Does Investor Risk Perception Drive Asset Prices in Markets? Experimental Evidence☆

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Abstract

What people perceive as risk clearly goes beyond variance. Several papers have shown that, e.g., probability of loss plays a more prominent role in perceived risk than does variance. We are the first to explore how individual risk perception influences prices and trading behavior in a market setting by exposing subjects to a number of differently shaped return distributions which they then trade on. We first elicit subjects' individual risk perceptions, finding results in line with earlier papers. We then let subjects trade assets with these return distributions on a continuous double auction market. In the markets we observe active trading and prices strongly driven by average risk perception. While standard finance theory predicts identical prices for most of our assets we find average prices to vary by up to 20 percent, with assets *perceived* as being less risky trading at significantly higher prices.

Keywords: Risk, risk perception, asset market, experiment

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1. Introduction

Do asset prices depend more on investor risk *perception* than finance theory predicts? Would, for example, a guarantee product trade at a premium just because investors *perceive* it to be less risky than other products with equal return volatility? If so, this would be at odds with most standard finance models and applications where volatility of returns and expected return are assumed to be the factors driving prices of risky assets. While deeply rooted in finance theory, recent studies have questioned whether volatility, i.e., return standard deviation, really is the risk measure investors use intuitively when evaluating risky assets (Nosić and Weber, 2010; Weber et al., 2013). In particular, Anzoni and Zeisberger (2017) compare various return distributions and risk measures and provide direct evidence that investors do not primarily focus on volatility, but that they evaluate asset return distributions mostly according to their probability of incurring a loss. In their study the loss probability is by far the best predictor for how risky asset return distributions are perceived to be and how willing individuals are to invest in these assets. Their results, as others, are obtained at the individual level. There, each experimental participant evaluates the risk and attractiveness of various assets with particular return distributions for herself. However, in behavioral finance there is an ongoing debate on whether individual biases and preferences are relevant for market prices (see, e.g., Barber et al., 2008; Coval and Shumway, 2005). Levy and Levy (2009) theoretically explore how asset prices and asset allocations would be affected by investors having non-standard preferences. They assume investors to follow a safety-first approach, originally proposed by Roy (1952), which is equivalent to an explicit aversion against the probability of experiencing a loss. Their theoretical results show implications for investor asset allocations and market prices in standard finance models. However, the heterogeneity in risk perception and preference makes it difficult to infer market predictions from results gained at the individual level.

Against this background we are the first to test whether the risk perception found at the individual level also plays a role in a market setting in which prices are the result of demand and supply, which in turn should depend on the perceived riskiness of the assets traded. In particular, we conduct a controlled laboratory experiment in which we present participants with different asset return distributions, holding mean and standard deviation constant. We then let them trade these assets in a continuous double auction market. Our novel setting allows us to compare market prices across assets and also to analyze to what extent individually stated risk perception predicts market prices as well as trading behavior of individuals in markets.

Our findings confirm previous studies on risk perception at the individual level, especially by Anzoni and Zeisberger (2017). In particular, we observe that investors perceive risk mostly as the probability of incurring a loss. More importantly, we further observe that individually elicited risk perception predicts prices in asset markets. Higher average perceived risk is associated with lower trading prices. Specifically, the probability of incurring a loss explains roughly 96 percent of the variation in perceived risk, which in turn explains roughly 94 percent of the variation in average prices. We further find that individually elicited risk perception also predicts traders' behavior in markets, as participants who state a relatively low risk perception are more likely to be net buyers compared to traders with high stated risk perception. Our findings are robust to using different subsets of our data.

2. Literature

Nosić and Weber (2010) and Weber et al. (2013) demonstrate the importance of perceived risk for investor behavior. However, there are only few studies which try to identify mathematical risk measures as proxies for risk perception, and most of them focus on simple lotteries. Keller et al. (1986) test four possible risk measures, previously only mathematically formulated in theoretical work by Luce (1980), and find that these are not empirically valid. Brachinger and Weber (1997) provide evidence for one-tailed risk perception, i.e., investors mainly focusing on the downside part of return distributions, in particular the probability of a loss and the potential loss amount. This finding is in line with Klos et al. (2005) who, using repeated runs of simple lotteries, find the probability of loss, the mean excess loss, and the coefficient of variation to be the main drivers of risk perception. Diecidue and Van De Ven (2008) and Zeisberger (2016) find evidence for the overall probability of losing to be the main driving factor for individuals' choice behavior between monetary gambles. Furthermore, Veld and Veld-Merkoulova (2008) present participants in their experiment with gambles in order to understand which objective risk measure(s) among standard deviation, probability of loss, expected value of loss and semi-variance corresponds most closely to subjects' perception of risk. By implicitly assuming that participants would choose the alternative they perceive as being least risky, the authors find evidence that investors focus on more than one risk measure at a time, including variance, and that whenever they seem to focus on only one risk measure, this is semi-variance.

It should be noted, however, that several authors propose that risk perception, and thus, by extension, risk-taking, is domain specific and that framing financial alternatives as gambles vs. investment decisions might lead to differences in risk-taking behavior (see, e.g., Rettinger and Hastie, 2001; Weber et al., 2002, 2005; Baucells and Rata, 2006; Nosić and Weber, 2010; Weber et al., 2013). This implies that a pure gamble task is likely perceived differently than a (more complex) investment task and that results might not be directly transferable to an investment context.

Within the investment domain, Weber and Milliman (1997) and Weber et al. (2005) provide evidence that previous outcomes can affect risk perception as well as risk-taking and choice behavior. MacGregor et al. (1999) and Koonce et al. (2005) asked financial experts to rate the risks of various general investment categories, and find that quantitative aspects (volatility, probability of loss, magnitude of loss) and qualitative aspects (particularly worry and knowledge) are both significant predictors of perceived risk, but the two studies do not analyze the relationship between perceived risk and willingness to invest. Sachse et al. (2012) obtain very similar results with a sample of non-professionals. Furthermore, in an experiment, Unser (2000) presents participants with hypothetical future price distributions of different stocks. He finds that for future returns and a variable hypothetical holding period, risk is perceived mainly as the duration of a stock price being below its current price, while volatility does not play a major role. The risk measures considered in the study are calculated based on prices rather than on returns (loss frequency is defined as the length of time an asset's price is below the starting price).

Most closely related to our study Anzoni and Zeisberger (2017) present a variety of return distributions calibrated to vary in different risk parameters, and ask experimental participants about the risk perception and individual investment propensity for these asset return distributions. These authors find surprisingly clear evidence that the probability of suffering a loss is the main driver for risk perception and willingness to invest. We make use of some of their return distributions to test whether individual risk perception also holds in asset markets in which investors' actions determine prices (and participants are not simply price-takers). Our design allows us to analyze how risk perception is related to trading behavior over time, and is thus not limited to a single allocation decision. We can also analyze how differences in risk perception drive differences in trading behavior in a market.

3. Design and Implementation of the Experiment

The idea of our experimental design is to assess individual investor risk perception and to analyze its influence on prices and trading behavior in asset markets. We use eight different assets, each with a distinct return distribution (see below), to disentangle which possible risk factor drives what subjects perceive as "risk". The main part of the experiment hence consists of eight periods, one for each of the assets. Each of the periods consists of two main parts: (I) the individual assessment of perceived risk and (II) the subsequent trading phase where eight participants trade the assets for three minutes in a continuous double auction market. Overall, we run 12 experimental sessions (with eight trading periods each). To prevent any influence of the presentation sequence, we randomize the order of the eight assets in each experimental session.

We select eight different return distributions such that, relative to the nominal buyback value (BBV) of 100, each has a mean return of close to 8 percent and a standard deviation of close to 18 percent (one of the assets had a standard deviation of 32 percent to explicitly study the role of this risk parameter). Our assets differ in terms of kurtosis, probability of incurring a loss, expected loss, skewness, as well as minimum and maximum return. Here we closely follow the design of Anzoni and Zeisberger (2017) and seven of our eight assets are also present in their study (they used ten assets of which we discarded three which closely resembled others). The one additional asset we designed is asset KURTOSIS which is leptocurtic, i.e., it is characterized by an excess kurtosis of 4.56. All distributions are depicted in Figure 1 and their properties and main characteristics are outlined in Table 1.

Table 1 shows that the mean returns of all assets are almost identical at between 7.9 and 8.4 percent. The standard deviation of seven of the eight assets is approx. 18 percent, with asset WIDER designed to have a higher standard deviation of 32 percent. Asset NORMAL is approximately normally distributed. Assets NegSKEWNESS and PosSKEWNESS display high negative and positive skewness of -1.256 and +1.276, respectively. Asset BigLOSS stands out with the possibility of losing up to 85 percent. Asset FrequentLOSS is characterized by 70 percent of cases leading to (moderate) losses, while asset NoLOSS never incurs losses (but usually only small gains). Finally, asset KURTOSIS has excess kurtosis of 4.56.

Distribution	Mean	StdDev	Semivar	PLoss	ELoss	Skewness	Kurtosis	MinReturn	MaxReturn
NORMAL	0.082	0.182	0.178	0.370	-0.038	0.002	-0.024	-0.360	0.550
NegSKEWNESS	0.082	0.179	0.280	0.200	-0.051	-1.256	0.098	-0.350	0.240
PosSKEWNESS	0.082	0.179	0.109	0.500	-0.021	1.276	0.204	-0.060	0.540
BigLOSS	0.084	0.183	0.185	0.280	-0.031	-0.985	5.442	-0.850	0.500
WIDER	0.080	0.315	0.306	0.370	-0.089	0.002	-0.527	-0.550	0.750
FrequentLOSS	0.080	0.185	0.108	0.700	-0.020	1.294	-0.171	-0.050	0.460
NoLOSS	0.079	0.180	0.063	0.000	0.000	3.266	10.544	0.000	0.990
KURTOSIS	0.081	0.183	0.178	0.340	-0.032	-0.729	4.561	-0.740	0.660

Table 1: Characteristics of the eight distributions used in the experiment. PLoss stands for the probability of incurring a loss and ELoss for the expected loss.

