What Drives Risk Perception? A Global Survey with Financial Professionals and Lay People

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Abstract

Risk is an integral part of many economic decisions, and is vitally important in finance. Despite extensive research on decision-making under risk, little is known about how risks are actually perceived by financial professionals, the key players in global financial markets. In a large-scale survey experiment with 2,213 finance professionals and 4,559 lay people in nine countries representing ∼50% of the world's population and more than 60% of the world's gross domestic product, we expose participants to return distributions with equal expected return and we systematically vary the distributions' next three higher moments. Of these, skewness is the only moment that systematically affects financial professionals' perception of financial risk. Strikingly, variance does not influence risk perception, even though return volatility is the most common risk measure in finance in both academia and the industry. When testing other, compound risk measures, the probability to experience losses is the strongest predictor of what is perceived as being risky. Analyzing professionals' propensity to invest, skewness and loss probability also have strong predictive power, while volatility and kurtosis have some additional effect. Our results are very similar for lay people, and they are robust across and within countries with different cultural backgrounds as well as for different job fields of professionals.

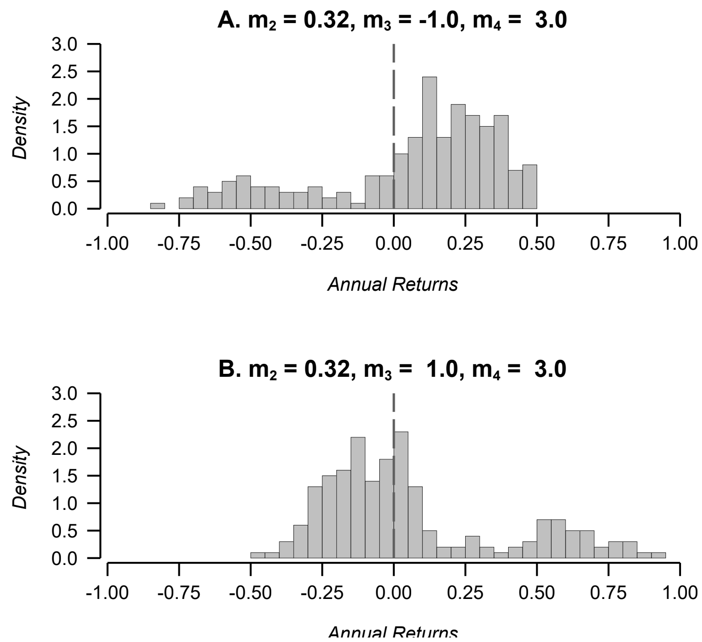
Keywords: Risk perception, investment propensity, financial professionals.

1 Introduction

The way in which people perceive risk shapes their behavior in a world with uncertain outcomes (Slovic, 1987), and it is of vital importance for investments (Nosić and Weber, 2010; Weber et al., 2013). Next to returns, risk is one of the two pivotal dimensions in financial decision-making (Bell, 1995; Ghysels et al., 2005), and of paramount importance in financial markets. Yet, while there are several studies that investigate how lay people perceive financial risks (Keller et al., 1986; Bontempo et al., 1997; Weber and Hsee, 1998; Unser, 2000; Klos et al., 2005; Diecidue and Van De Ven, 2008; Veld and Veld-Merkoulova, 2008; Levy and Levy, 2009; Zeisberger, 2018), little is known about the risk perception of financial professionals, who are the key players in global financial markets, which are central to the functioning of modern economies. In this paper, we report results from a large-scale survey experiment with finance professionals and lay people, allowing us to investigate the drivers of financial risk perception and investment propensity. In contrast to normative textbook models, we find that variance does not explain the risk perception of professionals and lay people, but skewness does. We also study participants' propensity to invest in risky assets where, again, skewness is a strong driver. In addition, we find that volatility and kurtosis have some effect on investment propensity.

Despite the importance of risk, there is little consensus on its definition (Brachinger and Weber, 1997). As we are interested in the *perception* of risk, what people perceive and define as risky is ultimately an empirical question. An alternative to this (positive) approach is to define risk from a normative theory perspective. In finance, at least since the influential paper of Nobel laureate Harry Markowitz (Markowitz, 1952), risk is widely defined and operationalized as the variance or standard deviation of returns (commonly referred to as return volatility). This does not only apply to leading textbooks (e.g. Vernimmen et al., 2014; Brealey et al., 2017) and widely used asset pricing models (Sharpe, 1964; Lintner, 1965; Mossin, 1966) but also to much of today's financial regulation and practice. For example, cornerstone regulations of financial markets (e.g., the Markets in Financial Instruments Directive, MiFID as well as Solvency II in the European Union) use return volatility (variance) as a risk measure for equities, currencies, interest rates, and property prices. Recent regulatory frameworks such as Basel III introduce more comprehensive conceptualizations of risk, such as value at risk (VaR) or expected shortfall (ES), both of which shift the focus to potential downside risks. Importantly, investment funds are required to provide a standardized Key Investor Information Document (KIID) in which a fund's historical volatility is the basis for calculation to communicate risks to investors. More generally, financial advisors often inform clients about the risk associated with investment opportunities by referring to the variance of their historical returns, and many financial institutions survey the risk appetite of their clients with variance-related questionnaires (Sachse et al., 2012).

To illustrate the implications of different definitions of risk, assume a decision maker has to choose one of the two financial assets characterized by the return distributions in Figure 1. Both distributions share the same mean (first moment), variance (second moment; m_2), and kurtosis (fourth moment; m_4), but they differ in skewness (third moment; m_3). If risk is defined as the variance of returns, a decision maker should be indifferent between the two alternatives. Intuitively, however, many people will perceive one of the assets as more risky. Indeed, recent studies call into question whether investors use volatility as the (only) risk measure when evaluating financial assets (Zeisberger, 2018) and suggest that the perception of risk relates to characteristics other than variance. In particular, downside risk measures (Fishburn, 1984; Unser, 2000; Veld and Veld-Merkoulova, 2008) and skewness (Ebert and Wiesen, 2011; Ebert, 2015) appear to resemble the conceptualization people have in mind when evaluating "risk" more closely than measures of symmetric variation around the mean, and they have been shown to affect pricing in experimental (Huber et al., 2017) and real asset markets (Boyer et al., 2010; Bali et al., 2011; Conrad et al., 2013).



Notes: Two histograms of 200 simulated annual returns (in 5% bins). Both distributions share a mean of 6%, a standard deviation (m_2) of 32%, and a kurtosis (m_4) of 3.0. The two distributions only differ in skewness: the returns in Panel A are negatively skewed with $m_3 = -1.0$ whereas the distribution in Panel B is positively skewed with $m_3 = +1.0$.

Figure 1: Two histograms of simulated annual returns

It may not come as a surprise that the perception of risk among lay people deviates from mean-variance models in finance, which equate risk with return volatility. Yet, there are good reasons to believe that financial professionals evaluate risks more in line with mean-variance. In contrast to lay people, financial professionals are trained through education and experience in the finance industry. From a psychological perspective, the *risk as feelings* hypothesis (Loewenstein et al., 2001) posits that individuals use an "analytic system," which processes risk using probability calculus or other logical operations (Slovic et al., 2004), and an "experiential system," which is more intuitive, fast, and frugal (Kahneman, 2011). The degree to which either system is activated is hypothesized to depend on the degree of emotional activation. Specifically, individual conditioning and personal experience with the risk characteristics at hand are expected to reduce emotional activation and to support a more analytic approach towards risk (Loewenstein et al., 2001; Kaufmann et al., 2013). Hence, compared to lay people, financial professionals could be expected to perceive risk more analytically along the normative definitions commonly applied in economics and finance models. In addition, an increasing body of experimental evidence suggests that financial professionals are quite "special" in the sense that their behavior systematically differs from other types of experimental subjects, e.g., with regard to anchoring (Kaustia et al., 2008), herding (Cipriani and Guarino, 2009), overconfidence (Puetz and Ruenzi, 2011; Gloede and Menkhoff, 2014), cheating (Cohn et al., 2014), risk-taking under social comparison and competition (Kirchler et al., 2018), and with respect to public signal updating in information cascades (Alevy et al., 2007). It would thus not be surprising if financial professionals differ in their perception of financial risk. In fact, it may even be one of the reasons that they chose to enter the finance profession. The discrepancy between the common definition of risk in finance and the actual perception of risk among lay people is potentially harmful, but it could be resolved if clients trust financial professionals to bridge the gap as "money doctors" (Gennaioli et al., 2015), with risk perception and investment strategies aligned with (normative) finance theory. However, there is neither large-scale empirical evidence on financial professionals' risk perception nor a direct comparison of their perspective with that of lay people. With this paper we fill this substantial research gap.

To examine which characteristics of return distributions actually determine professionals' and lay people's appraisal of financial risk, we conducted an experiment in which we sequentially showed participants distributions of annual asset returns calibrated to systematically differ in their higher moments and asking for their risk perception and investment propensity. By eliciting the participants' investment propensity, we get a more comprehensive picture about how risk perception shapes investment decisions. To address the question of whether people working in the finance industry systematically differ from lay people in evaluating financial risk, we recruited 2,213 finance professionals and 4,559 lay people in nine countries.

In particular, we show that variations in standard deviation do not trigger systematic differences in risk perception. The skewness of asset returns, however, induces pronounced differences in the cognition of financial risk, with positively skewed returns considered to be significantly more risky than symmetric distributions and negatively skewed returns. We believe that this finding is explained by the high probability of losing and the aversion to it. Moreover, we report that investment propensity is inversely related to risk perception. Differences in the distributions' standard deviation induce significant differences in participants' disposition to invest, with a higher standard deviation leading to a lower willingness to invest. When focusing on compound risk measures, we report strong evidence that the probability of suffering a loss is the main driver for both the perception of financial risk and investment propensity among financial professionals and lay people. This points towards loss aversion as the most important component of decision-making under risk. Finally, we show that our results are very robust and hold for financial professionals as well as laypeople with no significant differences between the two subject pools, and almost no differences across countries or job profiles. Given extensive training and experience in the industry, financial professionals might well be expected to perceive financial risk more in line with predominant risk measures than lay people. However, even though financial professionals, on average, react somewhat more sensitively to rather subtle variations in return distributions, differences in the evaluation of risk and the disposition to invest are negligible and insignificant between the two populations.

2 Methods

2.1 Participant Recruitment and Data Collection

We administered the experiment online using *oTree* (Chen et al., 2016) in nine countries: Brazil, China, Germany, India, Japan, Russia, Great Britain, the United States, and South Africa.[1] With this selection of countries, we cover the major financial markets and economies on five continents, representing ∼50% of the world's population and more than 60% of the world's gross domestic product.

In total, we recruited 2,371 individuals working in the finance industry and 4,565 lay people through an international network of partnered market research agencies. Respondents from the general population have been stratified by age, gender, and (not nested) education for each of the countries. Participants were pre-selected based on occupational information related to the user's account available only to the agency and were redirected to either of two separate (but identical) treatments of the survey (to distinguish between the subsamples of financial professionals and lay people). Before respondents have been passed on to our survey experiment, they were asked to complete a brief screening survey on the agency's platform without being informed about the purpose of the study. Besides some demographic filler questions, the survey asked respondents to indicate the sector they currently work in as well as their current occupation.[2]

On the first screen of our experimental platform, participants were again asked to report the sector/industry they currently work in (screener question). To ensure that our "financial professionals" subsample only includes participants actively employed in the finance or insurance industry, respondents that indicated *not* to work in the finance or insurance industry at this stage are excluded from the analysis. Similarly, respondents indicating to work *in* the finance or insurance industry at this stage are excluded from the analysis to ensure that our "lay people" subsample only includes participants not working in the finance or insurance sector. Importantly, participants have not been informed about the purpose of the study and the screening procedures. So, they were not aware which job functions we were screening for and consequently they were not able to choose strategically. Also, the screener question was administered in such a way that it was impossible to deduct which answers would lead to a continuation of the experiment. On the screen we offered in total 17 possible answers (e.g., construction; education; public administration; transport; etc.). For the finance professionals' subsample only two answers (i.e., finance and

[1]The instructions have been translated into the official language for each country by a professional translation agency. The experiment has been conducted in Portuguese (Brazil), Mandarin (China), German (Germany), English (Great Britain, India, the United States, and South Africa), Japanese (Japan), and Russian (Russia). For further details on the translation process and the English version of the instructions see Appendix A.

[2]Participants were only directed to the "financial professionals" treatment of our experiment if both their occupational information stored in their user's account *and* their answers in the pre-screening indicated that they are currently employed in the finance industry. Similarly, respondents were only passed on to the "lay people" treatment of our survey if their response to the pre-screening survey has been concordant with the information stored on the agency's behalf, indicating that they do *not* work in the finance or insurance sector. Due to technical reasons, the implementation of a pre-screening survey was impractical on the platforms of the partnered research agencies in Russia and South Africa. For these two countries, participants were forwarded to our survey platform only based on the occupational information available through the user's account data which is typically gathered during the sign-up procedures on the platform.

insurance), did not screen out. Hence, a random click had a chance of 2/17 to reach the next stage. In the overall sample, only 2.36% of participants were excluded after our consistency checks, indicating that the pre-screening by the market research agencies worked very well. For the finance professional sample, 6.66% were screened out with our consistency checks. Under the conservative assumption that the whole 6.66% of participants that were excluded from the finance professionals subsample tried to deceive us, the ones who were screened out constituted 15/17 of the total sample. Hence, about 0.89% of our sample was probably not working in finance but managed to get into the survey with a random click.[3] Apart from the consistency checks outlined above, no other exclusion criteria are applied. The number of observations before and after exclusions, demographics, and industry and occupational information are summarized in Table A1 (Appendix C).

2.2 Experimental Design

We designed nine return distributions (based on simulated Pearson distributions) with 200 observations each, which were calibrated to share the same expected return (m_1) of 6.0% but to differ—in fixed levels—in their higher moments.

