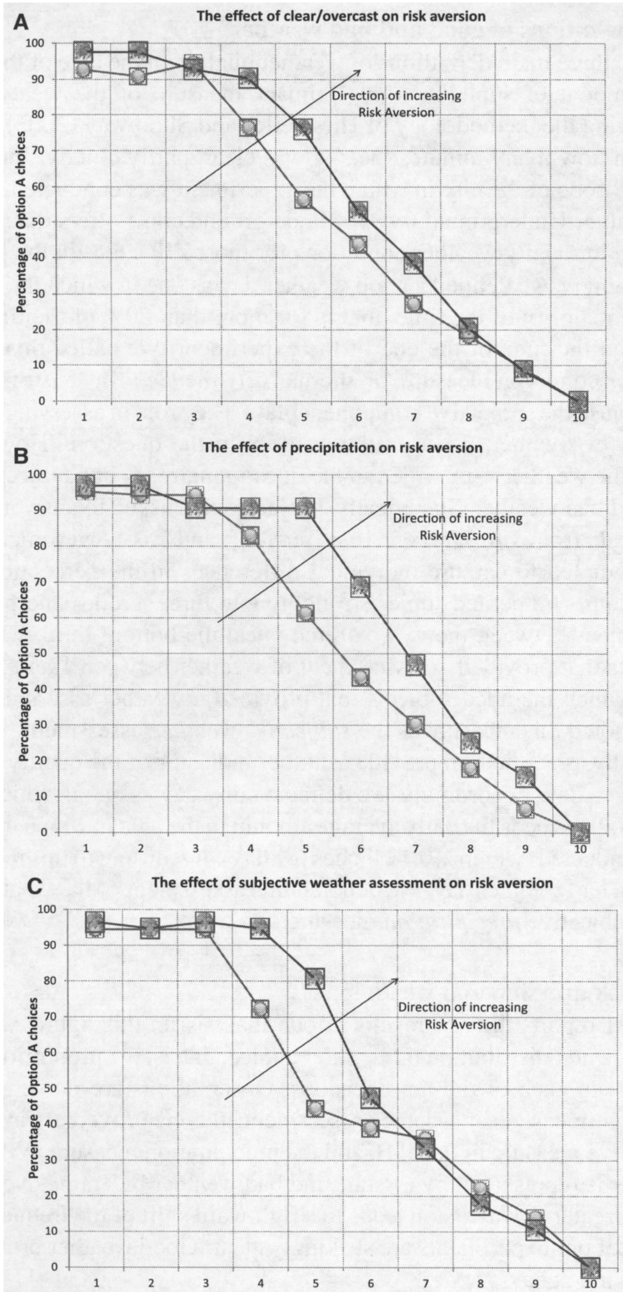


Figure 1
The effect of weather on risk aversion: Raw data, baseline case
The vertical axis reports the percentage of Option "A" (the safer lottery) choices. The horizontal axis reports the decision number. In each panel, the line with the "suns" refers to the case of good weather, whereas the other line refers to the case of bad weather. In the top two panels, observations are grouped according to the objective measures of weather. The bottom panel refers to the subjective weather assessment.

and between Decision 8 and 10. For these decisions most subjects choose either Option A (for Decisions 1–3) or Option B (for Decisions 8–10), possibly preventing a clear detection of any impact of weather conditions on risk aversion for these decisions.

2.4 Statistical significance

Are the differences in risk aversion documented in Figure 1 statistically significant? To answer this question we regress the total number of Option A choices (the safer option) on dummy variables representing each of our weather-related variables, plus some additional controls that we will discuss below. The explanatory variables we use are reported in the first column of Table 2. The *weather-related variables* are: precipitation (a dummy that equals 1 if the amount of precipitation exceeds the average daily amount, and is equal to -1 otherwise), overcast-clear (a dummy that equals 1 if the number of minutes of overcast weather and precipitation exceeds the number of minutes of clear sky, and is equal to -1 otherwise), and subjective weather (a dummy that equals 1, when the subjective assessment of weather is bad, and is equal to -1, when the subjective assessment of weather is good according to the definition reported in the previous section). The *personal characteristics variables* are: income (expressed in U.S. dollars), religious (a dummy that equals one if the subject answered "yes" to the question "Are you religious?"), and political leaning (a dummy that equals 1 if the subject self-declared as liberal or most liberal, and -1 if the subject self-declared as conservative or most conservative).[3] For all these variables the experimental distributions are reported in Table A.1.

Table 2 shows the results of our econometric analysis. All the weather-related variables appear to be strongly statistically significant at conventional confidence levels. The estimated coefficients indicate that on average our subjects shifted from Option A to Option B somewhere between Decision 5 and Decision 6 (the estimated intercept is about 5.5). This means that our subjects are, on average, risk averse, because a risk-neutral subject would switch to Option B at Decision 5. Bad weather pushed the marginal decision closer to Decision 6, whereas good weather moved the marginal decision closer to Decision 5 (the estimated coefficients on the weather-related dummies are about 0.3). The statistical significance of the weather-related variables is robust after controlling for income, religiousness, and political leaning.

The results also seem to indicate that the effect is strongest when the weather condition is measured in terms of precipitation. Although Hirshleifer and Shumway (2003) find that rain has no incremental effect on asset prices after controlling for cloud cover, we obtain that the statistical significance

[3] We have also conducted an empirical investigation involving additional controls, such as gender (a dummy that equals 1 for male and -1 for female), race, play lotteries (a dummy that equals 1 if the subject plays lotteries at least once a year), and economy concerned (a dummy that equals 1, if the subject responded "yes" to the question "Are you concerned about the economy?"). The main results are unchanged, and they are reported in the Online Appendix.

Table 2
Risk aversion (baseline)

	Precipitation	Overcast-clear	Subjective weather
Intercept	5.710	5.446	5.516
	(0.276)	(0.269)	(0.280)
Bad-good weather	0.327	0.244	0.256
	(0.084)	(0.119)	(0.093)
Income	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)
Religious	−0.270	−0.246	−0.248
(yes-no)	(0.368)	(0.374)	(0.372)
Political leaning	0.259	0.255	0.264
(liberal-conservative)	(0.236)	(0.241)	(0.242)

The table reports the estimated coefficients of the regressions of the number of A choices (the safer lottery) out of the ten decisions on a dummy variable that is equal to 1 when the weather is bad, to −1 when the weather is good, and to 0 when the weather is neither good nor bad. All regressions also include an intercept, as well as income, religiousness, and political leaning as control variables. The sample size is 194. The numbers in parentheses are the standard errors of the estimated coefficients.

of precipitation survives even after adding the clear/overcast variable to our regressions (the estimated coefficient, not reported in the table, drops to 0.256 with a t-statistic of 1.972). This difference may be due to the fact that the correlation between the two weather measures is relatively low (about 0.4) in our experimental data, thus resulting in precipitation providing additional explanatory power for the dependent variable in our regressions.

2.5 Risk aversion and high payoffs

Holt and Laury (2002) document that risk aversion is increasing in the dollar amounts at stakes in the lotteries. To control the robustness of our analysis to this effect, we repeated the experiment by multiplying all amounts by ten. Figure 2 reports the experimental frequencies for this high payoffs treatment. Just as in the case with low payoffs, bad weather reduces risk taking among the subjects. Table 3 reports the results of our analysis, which mirrors our approach in the baseline case of low payoffs. The results confirm the graphical intuition of Figure 2: For all three cases the average amount of safe choices appears to be statistically larger for the case of bad weather conditions.