After the instructions on the trading mechanism in the double auction market, subjects complete a trial period to get acquainted with the trading interface. We then hand out the second part of the instructions and explain how to read a return distribution and which tasks to perform in the experiment (see instructions in the Appendix). Specifically, for each of the eight assets, each subject first has to individually assess the perceived risk on a 7-point Likert scale (from 1 or lowest, to 7 or highest perceived risk). Then fixed groups of eight subjects trade the asset for three minutes.

The market uses a continuous double auction mechanism with open order book.[1] Traders can submit any combination of limit and/or market orders. The order book is emptied before the beginning of each period and provides information about prices and quantities of outstanding orders. Unexecuted limit orders can be canceled, without cost, at any time, and are executed according to price followed by time priority. Shorting stocks and borrowing money is not possible. No interest is paid on taler (experimental currency) holdings and there are no transaction costs.

Assets live for a single period and are bought back by the experimenter after market closing at the buyback value (BBV), which is equal for all traders. There are no other cash flows originating from assets. The BBV consists of the nominal buyback value of 100 $\pm$ a return drawn from the known return distribution, with a mean of close to 8 percent (see Figure 1 and Table 1). Hence, the expected payoff (and risk-neutral BBV) of each asset is 108 (rounded).

Each trader starts each period with an endowment of 5 assets and 800 taler. Cash and asset holdings are reset to these values at the beginning of each period. The ratio of outstanding taler to the value of outstanding assets, commonly referred to as the cash-to-asset ratio, is 1.48. This ensures that traders are able to make transactions at reasonable frequencies and prices but it is also reasonably low to avoid biasing our results by cash endowment effects (see Kirchler et al., 2012 and Noussair and Tucker, 2016 and the references therein for evidence on the effect of cash endowments on mispricing).

Traders' payoffs in the experiment are based on their wealth ($W_{p,T}$) determined at the end (time T) of a period p, with asset holdings evaluated at the realized BBV. To avoid diversification effects over the eight periods, after the final period the experimenter rolls an eight-sided die to determine one period that is to be payoff-relevant for all traders in the session. This is public knowledge.

Given this incentive scheme and the zero-sum nature of the design, an inactive trader's period earnings depend only on the realization of BBV. At the expected value of 108 taler per asset, traders earn $5 \cdot 108 + 800 = 1,340$ taler, or €13.40 on average from the trading phase (for subjects' payoffs at the end of the experiment, 100 taler equal €1.).

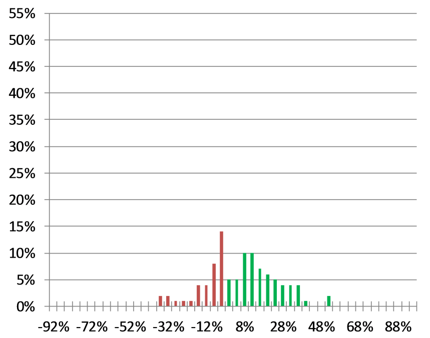
Finally, we ask subjects the financial literacy questions 2, 3, 4, 7, 10, 12, and 16 of van Rooij et al. (2011). The computer then randomly chooses one of the questions and subjects earn an additional €1.00 if their answer on this question is correct.

We conducted the experiment in four sessions at the Innsbruck EconLab in January 2017. For each session we recruited 24 subjects with hroot (Bock et al., 2014) from a

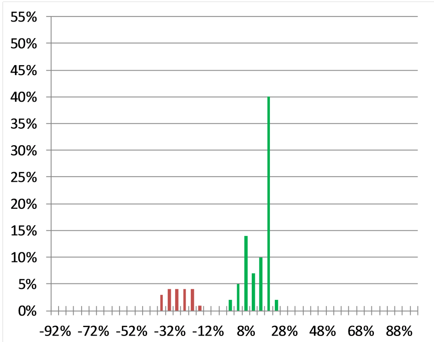
[1]See the Online Appendix for the experimental instructions and screenshots of the trading environment.

standard student subjects pool, for a total of 96 subjects. In each session we ran three parallel batches 8 traders who formed one market. Hence, each of our assets was traded in 12 separate markets. The software was implemented using GIMS (Palan, 2015) in z-Tree (Fischbacher, 2007).

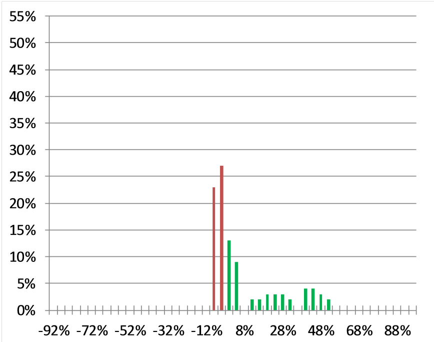
The experiment lasted approximately 60 minutes and the average payment was €13.90 per subject.



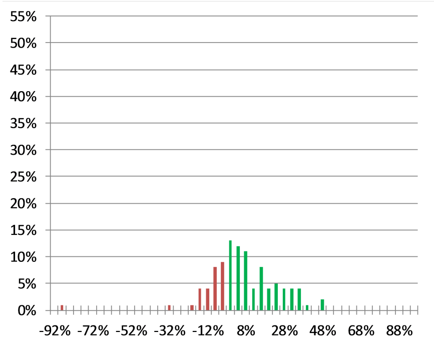
Distribution 1: NORMAL



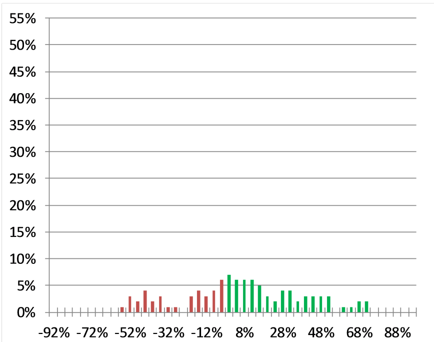
Distribution 2: NegSKEWNESS



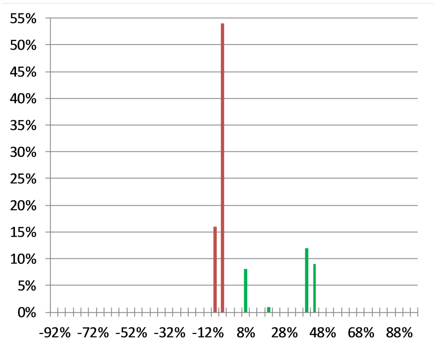
Distribution 3: PosSKEWNESS



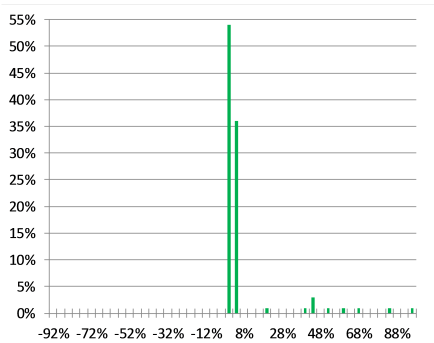
Distribution 4: BigLOSS



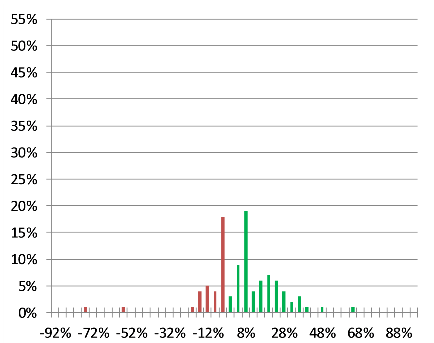
Distribution 5: WIDER



Distribution 6: FrequentLOSS



Distribution 7: NoLOSS



Distribution 8: KURTOSIS

Figure 1: Return distributions of the eight assets used in the experiment

4. Results

We first present results on the individual risk assessment and then turn to market prices, volume and the drivers of individual behavior in our markets.

4.1. Individual Risk Assessment

In each period, before trading started, subjects first had to individually assess the perceived risk of the asset on a 7-point Likert scale, as in Anzoni and Zeisberger (2017). As seven of our eight assets are also in the sample of Anzoni and Zeisberger (2017), this task can be seen as a replication of their work. The key finding in their paper was that the "probability of losing" is the key variable that their subjects perceived as "risk". Our results clearly confirm this result. As Figure 2 and Table 2 show, "Probability of a loss" is the only variable significantly driving risk perception. Each of the seven panels of Figure 2 shows one of seven possible risk drivers on the horizontal axis and average risk perception (across all 96 subjects) on the vertical axis. While most of the potential risk drivers show no clear pattern, the "probability of incurring a loss" stands out with a clear upward trend. The higher the probability of experiencing a loss, the higher the perceived risk of the asset. With an R^2 of 0.958 the linear trend is a very good fit for the data. In Figure 2 kurtosis also seems to be a driver of perceived risk. However, this is mostly due to the fact that the asset with no possible losses was also the one with the highest excess kurtosis of 10.54.[2]

In an additional analysis shown in Table 2, we use "perceived risk" as explained and seven possible risk drivers (standard deviation, semivariance, probability of a loss, expected loss, skewness, kurtosis, and minimum return) as explanatory variables in a series of regressions. We find that kurtosis shows no significant effect and that only "probability of a loss" is significant, confirming our individual correlation results.