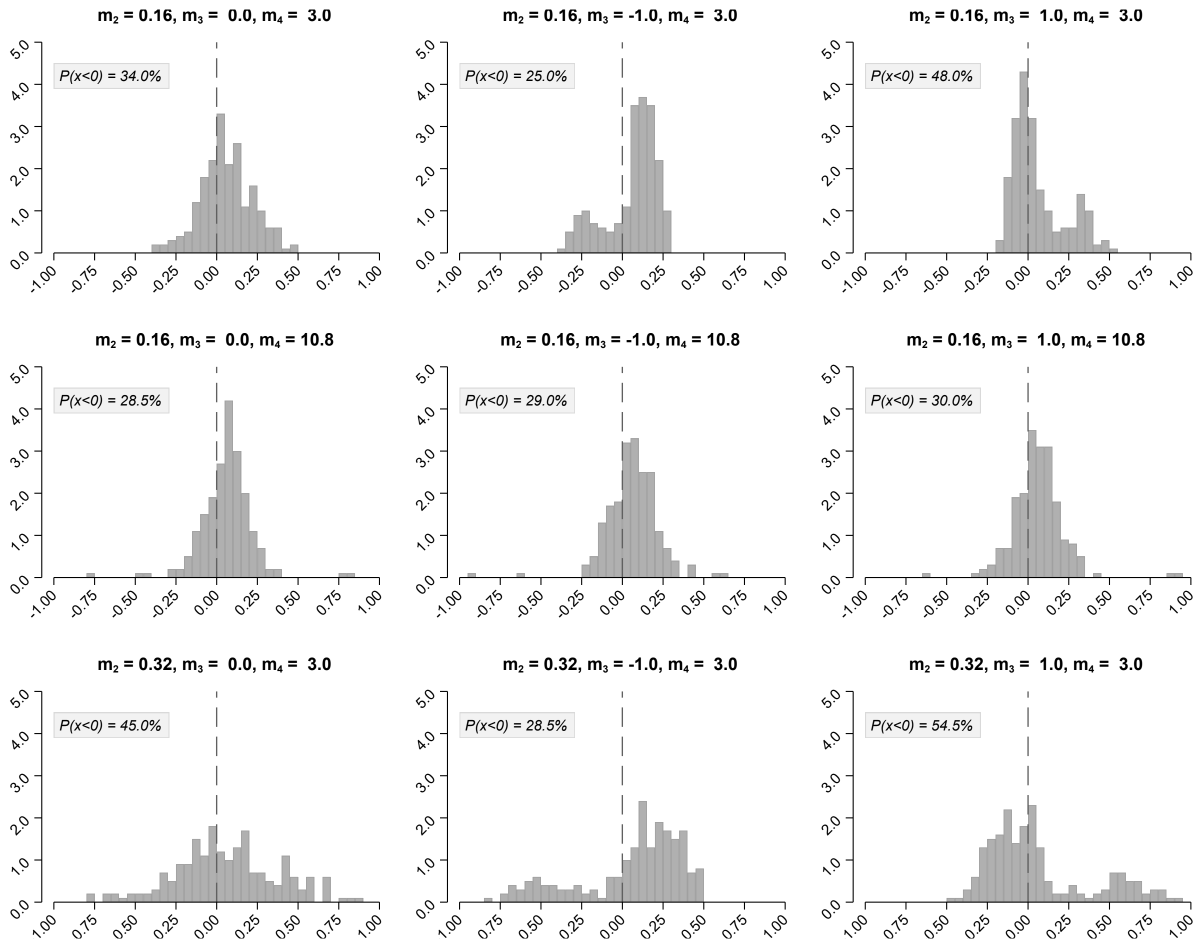
To causally infer which of the higher moments of a return distribution determines participants' risk perception and investment propensity, we systematically varied the standard deviation ($m_2 =$ 16% or $m_2 =$ 32%), skewness ($m_3 = -1$, $m_3 = 0$, or $m_3 = +1$), and kurtosis ($m_4 = 3.0$ or $m_4 = 10.8$) of the distributions while holding all other moments constant.[4] The systematic variation in moments allows for relating the variation in the dependent measures (self-reported risk perception and self-reported investment propensity) to *dichotomous* moderators. Histograms of the nine return distributions are presented in Figure 2.

The experimental implementation is inspired by and based on the design used by Zeisberger (2018). All participants were presented with histograms of all nine annual return distributions, each on a separate screen, in random order.[5] The horizontal axis showed the possible annual return realizations from –100% to +100% in steps of 5%, and the vertical axis displayed the likelihood of a realization in the corresponding bins (frequency in %).

[3]Based on data provided by the market research agency, the share of participants who completed but failed the initial screening (in the seven countries in which the pre-screening was implemented) varies between 5.5% (Japan) and 28.6% (India); the mean across the seven countries is 12.6%. Please note that even higher numbers of exclusions in the pre-screening process do not imply any deficiencies in data quality: participants' may simply have changed the industry they are working in since the last survey they have completed.

[4]Note that the systematic variations of higher moments as described above would give rise to a $2 \times 3 \times 2$ design, implying 12 different return distributions. To avoid fatigue or boredom given the repetitive nature of our experiment and to keep the overall time requirement for our online experiment at reasonable levels, we chose to reduce the number of return distributions to nine. In particular, we decided not to include the return distributions with high standard deviation *and* excess kurtosis for the three levels of skewness, since the simulations of returns with these properties turned out to result in highly artificial distribution shapes.

[5]Note that histograms are a commonly used way to communicate (return) distributions. Many other display formats (e.g., μ-σ-representations) come with the important shortcoming of only displaying certain properties of the distribution. Histograms have also been used frequently in previous research on subjects' risk perception and, thus, our paper can be seen in line of this strand of research (see, e.g., Lopes, 1987; Goldstein et al., 2008; Kaufmann et al., 2013; Bradbury et al., 2015). Yet, a downside of using histograms in our experiment is that inferring statistical properties of the distribution from graphical illustrations is a non-trivial task. We therefore discuss potential limitations of our findings due to the way of how return distributions are displayed in a separate section after presenting our results.



Notes: m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. The horizontal axis refers to annual returns (in 5% bins) and the vertical axis depicts the corresponding density. $P(x < 0)$ indicates the the return distribution's probability of loss. Note that histograms shown to participants were presented in terms of frequencies (in %) rather than densities and did not provide information on loss probabilities (see Figure A1 in Appendix B for an example).

Figure 2: Histograms of the nine return distributions based on 200 simulated observations each.

Below each return distribution, participants were asked to indicate their perception of risk associated with the particular financial asset by answering the question: "How risky do you perceive this investment product to be?" (1… "not risky at all" to 7… "very risky"). Note that our elicitation procedure of participant's perception of financial risk resembles the way how risk is frequently communicated between finance professionals and lay people in day to day practical application. Next to perceived risk, respondents were asked to indicate their propensity to invest in the respective financial asset by answering the question: "How likely would you invest in this investment product?" (1… "very unlikely" to 7… "very likely"). The instructions presented to participants at the beginning of the experiment are provided in Appendix A; a sample screen of the experiment is shown in Appendix B (Figure A1).

Given the subjective nature of our main question on risk perception, we refrained from paying performance-based incentives. This choice was also motivated by previous studies on risk perception, e.g., Nosić and Weber (2010); Zeisberger (2018), and studies on forecasting (Glaser et al., ming), which indicate that incentives do not systematically affect results in this domain. The experimental design has been reviewed and approved by the Internal Review Board of the University of Innsbruck.

3 Results

Throughout the reporting of our results, we follow Benjamin, D. J. et al. (2018) and set the default threshold for statistical significance to the 0.5% level. All analyses are based on subject-level demeaned data (i.e., controlling for subject-level fixed effects).

3.1 Risk Perception

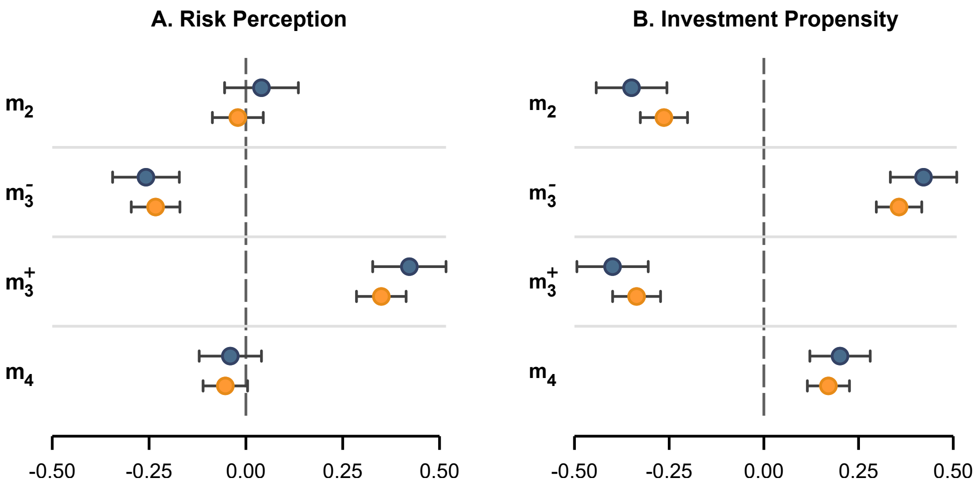
Figure 3 summarizes the main results, separated for financial professionals and the lay people subsamples: Panels A and B show the mean effects of variations in the return distributions' standard deviation (m_2), negative and positive skewness (m_3^-, m_3^+), and kurtosis (m_4) on perceived riskiness and investment propensity, respectively (see Table 1 for the corresponding regression analyses). We find that neither financial professionals' nor lay people's risk perception is systematically affected by the standard deviation of returns: even though standard deviation varies by a factor of two in our experimental setting, the effect on risk perception is negligible and not significantly different from zero in both subsamples. Similarly, variation in kurtosis does not systematically drive participants' appraisal of financial risk. Skewness, however, turns out to be a predictor of what both financial professionals and lay people consider as being risky: negatively skewed assets are, on average, perceived as carrying significantly less risk than symmetric assets, whereas positively skewed assets are, on average, assessed to be more risky than symmetric assets.[6] These results hold not only at the aggregate level but are also reflected in pairwise comparisons of risk perception between the nine distributions for financial professionals and lay people alike (see Figure 4).

Our findings indicate considerable differences between most return distributions *within* either the group of financial professionals and lay people. However, between the two participant groups there are almost no differences: there is only one out of nine distribution for which average risk perception differs significantly. Furthermore, the pairs of distributions for which we do or do not detect significant differences in average risk perception in the financial professionals group are almost identical to those pairs within the group of lay people. Overall, the results are strikingly similar on the average moment and single distribution level.

Moreover, our global study setup allows us to compare international differences in risk perception across the nine countries we analyzed. Summarizing the main result, we observe that differences in the evaluation of risk across the return distributions are remarkably homogeneous across the nine countries (Figures A2 and A3 in Appendix D). Hence, at least with regard to the analyzed distributions and main distributional moments we investigate, we do not find evidence for between-country differences with respect to risk perception.

Within our main participant group of financial professionals, this homogeneity holds across diverse job functions in the finance industry (Figures A4 and A5 in Appendix D). The differences we observe are rather small or negligible. The possibly most considerable difference can be observed for fund and portfolio managers. However, these differences to other job domains are

[6] While there are some papers reporting other findings with respect to positive and negative skewness, our result are consistent with findings about decision makers' aversion to negative outcomes (likelihood of a loss). This result will be discussed in detail in the section on Compound Risk Measures.



Notes: Mean effects of systematic variations in the return distributions' higher moments (standard deviation, skewness, and kurtosis) on subject-level demeaned risk perception (Panel A) and subject-level demeaned investment propensity (Panel B). The effects correspond to coefficients of dichotomous explanatory variables in an ordinary least squares regression (controlling for interaction effects), as reported in Tables 1. m_2: 1 if standard deviation = 32.0%, 0 if standard deviation = 16.0%; m_3^-: 1 if skewness = –1.0, 0 if skewness = 0; m_3^+: 1 if skewness = +1.0, 0 if skewness = 0; m_4: 1 if kurtosis = 10.8, 0 if kurtosis = 3.0. Error bars denote 99.5% confidence intervals based on standard errors clustered on the individual level. n = 19,917 (2,213 clusters) for the financial professionals and n = 41,031 (4,559 clusters) for the general population subsample.

Figure 3: Effects of variations in higher moments on risk perception (A) and investment propensity (B).

not systematic with respect to any particular distributional moment. For example, the results do not indicate that the group of fund and portfolio managers perceive volatility fundamentally different than the other occupational groups. Also, similar groups such as investment bankers or trading and brokerage professionals do not show qualitatively different results.

3.2 Investment Propensity

We now turn to our analysis on investment behavior. In contrast to risk perception, an individual's propensity to invest depends not only on the assessment of perceived risk associated with an investment but also on individual-level risk preferences, which includes the valuation of the reward, often also in light of a possible alternative, namely not to invest (Weber and Milliman, 1997). For the sake of illustration, we refer to Figure 1: Regardless of risk preferences, participants might perceive one of the two return distributions as carrying more risk than the other if their evaluation of risk appreciates skewness. Yet, very risk-averse individuals might be reluctant to invest in *any* of the two assets as both are perceived to entail some risk. Conversely, very risk-seeking individuals might invest fully in both distributions, despite the fact that they perceive one distribution to be more risky than the other. Hence, when it comes to investment propensity, the confounding nature of the perception of risk on the one hand and the appreciation of outcomes on the other makes it hard to disentangle the effects causally (Dyer and Sarin, 1982; Weber and Bottom, 1989; Weber and Milliman, 1997). Nevertheless, we consider the impact of higher moments on investment propensity as informative, since this measure resembles actual investment *decisions* more closely and ultimately could influence asset holdings and prices in financial markets.