2.6 Relative-risk aversion estimates

The results reported in the previous sections raise the question of assessing the quantitative impact of the weather conditions on the subjects' risk aversion. Using the proportion of safe choices in the high and low risk-aversion treatments (pooled and separately for low and high payoffs), we can estimate the preference parameters of the "power-expo" utility function proposed by Saha (1993):

$$U(x) = \frac{1-\exp\left\{-\alpha x^{1-r}\right\}}{\alpha}.$$

This specification nests the cases of constant relative-risk aversion ($\alpha \to 0$) and constant absolute-risk aversion ($r \to 0$). In this approach, for given choices of

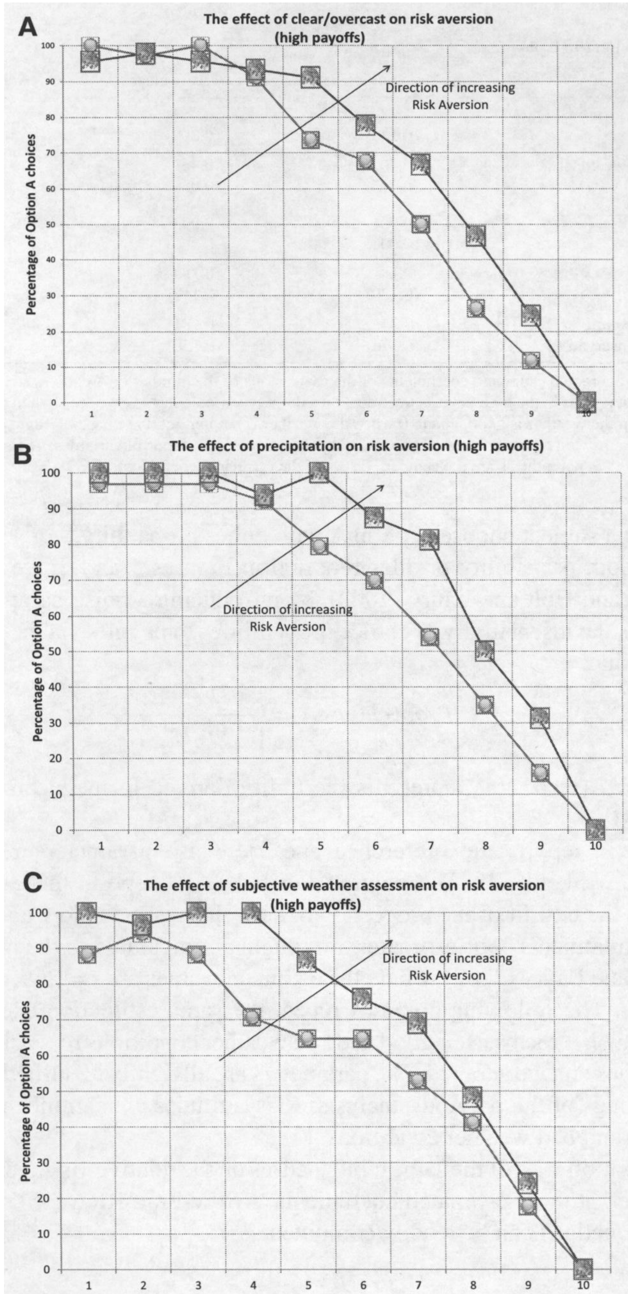


Figure 2
The effect of weather on risk aversion: Raw data, high payoffs
The vertical axis reports the percentage of Option "A" (the safer lottery) choices. The horizontal axis reports the decision number. In each panel, the line with the "suns" refers to the case of good weather, whereas the other line refers to the case of bad weather. In the top two panels, observations are grouped according to the objective measures of weather. The bottom panel refers to the subjective weather assessment.

Table 3
Risk aversion (high payoffs)

	Precipitation	Overcast-clear	Subjective weather
Intercept	6.882	6.457	6.595
	(0.143)	(0.209)	(0.187)
Bad-good weather	0.502	0.481	0.316
	(0.065)	(0.069)	(0.170)
Income	0.001	0.003	0.004
	(0.000)	(0.000)	(0.000)
Religious (yes-no)	0.181	0.183	0.175
	(0.120)	(0.117)	(0.124)
Political leaning (liberal-conservative)	0.243	0.181	0.230
	(0.176)	(0.150)	(0.157)

The table reports the estimated coefficients of the regressions of the number of A choices (the safer lottery) out of the ten decisions in the high payoffs treatment on a dummy variable that is equal to 1 when the weather is bad, to −1 when the weather is good, and to 0 when the weather is neither good nor bad. All regressions also include an intercept, as well as income, religiousness, and political leaning as control variables. The sample size is 134. The numbers in parenthesis are the standard errors of the estimated coefficients.

α and r a subject chooses option A with either probability 0 or 1. To better fit the smooth probability profiles reported in Figures 1 and 2, we follow Luce (1959), and Holt and Laury (2002), by introducing a noise parameter, μ, that captures the insensitivity of choice probabilities to payoffs via the probabilistic choice rule:

$$Prob(chooseA) = \frac{U_A^{1/\mu}}{U_A^{1/\mu} + U_B^{1/\mu}},$$

where U_A (resp. U_B) represents the utility derived from selecting Option A (resp. B).

Table 4 reports the preference and the noise parameters estimated via maximum likelihood. The column labeled "All" reports the estimates that provide the best fit of the proportion of safe choices in the low and in the high payoff treatments. Our estimates are roughly comparable to the ones reported in Holt and Laury (2002), where the estimated values are $r = .269, \alpha = .029$, and $\mu = .134$. The following columns repeat the same estimation exercise, while focusing on the subsets of good and bad weather conditions for each of the three definitions that we adopted. The parameters are all tightly identified, confirming the findings of the previous analysis: Risk attitudes are significantly different in good and bad weather conditions.

The bottom part of the same table focuses on the relative-risk aversion (RRA) computed at these estimated coefficients. Arrow-Pratt RRA for "power-expo" utility functions can be readily computed as:

$$\frac{-U''(x)\cdot x}{U'(x)} = r + \alpha(1-r)x^{1-r},$$

where x is the amount about which the RRA is being calculated. For the low payoffs treatment, we set $x = \$2.43$, and for the high payoffs treatment, we set

Table 4
Estimated preferences

	All	Subjective weather		Precipitation		Clear-overcast	
		Good	Bad	Good	Bad	Good	Bad
r	0.369	0.332	0.349	0.328	0.469	0.347	0.375
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α	0.144	0.104	0.164	0.111	0.303	0.072	0.182
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)
μ	0.128	0.180	0.109	0.139	0.078	0.149	0.114
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RRA	0.528	0.458	0.539	0.464	0.727	0.431	0.573
(low payoffs)			17.8%		56.8%		32.9%
RRA	1.050	0.916	1.197	0.966	1.344	0.724	1.209
(high payoffs)	98.7%†		30.6%		39.1%		67.2%

The top part of the table reports the estimated coefficients for the power-expo utility function, $U(x)=\left(1-\exp\{-\alpha x^{1-r}\}\right)/\alpha$, and the noise parameter μ. The numbers in parentheses are standard errors. Estimates were obtained via maximum likelihood estimation, using the proportion of safe choices in each of the ten decisions in the low and high payoffs' treatments. The bottom portion of the table reports the relative-risk aversions (RRA) computed at the estimated coefficients. For the case of "Low payoffs," the RRA was computed about the average amount at stake in the low payoff treatment, using the choices of a risk-neutral agent. For the case of "High payoffs," the RRA was computed about the average amount at stake in the high payoff treatment, using the choices of a risk-neutral agent. The percentage numbers represent the percentage increase in risk aversion within each weather category for each level of payoffs. The percentage number with the † represents the percentage increase in risk aversion between low and high payoffs.