[2]Figures A.5 and A.6 in the appendix present the same data without averaging across subjects, once for all periods and once excluding data from the first period. While the individual period data is of course more noisy, the relationship between the probability of a loss and the perceived risk is still very strong ($R^2 = 0.77$ in both figures).

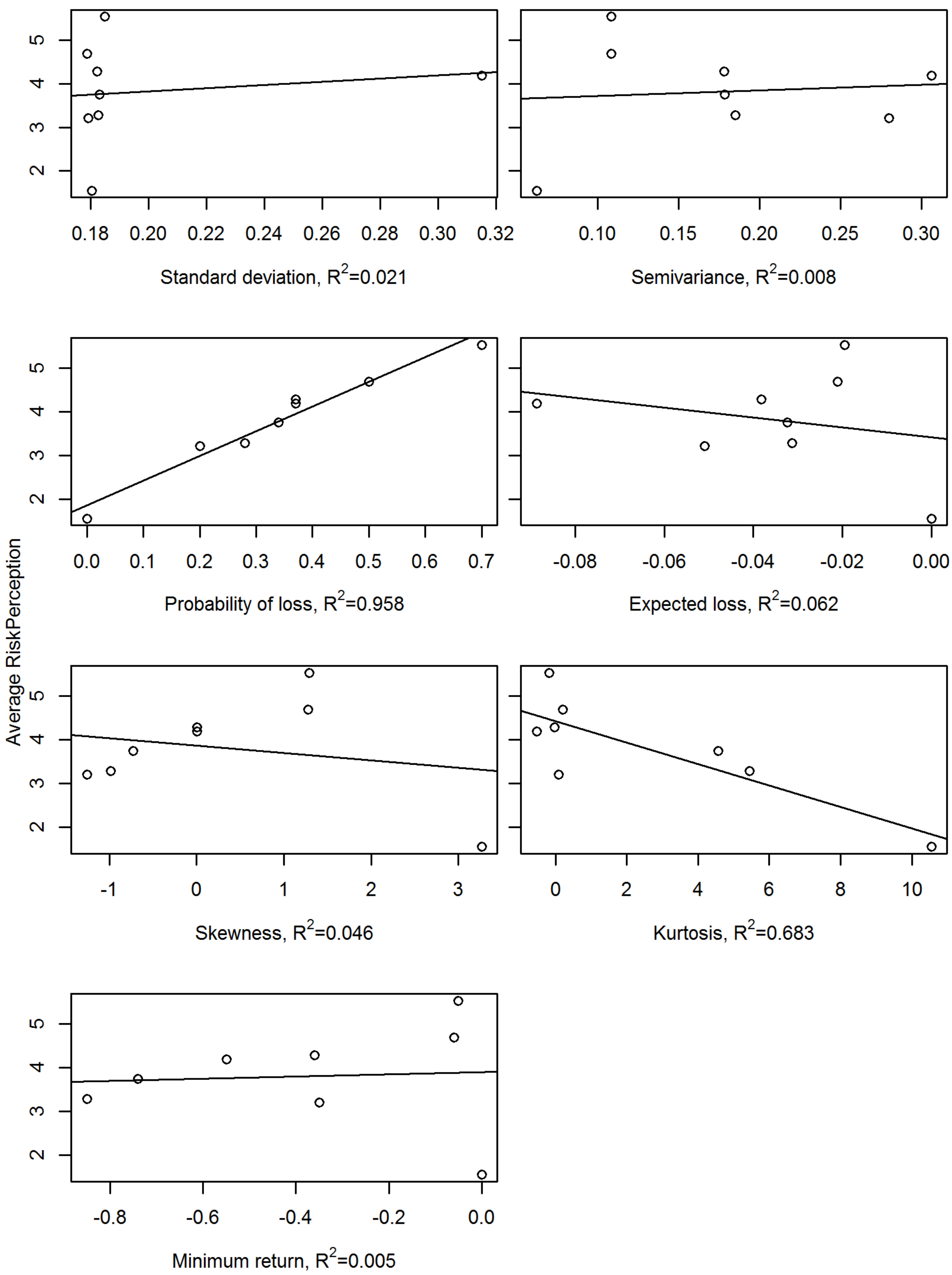


Figure 2: Scatter plots and correlations of risk perception and seven risk measures

	OLS	Subject fixed effects
Intercept	4.783^{*}	
	(2.526)	
StdDev	-19.017	-19.017
	(21.462)	(19.104)
Semivar	-10.520	-10.520
	(22.327)	(19.873)
PLoss	5.434^{***}	5.434^{***}
	(1.971)	(1.755)
ELoss	-75.537	-75.537
	(89.858)	(79.985)
Skewness	0.097	0.097
	(1.198)	(1.066)
Kurtosis	0.049	0.049
	(0.286)	(0.255)
MinReturn	0.185	0.185
	(3.710)	(3.303)
R^2	0.418	0.509
Adj. R^2	0.412	0.433
Num. obs.	768	768

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table 2: Regressions of RiskPerception (per trader) on distribution characteristics. PLoss stands for probability of a loss; ELoss for expected loss in case of a loss, and MinReturn for the minimum return possible.

4.2. Market Data

After the individual risk assessment task subjects can trade on a continuous double auction market for three minutes (one period). We observe relatively active trading in each market, with an average of 24 transactions per market. Given that subjects are initially endowed with 5 assets each, totaling 40 assets in a market, this implies that the average turnover in number of traded assets is 60 percent. Average total trading volume per subject is 6.092 assets (females 6.602 vs. males 5.489), and the average net change in subjects' asset balance is 2.995 (2.772 vs. 3.259).

We observe trading prices to be mostly between 95 and 135 taler, with some outliers. Each asset was traded for one period in each of the 12 sessions, so we have a total of 12 average period prices per asset.[3]

We first present market-level data on risk perception, prices and trading volume. We then proceed to a lower aggregation level, analyzing how an individual's risk perception and willingness to invest translated into actual actions in the market and how this affected prices.

The first and most prominent question we are interested in is whether risk perception affects market prices. At the highest aggregation level, we compare average risk perception for an asset across all subjects with average prices across all sessions in Figure 3. The results show very clearly that average risk perceptions drive prices, with higher perceived risk leading to lower prices. With an R^2 of 0.944, the relationship is very strong.[4] This is remarkable, given that seven of our eight assets have almost identical mean return and standard deviation. Given the risk-neutral BBV of about 108 for each asset we find average prices to deviate by roughly ± 10 percent, depending on perceived risk.[5]

Note that the return distributions we show to subjects are based on profits and losses relative to 100, and that the expected return is around 8 percent for each asset, leading to a risk-neutral price of 108 for each asset. At this price, however, asset NoLOSS can of course incur losses – if a subject buys the asset for 108 and the realized return is then 2 percent of the nominal BBV of 100, the subject only receives 102. As we observe an average trading price of 119 for asset NoLOSS, subjects actually incur losses with this asset in about 80

[3]The only major outlier occurred in the first period of session 7, in which the asset NORMAL was traded. Here the average price was 253 taler and trading volume was comparatively low (14 trades). Given the magnitude of this exceptional outlier, combined with the fact that it occurred in the first trading round and with low volume, we decided to discard it from the data analysis of prices, hence for asset NORMAL we have only 11 average period prices in all the analyses, tables and figures.

[4]It might be argued that asking subjects about their risk perception directly before the trading session might bias the results. However, first, it is not clear why this would particularly apply to the case of loss probability. Second, Anzoni and Zeisberger (2017) demonstrated that subjects' individual investment propensity is largely unaffected by asking for risk perception before the investment decision. Third, we find loss probability also to drive market prices in a setting where instead of asking for risk perception prior to trading, we ask subjects for perceived attractiveness of returns (this final finding stems from three exploratory classroom markets we conducted after the experiments reported here. Data available upon request.)

[5]Figure A.11 in the appendix shows the same relationship with data from the 96 individual markets. The four panels show results for the full data set and for three robustness checks.

percent of all cases (as 80 percent of the possible realizations are below 19 percent return). However, we find most subjects to be either ignorant of this fact or ready to accept the (moderate) losses associated with the asset, thus keeping prices at the comparatively high level we observe. Similar arguments hold for other assets. For example, asset FrequentLOSS has a loss probability of zero if bought at prices below 95, as the largest loss for this asset is -5 percent.

