Linking Subjective and Incentivized Risk Attitudes: The Importance of Losses [*]

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Abstract

The "general risk question" (GRQ) has been established as a quick way to meaningfully elicit subjective attitudes toward risk and correlates well with real-world behaviors involving risk. However, little is known about what aspects of attitudes toward financial risk are captured by the GRQ. We examine how answers to the GRQ correlate with different preference motives and biases toward financial risk using an incentivized choice task (n=1,730). We find that the GRQ has meaningful correlation with loss aversion and attitudes toward variation in financial losses, but much weaker to non-existent correlations with attitudes toward variation in financial gains, likelihood insensitivity, and certainty preferences. These results suggest that practical applications using the GRQ as an index for financial risk preferences may be most appropriate in settings where decisions rest on attitudes toward financial losses.

Keywords: Risk Aversion · Experimental Measurement · Prospect Theory · General Risk Question

JEL Classifications: C90 · D00 · D81

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1 Introduction

Risk attitudes play a major role in almost all economic decisions. They determine consumer preferences over products such as health care, insurance, and investment alternatives. This makes them crucial for policy analyses and highlights their importance in the design of social welfare systems. They also play a vital role in a variety of managerial decisions such compensation schemes, optimal investments, make-or-buy decisions or supply chain design.

One attractive method for assessing attitudes toward risk comes from Dohmen et al. (2011), who developed and validated a simple psychometric scale measuring willingness to take on risk. This measure is often called the "general risk question" (henceforth GRQ, Charness et al., 2013).[1] The GRQ has been found to correlate well with a number of real-world behaviors involving risk (Dohmen et al., 2011) and has high test-retest stability (Lönnqvist et al., 2015). Vieider et al. (2015) also found that the GRQ correlated with certainty equivalents for lotteries in populations across many countries. It has since been applied to various different economic questions, such as in extending the work on state-dependent utility functions by Evans and Viscusi (1991) to the domain of state-dependent risk preferences (Decker and Schmitz, 2016). Hence, the GRQ seems to be a useful simple index of risk attitudes for both applied and theory oriented work.

There are, however, two caveats to using the GRQ to measure risk attitudes. First, the GRQ measures risk *taking* rather than risk *preferences*. In addition to risk attitudes, other factors such as wealth or liquidity could influence responses to the GRQ. Second, even when focusing on the attitudes measured by the GRQ, it would be useful to know more about what aspects of attitudes toward financial risk are captured by it. The GRQ asks respondents how willing they are to take risks. Any answer to this question thus implicitly involves the respondent's interpretation of the term "risk." The decision-theoretic literature, namely due to the contribution of Rothschild and Stiglitz (1970), defines risk as variation in an outcome – a concept that is linked to the curvature of the utility function in an expected utility framework. The more colloquial definition in the Oxford English Dictionary defines "risk" as exposure to "the possibility of loss, injury, or other adverse or unwelcome circumstance" – a notion that is not automatically linked to utility curvature and requires differentiating possible outcomes into gains and losses. Since respondents are probably more likely to interpret risk by its colloquial meaning than to adopt the decision theoretical definition, it is possible that the GRQ does not measure risk attitudes according to the expected utility definition. This study focuses on determining which risk attitudes are most closely associated with GRQ responses.

The literature on financial risk attitudes has shown that they can involve a range of underlying preferences and biases. They are not limited to attitudes toward the variation in monetary outcomes, but can include concepts such as aversion to losses, preference for certainty, and non-linear weighting of probabilities (Kahneman and Tversky, 1979). Additionally, some of these attitudes may differ when considering gains or losses relative to a reference point (Harbaugh et al., 2010). These different

[1] Specifically, the GRQ asks respondents to rate their own willingness to take risks on a scale of 0 (not at all willing) to 10 (very willing). Our translation of Dohmen et al.'s original GRQ (from German) is displayed in Figure 1.

underlying sources of risk attitudes can have different implications for the outcomes of decision models (Wang and Webster, 2009; Barseghyan et al., 2013; Jaspersen and Peter, 2017). Knowing more about the links between the GRQ and different sources of risk attitudes can help determine whether the GRQ is likely to be a relevant index for particular applications.

In this study, we investigate the correlations between the GRQ and underlying financial risk preferences using an experimental study carried out both online and in the laboratory, with 1,730 total participants. We measure the five preference motives inherent in a full prospect theory preference functional (Tversky and Kahneman, 1992). Specifically, we examine utility curvature in the gain and loss domain, likelihood insensitivity in the gain and loss domain, and loss aversion. We also elicit one additional preference motive – the subjects' preference for certainty (Schmidt, 1998). Our experimental design is a modification and extension of the risk-preference elicitation techniques established by Tanaka et al. (2010) that requires few parametric assumptions. This allows us to create indices for each of the six preference motives.

We find that the GRQ correlates modestly – but statistically significantly – with preference motives involving losses, specifically aversion to variation in the loss domain (i.e., utility curvature in the loss domain) and loss aversion (i.e., difference in marginal utility between the gain domain and the loss domain). In contrast, we find no significant correlations between the GRQ and other preference motives and biases, including gain-domain utility curvature, likelihood insensitivity, and preference for certainty.

Our results suggest that individuals seem to interpret the concept of "risk-taking" in the GRQ as involving behavior towards losses. This is in line with several studies of managerial risk preferences, which similarly highlight the role of losses in the managerial interpretation of risk as a concept (March and Shapira, 1987; Koonce et al., 2005; Gómez-Mejía et al., 2007). The implication for practical applications is that the GRQ will most likely be a useful index of risk attitudes for settings in which financial risk involves a loss component. The GRQ may be less useful, though, for purely gain-side risks or in populations and settings where likelihood insensitivity is expected to be a main driver of behavior.