$x = \$24.28$. These values correspond to the average amounts at stake in the two treatments.

As a point of comparison, consider first the percentage increase in risk aversion between the low and high payoff treatments. In this case, from Table 4, RRA increases from 0.528, in the case of low payoffs, to 1.050, in the case of high payoffs, which represents an increase of almost 100%. Following a similar approach, the effect of bad weather on risk aversion can be assessed by noting that bad weather determines a percentage increase of RRA that ranges from 18% (in the case of the subjective measures of weather) to 70% (in the case of high payoffs and the clear/overcast measure).

These results lead us to an additional remark. Experimental estimates of risk aversion are often taken as a benchmark in the structural analysis of economics and finance models. The results of the current paper show that this exercise could be very misleading because measuring the parameters on different weather days (and, possibly, under different environmental conditions) will generate substantially different point estimates.

3. Interpretation of the Results

In this paper we have documented the impact of weather on risky choices in an experimental setting. An important question is to assess the possible channel by which weather affects decision making. We address this issue in this section.

3.1 Arithmetic skills

In our experiment we make an explicit attempt to minimize the presence of possible confounding effects on decision making that may derive from cognitive biases (such as over-optimism). This is because in our experimental setting subjects face choices where outcomes, payoffs, and probability distributions are exogenously and explicitly specified. This means that it is difficult for a subject to be, say, overoptimistic about the outcome of the lotteries, unless he/she either does not pay attention to the task at hand, or weather affects in a systematic way a subject's ability to perform the arithmetic calculations involved in the experiment (thus, inducing a cognitive bias). We control for the first possibility by eliminating from our experimental sample subjects that choose Option A in Decision 10, our control decision. We address the second possibility in this section.

We control for possible weather-induced biases related to the arithmetic skills of the subjects as follows. Note first that in each decision of the risk-aversion treatment, the two options differ only for mean and variance. This means that we can analyze the decision-making process involved in our experiments within a mean-variance expected utility paradigm. In this context, weather may affect the subjects' choice among risky gamble because it affects their risk-tolerance (i.e., precisely the channel whose effect we are trying to isolate in our study), or because weather may lead to a systematic misestimation of a gamble's risk or expected payoff (i.e., a cognitive bias).

To test for the possible interaction between weather and the specific arithmetic skills involved in the experiment, we asked a control group of seventy subjects to complete an arithmetic quiz.[4] The difficulty in designing the arithmetic test lies in the fact that, although most subjects in our pool are likely to be familiar with the concept of expected value, not everyone may be accustomed with the specific calculations involved in the calculation of variances. However, the experimental design of Holt and Laury (2002) makes this issue relatively straightforward, as it involves binomial lotteries.

A binomial distribution with payoffs x and y and corresponding probabilities p and $1-p$ has volatility equal to $(y-x)\cdot p\cdot(1-p)$. Given that for each decision Option A and Option B have identical probability distributions, but different payoffs, the ratio of volatilities boils down to the ratio of the spreads of the outcomes for each lottery. This means that to assess the relative degree of riskiness of the two lotteries, the subjects only need to compute the ratio of the spreads correctly (i.e., $(3.85-0.10)/(2-1.60)$).

The Appendix reports the entire quiz, which consists of twenty questions. Questions are divided into three categories: calculation of averages, calculation of volatilities, and miscellaneous calculus questions.

[4] After trimming the sample from the subjects that displayed inattention in any of the multiple price list treatments, the sample size was reduced to sixty-one.

Table 5
Arithmetic test

	Clear/overcast	Precipitation	Subjective weather
Panel A: All questions			
Bad weather	0.949	0.955	0.955
	(0.012)	(0.026)	(0.016)
Good weather	0.971	0.953	0.940
	(0.013)	(0.010)	(0.017)
Bad-good p-value	0.214	0.943	0.521
Panel B: Questions on averages			
Bad weather	0.931	0.945	0.937
	(0.020)	(0.037)	(0.023)
Good weather	0.950	0.933	0.908
	(0.026)	(0.018)	(0.031)
Bad-good p-value	0.562	0.771	0.452
Panel C: Questions on volatilities			
Bad weather	0.952	0.948	0.962
	(0.015)	(0.029)	(0.021)
Good weather	0.988	0.963	0.958
	(0.012)	(0.014)	(0.018)
Bad-good p-value	0.061	0.641	0.885

The table reports the mean across all subjects of the average number of correct answers for the arithmetic test. The definitions of weather conditions are reported in the first row of the table. The numbers in parentheses represent standard errors of the estimated values. "Bad-Good p-values" are the p-values associated to the null that the average number of correct answers in bad weather is equal to the average number of correct answers in good weather. The sample size is 61. Panel A reports the average number of correct answers across all the twenty questions; Panel B reports the average number of correct answers for questions 1–3, 5, 9–11, and 14–16; and Panel C reports the average number of correct answers for questions 6–8, 13, and 18–20.

Table 5 reports the results of our analysis. Panel A shows that the average percentage of correct answers was in the 90% range. These results are virtually identical in good and bad weather conditions, regardless of the specific definition of weather. This finding seems to suggest that our experimental subjects have a very good understanding of the questions being asked, and they are able to perform the basic set of analytical computations that are required in the experiment. More importantly, the percentage of correct answers is not significantly correlated with weather, which suggests absence of a systematic bias induced by weather. Panels B and C decompose this finding into specific arithmetic skills and reveal the same pattern.

Overall, we take the outcome of this test as validation of the hypothesis that the risk-tolerance channel is the main channel at work in our experimental analysis. Note, however, that our results do not rule out the possibility that a cognitive evaluation channel may still be present in more complex decision-making problems in which probabilities and outcomes are not clearly spelled out or are ambiguous.

3.2 Psychological test

We now turn to the question of what is a plausible channel by which weather affects risk aversion. Specifically, we ask the question: Can mood be the intermediate variable that determines the shift in risk aversion that we detect in our analysis? We investigate the effect of weather on mood by using the responses that our subjects provided to a psychological questionnaire called PANAS-X (Watson and Clark 1994).

The PANAS-X methodology is widely used in the psychology literature and it uses two main scales to measure positive and negative affect, the dominant dimensions of emotional experience. Positive affect is defined as feelings that reflect a level of pleasurable engagement with the environment, such as happiness, joy, excitement, enthusiasm, and contentment (Clark, Watson, and Leeka 1989). Negative affect measures feelings such as anger, anxiety, and depression. Importantly, the lack of positive engagement does not necessarily imply negative affect (Cohen and Pressman 2006). In addition to the two higher order scales, the PANAS-X measures eleven specific affects: fear, sadness, guilt, hostility, shyness, fatigue, surprise, joviality, self-assurance, attentiveness, and serenity. The PANAS-X thus provides for mood measurement at two different levels. The Appendix reports the questionnaire as it was presented to the subjects.