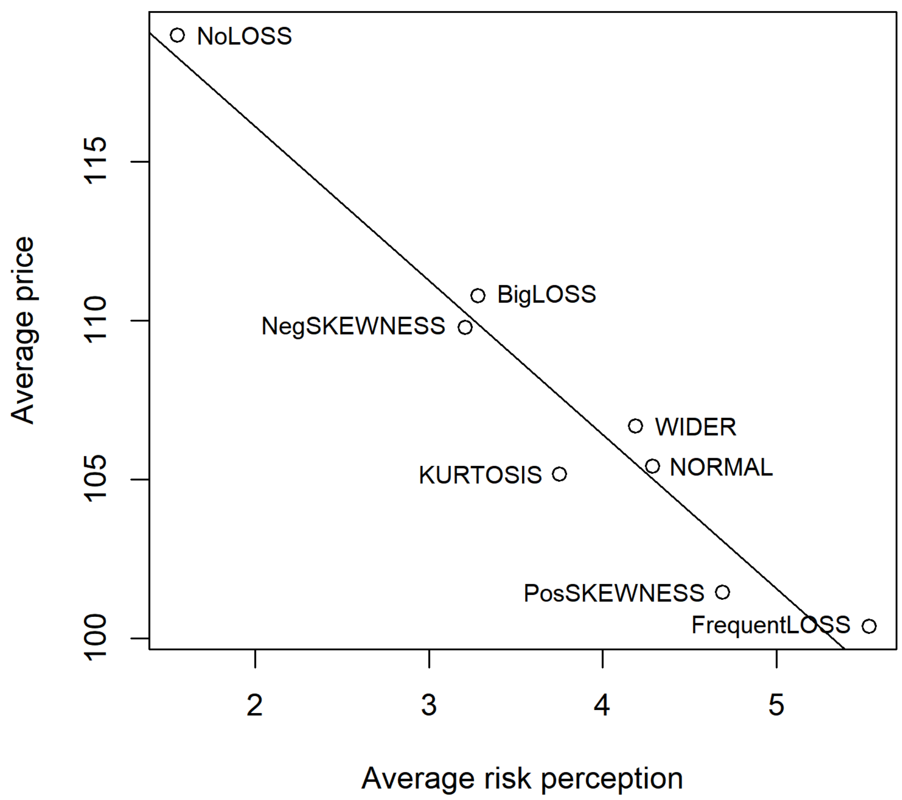


Figure 3: Distribution of average prices over average risk perception (aggregate data per asset averaged over all markets. Each dot represents one of the eight traded assets.)

Table 3 shows OLS regressions of average and median prices as well as trading volume per period per asset, with asset NORMAL serving as the benchmark. Due to the high variation of prices within each asset, only few of the differences are significant. Still, the pattern of the highest prices for asset NoLOSS and the lowest prices for asset FrequentLOSS is confirmed. These results are robust to whether session fixed effects are used or not. Trading volume does not vary significantly across assets, as shown in the last column of Table 3.

	AvgPrice (OLS)	AvgPrice (FE)	MedianPrice (OLS)	MedianPrice (FE)	Volume (OLS)	Volume (FE)
(Intercept)	105.424^{***}		105.705^{***}		25.818^{***}	
	(5.106)		(5.530)		(2.964)	
2.NegSKEWNESS	4.368	3.045	3.166	1.954	−0.402	0.550
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
3.PosSKEWNESS	−3.966	−5.289	−3.488	−4.700	−0.652	0.300
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
4.BigLOSS	5.357	4.034	6.408	5.196	−2.902	−1.950
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
5.WIDER	1.261	−0.062	1.241	0.029	−3.652	−2.700
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
6.FrequentLOSS	−5.034	−6.358	−5.455	−6.667	−0.735	0.216
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
7.NoLOSS	13.564^{*}	12.241^{**}	16.129^{**}	14.916^{**}	−1.902	−0.950
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
8.KURTOSIS	−0.254	−1.577	1.208	−0.004	−1.235	−0.284
	(7.069)	(5.425)	(7.656)	(6.369)	(4.103)	(2.408)
R^2	0.105	0.185	0.113	0.172	0.016	0.044
Adj. R^2	0.033	−0.008	0.041	−0.024	−0.063	−0.183
Num. obs.	95	95	95	95	95	95

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table 3: OLS and session fixed effects (FE) panel regressions of average and median prices as well as trading volume across assets.

4.3. Individual Trading Behavior and Profits

When we turn to individual trading behavior one key question we want to shed light on is whether subjects' final asset holdings are driven by their risk perception, i.e., whether within a group of eight traders those with comparatively high perceived risk for a given asset sell assets to those with comparatively low risk perception. Table 4 shows that the data support this conjecture. While the overall explanatory power is low due to noise, final asset holdings are highly significantly negatively related to perceived asset risk. Thus, risk perception clearly influences individual trading behavior.

In data column two of Table 4 we see that subjects with higher financial risk tolerance also have higher asset holdings, while the last column reveals that women are mostly among the net sellers. In fact, we find that female subjects sell a net average of 0.694 assets per period, while men on average net purchase 0.822 assets (p-value=0.000; numbers are not equal as we had more female than male participants).

	Final asset holdings	Final asset holdings	Final asset holdings
Intercept	6.022***	5.239***	6.418***
	(0.317)	(0.422)	(0.493)
RiskPerception	−0.269***	−0.254***	−0.245***
	(0.076)	(0.077)	(0.076)
FinLitScore		0.070	0.065
		(0.090)	(0.088)
FinancialRiskTolerance		0.164***	0.024
		(0.055)	(0.062)
FinancialLossTolerance		0.018	0.025
		(0.056)	(0.055)
Female			−1.358***
			(0.304)
R^2	0.016	0.033	0.058
Adj. R^2	0.015	0.028	0.051
Num. obs.	760	760	760

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table 4: OLS regressions of final asset holdings on RiskPerception and control variables

When we investigate this result in more detail, we find evidence for a gender effect in trading behavior which does not disappear when controlling for risk perception (females vs. males: 4.730 vs. 4.318, p-value=0.252), financial literacy score (3.962 vs. 4.500, p=0.033), financial risk tolerance (2.385 vs. 5.159, p=0.000) or financial loss aversion (4.558 vs. 5.545, p=0.056). Figure 4 documents that female subjects are net sellers in our markets and that their average net sales increase with average risk perception. Since risk perception is highly negatively correlated with price in our markets, female subjects thus sell most of precisely those assets which are most severely underpriced. Male subjects' net changes in asset holdings present essentially an inverted picture. Except for small differences due to the fact that we had more female subjects (52 vs. 44), male subjects on average buy to the extent that female subjects sell. These gender results impact also the object of our next analysis—subject profits.

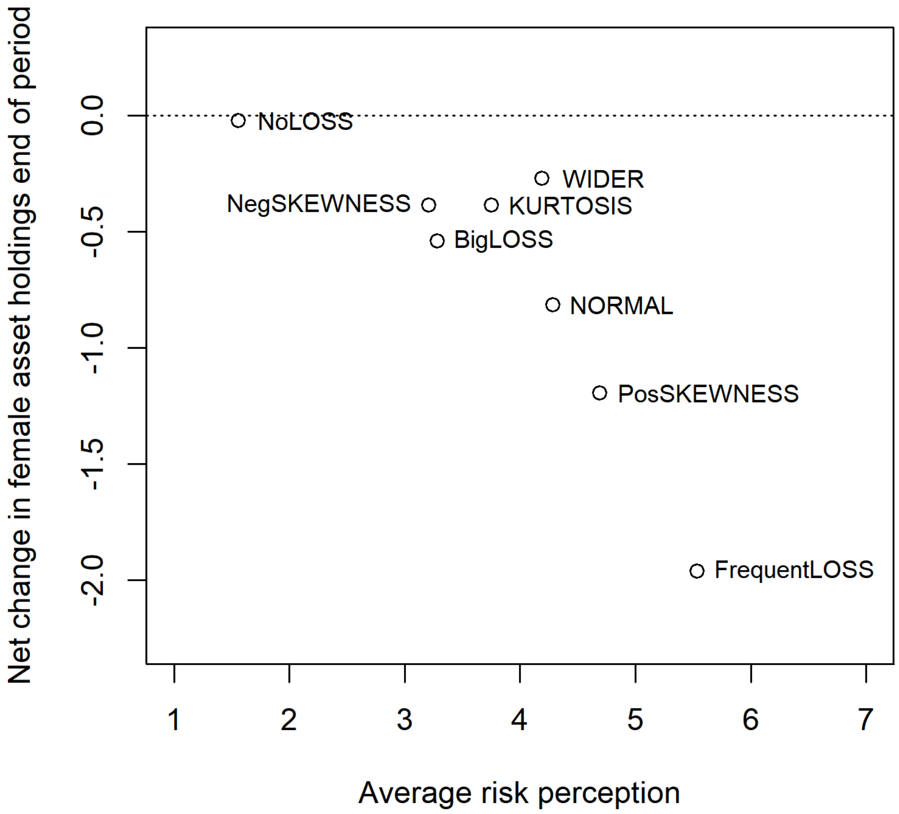


Figure 4: Change in net asset holdings by female subjects over average risk perception (aggregate data per asset averaged over all markets. Each dot represents one of the eight traded assets.)

We begin our analysis of subjects' profits by calculating subjects' holdings of cash and assets at the end of each period. We then aggregate them to a variable *PeriodEndWealth*, weighting the final asset holdings with the asset's expected ending value of around 108 to avoid distortions due to the realized random number. The first data column of Table 5 shows that final wealth is higher with higher financial risk tolerance, while financial literacy and loss tolerance are no significant drivers of final wealth. The second column adds a dummy variable for gender, approximately doubling the adjusted R^2, and documenting that women earned significantly lower profits. As our findings regarding women's asset holdings already led us to expect, the main driver for women's lower profits is that they are net sellers of – particularly strongly underpriced – assets. Female subjects sell for an average price of 103.88, while they buy for an average price of 110.64.[6] Hence, women sell below and buy above the unconditional expected value of 108. This behavioral difference may be partially explained by the lower average financial literacy among women. However, as Table 5 shows, FinLitScore does not help explain the results regarding subject profits.

	PeriodEndWealth	PeriodEndWealth
Intercept	1314.758***	1344.964***
	(8.675)	(14.183)
FinLitScore	0.277	−0.133
	(2.546)	(2.543)
FinancialRiskTolerance	7.421***	3.262*
	(1.568)	(1.796)
FinancialLossTolerance	−0.317	−0.134
	(1.609)	(1.588)
RiskPerception		1.790
		(2.174)
Female		−41.431***
		(8.735)
R^2	0.034	0.062
Adj. R^2	0.030	0.056
Num. obs.	760	760

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table 5: OLS regression of subjects' period end wealth on subject characteristics including risk and loss preferences (0=very risk/loss averse, 10=not at all risk/loss averse)

4.4. Robustness Checks

Our analyses are conducted with data from all markets and periods (except for the one outlier mentioned in footnote 3). To test the robustness of our results we re-run all analyses and tests with three alternative data sets.