Table 1: Regression Analysis

	Risk Perception			*Investment Propensity*		
	(1) Fin. Prof.	(2) Gen. Pop.	(3) (1) - (2)	(4) Fin. Prof.	(5) Gen. Pop.	(6) (4) - (5)
m_2	0.040	−0.021	0.061	−0.349*	−0.264*	−0.085
	(0.034)	(0.023)	[2.199]	(0.033)	(0.022)	[4.577]
m_3^-	−0.258*	−0.233*	−0.025	0.422*	0.357*	0.065
	(0.031)	(0.022)	[0.429]	(0.031)	(0.021)	[2.937]
m_3^+	0.422*	0.350*	0.072	−0.399*	−0.336*	−0.063
	(0.034)	(0.023)	[3.169]	(0.034)	(0.023)	[2.468]
m_4	−0.040	−0.053	0.013	0.201*	0.170*	0.031
	(0.029)	(0.020)	[0.134]	(0.028)	(0.020)	[0.786]
$m_2\times m_3^-$	−0.003	0.011	−0.015	0.128*	0.077	0.051
	(0.043)	(0.030)	[0.078]	(0.041)	(0.029)	[1.012]
$m_2\times m_3^+$	0.057	0.061	−0.004	0.074	0.068	0.006
	(0.045)	(0.030)	[0.006]	(0.044)	(0.029)	[0.014]
$m_3^-\times m_4$	0.274*	0.252*	0.022	−0.521*	−0.486*	−0.035
	(0.043)	(0.031)	[0.171]	(0.043)	(0.030)	[0.456]
$m_3^+\times m_4$	−0.465*	−0.357*	−0.107	0.384*	0.277*	0.107
	(0.044)	(0.030)	[4.035]	(0.044)	(0.030)	[4.085]
Constant	−0.040	−0.011	−0.029	0.035	0.031	0.004
	(0.018)	(0.013)	[1.716]	(0.018)	(0.013)	[0.025]
No. of Obs.	19,917	41,031		19,917	41,031	
No. of Clusters	2,213	4,559		2,213	4,559	
Adj. R^2	0.048	0.035		0.089	0.062	

Notes: Ordinary least squares regressions of risk perception and investment propensity on dichotomous covariates (and their interactions) capturing systematic variation in the distributions' higher moments. Models (1) and (2) report regressions of participants' risk perception (subject-level demeaned data) for the subsamples "financial professionals" and "general population," respectively; models (4) and (5) report regressions of participants' investment propensity (subject-level demeaned data) for the same subsamples. Standard errors, clustered on the individual level, are reported in parentheses. * indicates a statistically significant effect at the $p < 0.005$ level. Columns (3) and (6) report effect size differences between the two subsamples, i.e., differences between models (1) and (2) and (4) and (5), respectively; $\chi^2(1)$ statistics based on Wald tests after seemingly unrelated regressions are reported in brackets. m_2: 1 if standard deviation = 32.0%, 0 if standard deviation = 16.0%; m_3^-: 1 if skewness = –1.0, 0 if skewness = 0; m_3^+: 1 if skewness = +1.0, 0 if skewness = 0; m_4: 1 if kurtosis = 10.8, 0 if kurtosis = 3.0. × indicates interaction terms.

As would be expected based on the premise that people are generally risk averse, individuals' risk perception and investment propensity are inversely related: the higher the risk associated with a return distribution is perceived to be, the lower is the willingness to invest in the asset ($\rho = -0.399$, $p < 0.005$). When turning to the effects of variation in higher moments on respondents' investment propensity, skewness is again a determining moderator: On average, participants report a higher (lower) willingness to invest in assets with positively (negatively) skewed return distributions than in assets yielding symmetric returns. However, in contrast to their insignificant effects on risk perception, standard deviation and kurtosis do significantly affect participants' willingness to invest (see Panel B in Figure 3). In line with mean-variance models in finance (usually assuming risk averse agents), financial professionals' and lay people's investment propensity is, on average, significantly lower for return distributions with high volatility.

The fact that variance matters more for investment decisions than for risk perception is in line with the concept of relative risk attitudes, which disentangles expected utility theory's

	$m_2 = 0.16$, $m_3 = -1.0$, $m_4 = 3.0$	$m_2 = 0.32$, $m_3 = -1.0$, $m_4 = 3.0$	$m_2 = 0.16$, $m_3 = +1.0$, $m_4 = 10.8$	$m_2 = 0.16$, $m_3 = 0.0$, $m_4 = 10.8$	$m_2 = 0.16$, $m_3 = -1.0$, $m_4 = 10.8$	$m_2 = 0.32$, $m_3 = 0.0$, $m_4 = 3.0$	$m_2 = 0.16$, $m_3 = 0.0$, $m_4 = 3.0$	$m_2 = 0.16$, $m_3 = +1.0$, $m_4 = 3.0$	$m_2 = 0.32$, $m_3 = +1.0$, $m_4 = 3.0$
$m_2 = 0.16$, $m_3 = -1.0$, $m_4 = 3.0$	-0.054 (0.029)	0.037 (0.035)	0.175* (0.031)	0.218* (0.032)	0.234* (0.031)	0.298* (0.035)	0.258* (0.030)	0.680* (0.036)	0.777* (0.038)
$m_2 = 0.32$, $m_3 = -1.0$, $m_4 = 3.0$	-0.009 (0.024)	-0.007 (0.030)	0.138* (0.032)	0.181* (0.033)	0.197* (0.031)	0.261* (0.036)	0.221* (0.031)	0.643* (0.036)	0.740* (0.038)
$m_2 = 0.16$, $m_3 = +1.0$, $m_4 = 10.8$	0.172* (0.022)	0.182* (0.022)	-0.051 (0.024)	0.042 (0.030)	0.059 (0.028)	0.123* (0.033)	0.083* (0.027)	0.505* (0.033)	0.602* (0.035)
$m_2 = 0.16$, $m_3 = 0.0$, $m_4 = 10.8$	0.180* (0.023)	0.190* (0.023)	0.008 (0.020)	-0.016 (0.027)	0.016 (0.029)	0.080 (0.034)	0.040 (0.028)	0.462* (0.034)	0.559* (0.036)
$m_2 = 0.16$, $m_3 = -1.0$, $m_4 = 10.8$	0.199* (0.022)	0.209* (0.022)	0.027 (0.019)	0.019 (0.020)	-0.019 (0.024)	0.064 (0.032)	0.024 (0.026)	0.446* (0.033)	0.543* (0.035)
$m_2 = 0.32$, $m_3 = 0.0$, $m_4 = 3.0$	0.212* (0.024)	0.222* (0.024)	0.040 (0.022)	0.032 (0.023)	0.013 (0.022)	0.032 (0.031)	-0.040 (0.031)	0.382* (0.037)	0.479* (0.039)
$m_2 = 0.16$, $m_3 = 0.0$, $m_4 = 3.0$	0.233* (0.021)	0.243* (0.021)	0.061* (0.019)	0.053 (0.020)	0.034 (0.019)	0.021 (0.022)	-0.029 (0.022)	0.422* (0.032)	0.519* (0.034)
$m_2 = 0.16$, $m_3 = +1.0$, $m_4 = 3.0$	0.583* (0.024)	0.592* (0.025)	0.410* (0.022)	0.403* (0.023)	0.384* (0.022)	0.370* (0.025)	0.350* (0.022)	0.043 (0.031)	0.097 (0.039)
$m_2 = 0.32$, $m_3 = +1.0$, $m_4 = 3.0$	0.623* (0.026)	0.633* (0.026)	0.451* (0.024)	0.443* (0.025)	0.424* (0.024)	0.411* (0.026)	0.390* (0.023)	0.040 (0.026)	0.100* (0.035)

Notes: Pairwise differences in participants' mean risk perception (subject-level demeaned data) between the nine return distributions for the subsamples "financial professionals" (upper triangle; n = 2,213) and "general population" (lower triangle; n = 4,559). Effect sizes refer to "column minus row" in the upper triangle and "row minus column" in the lower triangle, respectively. Color shadings indicate the magnitude of effect sizes. The cells on the diagonal report differences between the two subsamples per distribution (n = 6,772). m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. Standard errors clustered on the individual level are reported in parentheses. Return distributions are sorted in ascending order of mean perceived riskiness in the pooled data. * indicates a significant difference with $p < 0.005$ based on paired-sample t-tests for off-diagonal differences and independent-sample t-tests for differences on the diagonal.

Figure 4: Pairwise differences in participants' mean risk perception between the nine return distributions.

labelling of the shape of the utility function as "risk preferences" into the separate appreciation of risk and rewards (Dyer and Sarin, 1982; Weber and Milliman, 1997). According to this approach, if two assets with the same expected return are perceived as equally risky, there is still room for different evaluations of the assets' attractiveness in an investment decision, because of the separate assessment of the monetary reward.[7] Another explanation for our results is the framework of perceived risk attitudes proposed by Weber and Bottom (1989), which relates risk perception of alternatives to choice behavior. Specifically, Weber and Milliman (1997) show

[7] As an illustration, let us assume that an investor's risk perception is only affected by an asset's loss probability (which is one of the key findings of our study). Suppose there are two investment alternatives: asset A yields \$–5 in 25% of the cases and \$10 otherwise; asset B yields \$–8 with 25% probability and \$11 otherwise. If loss probability is the only measure associated with financial risk, the investor will perceive assets A and B equally risky although the standard deviation of asset B is higher than the standard deviation of asset A (note that the expected return, skewness, and kurtosis are identical for A and B). Yet, the likelihood of whether or not to invest may depend on the assessment of monetary outcomes. For example, if an investor faces a decreasing (increasing) marginal utility of money (here we explicitly refrain from using "risk aversion" as a label for the shape of the utility function), he/she will likely prefer asset A (B).

that changes in alternatives can change the perception of risk. Translated to our context this approach suggests that, when the risk component is assessed in isolation, return distributions with different standard deviations are perceived as equally risky. However, when asked how much to invest, which automatically includes the alternative not to take any risk at all, then a return distribution with a higher (lower) standard deviation appears to be more (less) risky in relative terms, resulting in a lower (higher) investment propensity.

Similar to the results on risk perception, the identified patterns are reflected in pairwise comparisons of investment propensity across the nine return distributions and do not significantly differ between the two subsamples (see Figure 5). The number of pairwise comparisons between return distributions with significant differences in average investment propensity is higher than for risk perception *within* each group of participants. Between financial professionals and lay people again only one out of nine distributions shows a significant difference (the same distribution as for risk perception). Hence again, our results are strikingly similar between financial professionals and laymen (see also Panel B of Figure 3).

	m_2 = 0.16 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = 0.0 m_4 = 10.8	m_2 = 0.32 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 10.8	m_2 = 0.16 m_3 = -1.0 m_4 = 10.8	m_2 = 0.16 m_3 = 0.0 m_4 = 3.0	m_2 = 0.32 m_3 = 0.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 3.0	m_2 = 0.32 m_3 = +1.0 m_4 = 3.0
m_2 = 0.16 m_3 = -1.0 m_4 = 3.0	0.068 (0.028)	-0.221* (0.031)	-0.221* (0.033)	-0.236* (0.030)	-0.320* (0.030)	-0.422* (0.030)	-0.771* (0.034)	-0.821* (0.035)	-1.096* (0.037)
m_2 = 0.16 m_3 = 0.0 m_4 = 10.8	-0.186* (0.022)	0.034 (0.026)	-0.000 (0.032)	-0.015 (0.029)	-0.099* (0.029)	-0.201* (0.028)	-0.550* (0.032)	-0.601* (0.033)	-0.876* (0.035)
m_2 = 0.32 m_3 = -1.0 m_4 = 3.0	-0.186* (0.023)	0.000 (0.022)	0.034 (0.029)	-0.015 (0.031)	-0.099* (0.031)	-0.201* (0.030)	-0.550* (0.034)	-0.600* (0.035)	-0.875* (0.037)
m_2 = 0.16 m_3 = +1.0 m_4 = 10.8	-0.245* (0.021)	-0.059* (0.020)	-0.059 (0.021)	0.077* (0.024)	-0.084* (0.027)	-0.186* (0.027)	-0.535* (0.031)	-0.585* (0.032)	-0.860* (0.034)
m_2 = 0.16 m_3 = -1.0 m_4 = 10.8	-0.315* (0.021)	-0.129* (0.020)	-0.129* (0.021)	-0.070* (0.019)	0.064 (0.024)	-0.102* (0.027)	-0.451* (0.031)	-0.501* (0.032)	-0.776* (0.034)
m_2 = 0.16 m_3 = 0.0 m_4 = 3.0	-0.357* (0.020)	-0.170* (0.019)	-0.170* (0.021)	-0.112* (0.018)	-0.042 (0.018)	0.004 (0.022)	-0.349* (0.031)	-0.399* (0.032)	-0.675* (0.034)
m_2 = 0.32 m_3 = 0.0 m_4 = 3.0	-0.621* (0.023)	-0.434* (0.022)	-0.434* (0.024)	-0.376* (0.021)	-0.306* (0.021)	-0.264* (0.021)	-0.082 (0.029)	-0.050 (0.036)	-0.325* (0.037)
m_2 = 0.16 m_3 = +1.0 m_4 = 3.0	-0.693* (0.024)	-0.506* (0.023)	-0.506* (0.024)	-0.448* (0.022)	-0.378* (0.022)	-0.336* (0.021)	-0.072* (0.024)	-0.060 (0.031)	-0.275* (0.038)
m_2 = 0.32 m_3 = +1.0 m_4 = 3.0	-0.889* (0.024)	-0.703* (0.024)	-0.703* (0.025)	-0.644* (0.023)	-0.574* (0.023)	-0.532* (0.022)	-0.268* (0.025)	-0.196* (0.025)	-0.139* (0.033)

Notes: Pairwise differences in subjects' mean investment propensity (subject-level demeaned data) between the nine return distributions for the subsamples "financial professionals" (upper triangle; $n = 2{,}213$) and "general population" (lower triangle; $n = 4{,}559$). Effect sizes refer to "column minus row" in the upper triangle and "row minus column" in the lower triangle, respectively. Color shadings indicate the magnitude of effect sizes. The cells on the diagonal report differences between the two subsamples per distribution ($n = 6{,}772$). m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. Standard errors clustered on the individual level are reported in parentheses. Return distributions are sorted in descending order of mean propensity to invest in the pooled data. * indicates a significant difference with $p < 0.005$ based on paired-sample t-tests for off-diagonal differences and independent-sample t-tests for differences on the diagonal.

Figure 5: Pairwise differences in mean investment propensity between the nine return distributions

Furthermore, as for risk perception, participants' propensity to invest is strikingly consistent across countries (Figures A6 and A7 in Appendix D). For occupational categories in the finance sector (Figures A8 and A9 in Appendix D), we observe consistent results compared to our analysis on risk perception. The biggest difference is, again, for fund and portfolio managers where a *relative* preference for positively skewed investments can be observed, not affecting, however, our overall qualitative observations. Other groups such as professionals in risk management, investment banking, private banking and wealth management or trading do not differ in any systematic way from the average.