The scale consists of a number of words and phrases that describe different feelings and emotions, such as cheerful, sad, and active. A control group of seventy subjects were required to assess on a scale from 1 to 5 the extent they had felt each feeling and emotion during the day of the experiment. The individual scores for each feeling were added within each mood category and rescaled on a 0-1 scale.

Table 6 reports the differences of the scores between bad and good weather for all the PANAS-X mood characteristics. A negative number in this table means that the score is larger with good weather. The results suggest that weather has an effect on the extent of positive feelings, and less so on the extent of negative feelings. More specifically, feelings of self-assurance and attentiveness display a statistically significant increase in good weather conditions, in addition to the higher order scale of positive effect.

We investigate the importance of mood as an explanation of our results, by regressing the total number of choices of Option A (the safer option) across the low and high payoffs' treatments discussed above on the PANAS-X scores in the positive emotions' categories. Table 7 reports our findings. The results are very clear: Positive feelings decrease the likelihood of choosing the safer choice, or, equivalently, better mood promotes risk-taking behavior. This effect appears to be strongly statistically significant.

The middle panel of Table 7 sheds additional light on the plausibility of mood changes as a pathway for the described effect of weather on risk-taking behavior. We decompose mood into a weather-related component, namely, the projection of the four PANAS-X mood categories reported in the table on the three weather variables defined in Section 3, and a non-weather-related component, that is, the residual of the regression. We note that overall mood accounts between 10% and 15% of the observed decision-making behavior (see "Total R^2"), and

Table 6
PANAS test

	Clear/overcast	Precipitation	Subjective weather
Panel A: General dimensions scales			
Negative affect	−0.002	−0.023	−0.012
	[0.459]	[0.130]	[0.311]
Positive affect	−0.130	−0.079	−0.103
	[0.001]	[0.061]	[0.078]
Panel B: Basic negative emotion scales			
Fear	0.015	0.047	−0.025
	[0.272]	[0.078]	[0.234]
Hostility	−0.019	−0.024	−0.036
	[0.259]	[0.085]	[0.051]
Guilt	−0.021	−0.040	−0.015
	[0.287]	[0.017]	[0.290]
Sadness	0.015	−0.017	−0.013
	[0.236]	[0.239]	[0.316]
Panel C: Basic positive emotion scales			
Joviality	−0.021	−0.013	−0.005
	[0.313]	[0.421]	[0.473]
Self-assurance	−0.118	−0.081	−0.083
	[0.004]	[0.095]	[0.104]
Attentiveness	−0.128	−0.080	−0.151
	[0.001]	[0.048]	[0.017]
Panel D: Other affective states			
Shyness	−0.056	−0.025	−0.066
	[0.079]	[0.152]	[0.013]
Fatigue	0.136	0.050	0.056
	[0.014]	[0.242]	[0.292]
Serenity	−0.142	−0.081	−0.076
	[0.003]	[0.037]	[0.114]
Surprise	0.023	−0.002	−0.037
	[0.294]	[0.489]	[0.315]

Each entry reports the spread of the scores between bad and good weather conditions in the corresponding column. The definitions of weather conditions are reported in the first row of the table. The details of the PANAS psychological categories are reported in the Appendix. The numbers in squared brackets represent the p-values for the null hypothesis that the average score in bad weather conditions is larger than the average score in good weather conditions (when the spread is negative) or that the average score in bad weather conditions is smaller than the average score in good weather conditions (when the spread is positive). The sample size is 61.

that weather accounts for a large fraction of it (see "Weather Mood R^2"). The bottom panel of Table 7 reports the p-values associated with the Sobel (1982) mediation test. The results show that the null hypothesis of no mediation of mood in the documented effect of weather on risk aversion is always rejected at conventional levels of statistical significance.

We take this evidence as offering an explanation of our results on risk aversion in terms of our subjects being more or less in a good mood and therefore more or less willing to accept the risks at stake in the experimental treatment. We note, however, that our results are likely to overstate the component of mood that is affected by weather because we have chosen to conduct our sessions during days in which bad and good weather conditions were most apparent.

Table 7
Mood, weather, and risk aversion

	Positive affect	Joviality	Self-assurance	Attentiveness
Intercept	12.096	12.096	12.096	12.096
	(0.318)	(0.329)	(0.323)	(0.317)
Mood	−0.789	−0.598	−0.491	−0.552
	(0.160)	(0.222)	(0.163)	(0.162)
Total R^2	0.160	0.137	0.137	0.111
Weather mood R^2	0.126	0.099	0.131	0.101
Nonweather mood R^2	0.034	0.039	0.005	0.010
Sobel test	[0.000]	[0.057]	[0.033]	[0.016]

The top panel reports the estimated coefficients of the regressions of the combined number of A choices in the low and high payoffs treatments on an intercept and on the standardized scores of the PANAS-X categories reported on the first row. The numbers in parentheses are the standard errors of the estimated coefficients. In the bottom panel, mood is divided into a weather-related component, the projection of the standardized scores of the PANAS-X categories reported on the first row on the three weather dummies defined in Section 3, and a non-weather-related component, the residual. Total R^2 refers to the R^2 of the regressions of A choices on both weather and non-weather-related components, whereas Weather Mood R^2 and Nonweather Mood R^2 refer to the variance explained by the two subcomponents. The row labeled "Sobel test" reports the p-values for the null hypothesis of no mediation of mood in the effect of weather on the number of safe choices. The sample size is 61.

4. Further Robustness Checks

During our experimental sessions, we also conducted several robustness checks of our hypothesis of the effect of weather on risk-taking behavior. Specifically, the subjects were asked to choose between a number of additional paired lotteries that were designed to elicit various aspects of risk attitudes.

4.1 Certainty and uncertainty equivalent

We presented a control sample of seventy subjects with two additional sets of paired lotteries. We denote the first set of tables as *Certainty Equivalent*, in that the experimental subjects are asked to choose between a risk-free lottery, which pays an increasing amount of dollars ranging from \$0 to \$1.60, and a risky lottery, in which \$.50 or \$2.50 can be earned with equal probabilities. Panel A of Table 8 reports the actual table that was given to the subjects.