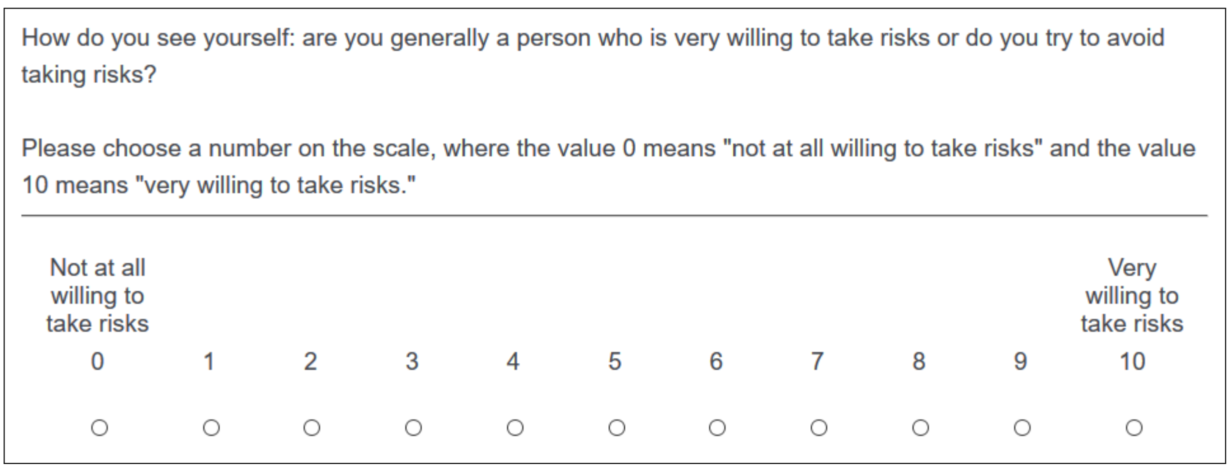
These results also contribute to a broader literature that seeks to determine the properties of different elicitation procedures for risk preferences (Charness et al., 2013, offer a review). The GRQ has been shown to correlate with lottery-based risk preferences in some prior work, including Dohmen et al. (2011), Vieider et al. (2015), and Koudstaal et al. (2015). Some prior studies have also shown no significant correlation between the GRQ and financial risk-taking for lotteries in the gain domain (Lönnqvist et al., 2015; Csermely and Rabas, 2016). The paper by Koudstaal et al. (2015) has some of the closest results to ours, finding correlations between the GRQ and measures of risk aversion over gains, loss aversion, and ambiguity aversion. They focus on the differences in risk attitudes between entrepreneurs and other workers. Their primary finding is that entrepreneurs report themselves as less risk averse in the GRQ and show lower loss aversion in the incentivized task. This importance of loss aversion is consistent with the findings in our study. They find overall that gain-domain risk aversion in their incentivized task is correlated with the GRQ. We also find positive one-way correlations between the GRQ and gain-domain risk aversion, but we find that the correlation is much stronger and more robust between GRQ and loss-domain risk aversion. Our study is the first to investigate the links between the GRQ and financial risk taking using a full prospect-theory functional that captures the primary motives identified in the literature on risk attitudes. Our findings that the GRQ correlates more strongly with loss aversion and risk aversion in the loss domain may help explain why the prior literature has found mixed results when investigating correlations of the GRQ and lottery decisions primarily in the gain domain.

2 Assumptions and Experimental Approach

2.1 General Risk Question

The variable of interest is *GRQ*, the response to the GRQ of Dohmen et al. (2011). We use our own English translation of the original German such that the question is framed as can be seen in Figure 1. As is common in applications of the GRQ, subjects could answer on a scale from 0 to 10 which was randomized to be either increasing or decreasing.

Figure 1: Experimental implementation of the GRQ


How do you see yourself: are you generally a person who is very willing to take risks or do you try to avoid taking risks?

Please choose a number on the scale, where the value 0 means "not at all willing to take risks" and the value 10 means "very willing to take risks."

Not at all willing to take risks										Very willing to take risks
0	1	2	3	4	5	6	7	8	9	10
○	○	○	○	○	○	○	○	○	○	○

2.2 Theoretical Framework for Risk Elicitation

We aim to capture individuals' underlying attitudes toward risk on a number of dimensions, including diminishing marginal utility, loss aversion, and likelihood insensitivity. In designing our elicitation task we relied on the familiar preference-functional structure from cumulative prospect theory (Tversky and Kahneman, 1992) with an addition that allows for a preference for certainty

(Schmidt, 1998). This model features several motives of risk preferences and nests certain other preference functionals.[2] We represent risk as prospects where each event $A_i \in A$ is assigned some value $x_i \in X \subset \mathbb{R}$. Preferences over prospects $(A_1, x_1; ...; A_n, x_n)$ with $x_1 \geq ... \geq x_n$ are represented by the function

$$V(\tilde{x}) = \sum_{i=1}^{n} \pi_i U(x_i). \tag{1}$$

Here, outcomes are evaluated by the function

$$U(x) = \begin{cases} u^+(x) & \text{for } x \geq 0 \\ \lambda u^-(x) & \text{for } x < 0 \end{cases} \tag{2}$$

and probabilities are weighted according to

$$\pi_i = \begin{cases} w^+(P(A_1 \cup ... \cup A_i)) - w^+(P(A_1 \cup ... \cup A_{i-1})) & \text{if } x_i \geq 0 \\ w^-(P(A_i \cup ... \cup A_n)) - w^-(P(A_{i+1} \cup ... \cup A_n)) & \text{if } x_i < 0. \end{cases} \tag{3}$$

We designed our choice task such that the decisions people made would identify the underlying preference motives toward risk within this model. The prospect theory functional has at least five such motives: utility curvature in $u^+(x)$ and $u^-(x)$, likelihood insensitivity due to the shape of the probability weighting functions in $w^+(p)$ and $w^-(p)$, and loss aversion. We assume each of these motives is determined by a single parameter, but we do not assume any further parametric structure.[3] Specifically, we assume there are parameters UC^+ and UC^- such that for all relevant values of x an increase in these parameters increases the Arrow-Pratt risk aversion coefficient (and thus, utility curvature) of $u^+(x)$ and $u^-(x)$, respectively. We assume the probability weighting function either has an S-shape or an inverse S-shape. An increase in the parameter LI^+ (LI^-) makes $w^+(p)$ ($w^-(p)$) have a less pronounced S-shape or more pronounced inverse S-shape, with greater weighting on low probabilities and lesser weighting on high probabilities. A more pronounced inverse S-shape increases the insensitivity individuals have towards changes in probabilities. Loss aversion (measured by parameter LA) appears if the slope of the utility function is steeper for losses than it is for gains.

[2]Specifically, when only considering the gain domain, the model nests expected utility theory, rank dependent expected utility and the dual theory of Yaari (1987). The prospect theory functional also acts very similar to the reference-dependent preference model of Köszegi and Rabin (2007) in surprise gambles which are arguably the correct model for lottery decisions in experiments. The model does, however, not allow for eliciting preference of certain other models, such as regret theory (Bell, 1982).