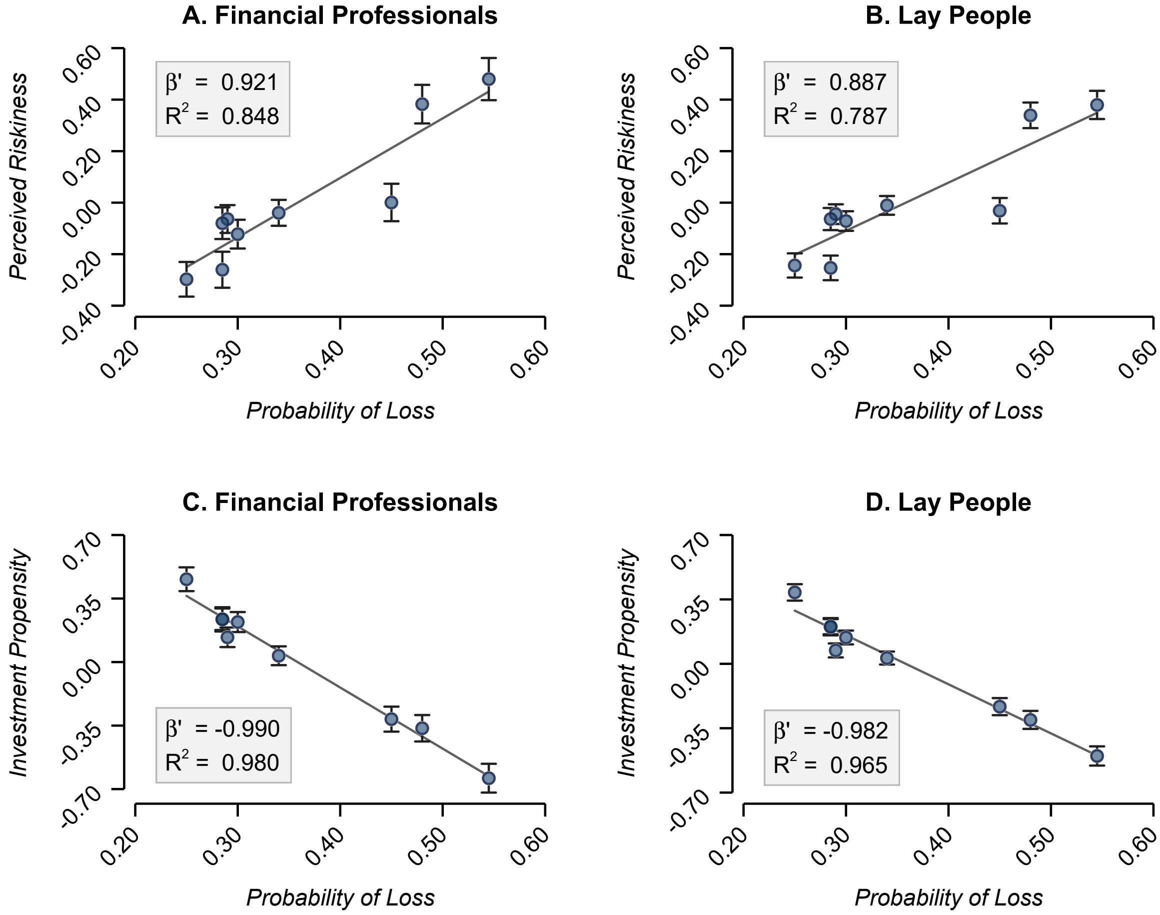
3.3 Compound Risk Measures

Aside from examining the effects of variation in higher moments, we investigate whether *compound* risk measures explain participants' risk perception and investment propensity. Indeed, experimental evidence suggests that compound measures focusing on downside risk—such as the expected value of a potential loss, lower partial moments, or the likelihood of ending up with negative outcomes (Weber and Hsee, 1998; Unser, 2000; Veld and Veld-Merkoulova, 2008; Zeisberger, 2018)—serve as more reliable predictors of individuals' actual risk-taking behavior than single higher moments. In an explorative analysis, we therefore compute a number of compound risk measures (Brachinger and Weber, 1997), some of which have recently been included in financial regulation (e.g., Basel III). In particular, we include the following conceptualizations of risk: (i) the absolute deviation from the mean, (ii) the semi-variance, (iii) the expected value of loss, (iv) the probability of loss, (v) the inter-quartile range, (vi) the maximum loss (i.e., minimum return), (vii) the 90% value at risk, and (viii) the 95% value at risk. In addition, we examine the explanatory power of (ix) Cumulative Prospect Theory (CPT) (Tversky and Kahneman, 1992), applying the authors' frequently used functional forms and parametrization: $\alpha = \beta = 0.88$, $\gamma = 0.61$, $\delta = 0.69$, and $\lambda = 2.25$.

We find that one of these nine measures consistently predicts both the perception of risk and investment propensity to a much larger degree than all other measures: the probability to incur losses (see Figure 6 for a regression analysis on loss probability as well as Figures A10 and A11 in Appendix D for results of the nine risk measures on risk perception and investment propensity).

We find that the probability to incur a loss explains the bulk of variation in mean perceived riskiness, and this is even slightly higher for financial professionals: 84.8% for professionals and 78.7% for lay people. This result is even stronger for participants' propensity to invest, where the distribution's loss probability explains 98.0% and 96.5% of the variation in means for financial professionals and lay people, respectively.[8]

[8]Note that this results suggests that the effects of skewness on perceived riskiness and investment propensity are primarily attributable to its effect on loss probability. In order to examine whether skewness has an additional effect beyond that, we regress mean (subject-level demeaned) risk perception on the distributions' probability of loss *and* two dummy variables indicating positive and negative skewness, respectively, for the finance professionals and general population sample. Notably, the two indicator variables for skewness are statistically insignificant for both samples. Moreover, comparing the adjusted R^2s of the models with and without skeweness indicators suggests that the reduced number of degrees of freedom outweighs the additional explanatory power from adding covariates to the model: for the finance professionals' sample, the adj. R^2 is reduced by 1.11 percentage points (p.p.; a 1.3% decrease); for the general population sample, the adj. R^2 increases by 0.75 p.p. (a 0.9% increase). Repeating the procedure for investment propensity (i.e., replacing the dependent variable in the models outlined



Notes: Ordinary least squares regressions of mean perceived riskiness (Panels A and B) and mean investment propensity (Panels C and D) on the distribution's probability of loss for the subsamples "financial professionals" and "lay people." Error bars indicate 99.5% confidence intervals. β' and R^2 denote the standardized correlation coefficient (equivalent to the Pearson correlation coefficient ρ) and the R^2 of the regression, respectively.

Figure 6: Regressions of perceived riskiness and investment propensity on the distribution's probability of loss.

3.4 Limitations

When designing the experiment, we had to make several choices regarding the overall experimental setting and the manipulation of the different conditions. One of these choices was how to present and communicate the potentially relevant drivers of risk perception and investment propensity. In this regard, we consciously opted for using histograms, as they do not include a time dimension, and as they constitute a commonly used form of representing (return) distributions. Yet, inferring empirical higher moments from histograms of returns is anything but straightforward, and our results crucially depend on participants' ability to discern differences in distributions' moments. Our result that risk perception and investment propensity are systematically driven by the distributions' higher moments (and the compound risk measure of loss probability) is indicative of participants' ability to detect even subtle differences in distribu-

above) corroborates this claim: the adjusted R^2 drops by 0.53 p.p. and 1.59 p.p. for the finance professionals and general population sample, respectively. The insignificant coefficients of the skewness indicators and the very small changes in R^2 suggest that there is no economically relevant lever through which risk perception and investment propensity are affected by skewness, beyond its impact on loss probability.

tional characteristics. This line of reasoning is further corroborated by the fact that the effects attributable to systematic variations in the distributions' higher moments are highly consistent across the nine countries in our sample (see Figures A2, A3, A6, and A7), as well as the 13 job functions within the subsample of finance professionals (see Figures A4, A5, A8, and A9). Eventually, the question whether people do associate the perceived differences in return distributions with the higher moment—which is actually driving the differences—cannot be addressed using our experimental design. We leave this question for further research.

4 Discussion and Conclusion

We contribute to a growing and highly relevant research area of experimental studies examining behavioral aspects in financial professionals' decision-making (Alevy et al., 2007; Kaustia et al., 2008; Cipriani and Guarino, 2009; Puetz and Ruenzi, 2011; Gloede and Menkhoff, 2014; Cohn et al., 2014; Kirchler et al., 2018). Utilizing an experimental design that allows for a systematic separation of higher moments, potentially driving risk perception and investment propensity, our study facilitates a more comprehensive understanding of how financial professionals assess risks in a financial context in comparison to lay people across nine major economies.

While standard deviation is the most commonly used measure to describe financial risks in theoretical models, finance textbooks, financial advice, and regulatory frameworks, our results suggest that variations in standard deviation do not trigger systematic differences in risk perception, not even for financial professionals. The skewness of the asset returns, however, induces pronounced differences in the cognition of financial risk: positively skewed returns are considered to be significantly more risky than symmetric distributions, and symmetric distributions are perceived as carrying significantly more risk than negatively skewed returns. We believe that this finding is explained by the probability of losing and the aversion to it. This conjecture is underpinned by the fact that the interaction effects between skewness and kurtosis ($p < 0.005$) are of similar magnitude as the effect of skewness, but point in the opposite direction (see Table 1). Wald tests suggest that there is indeed no statistically significant effect of skewness on risk perception for the distributions with high kurtosis, neither for the finance professionals ($m_3^- + m_3^- \times m_4 = 0$: $p = 0.625$; $m_3^+ + m_3^+ \times m_4 = 0$: $p = 0.202$) nor the general population subsample ($m_3^- + m_3^- \times m_4 = 0$: $p = 0.403$; $m_3^+ + m_3^+ \times m_4 = 0$: $p = 0.737$). Given that the probability to incur losses is—ceteris paribus—attenuated with increasing levels of kurtosis (conditional on the expected return being positive), this result is indicative of skewness being primarily perceived through the channel of loss probabilities.

Investment propensity, as would be expected for risk-averse agents, is inversely related to risk perception. Differences in the distributions' standard deviation do induce significant differences in participants' disposition to invest, with a higher standard deviation leading to a lower willingness to invest. Given the premise that investment propensity is a function of both risk perception and risk preferences, the discrepancy in volatility effects might indicate that people's risk attitude—but not risk perception—is responsive to volatility measures.

Furthermore, we find strong evidence that the probability of suffering a loss is the main driver for both the perception of financial risk and investment propensity among financial professionals and lay people. At the aggregate level, the probability to incur losses explains approx. 80% of the variation in average risk perception and more than 96% of the variation in average investment propensity. This points towards loss aversion as the most important component of decision-making under risk, in support of the notion that there might be no risk aversion beyond loss aversion (Novemsky and Kahneman, 2005; Dahmi, 2016). Given the strong effect of loss probabilities, Cumulative Prospect Theory (CPT; Tversky and Kahneman, 1992) comes into mind as a prominent explanation for our data. However, compared to the compound risk measures we tested, and in particular compared to loss probability, we find that CPT has little explanatory power.

Importantly, all patterns identified among financial professionals bear a striking similarity to the patterns observed among lay people. Given extensive training and experience in the industry, financial professionals might well be expected to perceive financial risk more in line with predominant risk measures than lay people. However, even though financial professionals, on average, react somewhat more sensitively to rather subtle variations in return distributions, differences in the evaluation of risk and the disposition to invest are negligible and insignificant between the two populations.

In a similar vein, risk perception and investment propensity are fairly homogeneous across countries. In particular, the identified patterns driving individual's perception of risk and their willingness to invest are largely similar in the different countries in our sample, even though the countries differ considerably in many cultural and social aspects.

Our results have important implications for financial regulation, particularly for the communication of risks to investors. Many regulations and directives still rely to a large extent on variance as a measure of risk (e.g., KIID, MiFID, Solvency II). Given that neither financial professionals nor lay people seem to perceive variance as the defining moment of risk, measures that include skewness and loss probabilities should be given more attention in financial regulation. This particularly applies to key investor information documents (KIID), where a one-dimensional synthetic risk and reward indicator (SRRI) communicates risk with seven categories of low to high variance. Such a reduction of risk to variance can be compared to reducing nutrition facts to calories. Just as food contains multiple ingredients, financial products contain multiple dimensions of risk that are, as we show, important and perceived very differently by investors. In the spirit of the "nutrition facts label" for food, we advocate the use of a "risk facts label" for financial products that includes not only the variance of returns but also skewness and, most importantly, loss probabilities. Our finding that financial professionals, including those in private banking and wealth management, do not differ substantially from lay people, highlights that retail investors' characteristic risk perception is not necessarily "advised away" when financial advisors are consulted.