In Robustness check I, learning from the outlier which happened in a first period, we discard all data from the first period, to allow for the possibility that subjects still need to learn to work in the market environment. We thus only analyze data from periods 2 to 8.

In Robustness check II we only look at data from the final 60 seconds of each of the 180 second periods. This way we only look at prices once the market has more or less settled on an equilibrium for a period.

[6] Men buy for an average price of 101.95 and sell for an average price of 111.37, thus generating positive net trading profits.

Finally, in Robustness check III we combine the criteria from the first two robustness checks. Hence, we take only data from periods 2 to 8 and we furthermore analyze only transactions which occurred in the final 60 seconds of each period.

Tables A.6, A.7, and A.8 in the appendix demonstrate that all of our results from the main analysis above also hold for each of the three robustness checks. While individual coefficients vary, the significance levels are almost identical to Table 3 for each of our three new data specifications. We conclude that our general findings are robust to specific trading time and asset order.

5. Conclusion

The question how investors perceive risk and how it should be presented to them has gained increasing academic and regulatory interest. Finance theory and textbooks clearly promote volatility as the main measure of risk, driven to some extent by the prominence of Markowitz' portfolio theory and the resulting focus on the normal distribution. However, recent literature has provided evidence that perceived risk is driven more by one-sided risk measures such as the probability of incurring a loss (e.g. Nosić and Weber, 2010; Weber et al., 2013; Anzoni and Zeisberger, 2017). These studies focus on the individual investor level. Our paper is the first to analyze how risk perception affects prices and trading behavior in asset markets.

We find evidence that individual investors' stated risk perception is mostly driven by the probability of incurring a loss. Importantly, this risk perception directly drives trading behavior and, by consequence, prices. Hence, variance of returns is not the main driver for risk perception or for market prices, while the probability of losing is, thus presenting evidence for the transferability of individual results on risk perception to market outcomes. Our findings can potentially also contribute to the discussion whether behavioral biases, preferences and beliefs affect market outcomes and prices (e.g., Barber et al., 2008; Coval and Shumway, 2005). We find that average risk perception strongly asset prices, and additionally, that individual risk perception drives asset holdings and trading in these markets.

With regard to trading behavior, we find that traders with comparatively higher perceived risk for an asset traded out of it, while those with comparatively lower risk perception were net buyers. Prices are strongly influenced by perceived risk, with the riskier assets trading at lower prices. With a risk-neutral BBV of 108, our eight assets trade at average prices of between 100 and 119. Asset prices and trading behavior in our experiments are driven by individual and average risk perception, and prices differ significantly for assets characterized by the same mean and standard deviation.

We believe that our results are of interest also for investors, financial professionals and regulators alike: practitioners designing financial products may well be aware that investors understand "risk" to a large extent as the probability of incurring a loss, and that issuers can thus demand a premium when they offer a product with supposedly low risk by ruling out losses (real losses due to inflation do of course occur, but seem to be neglected by many investors). This explains why so-called "guarantee products" (promising to pay back at least the full investment amount while offering the chance to earn a positive return if some benchmark performs well) are very popular among investors and issuing banks alike.

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Appendix A.

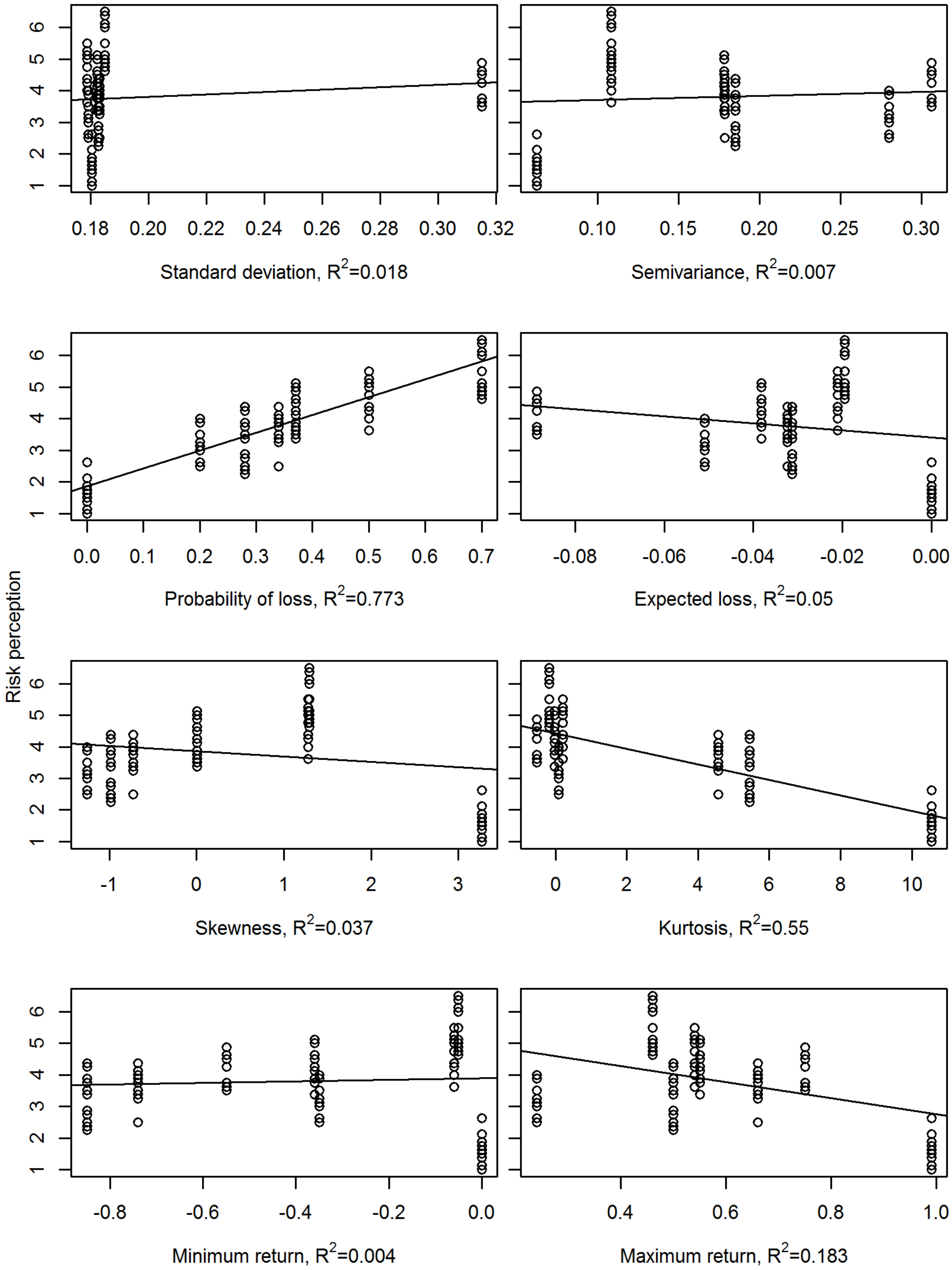


Figure A.5: Average risk perception in the market dependent on different risk measures