[3]For the exact technical assumptions, refer to Online Appendix A.

In addition to the five preferences in equations (1)–(3), we also consider a sixth preference motive, a preference for certainty. This motive has recently gained traction in the behavioral literature (Callen et al., 2014) and we model it by assuming that decisions involving certain consequences without any risk are evaluated by a function $v(x)$ instead of a function $u(x)$ (as, e.g., proposed in Schmidt, 1998). A general preference for certainty appears if $v(x) > u(x) \ \ \forall \ \ x \neq 0$.[4] We elicited the preference for certainty in the gain domain. We represent these preferences with the parameter CP.

The preference for certainty as we introduced it here is a variant of the so-called u/v models. These models were originally developed to explain Allais-type behavior and might be considered a substitute to introducing a probability weighting function. However, the implications of the preference for certainty are somewhat different than those of likelihood insensitivity. The commonly assumed inverse S-shaped probability weighting functions lead to more risk averse behavior for large probability gains and to more risk seeking behavior for small probability gains. The preference for certainty model as it is introduced here would predict more risk averse behavior for both large and small probability gains.

For our study, we measure the preference motives using the preference functional given above, without assuming any further parametric structure. If we assume parametric forms for the functions in equations (1)–(3), it would be possible to calibrate specific values for risk aversion coefficients, loss aversion, and others. However, such an approach adds little to the analysis of the question at hand. We nevertheless repeat our analysis using parametric preferences, finding qualitatively comparable results with only slight changes in significance. We provide the details of our parametric elicitation and the results of our analysis using these measures in Online Appendix B.

2.3 Choice Task for Eliciting Risk Attitudes

Our experiment was a modified and expanded version of the calibration procedure of Tanaka et al. (2010). They use three decision tables to elicit UC^+, LI^+ and LA. They then assume $\text{LI}^- = \text{LI}^+$ and that $u^-(x)$ is point-symmetric to $u^+(x)$ around the origin. Because we expect losses to play a crucial part in the concept of risk as it is used in the GRQ, we do not want to assume this structure ex-ante.[5] We thus amend the procedure by Tanaka et al. (2010) by adding two lottery tables which determine UC^- and LI^-. We also adjust the outcomes and probabilities in the original tables for the gain domain, such that they allow for more extreme utility curvature. For eliciting loss aversion, we use a table with fixed payments and varying probabilities, which significantly increases the range of feasible LA parameters which can be elicited.

[4] $v(0) = u(0)$ needs to be maintained such that a preference for certainty can exist within the framework of cumulative prospect theory.

[5] Furthermore, differences in utility curvature and likelihood insensitivity between gains and losses have been documented by several studies (see, e.g., Harbaugh et al., 2010; Etchart-Vincent and l'Haridon, 2011).

The six decision tables for the preference motive elicitation task are displayed in Tables 1 and 2.[6] All tables except the certainty preference table were designed such that some of the corner solutions lead to violations of first order stochastic dominance. The stochastically-dominated choices are denoted with italics in the tables. We enforced monotonicity in choices by the decision maker—once they chose Lottery B in any of the tables, the computer automatically selected Lottery B for all rows below. If they switched a preference from Lottery B back to Lottery A, all rows above switched to Lottery A. For the visualization of the probabilities we chose a simple graphical representation in the form of urns. The frequency format of probabilities implied by urns is intuitive and can easily be interpreted by subjects (Gigerenzer and Hoffrage, 1995).

We construct our scales for the preference motives by combining choices for Lotteries A and B in Tables 1 and 2.[7] For utility curvature in the gain domain, selecting Lottery A more often in GD1 and GD2 implies a more concave utility function and thus an increase in UC$^+$. We interpret this information in an ordinal sense and simply count the total number of choices for Lottery A in these two tables ($UC^+ = GD1_A + GD2_A$). The procedure for the loss domain is analogous except that here more choices of Lottery B in LD1 and LD2 increase concavity of u^-, so $UC^- = LD1_B + LD2_B$.

We structured both the gain domain and loss domain tables such that the most extreme outcome either has a small probability ($< 30\%$) or a large probability ($> 70\%$). We assume both the inflection point (for which $w''(p) = 0$) and the identity point (for which $w(p) = p$) of the probability weighting functions lie between these two probabilities. Likelihood insensitivity due to an inverse S-shaped probability weighting function then increases the preference for Lottery B in Tables GD1 and LD1 and decreases it in Tables GD2 and LD2. For identification of the concept, we use the difference in the number of choices for Lottery B in GD1 and GD2 for the gain domain ($LI^+ = GD1_B - GD2_B$) and in LD1 and LD2 for the loss domain ($LI^- = LD1_B - LD2_B$).

For the certainty preference, we adopt a procedure similar to that of Callen et al. (2014). The only table in which a certain payment appears is CP. We structured the CP table as a copy of GD1, adjusting Lottery A to have a certain outcome of \$2.00 (which is the lower outcome of Lottery A in GD1). Thus, if more choices are made for Lottery A in CP than in GD1, $v(x) > u(x)$ must hold. As we show in Online Appendix A, both expected utility theory and cumulative prospect theory with a status quo reference point predict weakly fewer choices for Lottery A in Table CP than in GD1. We thus measure the preference for certainty as the difference of Lottery A choices in CP and GD1 ($CP = CP_A - GD1_A$). In the LA table, more choices for Lottery A imply higher loss aversion, so $LA = LA_A$.

[6] The order of the risk preferences elicitation tables was randomized. Additionally, we randomized whether the safe choices were displayed on the left or on the right and whether payments and probability were vertically increasing or decreasing.

[7] In a slight abuse of terminology, we henceforth refer to these measures of preference motives as "preference scales." For ease of reference, the calculations for all preference scales are also given in the captions of Figure 2. We provide detailed proofs supporting our construction of these preference scales in Online Appendix A.