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Appendix A Experimental instructions

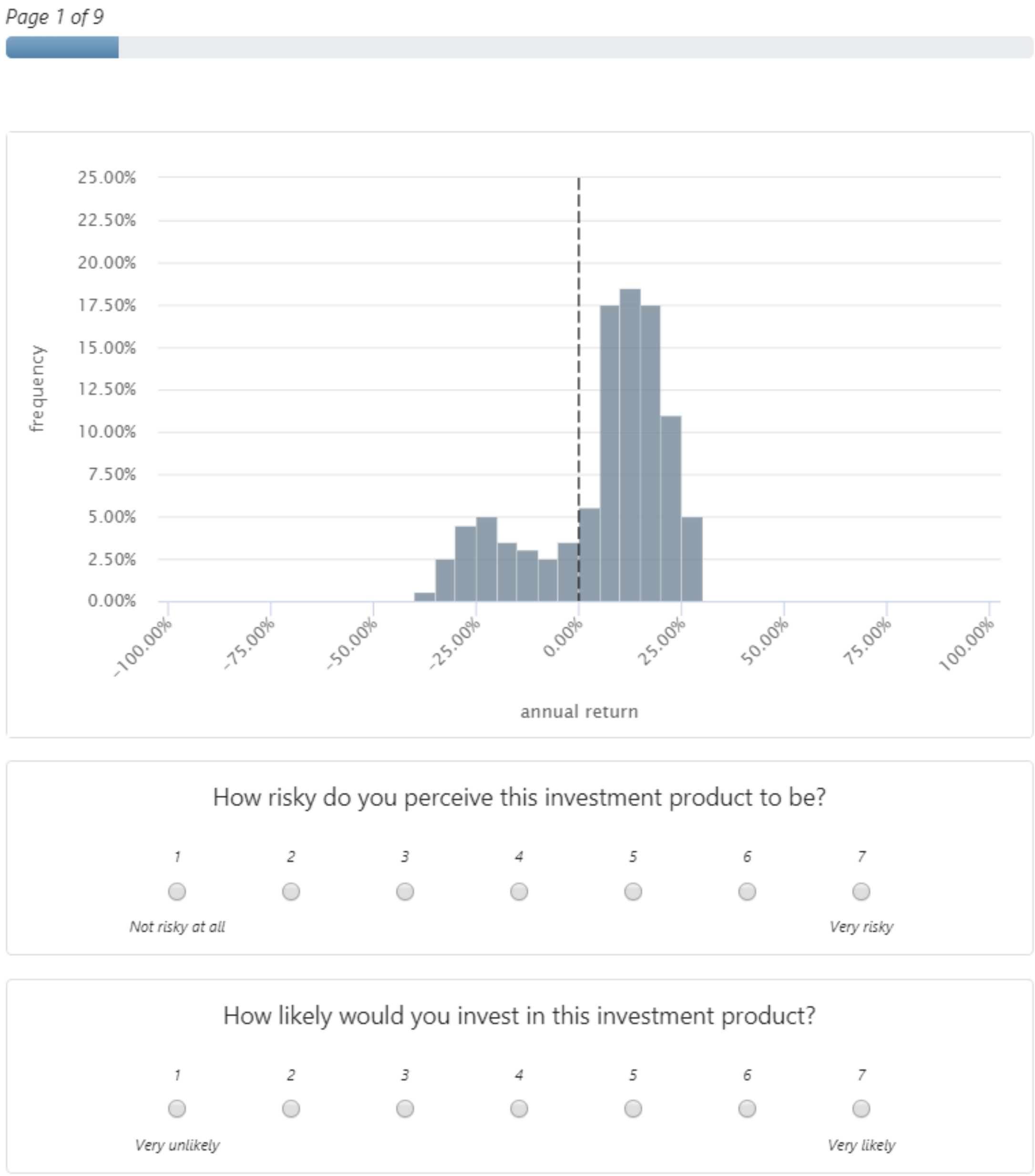
The box below presents the English version of the instructions as shown to participants in the online survey. The instructions have been translated into the official language for each country by a professional translation agency. For countries with more than one official language, the most common language in the respective country was used. The sampling procedures employed by the partnered market research agencies ensured that only respondents with knowledge in the particular language were recruited. The experiment has been conducted in Portuguese (Brazil), Mandarin (China), German (Germany), English (Great Britain, India, the United States, and South Africa), Japanese (Japan), and Russian (Russia). The translation process involved a back- and forth-translation loop (based on the English version as depicted below) to guarantee high quality translations. Furthermore, for each of the six languages, we asked scholars whose mother tongue is one of the particular languages, and who are familiar with the economic terminology, to review the translated version of the experiment. By that means, we ensured that the translations are not only immaculate in linguistic and grammatical terms, but also terminology- and content-wise.

To explain how to read and interpret the histograms of annual returns, a sample distribution was depicted below the instructions on the introductory screen. The mean, standard deviation, skewness, and excess kurtosis of this sample distribution were 6.0%, 16.0%, -0.12, and -0.79, respectively.

In the following, you will be presented with nine hypothetical annual return distributions, each referring to different investment products. For each investment product, you will be asked to indicate how risky you perceive the investment to be on a 7-point scale from “Not risky at all” to “Very risky” and how likely you would invest in this investment product on a 7-point scale from “Very unlikely” to “Very likely”.

On the horizontal axis you see the possible annual return realizations from -100.0% to +100.0% in 5%-steps. On the vertical axis you see how likely such a realization is. The higher a bar, the more likely a given outcome is. All nine return distributions you will see have the same average (= expected) return of 6.00%.

Appendix B Sample screen of the online experiment



Notes: The example shows an annual return distribution with mean (m_1) of 6.0%, standard deviation (m_2) of 16.0%, skewness (m_3) of -1.0, and kurtosis (m_4) = 3.0. The horizontal axis depicts the annual returns (in 5% bins) and the vertical axis is scaled in terms of frequencies (in %). The nine distributions were presented sequentially (on separate screens) in random order.

Figure A1: Sample screen of the online experiment.

Appendix C Participant Descriptive Data and Exclusions

Table A1: Descriptive statistics.

Finance Sector	**BR**	**CN**	**DE**	**IN**	**JP**	**RU**	**UK**	**US**	**ZA**	**Total**
Exclusions:										
N (total)	202	342	243	227	265	232	226	354	280	2,371
No. of exclusions	0	4	0	11	0	90	0	1	52	158
N (after exclusions)	202	338	243	216	265	142	226	353	228	2,213
Demographics:										
Females	49.0%	43.6%	47.7%	37.5%	33.5%	69.0%	50.0%	54.7%	68.9%	49.4%
Age	38.36	33.45	46.16	37.39	47.59	36.67	44.28	46.46	35.71	41.00
	(12.47)	(8.47)	(11.82)	(10.53)	(10.96)	(8.96)	(12.39)	(12.22)	(10.38)	(12.23)
Industry:										
Finance	86.1%	91.7%	70.4%	86.6%	67.2%	95.8%	82.3%	62.3%	78.1%	78.6%
Insurance	13.9%	8.3%	29.6%	13.4%	32.8%	4.2%	17.7%	37.7%	21.9%	21.4%
Occupation:										
Accounting & Controlling	22.3%	16.9%	14.4%	19.0%	4.2%	26.8%	16.4%	13.3%	35.1%	17.7%
Advisory Services	6.4%	4.4%	7.4%	4.2%	6.8%	1.4%	4.9%	4.8%	6.6%	5.3%
Analysis & Research	6.4%	7.1%	2.1%	5.1%	3.0%	5.6%	4.9%	6.2%	4.0%	5.0%
Fund & PF Management	2.0%	6.8%	0.8%	7.4%	2.3%	3.5%	1.3%	2.6%	1.3%	3.2%
Administration	13.4%	8.6%	17.7%	10.7%	10.6%	2.8%	20.8%	16.2%	16.7%	13.4%
Investment Banking	7.4%	6.8%	2.1%	12.0%	2.6%	9.2%	8.4%	5.7%	3.5%	6.2%
Private Banking	0.5%	4.1%	9.1%	5.1%	0.8%	9.9%	2.7%	2.0%	0.9%	3.6%
Risk Management	4.0%	6.8%	1.7%	11.6%	3.8%	8.5%	3.1%	5.1%	4.0%	5.2%
Sales	8.9%	5.9%	11.9%	5.1%	20.0%	9.2%	6.2%	7.4%	3.5%	8.7%
Management	3.5%	15.7%	2.1%	9.3%	11.3%	3.5%	9.3%	5.7%	7.0%	8.0%
Trading, Brokerage	6.4%	1.8%	1.7%	2.3%	3.0%	4.2%	0.9%	1.4%	2.6%	2.5%
Other: Finance	17.3%	12.7%	21.4%	8.3%	23.4%	13.4%	18.1%	17.3%	14.0%	16.4%
Other: Non-Finance	1.5%	2.4%	7.8%	0.0%	8.3%	2.1%	3.1%	12.5%	0.9%	4.9%

Lay People	**BR**	**CN**	**DE**	**IN**	**JP**	**RU**	**UK**	**US**	**ZA**	**Total**
Exclusions:										
N (total)	437	687	452	429	505	438	463	681	473	4,565
No. of exclusions	1	0	0	1	1	1	0	1	1	6
N (after exclusions)	436	687	452	428	504	437	463	680	472	4,559
Demographics:										
Females	52.5%	49.3%	53.1%	47.0%	51.8%	49.4%	49.8%	51.3%	51.1%	50.6%
Age	38.45	38.08	43.40	37.53	44.20	39.19	42.68	42.68	37.03	40.37
	(12.48)	(11.20)	(13.27)	(11.93)	(13.59)	(10.29)	(13.58)	(13.58)	(12.79)	(12.85)
Industry:										
Agriculture	1.4%	2.3%	0.0%	1.2%	1.2%	2.3%	0.4%	1.0%	5.1%	1.7%
Automotive	1.4%	0.7%	2.4%	0.7%	1.4%	1.8%	1.1%	0.7%	2.3%	1.3%
Business Services	6.0%	3.5%	3.1%	4.9%	6.4%	7.8%	3.2%	4.0%	8.3%	5.1%
Communications	2.3%	2.9%	0.9%	2.6%	0.4%	1.1%	0.9%	0.9%	2.8%	1.7%
Construction	2.3%	6.7%	4.7%	2.3%	3.6%	10.3%	3.7%	4.7%	4.2%	4.8%
Education	10.3%	8.9%	4.4%	15.9%	2.4%	6.4%	10.4%	10.6%	9.5%	8.8%
Health & Social Work	3.2%	3.2%	9.3%	4.0%	3.8%	3.9%	6.9%	6.3%	5.1%	5.0%
Hotels & Catering	0.9%	1.3%	1.1%	0.7%	1.0%	2.1%	3.7%	0.7%	1.1%	1.4%
IT Services	9.4%	10.6%	5.3%	30.4%	7.5%	6.2%	5.4%	4.4%	13.6%	9.9%
Manufacturing	3.0%	23.1%	7.5%	11.7%	11.1%	11.9%	4.1%	4.6%	7.8%	9.9%
Mining & Utilities	0.7%	2.6%	0.4%	1.4%	1.8%	1.6%	0.7%	0.3%	1.3%	1.2%
Public Administration	5.7%	4.5%	6.4%	2.8%	1.8%	3.7%	4.1%	2.2%	3.0%	3.7%
Transport	2.8%	3.6%	4.4%	2.6%	2.6%	2.5%	3.2%	2.5%	3.0%	3.0%
Wholesale & Retail Trade	10.1%	7.1%	10.0%	3.3%	9.1%	11.2%	6.9%	6.5%	6.1%	7.7%
Other	40.6%	18.8%	40.0%	15.7%	46.0%	27.2%	45.4%	50.6%	26.5%	34.7%

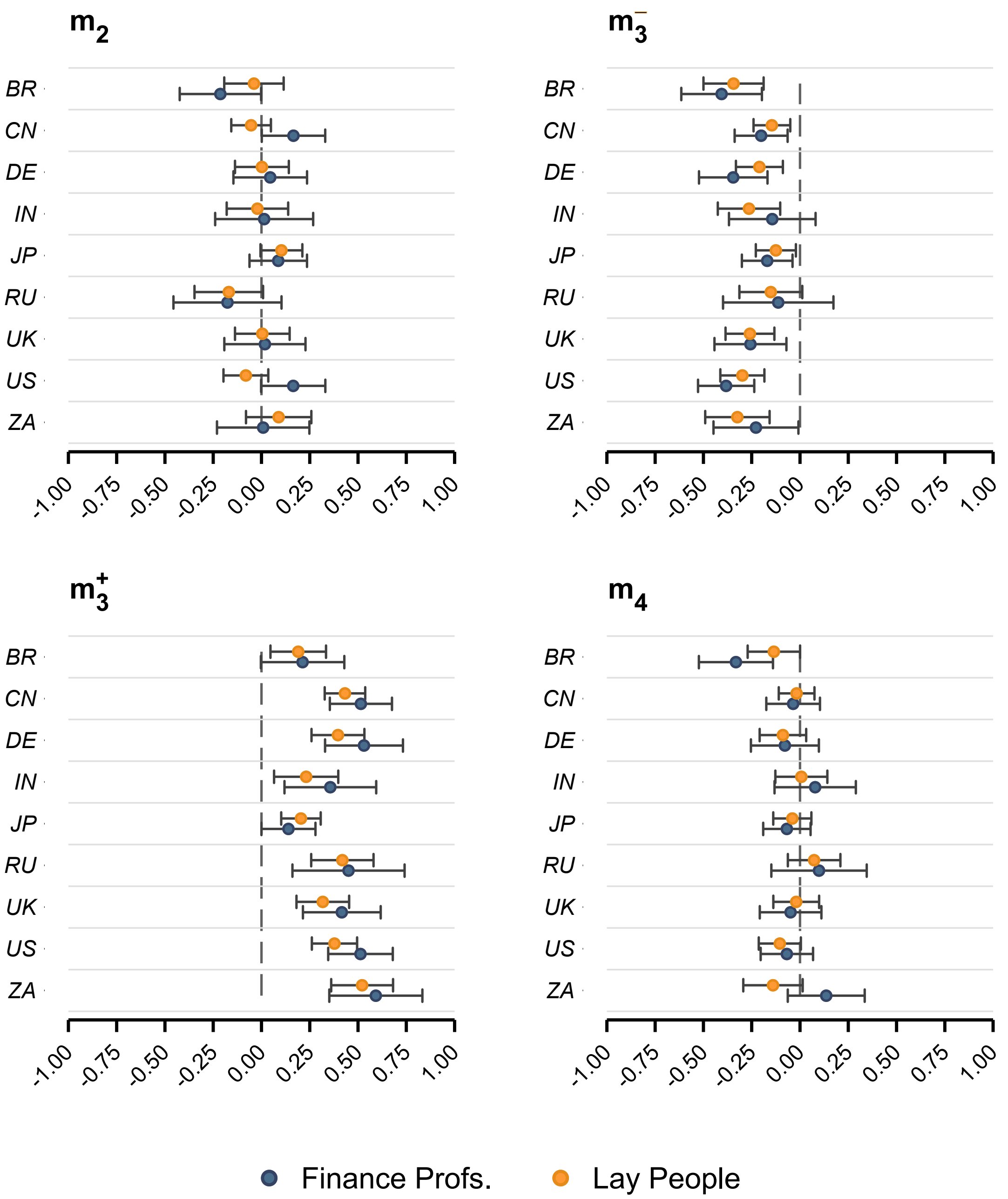
Notes: Number of exclusions, demographics (gender ratio and age; standard deviations are provided in parentheses), industry, and occupational information separated by subsamples and countries. Number of exclusions refer to respondents indicating to work in an industry not matching the information provided in the market research agency's database and/or the responses in the pre-screening survey (see Section Methods for details). *BR* – Brazil, *CN* – China, *DE* – Germany, *IN* – India, *JP* – Japan, *RU* – Russia, *UK* – Great Britain, *US* – United States, *ZA* – South Africa.