We repeated the same regression analysis of the previous section, using the responses to this treatment. Panel B of Table 8 documents that bad weather produces an increase in risk aversion, which confirms the findings of our main treatment. Panel C of the same table shows that this effect is still present after multiplying the amounts at stake by ten. It has to be noted that the results are not always significant at conventional levels for the low payoffs' treatment. A possible interpretation of this result is that it could be a manifestation of the disproportionate preference for certainty, a feature that has been well established in the experimental literature (see, e.g., Gneezy, List, and Wu 2006;

Table 8
Certainty equivalent

	Option A		Option B
Panel A: Payoffs table			
Decision 1 :	\$0.00 w.p 100%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 2 :	\$0.80 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 3 :	\$0.90 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 4 :	\$1.00 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 5 :	\$1.10 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 6 :	\$1.20 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 7 :	\$1.30 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 8 :	\$1.40 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 9 :	\$1.50 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
Decision 10 :	\$1.60 w.p 50%		\$0.50 w.p 50% , \$2.50 w.p 50%
	Precipitation	Overcast-clear	Subjective weather
Panel B: Low payoffs treatment			
Intercept	3.672	3.333	3.509
	(0.344)	(0.502)	(0.521)
Bad-good weather	0.446	0.379	0.005
	(0.098)	(0.298)	(0.263)
Panel C: High payoffs treatment			
Intercept	3.075	2.699	2.677
	(0.136)	(0.159)	(0.194)
Bad-good weather	0.536	0.388	0.566
	(0.144)	(0.144)	(0.159)

Panel A reports the table of payoffs for the low payoffs treatment. In the high payoffs treatment (data not reported) all payoffs are multiplied by ten. Panels B and C report the estimated coefficients of the regressions of the number of A choices out of the ten decisions in the low and high payoffs treatment on a dummy variable that is equal to 1 when the weather is bad and −1 when the weather is good. All regressions also include an intercept, as well as income, religiousness, and political leaning as control variables. The estimates of the coefficients of the control variables are not reported in the interest of space. The sample size is 61. The numbers in parentheses are the standard errors of the estimated coefficients.

Rydval et al. 2009; Keren and Willemsen 2008; Simonsohn 2009; Andreoni and Sprenger 2012).

We control for the possible bias introduced by the presence of a risk-free option by employing the *Uncertainty Equivalent* methodology suggested by Andreoni and Sprenger (2012). Given a specific gamble, the certainty equivalent identifies the certain amount that generates indifference to such gamble, whereas the uncertainty equivalent identifies the probability mixture over the gamble's best outcome and zero that generates indifference with the same gamble. For example, consider a gamble over \$10 and \$30 that may occur with identical probabilities. The uncertainty equivalent identifies the $(q, 1-q)$ gamble over \$30 and \$0 that generates indifference. Panel A of Table 9 reports the lotteries that were presented to the subjects for this part of the experiment. This type of table has been shown to yield more robust results compared with the *Certainty Equivalent* approach that we discussed above.

Panels B and C of Table 9 document that the effect of weather on risk aversion is in general statistically significant, both in the case of low and of

Table 9
Uncertainty equivalent

	Option A	Option B
Panel A: Payoffs table		
Decision 1 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 45% , \$3.00 w.p 55%
Decision 2 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 40% , \$3.00 w.p 60%
Decision 3 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 35% , \$3.00 w.p 65%
Decision 4 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 30% , \$3.00 w.p 70%
Decision 5 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 25% , \$3.00 w.p 75%
Decision 6 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 20% , \$3.00 w.p 80%
Decision 7 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 15% , \$3.00 w.p 85%
Decision 8 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 10% , \$3.00 w.p 90%
Decision 9 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 5% , \$2.20 w.p 95%
Decision 10 :	\$1.00 w.p 50% , \$3.00 w.p 50%	\$0.00 w.p 0% , \$2.20 w.p 100%

	Precipitation	Overcast-clear	Subjective weather
Panel B: Low payoffs treatment			
Intercept	4.320	4.118	4.308
	(0.439)	(0.367)	(0.336)
Bad-good weather	0.338	0.255	0.430
	(0.093)	(0.185)	(0.106)
Panel C: High payoffs treatment			
Intercept	6.066	5.518	6.096
	(0.473)	(0.536)	(0.342)
Bad-good weather	0.561	0.843	0.707
	(0.152)	(0.215)	(0.120)

Panel A reports the table of payoffs for the low payoffs treatment. In the high payoffs treatment (data not reported) all payoffs are multiplied by ten. Panels B and C report the estimated coefficients of the regressions of the number of A choices out of the ten decisions in the low and high payoffs treatment on a dummy variable that is equal to 1 when the weather is bad and -1 when the weather is good. All regressions also include an intercept, as well as income, religiousness, and political leaning as control variables. The estimates of the coefficients of the control variables are not reported in the interest of space. The sample size is 61. The numbers in parentheses are the standard errors of the estimated coefficients.

high payoffs. We conclude that our main result on risk aversion is robust to alternative specifications of the experimental setup.

4.2 Skewness aversion

We conducted one additional robustness check involving the effect of weather on the willingness to accept gambles with varying levels of skewness. Our results suggest that bad weather increases the likelihood of the subjects choosing the option that offers a lower expected value, to avoid being exposed to negative skewness. This result holds for both low and high payoffs. We interpret these results as indication that weather increases individuals' aversion to negatively skewed gambles. The details of this analysis are reported in the Online Appendix of the paper. For an extended analysis about the preference for skewness in laboratory experiments see Bassi, Colacito, and Fulghieri (2012).

5. Concluding Remarks

This paper provides the necessary starting point of a more ambitious research agenda aimed at assessing the impact of mood on decision making under uncertainty. We provided experimental evidence of the effect of weather on risk aversion. After measuring bad and good weather conditions with a large set of variables, we concluded that bad weather increases risk aversion, whereas good weather conditions promote risk-taking behavior. We have also argued that weather affects risk aversion through its impact on mood. Thus, our results enable us to assess the effect of weather-induced changes of mood on risk aversion.

Our results are relevant to at least two research strands of the finance literature. First, we offer direct evidence for the behavioral channel underlying many empirical asset pricing studies (such as Hirshleifer and Shumway 2003 and Kamstra, Kramer, and Levi 2003). Specifically, we establish the plausibility of weather as a key factor driving fluctuations in risk aversion due to changes in mood. In this way, changes of risk aversion and, thus, discount rates are a plausible direct channel by which weather affects stock prices. Note that the channel we identify is not mutually exclusive, but rather complementary with other behavioral channels, such as overoptimism.

Second, and perhaps more importantly, our results are of particular relevance for the growing body of the finance literature that offers mood-based explanations to interpret investors' behavior and the dynamics of assets returns (see, e.g., Mehra and Sah 2002; Dougal et al. 2012; Bodoh-Creed 2012). In this paper we show in an experimental setting that mood can indeed affect risk aversion and thus stock prices.

Appendix

A.1 Instructions for Preference Elicitation

You will be distributed seven sheets. The first six sheets are numbered from 1 to 6. The last sheet is not numbered, and it will be used to report your earnings. Each numbered sheet shows ten decisions, which are numbered on the left. Each decision is a paired choice between "Option A" and "Option B." You will make sixty choices, and record your choice in the column at the far right. Only one decision will be used to determine your earnings. Before you start making your sixty choices, please let me explain how these choices will affect your earnings for this part of the experiment.

There are four dice that will be used to determine payoffs:

- The first die has six faces numbered from 1 to 6.
- The second die has ten faces numbered from 0 to 9.
- The third die has ten faces numbered from 00 to 90 in increments of ten (i.e., 00, 10, 20,...90).
- The fourth die has ten faces numbered from 0 to 9.