Table 1: Preference motive elicitation tables for utility curvature and likelihood insensitivity in the gain and loss domain

	Gain Domain Table 1 (GD1)					**Gain Domain Table 2 (GD2)**			
	Lottery A		Lottery B			Lottery A		Lottery B	
p	20%	80%	20%	80%	p	90%	10%	90%	10%
$	*2.50*	*2.00*	*2.50*	*1.00*	$	*2.00*	*1.50*	*2.00*	*0.50*
	2.50	2.00	4.50	1.00		2.00	1.50	2.05	0.50
	2.50	2.00	4.75	1.00		2.00	1.50	2.10	0.50
	2.50	2.00	5.00	1.00		2.00	1.50	2.15	0.50
	2.50	2.00	5.50	1.00		2.00	1.50	2.20	0.50
	2.50	2.00	6.00	1.00		2.00	1.50	2.25	0.50
	2.50	2.00	6.50	1.00		2.00	1.50	2.30	0.50
	2.50	2.00	7.00	1.00		2.00	1.50	2.35	0.50
	2.50	2.00	8.00	1.00		2.00	1.50	2.45	0.50
	2.50	2.00	9.00	1.00		2.00	1.50	2.55	0.50
	2.50	2.00	10.00	1.00		2.00	1.50	2.65	0.50
	2.50	2.00	12.00	1.00		2.00	1.50	2.80	0.50
	2.50	2.00	15.00	1.00		2.00	1.50	3.00	0.50
	2.50	2.00	20.00	1.00		2.00	1.50	3.25	0.50
	2.50	2.00	30.00	1.00		2.00	1.50	3.50	0.50
	2.50	2.00	60.00	1.00		2.00	1.50	3.75	0.50

	Loss Domain Table 1 (LD1)					**Loss Domain Table 2 (LD2)**			
	Lottery A		Lottery B			Lottery A		Lottery B	
p	10%	90%	10%	90%	p	80%	20%	80%	20%
$	*-0.75*	*-0.25*	*-0.75*	*-0.50*	$	*-1.75*	*-0.10*	*-1.75*	*-1.25*
	-1.20	-0.25	-0.75	-0.50		-1.95	-0.10	-1.75	-1.25
	-1.25	-0.25	-0.75	-0.50		-2.00	-0.10	-1.75	-1.25
	-1.30	-0.25	-0.75	-0.50		-2.05	-0.10	-1.75	-1.25
	-1.40	-0.25	-0.75	-0.50		-2.10	-0.10	-1.75	-1.25
	-1.50	-0.25	-0.75	-0.50		-2.15	-0.10	-1.75	-1.25
	-1.60	-0.25	-0.75	-0.50		-2.20	-0.10	-1.75	-1.25
	-1.70	-0.25	-0.75	-0.50		-2.30	-0.10	-1.75	-1.25
	-1.85	-0.25	-0.75	-0.50		-2.40	-0.10	-1.75	-1.25
	-2.00	-0.25	-0.75	-0.50		-2.50	-0.10	-1.75	-1.25
	-2.15	-0.25	-0.75	-0.50		-2.60	-0.10	-1.75	-1.25
	-2.35	-0.25	-0.75	-0.50		-2.75	-0.10	-1.75	-1.25
	-2.65	-0.25	-0.75	-0.50		-2.90	-0.10	-1.75	-1.25
	-3.00	-0.25	-0.75	-0.50		-3.05	-0.10	-1.75	-1.25
	-3.40	-0.25	-0.75	-0.50		-3.25	-0.10	-1.75	-1.25
	-4.00	-0.25	-0.75	-0.50		-3.50	-0.10	-1.75	-1.25

Note: A row in each of the four tables above represents a choice set presented to the subject. Row values are the possible dollar outcomes from the displayed lotteries. Column headings are the probability of obtaining the given outcome. Losses and gains are relative to the $5.00 earned in the real effort task to begin the experiment.

Table 2: Preference motive elicitation tables for certainty preference and loss aversion

	Certainty Preference Table (CP)				**Loss Aversion Table (LA)**			
	Lottery A	Lottery B			Lottery A		Lottery B	
p	100%	20%	80%	$	+0.50	−0.20	+5.00	−2.00
$	2.00	2.50	1.00	p	*0%*	*100%*	*0%*	*100%*
	2.00	4.50	1.00		5%	95%	5%	95%
	2.00	4.75	1.00		10%	90%	10%	90%
	2.00	5.00	1.00		15%	85%	15%	85%
	2.00	5.50	1.00		20%	80%	20%	80%
	2.00	6.00	1.00		25%	75%	25%	75%
	2.00	6.50	1.00		30%	70%	30%	70%
	2.00	7.00	1.00		35%	65%	35%	65%
	2.00	8.00	1.00		40%	60%	40%	60%
	2.00	9.00	1.00		45%	55%	45%	55%
	2.00	10.00	1.00		50%	50%	50%	50%
	2.00	12.00	1.00		55%	45%	55%	45%
	2.00	15.00	1.00		60%	40%	60%	40%
	2.00	20.00	1.00		65%	35%	65%	35%
	2.00	30.00	1.00		70%	30%	70%	30%
	2.00	60.00	1.00		75%	25%	75%	25%
					80%	20%	80%	20%
					85%	15%	85%	15%
					90%	10%	90%	10%
					95%	5%	95%	5%
					100%	*0%*	*100%*	*0%*

Note: A row in each of the two tables above represents a choice set presented to the subject. In the certainty preference table (left), row values are the possible dollar outcomes and column headings are the probabilities of obtaining the given outcome. In the loss aversion table (right), column headings are the dollar outcomes and row values are the probabilities of obtaining each outcome. Losses and gains are relative to the $5.00 earned in the real effort task to begin the experiment.

2.4 Data Collection

The experiment was implemented in the Qualtrics online survey platform and was conducted March 15–26, 2018, online and in a university laboratory. Subjects agreed to a consent form and then faced two real-effort earning tasks. They were given pictures of texts, which were quotes from famous individuals or brief excerpts from books. The task was to type the text from the picture into a field provided below. Subjects were endowed with $5 for successfully completing this task. Subjects were then informed about the tasks in the experiment. After passing a comprehension test, they faced either the preference elicitation task or twelve questions in another, unrelated task (making insurance decisions when facing a potential loss to their earnings).[8] After fulfilling all tasks, one of the questions was randomly selected for pay-out and the subjects were informed about the result. They were then asked the GRQ and a follow-up questionnaire about demographic information.

We targeted recruitment of 1,350 online subjects and 350 in-person subjects based on a pre-analysis power calculation. These target sample sizes were registered in the American Economic Association Randomized Control Trial Registry. We recruited 1,352 subjects online through Amazon's Mechanical Turk platform and 378 subjects in a university laboratory, and we include all participants in our analysis. Subjects were on average 33 years old and 47% of subjects were female. The average payment to mTurk subjects was $6.23, while university subjects earned an average of $6.41.[9] On average, university and online sessions each lasted approximately 25 minutes.