Appendix D Supplementary Figures

	m_2 = 0.16 m_3 = -1.0 m_4 = 3.0	m_2 = 0.32 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 10.8	m_2 = 0.16 m_3 = 0.0 m_4 = 10.8	m_2 = 0.16 m_3 = -1.0 m_4 = 10.8	m_2 = 0.32 m_3 = 0.0 m_4 = 3.0	m_2 = 0.16 m_3 = 0.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 3.0	m_2 = 0.32 m_3 = +1.0 m_4 = 3.0
BR	-0.262* (0.047)	-0.224* (0.045)	-0.068 (0.038)	-0.096 (0.042)	-0.008 (0.038)	0.008 (0.047)	0.102 (0.036)	0.299* (0.049)	0.249* (0.052)
CN	-0.216* (0.032)	-0.328* (0.034)	-0.065 (0.027)	-0.075 (0.030)	-0.046 (0.027)	-0.033 (0.034)	-0.052 (0.024)	0.408* (0.035)	0.407* (0.038)
DE	-0.288* (0.041)	-0.252* (0.039)	-0.072 (0.033)	-0.115* (0.039)	-0.079 (0.033)	-0.013 (0.043)	-0.031 (0.030)	0.413* (0.046)	0.439* (0.050)
IN	-0.219* (0.050)	-0.202* (0.050)	-0.135* (0.040)	0.036 (0.043)	-0.062 (0.039)	-0.004 (0.050)	0.005 (0.039)	0.278* (0.051)	0.302* (0.054)
JP	-0.206* (0.032)	-0.085 (0.035)	-0.126* (0.026)	-0.115* (0.028)	-0.080* (0.026)	0.032 (0.034)	-0.066 (0.024)	0.116* (0.036)	0.530* (0.042)
RU	-0.170* (0.054)	-0.320* (0.058)	-0.015 (0.042)	0.051 (0.047)	0.091 (0.045)	-0.200* (0.057)	-0.029 (0.042)	0.398* (0.053)	0.194* (0.061)
UK	-0.281* (0.042)	-0.243* (0.039)	-0.094 (0.034)	-0.052 (0.037)	-0.076 (0.034)	-0.014 (0.044)	-0.023 (0.031)	0.327* (0.045)	0.456* (0.049)
US	-0.341* (0.035)	-0.299* (0.037)	-0.104* (0.028)	-0.106* (0.033)	-0.074* (0.026)	-0.011 (0.038)	-0.014 (0.026)	0.410* (0.038)	0.540* (0.044)
ZA	-0.339* (0.048)	-0.313* (0.050)	-0.102 (0.042)	-0.096 (0.046)	-0.083 (0.040)	0.017 (0.053)	-0.046 (0.039)	0.498* (0.052)	0.464* (0.055)

Notes: Mean risk perception (subject-level demeaned data) for the nine return distributions separated by countries. Return distributions are sorted in ascending order of mean perceived riskiness in the pooled data. Color shadings indicate the magnitude of effect sizes. m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. Standard errors clustered on the individual level are reported in parentheses. * indicates a significant difference with $p < 0.005$ based on one-sample t-tests (for a test size $\mu_0 = 0$). *BR* – Brazil (n = 638), *CN* – China (n = 1,025), *DE* – Germany (n = 695), *IN* – India (n = 644), *JP* – Japan (n = 769), *RU* – Russia (n = 579), *UK* – Great Britain (n = 689), *US* – United States (n = 1,033), *ZA* – South Africa (n = 700).

Figure A2: Mean risk perception for the nine return distributions separated by countries.



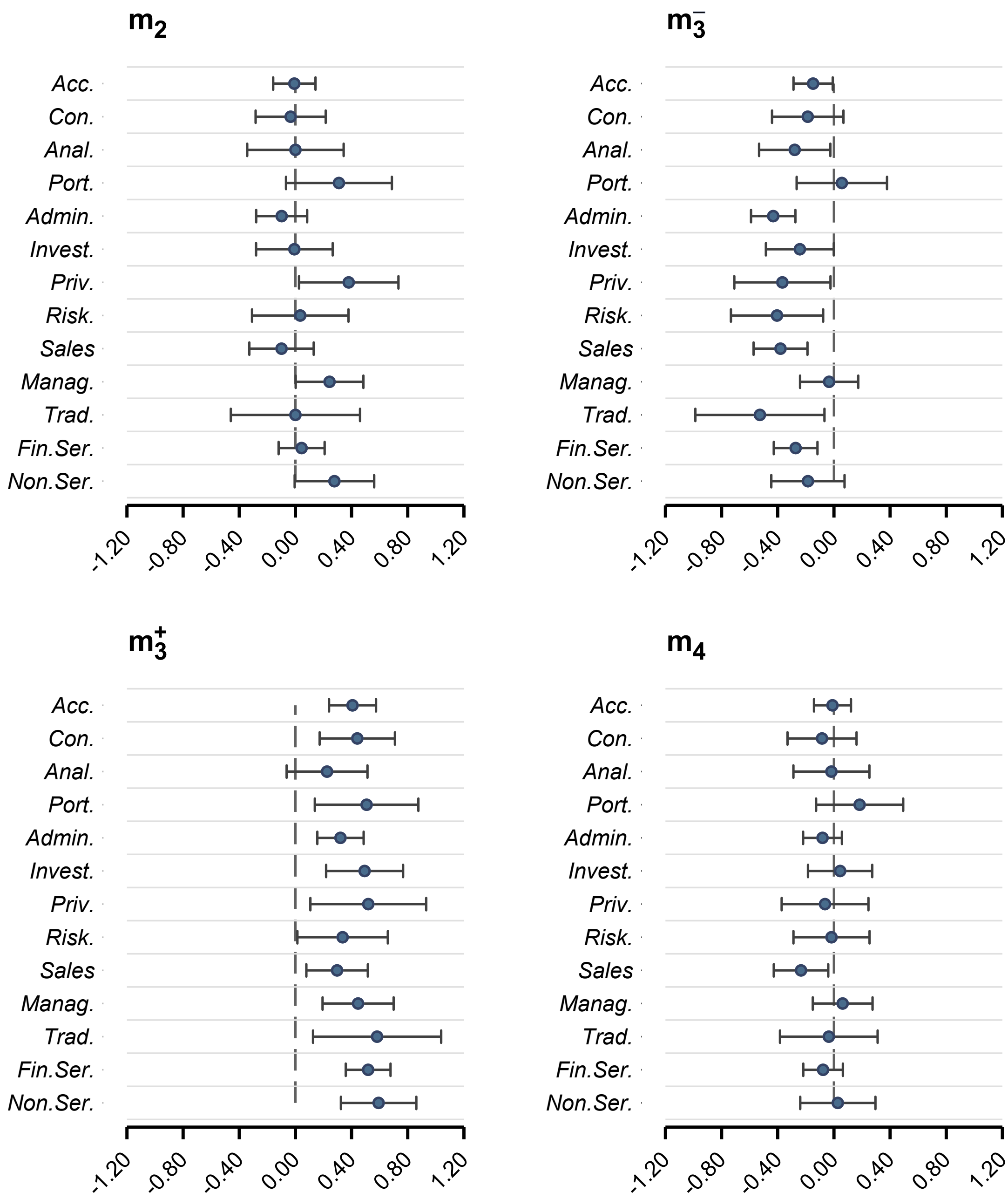
Notes: Mean effects of systematic variations in the return distributions' higher moments (standard deviation, skewness, and kurtosis) on subject-level demeaned risk perception. The effects correspond to coefficients of dichotomous explanatory variables in an ordinary least squares regression (controlling for interaction effects). m_2: 1 if standard deviation = 32.0%, 0 if standard deviation = 16.0%; m_3^-: 1 if skewness = −1.0, 0 if skewness = 0; m_3^+: 1 if skewness = +1.0, 0 if skewness = 0; m_4: 1 if kurtosis = 10.8, 0 if kurtosis = 3.0. Error bars denote 99.5% confidence intervals based on standard errors clustered on the individual level. *BR* – Brazil (n_{FP} = 202, n_{GP} = 436), *CN* – China (n_{FP} = 338, n_{GP} = 687), *DE* – Germany (n_{FP} = 243, n_{GP} = 452), *IN* – India (n_{FP} = 216, n_{GP} = 428), *JP* – Japan (n_{FP} = 265, n_{GP} = 504), *RU* – Russia (n_{FP} = 142, n_{GP} = 437), *UK* – Great Britain (n_{FP} = 226, n_{GP} = 463), *US* – United States (n_{FP} = 353, n_{GP} = 680), *ZA* – South Africa (n_{FP} = 228, n_{GP} = 472).

Figure A3: Effects of variations in higher moments on risk perception separated by countries.

	$m_2 = 0.16$ $m_3 = -1.0$ $m_4 = 3.0$	$m_2 = 0.32$ $m_3 = -1.0$ $m_4 = 3.0$	$m_2 = 0.16$ $m_3 = +1.0$ $m_4 = 10.8$	$m_2 = 0.16$ $m_3 = 0.0$ $m_4 = 10.8$	$m_2 = 0.16$ $m_3 = -1.0$ $m_4 = 10.8$	$m_2 = 0.16$ $m_3 = 0.0$ $m_4 = 3.0$	$m_2 = 0.32$ $m_3 = 0.0$ $m_4 = 3.0$	$m_2 = 0.16$ $m_3 = +1.0$ $m_4 = 3.0$	$m_2 = 0.32$ $m_3 = +1.0$ $m_4 = 3.0$
Acc.	-0.162 (0.059)	-0.318* (0.060)	-0.075 (0.046)	-0.024 (0.052)	-0.141* (0.045)	-0.013 (0.042)	-0.021 (0.057)	0.393* (0.067)	0.360* (0.069)
Con.	-0.254 (0.102)	-0.195 (0.099)	-0.068 (0.088)	-0.153 (0.100)	-0.085 (0.084)	-0.068 (0.068)	-0.102 (0.109)	0.373* (0.106)	0.551* (0.132)
Anal.	-0.261 (0.108)	-0.279 (0.120)	-0.054 (0.089)	-0.000 (0.113)	-0.153 (0.087)	0.018 (0.081)	0.018 (0.129)	0.243 (0.119)	0.468* (0.134)
Port.	-0.166 (0.130)	-0.180 (0.160)	-0.011 (0.097)	-0.039 (0.116)	0.059 (0.122)	-0.222 (0.097)	0.088 (0.136)	0.285 (0.142)	0.186 (0.164)
Admin.	-0.364* (0.062)	-0.415* (0.065)	-0.172* (0.050)	-0.013 (0.056)	-0.033 (0.051)	0.068 (0.047)	-0.030 (0.070)	0.389* (0.070)	0.568* (0.074)
Invest.	-0.297* (0.098)	-0.422* (0.095)	-0.083 (0.085)	-0.010 (0.087)	0.005 (0.076)	-0.054 (0.076)	-0.061 (0.107)	0.439* (0.104)	0.483* (0.126)
Priv.	-0.544* (0.129)	-0.051 (0.127)	-0.101 (0.121)	-0.241 (0.122)	0.177 (0.108)	-0.177 (0.099)	0.203 (0.129)	0.342 (0.139)	0.392 (0.168)
Risk.	-0.413* (0.112)	-0.085 (0.127)	-0.137 (0.098)	-0.025 (0.102)	-0.102 (0.088)	-0.008 (0.096)	0.027 (0.122)	0.329 (0.125)	0.415* (0.123)
Sales	-0.344* (0.079)	-0.204 (0.080)	-0.037 (0.066)	-0.198 (0.074)	-0.032 (0.066)	0.036 (0.056)	-0.063 (0.092)	0.333* (0.094)	0.510* (0.097)
Manag.	-0.204 (0.086)	-0.102 (0.096)	-0.210* (0.073)	-0.108 (0.080)	-0.142 (0.066)	-0.170 (0.066)	0.073 (0.093)	0.276 (0.101)	0.587* (0.105)
Trad.	-0.527* (0.164)	-0.309 (0.170)	-0.091 (0.141)	-0.036 (0.121)	0.018 (0.127)	-0.000 (0.123)	-0.000 (0.172)	0.582* (0.167)	0.364 (0.182)
Fin.Ser.	-0.333* (0.059)	-0.239* (0.058)	-0.193* (0.050)	-0.137 (0.051)	-0.038 (0.048)	-0.060 (0.045)	-0.016 (0.064)	0.458* (0.064)	0.560* (0.070)
Non.Ser.	-0.309* (0.099)	-0.281 (0.104)	-0.198 (0.074)	-0.096 (0.107)	-0.105 (0.081)	-0.123 (0.070)	0.154 (0.117)	0.469* (0.111)	0.488* (0.139)

Notes: Mean risk perception (subject-level demeaned data) for the nine return distributions separated by participants' occupations. Return distributions are sorted in ascending order of the mean perceived riskiness in the pooled data. Color shadings indicate the magnitude of effect sizes. m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. Standard errors clustered on the individual level are reported in parentheses. * indicates a significant difference with $p < 0.005$ based on one-sample t-tests (for a test size $\mu_0 = 0$). *Acc.* – Accounting, Controlling, or Compliance ($n = 392$); *Con.* – Advisory Services or Consulting ($n = 118$); *Anal.* – Analysis, Research, or Valuation ($n = 112$); *Port.* – Fund or Portfolio Management ($n = 71$); *Admin.* – Office Administration, Human Resources, or IT ($n = 297$); *Invest.* – Investment Banking or Investment Services ($n = 137$); *Priv.* – Private Banking or Wealth Management ($n = 80$); *Risk.* – Risk Management, Treasury, or Financial Planing ($n = 116$); *Sales.* – Sales ($n = 192$); *Manag.* – Top- or Middle Management ($n = 177$); *Trad.* – Trading or Brokerage ($n = 55$); *Fin.Ser.* – Other Finance-Related Services ($n = 364$); *Non.Ser.* – Other Non-Finance-Related Services ($n = 108$).

Figure A4: Mean risk perception for the nine return distributions separated by occupations.