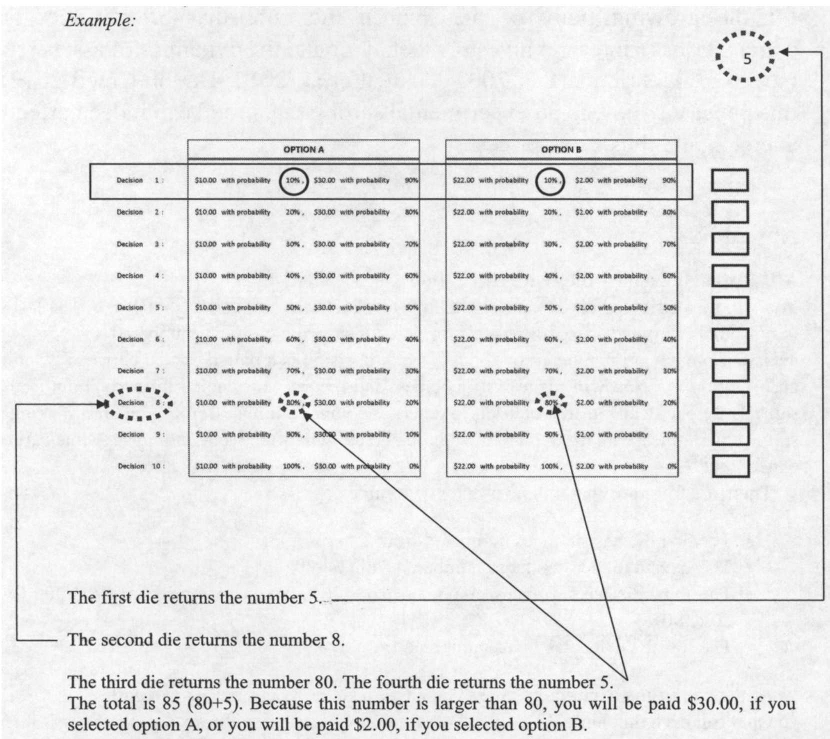
At the end of the experiment, after you have made all your choices, we will come to each of you and roll each die once. We will roll the first die to select one the six sheets. We will then roll the second die to select one of the ten decisions. We will interpret the number 0 as 10. We will use this decision to determine your earnings, as follows.

We will roll the third and fourth dice together, and we will take the sum of the numbers of the two dice; we will interpret the number 0 as 100. Now, please look at Decision 1 in the example on the following page. Option A will pay \$10 if the sum of the numbers on the third and fourth dice is ten or less, and it will pay $30 if the sum of the numbers is eleven or more. Option B will pay $22 if the sum of the numbers on the dice is ten or less, and it will pay $2 if the sum of the numbers on the dice is eleven or more. The other decisions are treated in a similar way.

In this example, the first die has returned 5, which determines the sheet number at the top right of the page; the second die has returned 8, which determines Decision 8; the third and forth dice have returned 80 and 5, respectively, with a total of 85. Because this number is greater than 80, you will be paid $30 if you selected Option A, or you will be paid $2.00 if you selected Option B.

To summarize, you will make sixty choices: For each decision row you will have to choose between Option A and Option B. You may choose A for some decisions and B for other decisions; you may change your decisions and make them in any order. When you are finished, we will roll the first die to select which of the six sheets will be used. Then we will roll the second die to select which of the ten decisions will be used. Then we will roll the third and fourth dice to determine your money earnings for the selected decision. Earnings for this choice will be paid in cash when we finish. Even though you will make sixty decisions, only one of these will end up affecting your earnings, but you will not know in advance which decision will be used. Obviously, each decision has an equal chance of being used.

Are there any questions? Now you may begin making your choices. Please does not talk with anyone while we are doing this; raise your hand if you have a question.



<u>Note</u>: In this example, if the total is 80 or less, you will be paid $10.00 if you selected "Option A" or $22.00 if you selected "Option B."

A.2 Arithmetic Test

Please answer the twenty following questions. When you are done answering, we will collect the sheets and reward you \$0.25 for each correct answer, and \$0 for each wrong answer that you provided. You can earn up to \$5.00 from this part of the experiment.

1. What is the average of 1 and 3?
2. What is the average of 2 and 6?
3. Compute the ratio of the answers to question #2 and question #1 (i.e. answer #2 divided by answer #1):
4. Please calculate 0.5×8:
5. Please calculate $(0.8 \times 1 + 0.2 \times 6)$:
6. If you have a 50% probability of winning \$1 and a 50% probability of winning \$3, how large is the difference between the two possible outcomes (e.g., \$1, \$2, \$3, ...)?
7. If you have a 50% probability of winning \$2 and a 50% probability of winning \$6, how large is the difference between the two possible outcomes (e.g., \$1, \$2, \$3, ...)?
8. Compute the ratio of the answers that you provided for question #7 and question #6 (i.e. answer #7 divided by answer #6):
9. Suppose that a flip of a fair coin gives you a win of \$1 if it lands heads up and \$3 if it lands heads down. If you flip the coin over and over, keeping track of the results, what is the average of all the wins?
10. Suppose that a flip of a fair coin gives you a win of \$2 if it lands heads up and \$6 if it lands heads down. If you flip the coin over and over, keeping track of the results, what is the average of all the wins?
11. Compute the ratio of the answers to question #10 and question #9 (i.e. answer #10 divided by answer #9):
12. Please calculate $0.5 \times (3-1)^2$:
13. Please calculate $0.8 \times (1^2) + 0.2 \times (4^2)$:
14. Suppose that a toss of a fair ten-sided die gives you a win of \$1 if it lands on 1 to 4, and \$6 if it lands on 5 to 10. This means that you have a 40% probability of winning \$1 and a 60% probability of winning \$6. If you toss the die over and over, keeping track of the results, what is the average of all the wins?
15. Suppose that a toss of a fair ten-sided die gives you a win of \$2 if it lands on 1 to 6, and \$7 if it lands on 7 to 10. This means that you have a 60% probability of winning \$2 and a 40% probability of winning \$7. If you toss the die over and over, keeping track of the results, what is the average of all the wins?
16. Compute the ratio of the answers to question #15 and question #14 (i.e., answer #15 divided by answer #14):
17. Please calculate $(4^2)/8$:
18. If you have a 40% probability of winning \$1 and a 60% probability of winning \$6, how large is the difference between the two possible outcomes (e.g., \$1, \$2, \$3, ...)?
19. If you have a 60% probability of winning \$2 and a 40% probability of winning \$7, how large is the difference between the two possible outcomes (e.g., \$1, \$2, \$3, ...)?
20. Compute the ratio of the answers to question #19 and question #18 (i.e., answer #19 divided by answer #18):

A.3 PANAS-X Test

The following is the table that was presented to the experimental subjects.