3 Results

We illustrate the distribution of *GRQ* as well as the distributions of all six preference scales in Figure 2. Panel (a) shows substantial variation in the distribution of *GRQ*. Subjects seem to shy away from extreme and centrist answers to the question such that a bimodal pattern emerges.[10] Panels (b) through (g) show the distributions of the six preference scales. These also show significant variation which mostly covers the entire spectrum of possible answers. We see marked differences in the distributions of the different preference motives and between the gain and the loss domain, indicating that subjects carefully considered their responses and did not simply answer in a random pattern. Additionally, we observe relatively few corner solutions in our preference scales such that we are confident to have captured the main spectrum of the subject population's preference

[8] The analysis of those insurance choices and their link to preference measures is the focus of a separate research paper. That paper does not analyze the correlations with *GRQ*.

[9] In compliance with local laboratory standards regarding hourly wages, university subjects were also paid a flat show-up fee of $6.00. This payment was not disclosed until the end of the experiment. No additional payments were made to mTurk subjects.

[10] This pattern is not a product of randomizing the direction of the GRQ response scale. Both the group that answered on a 0-10 scale and the group that answered on a 10-0 scale show a bimodal pattern of responses.

distribution with our scales. It should be noted that the absolute levels of the preference scales are not interpretable. One should thus not make comparisons between the different scales based on their absolute values or changes, but rather in terms of relative changes which can, for example, be measured in standard distribution units.[11]

For the LI^+, LI^- and CP scales, Figure 2 shows 0 as the most common value. Since these scales are the difference in the switching row of two choice lists, such values imply subjects switched in the same row in two different tables. LI^+ and LI^- are derived from the GD and LD tables, respectively. Choosing the same switching row in both GD tables or both LD tables could signal inattentive choices by the subjects. Even though the share of subjects switching in the same row is relatively low compared to other studies, we provide a robustness check of our results excluding such subjects in Section 4.[12] The CP scale shows the largest share of 0 values. However, in this scale, such answers are less concerning. Because the CP and $GD1$ choice tables are fairly similar, changing at the same row in these two tables is a reasonable choice pattern if there is no preference for certainty.

We outline ordered probit regressions of each preference scale on GRQ in Table 3. Here and in all other tables where we report statistical significance, we are simultaneously testing six hypotheses. To mitigate the increased chance of Type I error in multiple hypothesis testing, we adjust the p-values of our coefficient estimates using the Šidák-Holm correction procedure (Holm, 1979; Šidák, 1967). The "stars" in our tables refer to significance using the Šidák-Holm corrected p-values; we also report the unadjusted p-value for each coefficient estimate in square brackets.

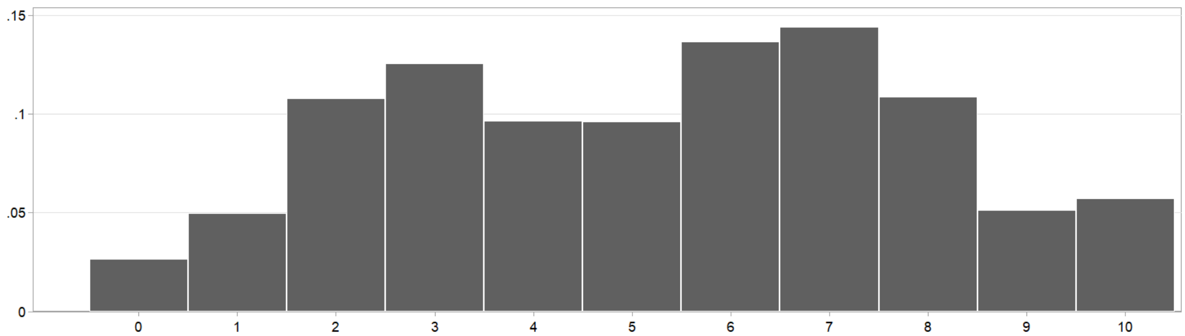
Panel A of Table 3 displays the result of an ordered probit regression of each preference scale on GRQ, with the full set of subjects and no controls included. The results show relatively strong correlations between GRQ and both loss-domain utility curvature (UC^-) and loss aversion (LA). We also observe a significant correlation with gain-domain utility curvature, consistent with prior results by Dohmen et al. (2011). The relationship, however, is roughly two-thirds to half the size of the correlations we see with loss-domain utility curvature and loss aversion. We see only marginally significant and small correlations between GRQ and certainty preference or either likelihood insensitivity measure.

In Panel B of Table 3, we add a number of controls to the Panel A regressions. These include demographic characteristics, namely information on age, gender, ethnicity, and education. We include a dummy to indicate the display direction of the GRQ, which is not significant in any specification. We also include dummies for the left-right and top-bottom ordering of the preference elicitation lotteries, which are significant in some cases. Since the GRQ was asked at the end of the experiment (after the subject had learned the outcome), we include a control for the probability of

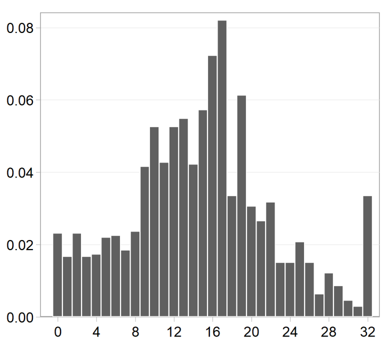
[11]Specifically, our measure of loss aversion ranges from 0 to 21, while the other preferences are on a 33-point scale (UC measures are 0 to 32, while LI and CP are -16 to 16). GRQ is on an 11-point scale (0 to 10). To address this in our analysis, we standardize GRQ and the preference scales by subtracting the mean and dividing by the standard deviation, denoting these standardized values with the subscript *std*. We evaluate the correlations and regression coefficients as shifts in standard deviation rather than comparing unit changes of unequal measure.

[12]Callen et al. (2014), for example, report that 69% of their subjects switched in the same row after excluding dominance-violating choices. Our GD or LD tables show this pattern in less than 20% of the cases.