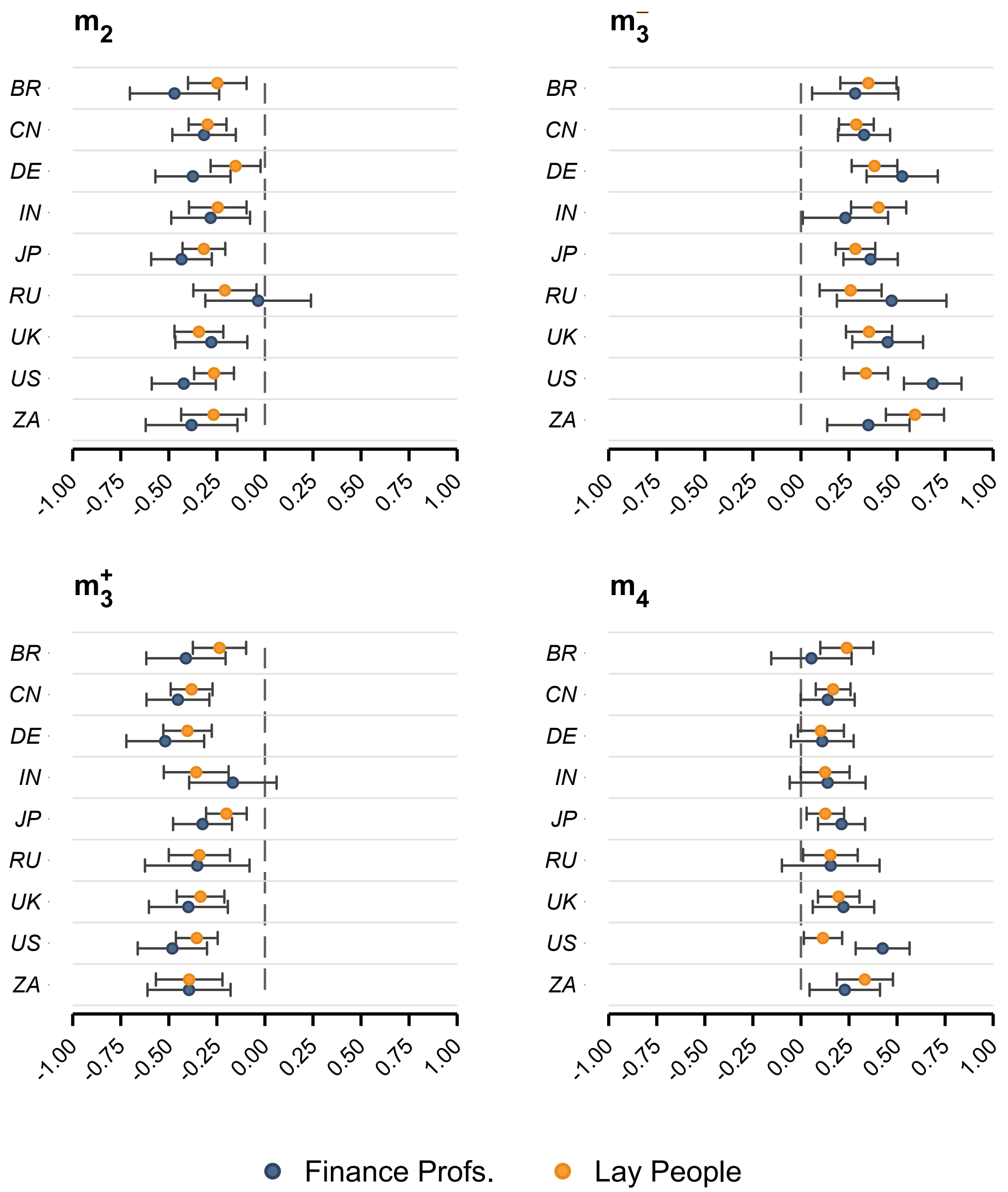
Notes: Mean effects of systematic variations in the return distributions' higher moments (standard deviation, skewness, and kurtosis) on subject-level demeaned risk perception. The effects correspond to coefficients of dichotomous explanatory variables in an ordinary least squares regression (controlling for interaction effects). m_2: 1 if standard deviation = 32.0%, 0 if standard deviation = 16.0%; m_3^-: 1 if skewness = –1.0, 0 if skewness = 0; m_3^+: 1 if skewness = +1.0, 0 if skewness = 0; m_4: 1 if kurtosis = 10.8, 0 if kurtosis = 3.0. Error bars denote 99.5% confidence intervals based on standard errors clustered on the individual level. *Acc.* – Accounting, Controlling, or Compliance (n = 392); *Con.* – Advisory Services or Consulting (n = 118); *Anal.* – Analysis, Research, or Valuation (n = 112); *Port.* – Fund or Portfolio Management (n = 71); *Admin.* – Office Administration, Human Resources, or IT (n = 297); *Invest.* – Investment Banking or Investment Services (n = 137); *Priv.* – Private Banking or Wealth Management (n = 80); *Risk.* – Risk Management, Treasury, or Financial Planing (n = 116); *Sales.* – Sales (n = 192); *Manag.* – Top- or Middle Management (n = 177); *Trad.* – Trading or Brokerage (n = 55); *Fin.Ser.* – Other Finance-Related Services (n = 364); *Non.Ser.* – Other Non-Finance-Related Services (n = 108).

Figure A5: Effects of variations in higher moments on risk perception separated by occupations.

	m_2 = 0.16 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = 0.0 m_4 = 10.8	m_2 = 0.32 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 10.8	m_2 = 0.16 m_3 = -1.0 m_4 = 10.8	m_2 = 0.16 m_3 = 0.0 m_4 = 3.0	m_2 = 0.32 m_3 = 0.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 3.0	m_2 = 0.32 m_3 = +1.0 m_4 = 3.0
BR	0.390* (0.046)	0.241* (0.043)	0.125 (0.048)	0.144* (0.039)	0.033 (0.039)	0.061 (0.036)	-0.257* (0.048)	-0.231* (0.047)	-0.505* (0.049)
CN	0.357* (0.030)	0.214* (0.029)	0.193* (0.032)	0.175* (0.027)	0.137* (0.026)	0.056 (0.024)	-0.248* (0.032)	-0.349* (0.036)	-0.534* (0.040)
DE	0.455* (0.039)	0.128* (0.037)	0.210* (0.040)	0.185* (0.034)	0.109* (0.032)	0.021 (0.030)	-0.209* (0.041)	-0.422* (0.044)	-0.478* (0.045)
IN	0.368* (0.044)	0.152* (0.039)	0.220* (0.044)	0.200* (0.038)	0.074 (0.039)	0.022 (0.037)	-0.236* (0.046)	-0.272* (0.051)	-0.528* (0.054)
JP	0.351* (0.031)	0.197* (0.029)	0.184* (0.033)	0.189* (0.024)	0.141* (0.026)	0.041 (0.025)	-0.317* (0.034)	-0.203* (0.035)	-0.582* (0.040)
RU	0.318* (0.052)	0.161* (0.046)	0.299* (0.056)	0.071 (0.045)	0.009 (0.044)	0.007 (0.042)	-0.159* (0.051)	-0.336* (0.052)	-0.371* (0.056)
UK	0.433* (0.039)	0.252* (0.035)	0.188* (0.039)	0.159* (0.032)	0.066 (0.033)	0.047 (0.029)	-0.275* (0.040)	-0.308* (0.041)	-0.561* (0.046)
US	0.486* (0.034)	0.249* (0.030)	0.240* (0.036)	0.185* (0.027)	0.161* (0.027)	0.029 (0.027)	-0.290* (0.035)	-0.369* (0.038)	-0.691* (0.040)
ZA	0.510* (0.048)	0.294* (0.044)	0.263* (0.049)	0.177* (0.040)	0.034 (0.041)	-0.005 (0.038)	-0.309* (0.052)	-0.399* (0.052)	-0.565* (0.056)

Notes: Mean investment propensity (subject-level demeaned data) for the nine return distributions separated by countries. Return distributions are sorted in descending order of mean propensity to invest in the pooled data. Color shadings indicate the magnitude of effect sizes. m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. Standard errors clustered on the individual level are reported in parentheses. * indicates a significant difference with $p < 0.005$ based on one-sample t-tests (for a test size $\mu_0 = 0$). *BR* – Brazil (n = 638), *CN* – China (n = 1,025), *DE* – Germany (n = 695), *IN* – India (n = 644), *JP* – Japan (n = 769), *RU* – Russia (n = 579), *UK* – Great Britain (n = 689), *US* – United States (n = 1,033), *ZA* – South Africa (n = 700).

Figure A6: Mean investment propensity for the nine return distributions separated by countries



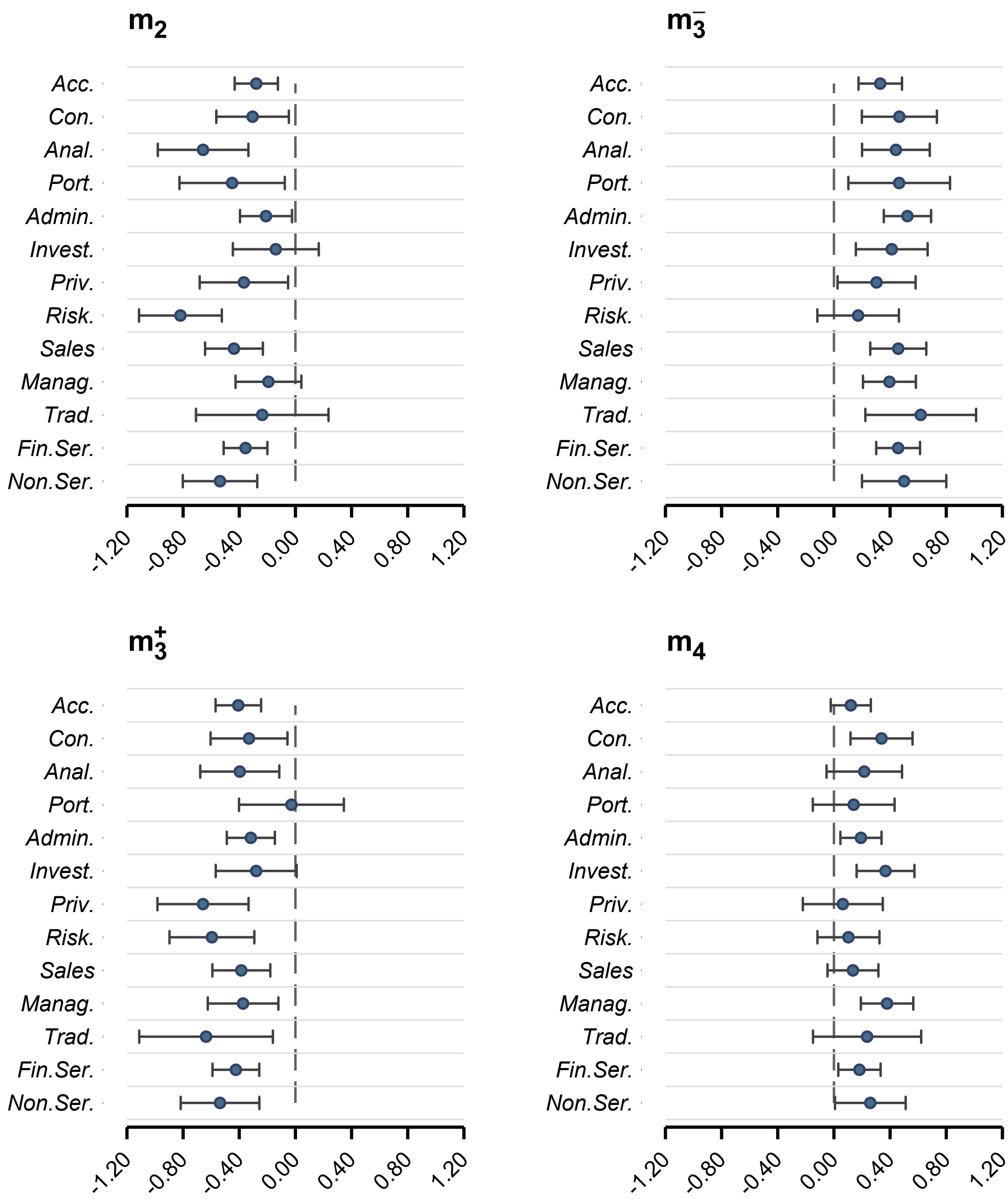
Notes: Mean effects of systematic variations in the return distributions' higher moments (standard deviation, skewness, and kurtosis) on subject-level demeaned investment propensity. The effects correspond to coefficients of dichotomous explanatory variables in an ordinary least squares regression (controlling for interaction effects). m_2: 1 if standard deviation = 32.0%, 0 if standard deviation = 16.0%; m_3^-: 1 if skewness = −1.0, 0 if skewness = 0; m_3^+: 1 if skewness = +1.0, 0 if skewness = 0; m_4: 1 if kurtosis = 10.8, 0 if kurtosis = 3.0. Error bars denote 99.5% confidence intervals based on standard errors clustered on the individual level. *BR* – Brazil (n_{FP} = 202, n_{GP} = 436), *CN* – China (n_{FP} = 338, n_{GP} = 687), *DE* – Germany (n_{FP} = 243, n_{GP} = 452), *IN* – India (n_{FP} = 216, n_{GP} = 428), *JP* – Japan (n_{FP} = 265, n_{GP} = 504), *RU* – Russia (n_{FP} = 142, n_{GP} = 437), *UK* – Great Britain (n_{FP} = 226, n_{GP} = 463), *US* – United States (n_{FP} = 353, n_{GP} = 680), *ZA* – South Africa (n_{FP} = 228, n_{GP} = 472).