This scale consists of a number of words and phrases that describe different feelings and emotions. Read each item and then mark the appropriate answer in the space next to that word. Indicate to what extent you have felt this way today. Use the following scale to record your answers:

1	2	3	4	5
very slightly or not at all	**a little**	**moderately**	**quite a bit**	**extremely**

______ cheerful	______ sad	______ active	______ angry at self
______ disgusted	______ calm	______ guilty	______ enthusiastic
______ attentive	______ afraid	______ joyful	______ downhearted
______ bashful	______ tired	______ nervous	______ sheepish
______ sluggish	______ amazed	______ lonely	______ distressed
______ daring	______ shaky	______ sleepy	______ blameworthy
______ surprised	______ happy	______ excited	______ determined
______ strong	______ timid	______ hostile	______ frightened
______ scornful	______ alone	______ proud	______ astonished
______ relaxed	______ alert	______ jittery	______ interested
______ irritable	______ upset	______ lively	______ loathing
______ delighted	______ angry	______ ashamed	______ confident
______ inspired	______ bold	______ at ease	______ energetic
______ fearless	______ blue	______ scared	______ concentrating
______ disgusted with self	______ shy	______ drowsy	______ dissatisfied with self

A.4 Classification of PANAS-X Categories

General Dimension Scales

Negative Affect: afraid, scared, nervous, jittery, irritable, hostile, guilty, ashamed, upset, distressed
Positive Affect: active, alert, attentive, determined, enthusiastic, excited, inspired, interested, proud, strong

Basic Negative Emotion Scale

Fear: afraid, scared, frightened, nervous, jittery, shaky
Hostility: angry, hostile, irritable, scornful, disgusted, loathing
Guilt: guilty, ashamed, blameworthy, angry at self, disgusted with self, dissatisfied at self
Sadness: sad, blue, downhearted, alone, lonely

Basic Positive Emotion Scale

Joviality: happy, joyful, delighted, cheerful, excited, enthusiastic, lively, energetic
Self-Assurance: proud, strong, confident, bold, daring, fearless
Attentiveness: alert, attentive, concentrating, determined

Other Affective States

Shyness: shy, bashful, sheepish, timid
Fatigue: sleepy, tired, sluggish, drowsy
Serenity: calm, relaxed, at ease
Surprise: amazed, surprised, astonished

Table A.1
Demographic statistics

	1	2	3	4	5	6	7
In which year were you born? (1=(–,80], 2=(80,85], 3=(85,87], 4=(87,89], 5=(89,90], 6=(90,91], 7=(91,+))	18.18	5.26	5.74	15.79	13.88	19.62	21.53
Gender? (1=Male, 2=Female)	41.15	58.85					
Racial or ethnic group (1=White, 2=Black, 3=Hispanic, 4=Am Indian, 5=Asian, 6=Pacific, 7=Multi)	51.20	21.53	5.26	0.00	17.70	0.48	3.83
Marital status (1=Married, 2=Single, 3=Divorced, 4=Widowed, 5=Other)	11.48	85.17	1.44	0.96	0.96		
Current employment (1=Full-time outside, 2=Part-time outside, 3=Student, 4=Research Assistant, 5=Other part time at school)	10.53	24.40	42.11	5.74	16.75		
Major (1=Natural Sc, 2=Humanities, 3=Social Sc, 4=NA)	22.01	4.31	65.07	8.61			
Current school year (1=Fr, 2=So, 3=Jr, 4=Sr, 5=Graduate, 6=Law, 7=NA)	5.74	17.70	23.92	23.92	11.48	0.96	16.27
Personal income (1=[0–5], 2=[6–15], 3=[16–30], 4=[31–45], 5=[46–60], 6=60+)	54.07	18.66	12.44	8.13	1.44	4.78	
Family income (1=[0–40], 2=[41–80], 3=[81–120], 4=[121–160], 5=[161 – 200], 6=200+)	28.71	24.40	24.40	5.74	7.66	4.78	
Family size (Actual size; 7=7 or more)	16.27	12.44	18.18	29.67	15.79	4.78	2.87
Highest education (1=some HS, 2=HS, 3=some college, 4=college, 5=Master, 6=Doctorate)	2.87	5.74	16.27	29.19	33.49	12.44	
Geographic area of birth (1=North America, 2=South America, 3=Europe, 4=Asia, 5=Australia, 6=Africa)	82.30	1.44	2.87	11.48	0.00	0.96	
Geographic area in which lived longest (1=North America, 2=South America, 3=Europe, 4=Asia, 5=Australia, 6=Africa)	89.47	1.44	1.44	6.22	0.00	0.96	
Voted in last presidential election (1=Yes, 2=No)	48.33	51.67					
Candidate voted in last presidential election (1=Democrat, 2=Republican)	78.22	21.78					

(*continued*)

Table A.1
Continued

	1	2	3	4	5	6	7
Chance to vote in next legislative election (1=[0–20], 2=(20,40], 3=(40,60], 4=(60,80], 5=(80,100])	51.96	3.92	9.80	7.84	26.47		
Chance to vote in next presidential primary (1=[0–20], 2=(20,40], 3=(40,60], 4=(60,80], 5=(80,100])	37.35	3.01	9.64	9.64	40.36		
Chance to vote in next presidential election (1=[0–20], 2=(20,40], 3=(40,60], 4=(60,80], 5=(80,100])	12.20	1.46	3.90	4.39	78.05		
How often do you play lotteries? (1=once/week, 2=once/mo, 3=once/yr, 4=never)	1.44	4.78	22.49	70.81			
Do you gamble? (1=once/week, 2=once/mo, 3=once/yr, 4=never)	0.96	5.26	19.14	74.16			
Are you religious? (1=Yes, 2=No)	50.24	49.76					
Do you attend religious service? (1=Never, 2=Special occ, 3=once/yr, 4=once/mo, 5=evry oth wk, 6=once/week, 7=more than once/week)	16.35	21.63	16.83	15.87	9.62	15.38	4.33
Religious faith (1=Christianity, 2=Judaism, 3=Islam, 4=Buddism, 5=Induism, 6=Unaffiliated, 7=Other)	68.33	2.22	2.22	0.56	1.67	20.00	3.89
Interested in gvt and politics? (1=Uninterested, 7=Very interested)	1.44	7.18	11.96	13.88	27.75	21.53	16.27
Can people affect gvt? (1=No effect, 7=Large effect)	3.83	15.79	19.14	20.57	21.53	13.88	5.26
Describe your political leaning (1=Most liberal, 7=Most conservative)	7.18	25.84	25.84	21.05	12.44	5.74	1.91
Do you support the Tea Party? (1=Oppose, 7=Support)	26.79	10.53	13.40	39.23	7.18	1.44	0.48
Can you trust Federal gvt? (1=Almost never, 7=Almost always)	3.83	18.66	19.62	32.06	20.10	4.31	0.96
US political party you most agree with (1=Most liberal, 7=Most conservative)	8.61	29.19	20.10	24.40	10.53	5.26	1.91
Was economic stimulus good for economy? (1=Mostly bad, 7=Mostly good)	2.39	8.13	8.61	18.18	37.80	19.14	4.78
Concerned about financial situation? (1=Not at all, 7=Extremely)	5.74	15.79	16.27	11.96	24.40	14.35	11.00
How is the economy with respect to 1 yr ago? (1=Much worse, 7=Much better)	1.44	6.22	13.88	25.84	37.80	11.48	2.87
What about 1yr from now? (1=Much worse, 7=Much better)	0.48	2.39	10.53	24.88	40.67	16.27	3.83
Describe your health (1=Poor, 7=Very good)	0.00	0.00	1.91	3.83	11.96	49.28	32.54
How happy do you feel? (1=Depressed, 7=Very happy)	1.44	1.91	4.78	15.31	27.27	40.67	7.18
How do you feel about the weather? (1=Terrible, 7=Awesome)	4.78	13.40	14.83	19.14	15.79	17.70	13.40
Weather forecast in the next few weeks? (1=Much poorer, 7=Much better)	0.96	3.83	7.18	18.66	22.97	28.23	16.75

The table reports the percentages of the sample giving each response in the questionnaire. The meaning of each rating is reported underneath each question. The total sample consists of 221 subjects.