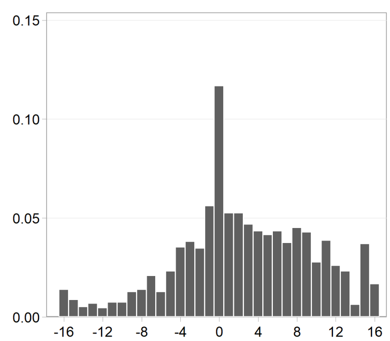
Figure 2: Distributions of GRQ and preference scales



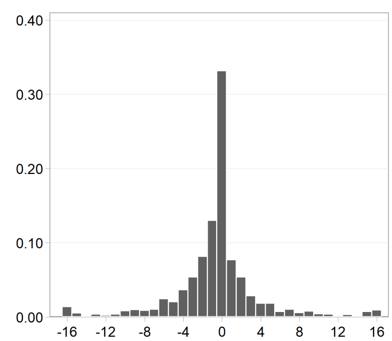
(a) GRQ (Higher $\rightarrow$ more willing to take risk)



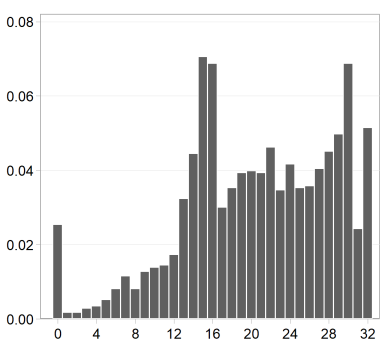
(b) Utility curvature gains.
$UC^{+} = GD1_A + GD2_A$
Higher $\rightarrow$ more concave



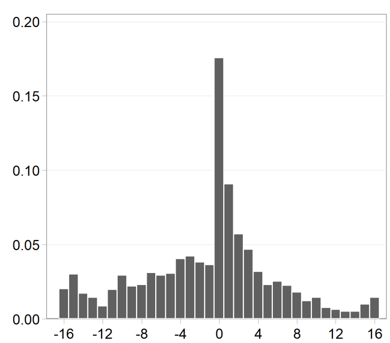
(c) Probability weighting gains
$LI^{+} = GD1_B - GD2_B$
Higher $\rightarrow$ more inverse-S



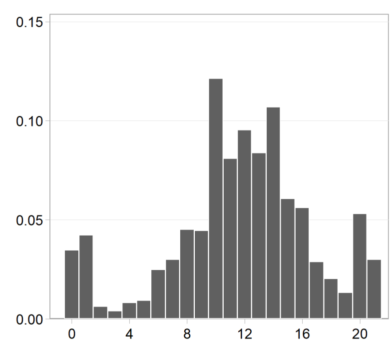
(d) Certainty preference
$CP = CP_A - GD1_A$
Higher $\rightarrow$ stronger preference



(e) Utility curvature losses
$UC^{-} = LD1_B + LD2_B$
Higher $\rightarrow$ more concave



(f) Probability weighting losses
$LI^{-} = LD1_B - LD2_B$
Higher $\rightarrow$ more inverse-S



(g) Loss aversion
$LA = LA_A$
Higher $\rightarrow$ more loss averse

the bad outcome in the randomly-selected decision to play out, a dummy indicating whether the subject experienced the bad outcome, and those terms interacted together. In addition, we include a dummy for subjects who did not pass the instructions test on their first try. The relationships between preference scales and GRQ weaken somewhat once these controls are included, but remain statistically significant for UC^- and LA (and marginally so for CP). When considering the Panel B regression for online and in-person subjects separately (Panels C and D, respectively), coefficient size stays roughly the same for UC^- and LA, but the statistical significance for the in-person experiments becomes weaker due to the combination of smaller sample size and p-value adjustment.

The elicitation method used for our preference parameters leads to interdependence between the different measures. This can, for example, be seen in the loss aversion lotteries (the right panel of Table 2). Here, more Lottery A choices are interpreted as increasing loss aversion. They can, however, also stem from an increased utility curvature of the individual. To control for such possible correlations, we also conduct a multivariate regression analysis of GRQ on all preference scales.

We begin the analysis in model (1) by including only the preference scales as explanatory variables, without controls. In this model, coefficient size is relatively low for the gain domain preferences, certainty preference, and likelihood insensitivity in both domains. After adjusting p-values for multiple hypothesis testing, none of these four motives show a statistically significant association with GRQ. The coefficients on loss aversion and loss domain utility curvature are negative and significant at the 1% level. To provide a frame of reference for the magnitude of the effects, each of the two coefficients is approximately half as large as the effect of a subject being female, which is approximately -0.278 in the models including control variables.[13] Neither coefficient differs strongly from the univariate analysis reported in Table 3, indicating that the preference scales are independently related to GRQ.

When demographic control variables are added (model (2)), the correlations weaken somewhat but remain statistically significant for utility curvature in the loss domain and loss aversion. Results remain significant if subjects violating first-order stochastic dominance are excluded from the analysis, as reported in model (3). For this subset of participants, the relationship between GRQ and the two preference scales appears stronger. The multiple-preference results in Table 4 thus corroborate the single-preference findings reported in Table 3. Excluding dominance-violating subjects also increases the coefficient on the preference for certainty and makes it marginally significant. However, since this is the only subsample analysis in which such statistical significance appears (see Section 4), we refrain from interpreting this finding.

[13]There is a substantial literature showing the gender effect on risk preferences. See Charness and Gneezy (2012) for a meta analysis.

Table 3: Results of the single-preference ordered probit regressions, with GRQ_{std} as the dependent variable

Dependent var:	GRQ_{std}					
Explanatory var:	UC^+_{std}	LI^+_{std}	CP_{std}	UC^-_{std}	LI^-_{std}	LA_{std}
Panel A: Scales only						
Est coefficient	−0.067**	−0.053*	−0.043	−0.135***	0.013	−0.177***
	(0.027)	(0.025)	(0.025)	(0.027)	(0.025)	(0.028)
	[0.012]	[0.030]	[0.086]	[0.000]	[0.593]	[0.000]
Controls	No	No	No	No	No	No
Pseudo R^2	0.001	0.001	0.000	0.004	0.000	0.006
χ^2	6.35	4.70	2.94	25.76	0.29	39.00
N	1,730	1,730	1,730	1,730	1,730	1,730
Panel B: Include controls						
Est coefficient	−0.044	−0.046	−0.045	−0.119***	0.001	−0.140***
	(0.026)	(0.025)	(0.025)	(0.027)	(0.025)	(0.029)
	[0.099]	[0.064]	[0.069]	[0.000]	[0.960]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.022	0.022	0.022	0.025	0.022	0.026
χ^2	167.54	170.03	169.91	193.14	167.27	181.08
N	1,730	1,730	1,730	1,730	1,730	1,730
Panel C: mTurk only						
Est coefficient	−0.041	−0.057	−0.041	−0.106***	0.016	−0.127***
	(0.029)	(0.028)	(0.027)	(0.029)	(0.029)	(0.029)
	[0.154]	[0.041]	[0.128]	[0.000]	[0.585]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.027	0.027	0.027	0.029	0.026	0.030
χ^2	167.37	170.61	169.94	189.71	168.31	175.92
N	1,352	1,352	1,352	1,352	1,352	1,352
Panel D: In-person only						
Est coefficient	−0.078	0.004	−0.058	−0.180**	−0.077	−0.224
	(0.062)	(0.060)	(0.053)	(0.068)	(0.062)	(0.103)
	[0.209]	[0.943]	[0.276]	[0.008]	[0.216]	[0.029]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.007	0.006	0.006	0.010	0.007	0.011
χ^2	11.53	9.64	10.60	15.67	10.86	14.15
N	378	378	378	378	378	378