Figure A7: Effects of variations in higher moments on investment propensity separated by countries.

	m_2 = 0.16 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = 0.0 m_4 = 10.8	m_2 = 0.32 m_3 = -1.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 10.8	m_2 = 0.16 m_3 = -1.0 m_4 = 10.8	m_2 = 0.16 m_3 = 0.0 m_4 = 3.0	m_2 = 0.32 m_3 = 0.0 m_4 = 3.0	m_2 = 0.16 m_3 = +1.0 m_4 = 3.0	m_2 = 0.32 m_3 = +1.0 m_4 = 3.0
Acc.	0.382* (0.058)	0.172* (0.054)	0.246* (0.060)	0.218* (0.046)	0.075 (0.047)	0.052 (0.045)	-0.227* (0.057)	-0.355* (0.063)	-0.564* (0.070)
Con.	0.477* (0.102)	0.350* (0.087)	0.215 (0.097)	0.172 (0.089)	0.037 (0.090)	0.011 (0.074)	-0.294* (0.102)	-0.319* (0.106)	-0.650* (0.120)
Anal.	0.557* (0.092)	0.331* (0.112)	0.151 (0.118)	0.151 (0.085)	0.223 (0.090)	0.115 (0.076)	-0.543* (0.122)	-0.281 (0.121)	-0.705* (0.132)
Port.	0.459* (0.138)	0.135 (0.129)	0.092 (0.138)	0.219 (0.107)	-0.020 (0.119)	-0.006 (0.105)	-0.457* (0.130)	-0.034 (0.143)	-0.387 (0.162)
Admin.	0.500* (0.064)	0.169* (0.054)	0.226* (0.065)	0.239* (0.052)	0.077 (0.050)	-0.024 (0.051)	-0.233* (0.068)	-0.342* (0.070)	-0.612* (0.074)
Invest.	0.328* (0.100)	0.284* (0.076)	0.431* (0.088)	0.240* (0.082)	0.093 (0.080)	-0.083 (0.082)	-0.223 (0.109)	-0.363* (0.108)	-0.708* (0.127)
Priv.	0.466* (0.110)	0.225 (0.113)	0.136 (0.132)	0.301 (0.114)	0.060 (0.110)	0.162 (0.089)	-0.205 (0.113)	-0.496* (0.113)	-0.648* (0.145)
Risk.	0.400* (0.109)	0.331* (0.090)	0.219 (0.109)	0.254* (0.081)	0.237* (0.080)	0.228* (0.079)	-0.591* (0.105)	-0.367* (0.118)	-0.712* (0.131)
Sales	0.496* (0.074)	0.173 (0.069)	0.251* (0.082)	0.209* (0.065)	0.189* (0.063)	0.038 (0.055)	-0.400* (0.079)	-0.348* (0.086)	-0.608* (0.090)
Manag.	0.370* (0.083)	0.353* (0.070)	0.200 (0.091)	0.206* (0.065)	0.274* (0.061)	-0.026 (0.059)	-0.218 (0.088)	-0.399* (0.099)	-0.760* (0.101)
Trad.	0.683* (0.146)	0.301 (0.141)	0.283 (0.180)	0.119 (0.142)	0.010 (0.135)	0.065 (0.121)	-0.172 (0.189)	-0.572* (0.170)	-0.717* (0.194)
Fin.Ser.	0.487* (0.057)	0.212* (0.052)	0.204* (0.052)	0.248* (0.052)	0.204* (0.048)	0.030 (0.049)	-0.325* (0.059)	-0.394* (0.062)	-0.664* (0.067)
Non.Ser.	0.546* (0.100)	0.306* (0.088)	0.380* (0.089)	0.185 (0.084)	0.167 (0.079)	0.046 (0.081)	-0.491* (0.104)	-0.491* (0.116)	-0.648* (0.122)

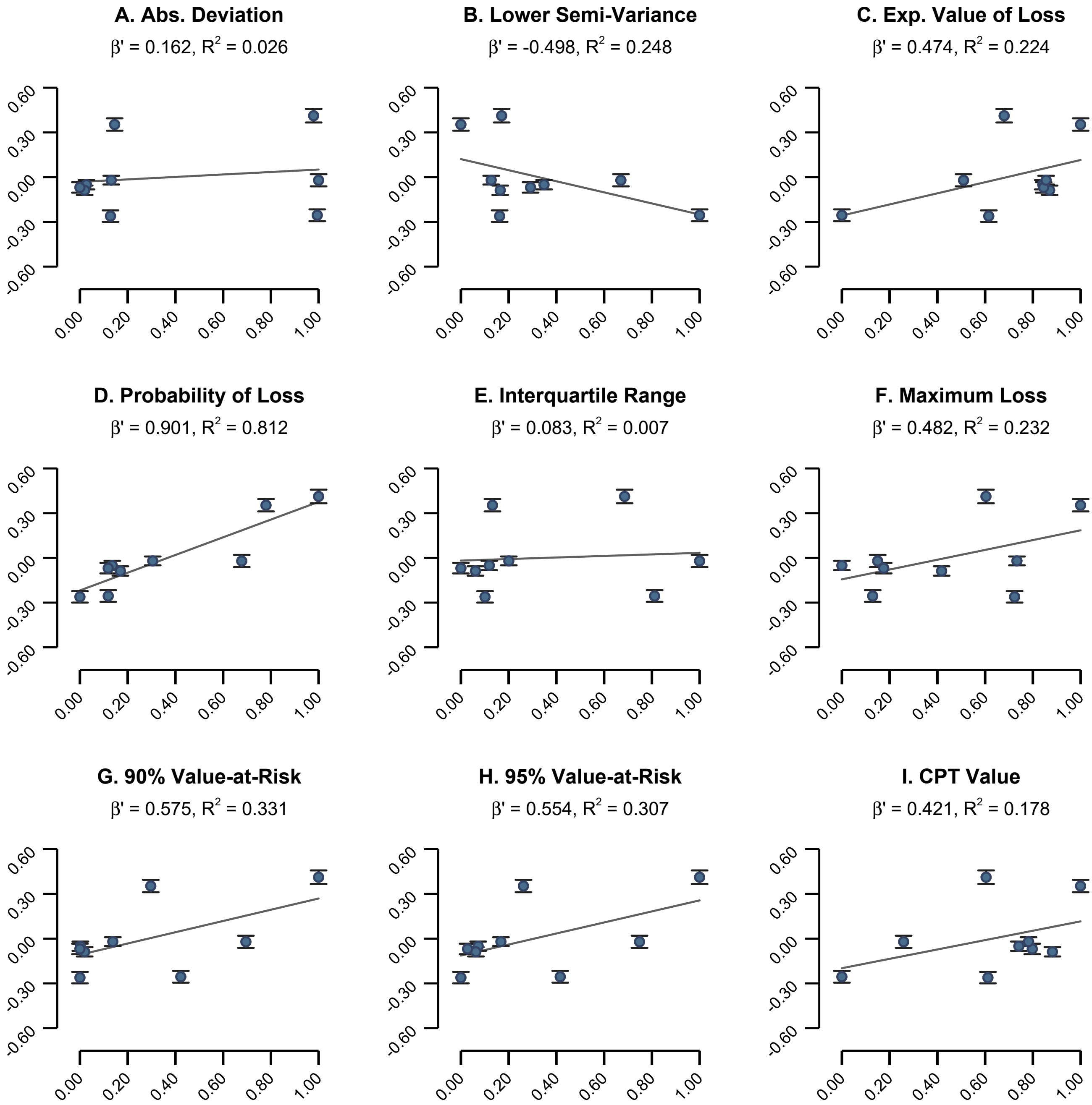
Notes: Mean investment propensity (subject-level demeaned data) for the nine return distributions separated by participants' occupations. Return distributions are sorted in descending order of the mean propensity to invest in the pooled data. Color shadings indicate the magnitude of effect sizes. m_2, m_3, and m_4 denote standard deviation, skewness, and kurtosis, respectively. Standard errors clustered on the individual level are reported in parentheses. * indicates a significant difference with $p < 0.005$ based on one-sample t-tests (for a test size $\mu_0 = 0$). *Acc.* – Accounting, Controlling, or Compliance ($n = 392$); *Con.* – Advisory Services or Consulting ($n = 118$); *Anal.* – Analysis, Research, or Valuation ($n = 112$); *Port.* – Fund or Portfolio Management ($n = 71$); *Admin.* – Office Administration, Human Resources, or IT ($n = 297$); *Invest.* – Investment Banking or Investment Services ($n = 137$); *Priv.* – Private Banking or Wealth Management ($n = 80$); *Risk.* – Risk Management, Treasury, or Financial Planing ($n = 116$); *Sales.* – Sales ($n = 192$); *Manag.* – Top- or Middle Management ($n = 177$); *Trad.* – Trading or Brokerage ($n = 55$); *Fin.Ser.* – Other Finance-Related Services ($n = 364$); *Non.Ser.* – Other Non-Finance-Related Services ($n = 108$).

Figure A8: Mean investment propensity for the nine return distributions separated by occupations.



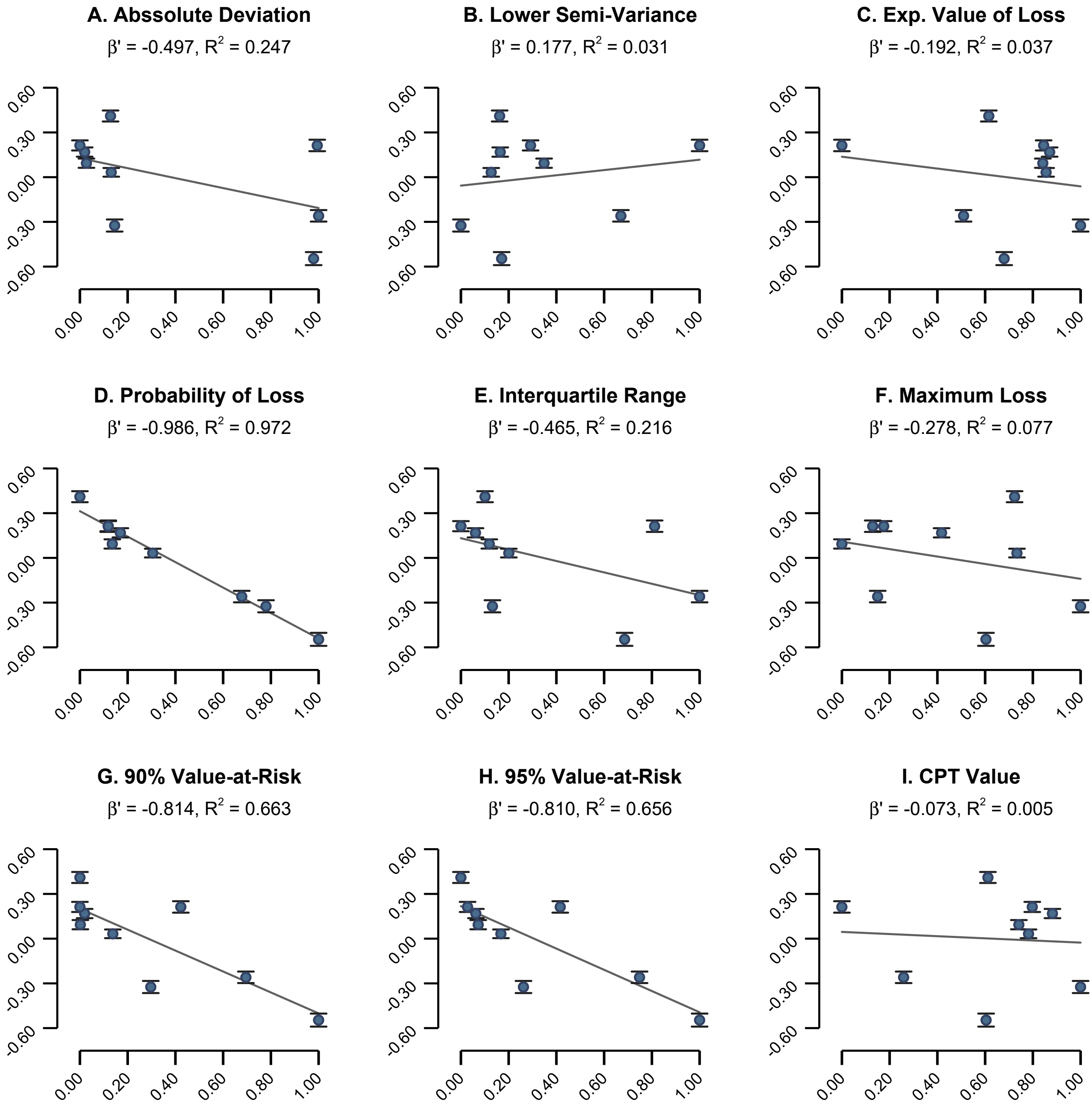
Notes: Mean effects of systematic variations in the return distributions' higher moments (standard deviation, skewness, and kurtosis) on subject-level demeaned invstment propensity. The effects correspond to coefficients of dichotomous explanatory variables in an ordinary least squares regression (controlling for interaction effects). m_2: 1 if standard deviation = 32.0%, 0 if standard deviation = 16.0%; m_3^-: 1 if skewness = −1.0, 0 if skewness = 0; m_3^+: 1 if skewness = +1.0, 0 if skewness = 0; m_4: 1 if kurtosis = 10.8, 0 if kurtosis = 3.0. Error bars denote 99.5% confidence intervals based on standard errors clustered on the individual level. *Acc.* – Accounting, Controlling, or Compliance (n = 392); *Con.* – Advisory Services or Consulting (n = 118); *Anal.* – Analysis, Research, or Valuation (n = 112); *Port.* – Fund or Portfolio Management (n = 71); *Admin.* – Office Administration, Human Resources, or IT (n = 297); *Invest.* – Investment Banking or Investment Services (n = 137); *Priv.* – Private Banking or Wealth Management (n = 80); *Risk.* – Risk Management, Treasury, or Financial Planing (n = 116); *Sales.* – Sales (n = 192); *Manag.* – Top- or Middle Management (n = 177); *Trad.* – Trading or Brokerage (n = 55); *Fin.Ser.* – Other Finance-Related Services (n = 364); *Non.Ser.* – Other Non-Finance-Related Services (n = 108).

Figure A9: Effects of variations in higher moments on investment propensity separated by occupations.



Notes: Mean perceived riskiness of each of the return distributions regressed on nine different compound risk measures (pooled data). CPT refers to Cumulative Prospect Theory and is based on the following parameterization: $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$. The vertical axis depicts participants' mean perception of risk associated with the nine return distributions; the horizontal axis depicts the particular compound risk measure, normalized to values between 0.0 and 1.0. Error bars denote 99.5% confidence intervals. β' and R^2 denote the corresponding standardized regression coefficient (equivalent to the Pearson correlation coefficient ρ) and the regressions' R_2, respectively.

Figure A10: Regressions of mean perceived riskiness on nine different compound risk measures



Notes: Mean investment propensity of each of the return distributions regressed on nine different compound risk measures (pooled data). CPT refers to Cumulative Prospect Theory and is based on the following parametrization: $\alpha = \beta = 0.88$, $\lambda = 2.25$, $\gamma = 0.61$, and $\delta = 0.69$. The vertical axis depicts participants' mean propensity to invest in the nine return distributions; the horizontal axis depicts the particular compound risk measure, normalized to values between 0.0 and 1.0. Error bars denote 99.5% confidence intervals. β' and R^2 denote the corresponding standardized regression coefficient (equivalent to the Pearson correlation coefficient ρ) and the regressions' R_2, respectively.

Figure A11: Regressions of mean investment propensity on nine different compound risk measures