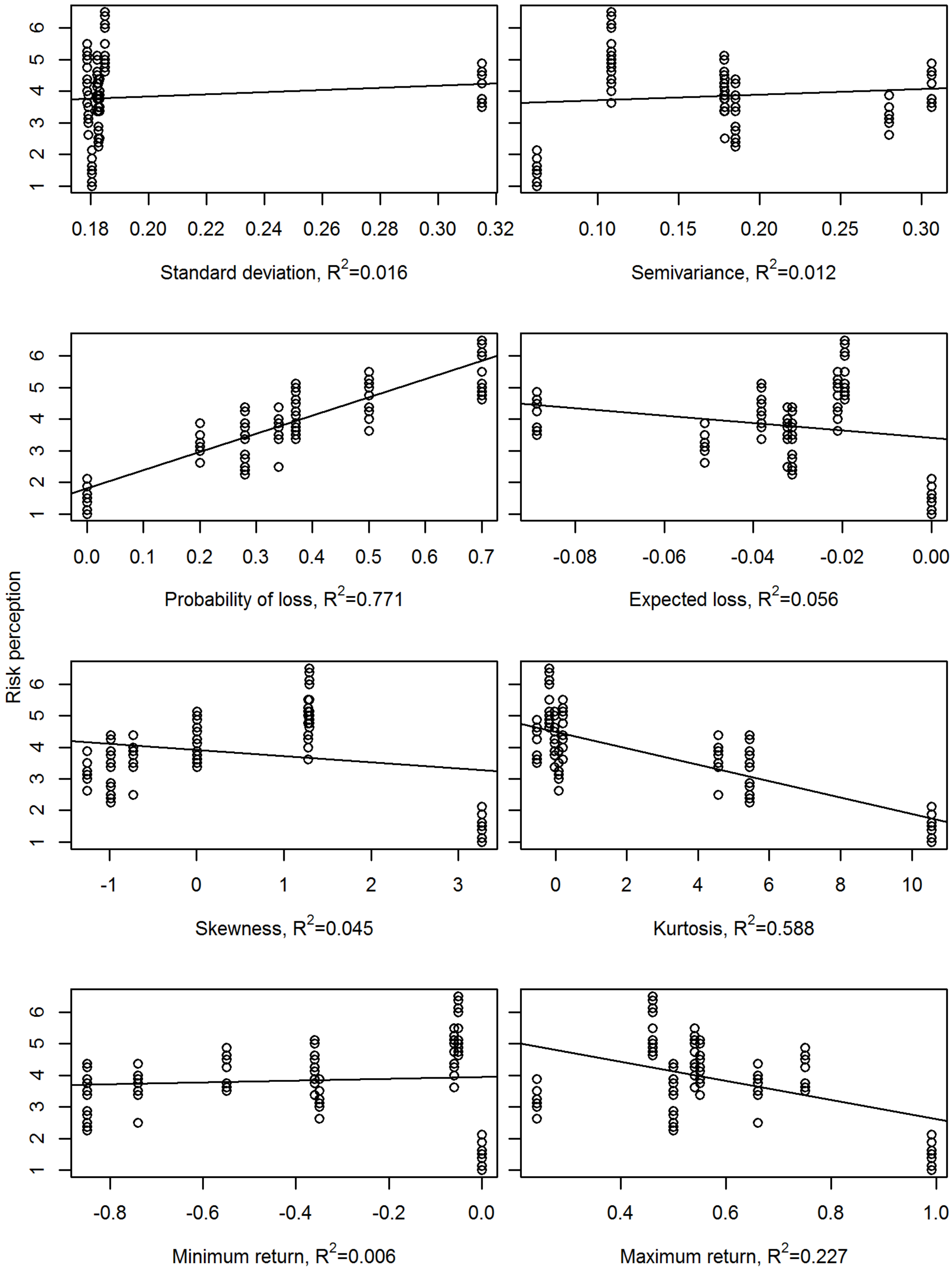


Figure A.6: Robustness check: Average risk perception in the market dependent on different risk measures in periods 2 through 8

	AvgPrice.P2.8	MedianPrice.P2.8	Volume.P2.8
(Intercept)	105.424^{***}	105.705^{***}	25.818^{***}
	(4.368)	(4.506)	(3.049)
2.NegSKEWNESS	6.523	5.102	0.557
	(6.731)	(6.944)	(4.699)
3.PosSKEWNESS	−3.944	−3.345	1.082
	(6.330)	(6.530)	(4.419)
4.BigLOSS	5.357	6.408	−2.902
	(6.047)	(6.238)	(4.222)
5.WIDER	1.261	1.241	−3.652
	(6.047)	(6.238)	(4.222)
6.FrequentLOSS	−2.914	−3.614	−1.455
	(6.177)	(6.373)	(4.312)
7.NoLOSS	12.793^{**}	12.695^{*}	−2.618
	(6.330)	(6.530)	(4.419)
8.KURTOSIS	−2.543	−2.310	−1.518
	(6.330)	(6.530)	(4.419)
R^2	0.128	0.120	0.027
Adj. R^2	0.048	0.039	−0.063
Num. obs.	84	84	84

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table A.6: OLS regressions of average and median price as well as trading volume across assets, limited to periods 2 through 8.

	AvgPriceLast60	MedianPriceLast60	VolumeLast60
(Intercept)	105.061***	106.341***	12.000***
	(4.116)	(5.097)	(1.627)
2.NegSKEWNESS	3.997	1.317	−0.083
	(5.699)	(7.056)	(2.252)
3.PosSKEWNESS	−2.996	−3.648	−0.333
	(5.699)	(7.056)	(2.252)
4.BigLOSS	4.057	4.555	−0.167
	(5.699)	(7.056)	(2.252)
5.WIDER	−0.346	−1.137	−2.083
	(5.699)	(7.056)	(2.252)
6.FrequentLOSS	−4.458	−6.466	−0.750
	(5.699)	(7.056)	(2.252)
7.NoLOSS	10.653*	11.346	−2.333
	(5.699)	(7.056)	(2.252)
8.KURTOSIS	0.998	1.300	−0.417
	(5.821)	(7.208)	(2.252)
R^2	0.106	0.090	0.027
Adj. R^2	0.033	0.016	−0.051
Num. obs.	94	94	95

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table A.7: OLS regressions of average and median price as well as trading volume across assets, limited to the last 60 seconds.

	AvgPriceLast60.P2.8	MedianPriceLast60.P2.8	VolumeLast60.P2.8
(Intercept)	105.061^{***}	106.341^{***}	12.000^{***}
	(3.124)	(3.842)	(1.675)
2.NegSKEWNESS	3.999	2.159	-0.500
	(4.814)	(5.920)	(2.582)
3.PosSKEWNESS	-2.918	-3.509	-0.200
	(4.527)	(5.567)	(2.428)
4.BigLOSS	4.057	4.555	-0.167
	(4.325)	(5.319)	(2.319)
5.WIDER	-0.346	-1.137	-2.083
	(4.325)	(5.319)	(2.319)
6.FrequentLOSS	-2.736	-5.114	-1.364
	(4.418)	(5.433)	(2.369)
7.NoLOSS	7.545^{*}	7.084	-3.100
	(4.527)	(5.567)	(2.428)
8.KURTOSIS	-2.696	-2.891	-0.400
	(4.657)	(5.727)	(2.428)
R^2	0.118	0.096	0.037
Adj. R^2	0.035	0.011	-0.051
Num. obs.	83	83	84

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors in parentheses.

Table A.8: OLS regressions of average and median price as well as trading volume across assets, limited to the last 60 seconds of periods 2 through 8.