Note: The dependent variable in each column is GRQ_{std}, with the explanatory variable of interest the standardized preference scale listed in the table header. Stars *, **, and *** denote statistical significance with Šidák-Holm-corrected p-values at the 0.10, 0.05, and 0.01 levels, respectively. Heteroskedasticity-robust standard errors are in parentheses, and the unadjusted p-values are in square brackets. Controls include age, gender, ethnicity, education, the probability of a "bad" outcome in the randomly-selected lottery to play out, a dummy for whether the subject experienced the bad outcome, an interaction of these two, a dummy for incorrectly answering one of the "understanding" questions following the lottery instructions, and dummies for the menu display of the GRQ and the preference elicitation lotteries. In Panels C and D, we repeat our Panel B regressions using only mTurk responses and in-person responses, respectively. We omit education from the regressions reported in Panel D, as there is insufficient variation in education for our sample comprised primarily of college students.

Table 4: Results of the multiple-preference ordered probit regression analysis with GRQ_{std} as the dependent variable

	(1)	(2)	(3)
Utility curvature gains (UC^{+}_{std})	−0.054	−0.037	−0.033
	(0.030)	(0.030)	(0.036)
	[0.070]	[0.220]	[0.359]
Likelihood insensitivity gains (LI^{+}_{std})	−0.039	−0.034	−0.008
	(0.028)	(0.028)	(0.035)
	[0.164]	[0.236]	[0.809]
Certainty preference (CP_{std})	−0.047	−0.045	−0.086*
	(0.028)	(0.028)	(0.038)
	[0.091]	[0.107]	[0.023]
Utility curvature losses (UC^{-}_{std})	−0.147***	−0.130***	−0.170***
	(0.028)	(0.029)	(0.036)
	[0.000]	[0.000]	[0.000]
Likelihood insensitivity losses (LI^{-}_{std})	0.051	0.033	0.041
	(0.028)	(0.028)	(0.035)
	[0.064]	[0.241]	[0.237]
Loss aversion (LA_{std})	−0.161***	−0.133***	−0.216***
	(0.029)	(0.029)	(0.039)
	[0.000]	[0.000]	[0.000]
Controls	No	Yes	Yes
FOSD Violators	Yes	Yes	No
Pseudo R^2	0.012	0.030	0.037
χ^2	66.20	206.90	210.82
N	1,730	1,730	1,276

Note: The dependent variable in each column is GRQ_{std}. GRQ_{std} and the preference scales are standardized values. Stars *, **, and *** denote statistical significance with Šidák-Holm-corrected p-values at the 0.10, 0.05, and 0.01 levels, respectively. Heteroskedasticity-robust standard errors are in parentheses, and the unadjusted p-values are in square brackets. Controls include age, gender, ethnicity, education, a dummy for mTurk subjects, the probability of a "bad" outcome in the randomly-selected lottery to play out, a dummy for whether the subject experienced the bad outcome, an interaction of these two, a dummy for incorrectly answering one of the "understanding" questions following the lottery instructions, and dummies for the menu display of the GRQ and the preference elicitation lotteries.

4 Discussion and Robustness

The reported results are subject to the limitations of the elicitation procedure employed in the experiment. The methods used here measure preference motives based on answers in choice lists. If subjects fail to understand those choice lists or the stakes are not high enough to incentivize thoroughly reflected answers, subjects might simply answer in a random pattern. Since our procedure does not allow for noise in the decision process of the subjects, such random patterns would be interpreted as preferences. Interpreting noise in this way could lead to spurious results as has been demonstrated, for example, by Andersson et al. (2016) or Vieider (2018).

Regarding the stakes of the experiment, our payments to mTurk subjects is above-average when compared to the mean hourly wage earned by mTurk workers. On average, we paid mTurk subjects \$6.23 for 25 minutes of work, making an implied hourly wage of \$14.95. Hara et al. (2018) find in an analysis of 3.8 million tasks conducted by 2,676 workers that the average hourly wage was between \$4.80 and \$6.19. These statistics are supported anecdotally by the comments left by some subjects on turkerhub.com, an online forum for mTurk workers in which several commenters emphasized the large possible payments of the experiment.

To assess the extent to which our results might be driven by random or inattentive choices, we conduct analyses on several subsamples of our total subject population. We conduct the same regression as in column (2) of Table 4, and report our results in Table 5. To filter out inattentive choices, column (1) of Table 5 excludes subjects who took less than 25 seconds for any lottery decision[14], while column (2) excludes subjects who clicked only once on any lottery. To filter out subjects who had difficulty understanding the instructions or choice tables, column (3) excludes all subjects who got any of the five "attention check" questions wrong on the first attempt, while column (4) excludes subjects who did not rate the study as either "easy" or "very easy" to understand in the post-study questionnaire. To filter out seemingly random choice patterns, column (5) excludes subjects who always switched at the beginning or end of the table (first or last 5 rows), while column (6) excludes subjects who always switched within the same small range of less than 5 rows. This last exclusion is targeted specifically at the choice pattern of always switching in a similar row, which Vieider (2018) identifies as particularly problematic in some choice list based experiments. The results of these subsample analyses in Table 5 show nearly identical significance levels and similar coefficient sizes as the main analysis reported in column (2) of Table 4. While we cannot completely rule out that the limitations of our elicitation procedure might drive our results, these results give us some confidence in our conclusions.