References

Andreoni, J., and C. Sprenger. 2012. Uncertainty equivalents: Testing the limits of the independence axiom. Working Paper, Stanford and UCSD.

Bassi, A., R. Colacito, and P. Fulghieri. 2012. Someone likes it skewed: An experimental analysis of skewness and risk aversion. Working Paper, University of North Carolina.

Benjamin, D. J., J. J. Choi, and G. Fisher. 2010. Religious identity and economic behavior. Working Paper, Cornell University and Yale University.

Bodoh-Creed, A. 2012. Mood, associative memory, and the evaluation of asset prices. Working Paper, Cornell University.

Bossaerts, P., P. Ghirardato, S. Guarnaschelli, and W. R. Zame. 2012. Ambiguity in asset markets: Theory and experiment. *Review of Financial Studies* 23:1325–59.

Chhaochharia, V., G. M. Korniotis, and A. Kumar. 2012. Prozac for depressed states? Effect of mood on local economic recessions. Mimeo.

Clark, L. A., D. Watson, and J. Leeka. 1989. Diurnal variation in the positive affects. *Motivation and Emotion* 13:205–34.

Cohen, S., and S. D. Pressman. 2006. Positive affect and health. *Current Directions in Psychological Science* 15:122–5.

Cox, J. C., and G. Harrison, eds. 2008. Risk aversion in experiments, Vol. 12. *Research in Experimental Economics*. Bingley, UK: Emerald.

Cunnigham, M. R. 1979. Weather, mood, and helping behavior: Quasi-experiments with sunshine samaritan. *Journal of Personality and Social Psychology* 37:1947–56.

Dohmen, T., A. Falk, D. Hoffman, and U. Sunde. 2011. Individual risk attitudes: Measurement, determinants and behavioral consequences. *Journal of The European Economic Association* 9:522–50.

Dougal, C., J. Engelberg, D. Garcia, and C. Parsons. 2012. Journalists and the stock market. *Review of Financial Studies* 25:639–79.

Eckel, C., and P. Grossman. 2007. Men, women and risk aversion: Experimental evidence. In *Handbook of Experimental Results*. Eds. C. Plott and V. Smith. North Holland: Elsevier Science.

Gneezy, U., J. A. List, and G. Wu. 2006. The uncertainty effect: When a risky prospect is valued less than its worst possible outcome. *Quarterly Journal of Economics* 121:1283–309.

Goetzmann, W. N., and N. Zhu. 2005. Rain or shine: Where is the weather effect. European Financial Management. 11:559–78.

Goldstein, K. M. 1972. Weather, mood, and internal-external control. *Perceptual Motor Skills* 35:786.

Guiso, L., and M. Paiella. 2008. Risk aversion, wealth, and background risk. *Journal of the European Economic Association* 6:1109–50.

Halevy, Y. 2007. Ellsberg revisited: An experimental study. *Econometrica* 75:503–36.

Hibbert, A. M., E. Lawrence, and A. Prakash. 2008. Are women more risk-averse than men? Working Paper, West Virginia University and Florida International University.

Hilary, G., and K. W. Hui. 2009. Does religion matter in corporate decision making in America. *Journal of Financial Economics* 93:455–73.

Hirshleifer, D., and T. Shumway. 2003. Good day sunshine: Stock returns and the weather. *Journal of Finance* 58:1009–32.

Holt, C. A., and S. K. Laury. 2002. Risk aversion and incentive effects. *American Economic Review* 92:1644–55.

———. 2005. Risk aversion and incentives: New data without order effects. *American Economic Review* 95: 902–12.

Howarth, E., and M. S. Hoffman. 1984. A multidimensional approach to the relationship between mood and weather. *British Journal of Psychology* 75:15–23.

Isen, A. 2000. Positive affect and decision making. In *Handbook of Emotion*. Eds. M. Lewis and J. Haviland-Jones. New York: Guilford.

Isen, A., and R. Patrick. 1983. The effect of positive feelings on risk taking: When the chips are down. *Organizational Behavior and Human Performance* 31:194–202.

Kaplanski, G., and H. Levy. 2008. Seasonal affective disorder and perceived market risk. Working Paper, Hebrew University.

Kamstra, M. J., L. A. Kramer, and M. D. Levi. 2003. Winter blues: A SAD stock market cycle. *American Economic Review* 93:324–43.

Kramer, L. A., and J. M. Weber. 2012. This is your portfolio on winter: Seasonal affective disorder and risk aversion in financial decision making. *Social Psychology and Personality Science* 3:193–9.

Keren, G., and M. C. Willemsen. 2008. Decision anomalies, experimenter assumptions and participants comprehension: Revaluating the uncertainty effect. *Journal of Behavioral Decision Making* 22:301–17.

Kuhnen, C. M., and B. Knutson. 2011. The influence of affect on beliefs, preferences, and financial decisions. *Journal of Financial and Quantitative Analysis* 46:605–26.

Lo, K., and S. S. Wu. 2010. The impact of seasonal affective disorder on financial analysts and equity market returns. Working Paper, The University of British Columbia, Sauder School of Business.

Loewenstein, G. F., C. K. Hsee, E. U. Weber, and N. Welch. 2001. Risk as feelings. *Psychological Bulletin* 127:267–86.

Luce, D. 1959. Individual choice behavior. New York: John Wiley & Sons.

Mehra, R., and R. Sah. 2002. Mood fluctuations, projection bias, and volatility of equity prices. *Journal of Economic Dynamics and Control* 26:869–87.

Parrot, W. G., and J. Sabini. 1990. Mood and memory under natural conditions: Evidence for mood incongruent recall. *Journal of Personality and Social Psychology* 59:321–36.

Renneboog, L., and C. Spaenjers. 2011. Religion, economic attitudes, and household finance. *Oxford Economic Papers* 64:103.

Rydval, O., A. Ortmann, S. Prokosheva, and R. Hertwig. 2009. How certain is the uncertainty effect. *Experimental Economics* 12:473–87.

Saha, A. 1993. Expo-power utility: A flexible form for absolute and relative risk aversion. *American Journal of Agricultural Economics* 75:905–13.

Sanders, J. L., and M. S. Brizzolara. 1982. Relationships between weather and mood. *Journal of General Psychology* 107:155–6.

Saunders, E. M., Jr. 1993. Stock prices and Wall Street weather. *American Economic Review* 83:1337–45.

Schwarz, N., and G. L. Clore. 1983. Mood, misattribution, and judgments of well-being: Informative and directive functions of affective states. *Journal of Personality and Social Psychology* 45:513–23.

Shu, T., J. Sulaeman, and P. E. Yeung. 2010. Local religious beliefs and organizational risk taking behaviors. Working Paper, University of Georgia and Southern Methodist University.

Simonsohn, U. 2009. Direct risk aversion: Evidence from risky prospects valued below their worst outcome. *Psychological Science* 20:686–92.

Sobel, M. E. 1982. Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology* 13:290–312.

Watson, D., and L. A. Clark. 1994. The PANAS-X: Manual for the positive and negative affect schedule - expanded form. The University of Iowa. Available at: http://ir.uiowa.edu/psychology_pubs/11.