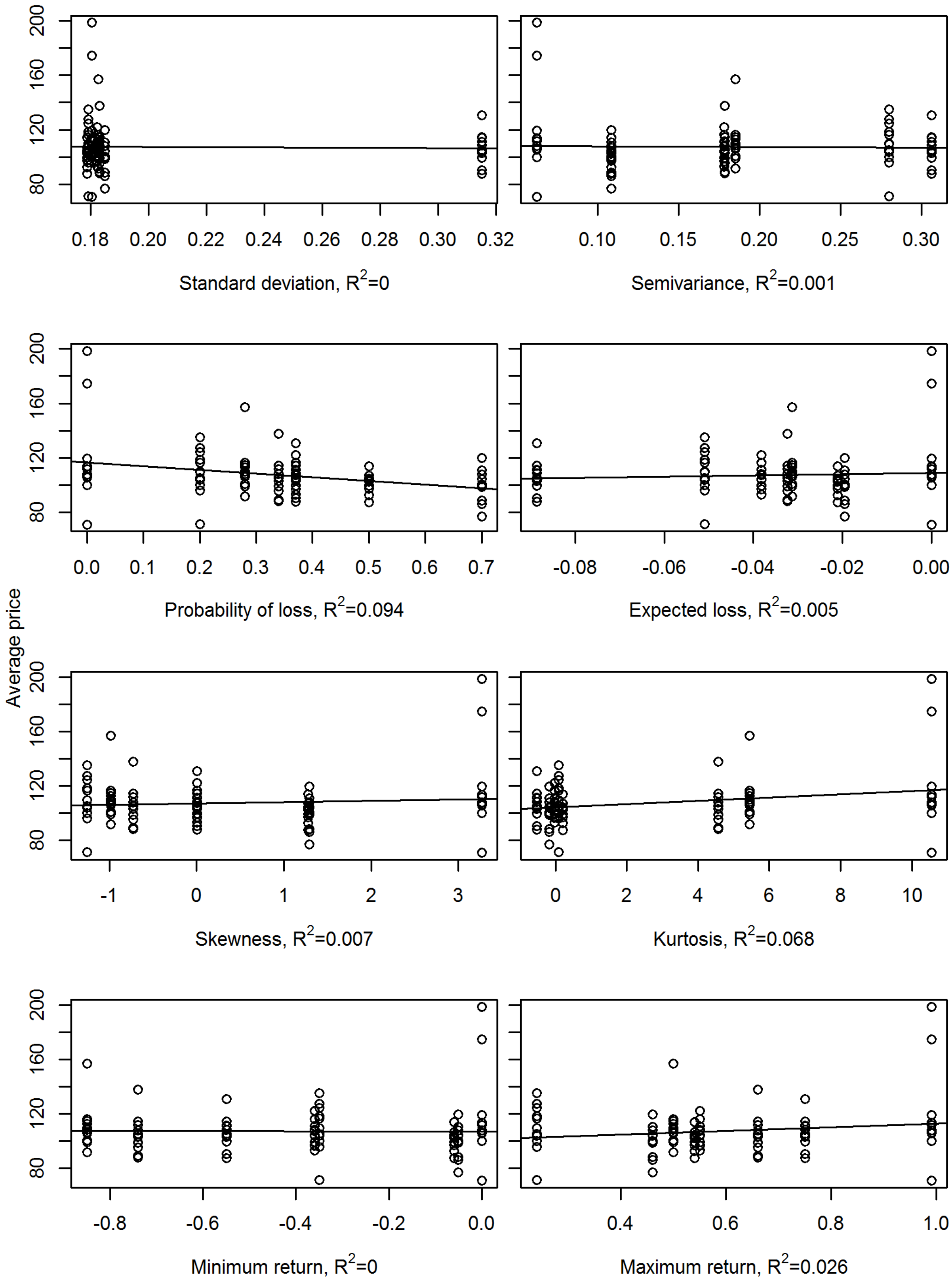


Figure A.7: Average price per period and distribution across all periods

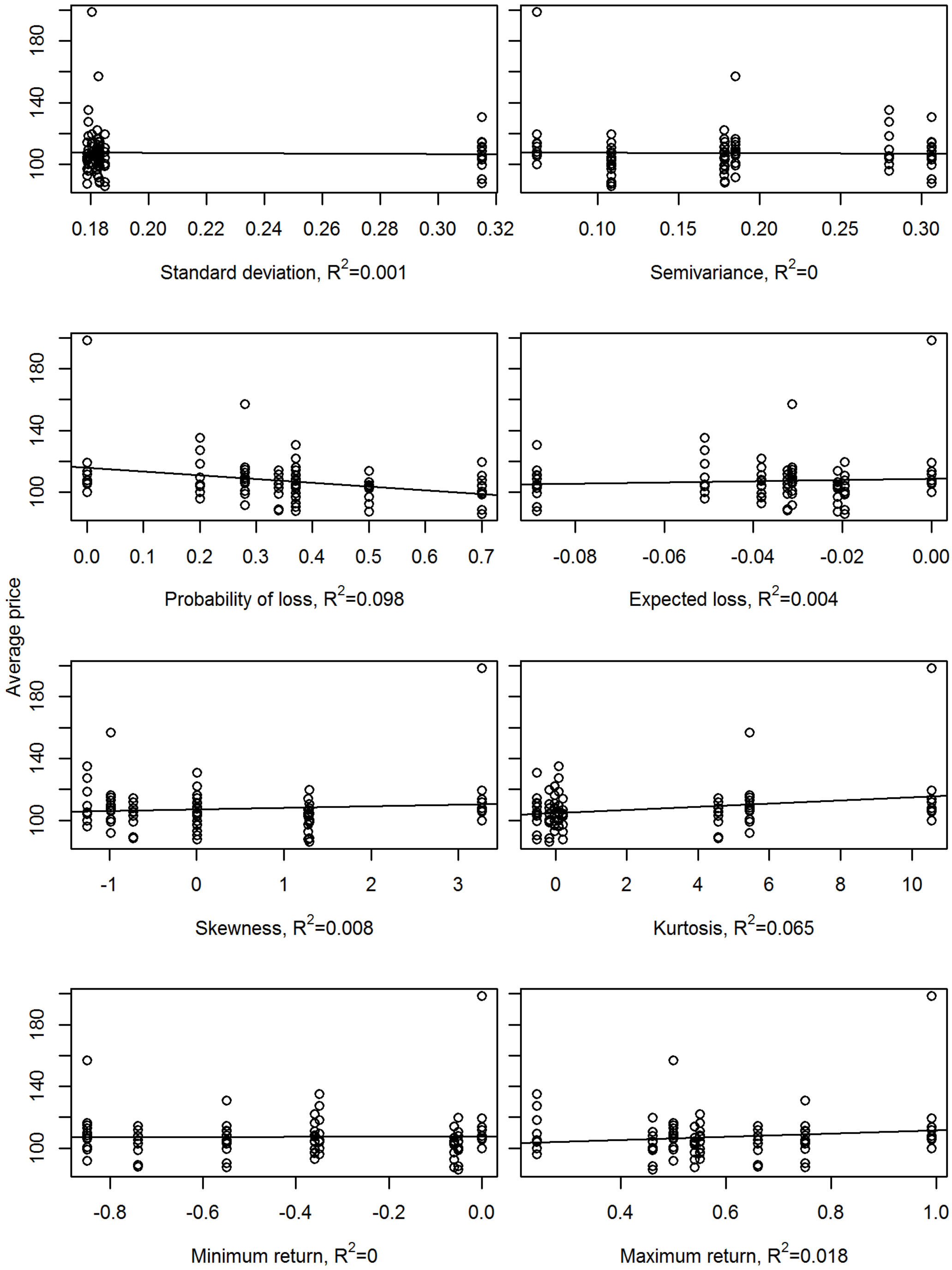


Figure A.8: Robustness check I: Average price per period and distribution of periods 2 through 8

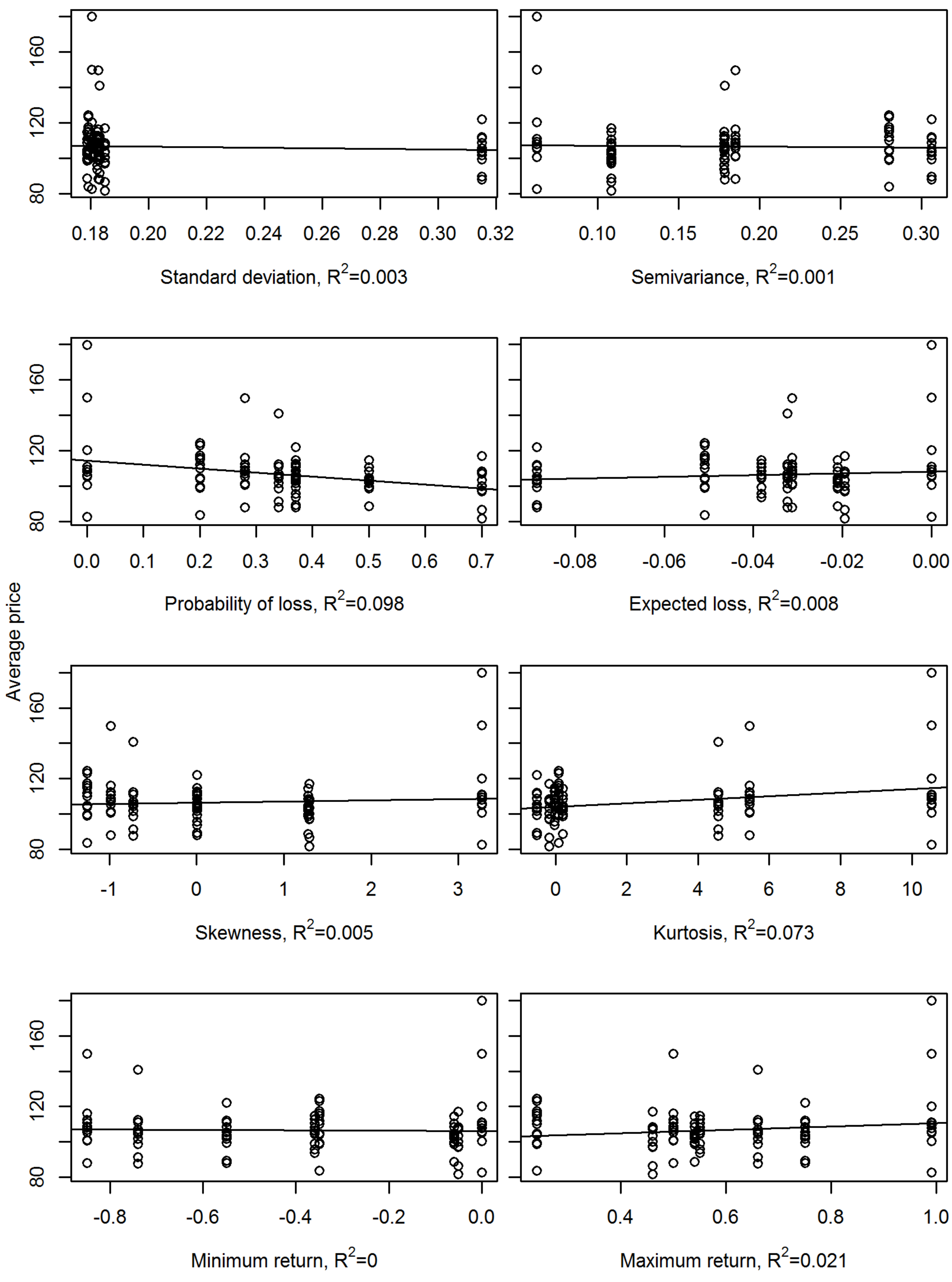


Figure A.9: Robustness check II: Average price per period and distribution in the last 60 seconds