Our results show no consistent connection between a preference for certainty and the GRQ. However, our measure for the preference for certainty requires a caveat identified by Vieider (2018). A table in which one option involves a certain outcome could endogenously set a reference point for the subjects such that the outcomes on the uncertain lottery are coded as gains and losses relative to

[14] In the experiment, the "Next" button was hidden for 20 seconds on each lottery page to encourage thoughtful consideration of the lottery choices (and to prevent subjects from clicking through as soon as the page loads). The subsample in column (1) thus includes only subjects who always took at least 5 seconds more than the minimum requirement.

Table 5: Results of the multiple-preference ordered probit regression analysis with GRQ_{std} as the dependent variable for different subsamples

	Excluded subjects					
	(1) Time $< 25s$	(2) Click Once	(3) Attention Check	(4) Not Easy	(5) Corner Rows	(6) Similar Rows
UC^{+}_{std}	-0.019	-0.043	-0.033	-0.047	-0.029	-0.031
	(0.046)	(0.036)	(0.037)	(0.032)	(0.032)	(0.034)
	[0.686]	[0.240]	[0.365]	[0.141]	[0.368]	[0.357]
LI^{+}_{std}	-0.076	-0.028	-0.061	-0.028	-0.020	-0.038
	(0.043)	(0.036)	(0.033)	(0.030)	(0.030)	(0.029)
	[0.076]	[0.432]	[0.063]	[0.343]	[0.501]	[0.197]
CP_{std}	-0.013	-0.034	-0.056	-0.064	-0.061	-0.047
	(0.044)	(0.038)	(0.035)	(0.031)	(0.031)	(0.029)
	[0.774]	[0.375]	[0.105]	[0.040]	[0.047]	[0.112]
UC^{-}_{std}	-0.123**	-0.134***	-0.168***	-0.128***	-0.163***	-0.141***
	(0.045)	(0.035)	(0.035)	(0.031)	(0.031)	(0.032)
	[0.007]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
LI^{-}_{std}	0.036	0.012	0.061	0.035	0.041	0.033
	(0.044)	(0.034)	(0.033)	(0.030)	(0.030)	(0.029)
	[0.405]	[0.733]	[0.064]	[0.240]	[0.169]	[0.257]
LA_{std}	-0.166***	-0.158***	-0.222***	-0.182***	-0.167***	-0.145***
	(0.050)	(0.036)	(0.036)	(0.032)	(0.036)	(0.033)
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FOSD Violators	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.029	0.029	0.033	0.031	0.030	0.030
χ^2	113.39	158.63	165.63	187.70	206.66	175.49
N	810	1,231	1,271	1,500	1,541	1,476

Note: The dependent variable is GRQ_{std}. GRQ_{std} and the preference scales are standardized values. Stars *, **, and *** denote statistical significance with Šidák-Holm-corrected p-values at the 0.10, 0.05, and 0.01 levels, respectively. Heteroskedasticity-robust standard errors are in parentheses, and the unadjusted p-values are in square brackets. Column (1) excludes subjects who took less than 25 seconds for any lottery decision. Column (2) excludes subjects who clicked only once on any lottery. Column (3) excludes all subjects who got any attention check question wrong on the first attempt. Column (4) excludes subjects who did not rate the study as either "easy" or "very easy" to understand in the post-study questionnaire. Column (5) excludes subjects who always chose a switch row in the first and/or last 5 rows of the table. Column (6) excludes subjects who always chose a switch row within a range of 5 or fewer rows.

the certain payment. In this case, loss aversion could lead to more choices for Lottery A in Table CP than in GD1. While we cannot rule out this explanation, our data does not support it. If we assume that the same loss aversion parameter governs all choices of a subject, the endogenous reference point explanation would imply a positive correlation between the LA and CP scales. The correlation coefficient between both scales is -0.015, which is not significantly different from zero. The difference between our results and those of Vieider (2018) likely stems from the different elicitation procedures analyzed in the two papers. While Vieider (2018) analyzes a probability-matching task, we employ an outcome-matching task which is less susceptible to setting endogenous reference points (Hershey and Schoemaker, 1985).

5 Conclusions

The GRQ has gathered substantial traction in the literature on risk preferences. This is due to its brevity, its easy implementation, its good test-retest reliability (Lönnqvist et al., 2015) and the fact that it correlates with many naturally-occurring decisions under risk (Dohmen et al., 2011). However, it has been somewhat unclear how the question relates to the common lottery-based measures of risk preferences. Prior literature has found relatively low correlations with inconsistent levels of statistical significance. Based on an experimental study, we show in this paper that the GRQ shows statistically significant correlations with lottery-based preference motives, but only for those elicited in the domain of losses. Specifically, the GRQ is significantly associated only with loss aversion and utility curvature in the loss domain. It should be noted, however, that risk attitudes concerning losses are not the only factors influencing responses to the GRQ. By its very phrasing, the GRQ measures risk taking rather than risk preferences. While preferences will influence decisions, other factors, such as liquidity restrictions, wealth, or beliefs, will also affect risk taking and thus likely also drive responses to the GRQ. Even though the influences of loss aversion and loss-domain utility curvature on the GRQ are statistically significant, effect sizes are only modest. This lends further credibility to the presence of other influencing variables. If the GRQ is applied in economic research, this should be kept in mind.

These results are in line with the literature on managerial risk preference that has developed somewhat independently from the literature on experimental risk preferences. In the former literature, it has long been established that the perception of a prospect's riskiness is strongly tied to the possible losses which the prospect implies. March and Shapira (1987) note that managers cherish risk-taking if they can ensure the potential losses of this activity to be low. This perspective is more closely related to downside risk aversion than to risk aversion in general (Jaspersen and Peter, 2017). Other studies have corroborated March and Shapira's (1987) findings. For example, Koonce et al. (2005) and Huber and Huber (2019) each show that potential losses are a major determinant in the subjective riskiness of investment opportunities. These results may also help explain why entrepreneurs can be differentiated from managers by their loss aversion, but not by their risk aversion (Koudstaal et al., 2015).

The insight that general attitudes towards risk relate more closely to preventing possible losses than to preventing overall variability renders important implications for both further theory development and applied work. For theory development, further exploration is necessary about how individuals interpret the concept of risk and what this implies for behavioral theories of decisions under risk. For applied work, the important implication is that the GRQ can be a useful control for risk preferences over losses but may be a poor control for classic (i.e., "expected utility theory") risk aversion.

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The following appendices are available in a separate document online:

Online Appendix A Theory on Preference Elicitation

Online Appendix B Analysis Using Parametric Preference Measures

Online Appendix C Experiment Implementation