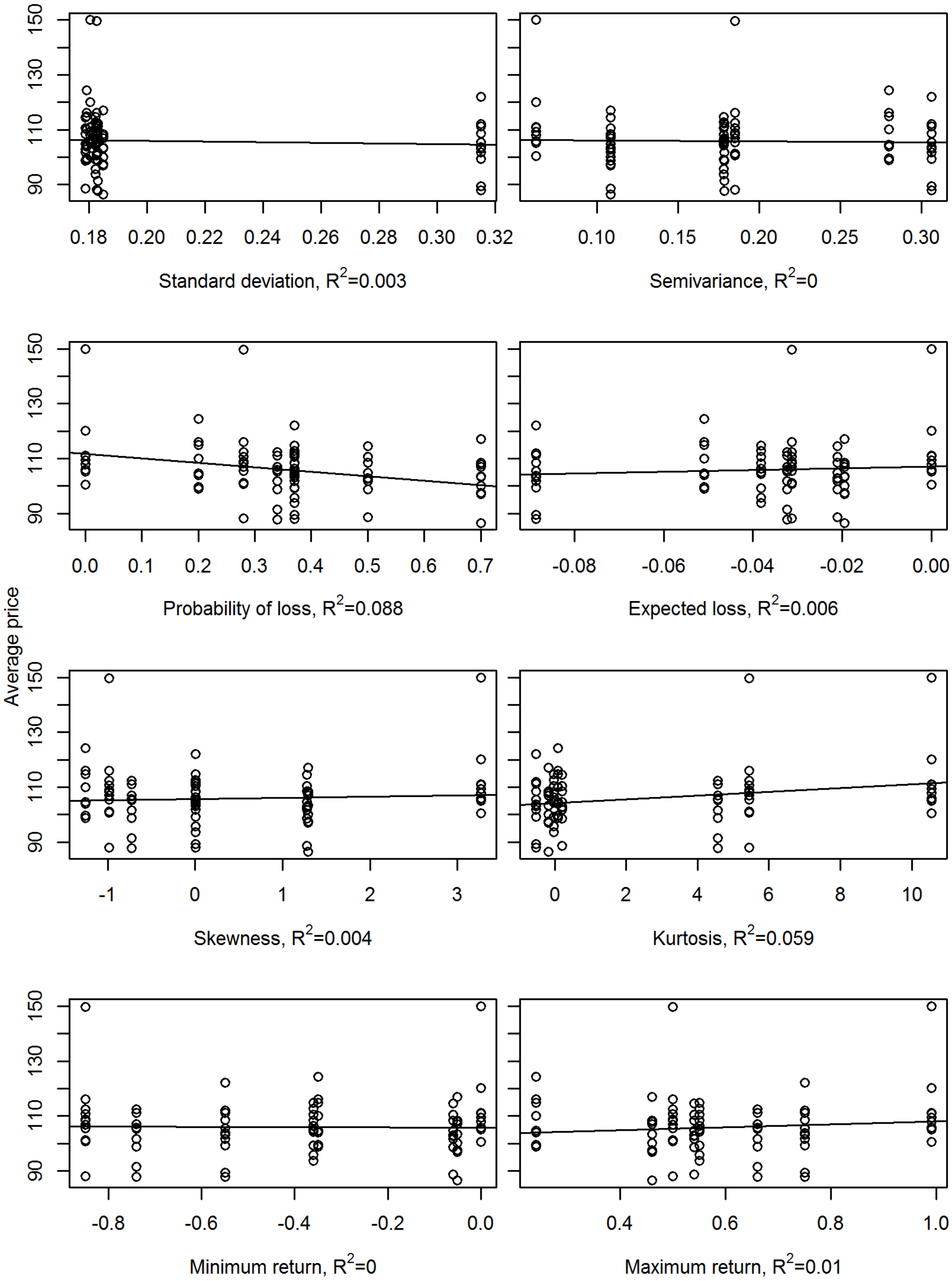


Figure A.10: Robustness check III: Average price per period and distribution in the last 60 seconds of periods 2 through 8

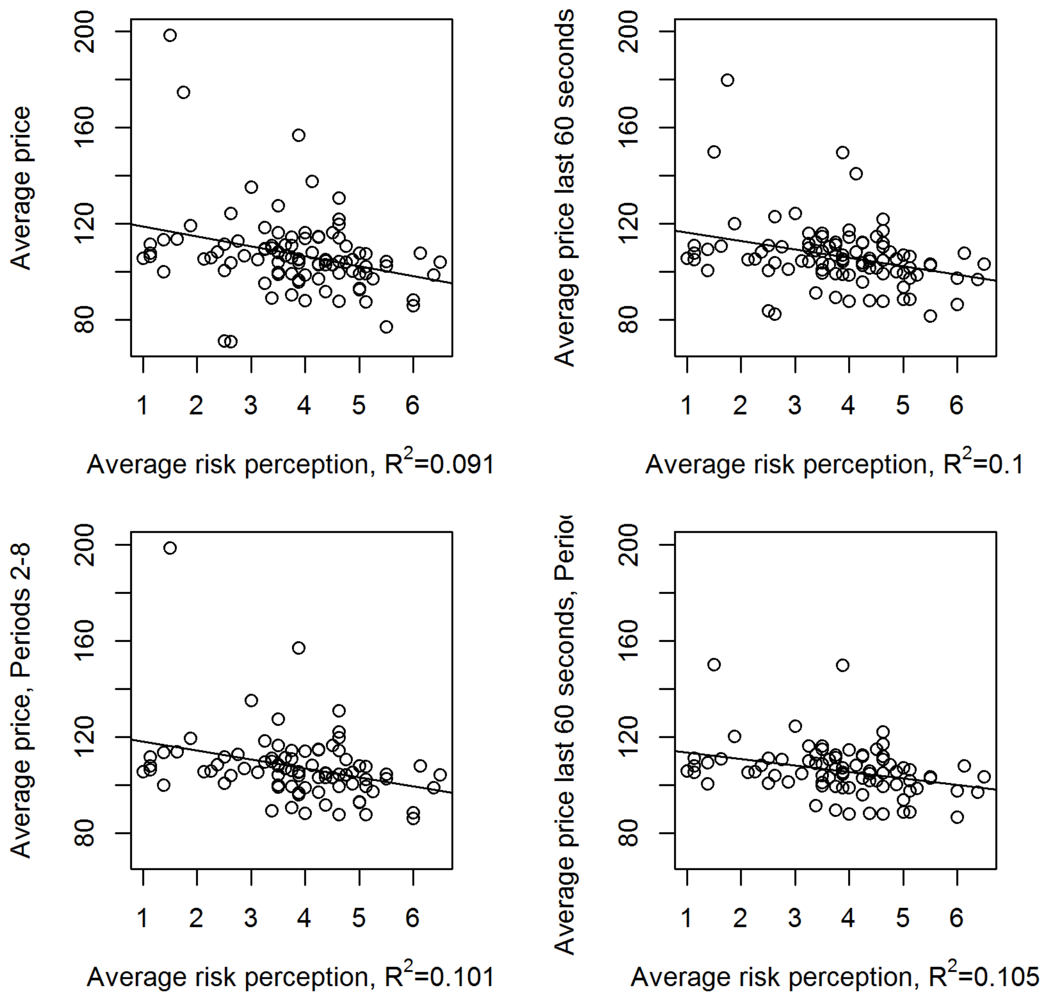


Figure A.11: Prices vs. average risk perception across all periods. Top left: full data. Bottom left: robustness check 1 with data from periods 2-8. Top right: robustness check II with data only from the last 60 periods. Bottom right: robustness check III with data only from the last 60 seconds of periods 2-8.

Appendix B. Experimental instructions (translated)

Innsbruck EconLab

Dear Participant,

welcome to today's experiment.

Please read the following instructions carefully. All statements in these instructions are true. Your payout will also depend on how well you understood the instructions. If you have any questions please raise your hand and we will answer your question privately. The whole experiment and any data analysis will be conducted anonymously.

We kindly ask you to refrain from talking to any other participant in the experiment from now on and to use only the tools we as experimenters provide to you. Please switch off all electronic devices. On the computer you may only use the functions and programs that are necessary for the experiment. Violating these rules will lead to exclusion from this and future experiments and you will receive no payout for todays experiment.

Thanks again for your attention and for participating in this experiment.

Sequence in this experiment:

This experiment consists of a market experiment and further short decision-making situations where you can earn money. Before the start of each part of the experiment you will receive separate instructions to learn about the rules in the respective experiment.

Experiment 1: market experiment

Instruction for the trading screen

Trial period

Instruction for the asset traded

Experiment

Experiment 2: short decision-making situations

Instructions and experiment

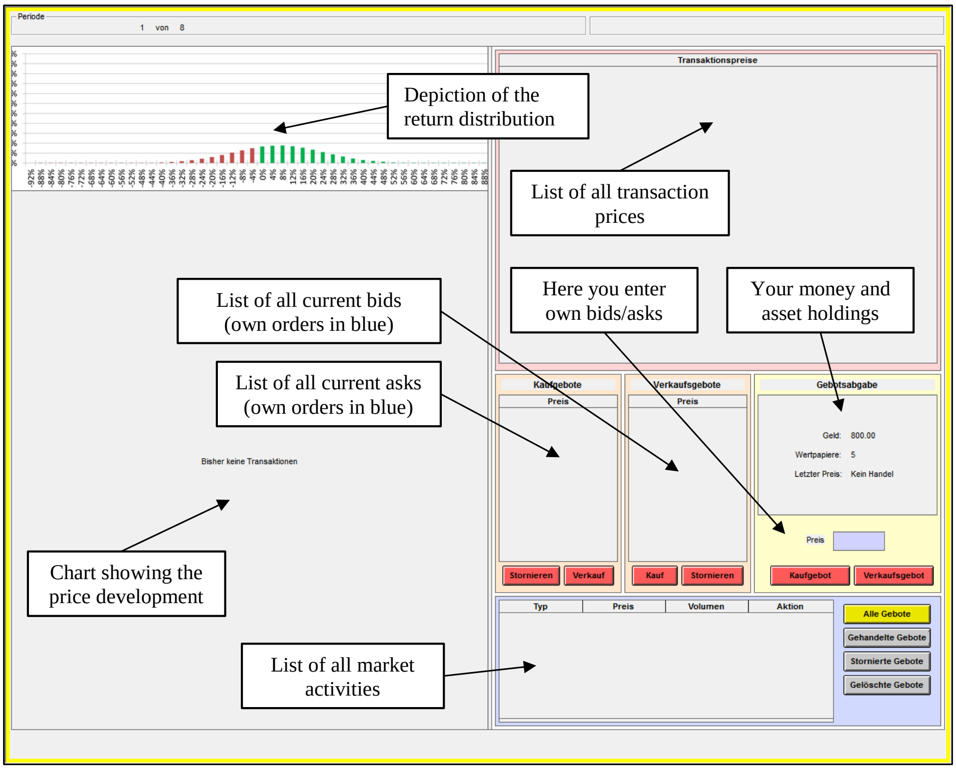
Payout

Experiment 1 – market experiment

(1) INSTRUCTION FOR THE TRADING SCREEN:

In this experiment you can buy and sell assets which are traded in a double auction. This means that each trader can act as buyer as well as as seller. To trade you can submit bids (offers to buy) and asks (offers to sell) by specifying a price you want to trade for (with a maximum of two decimal places). Each offer is always for one asset.

If you ***buy*** an asset you money holdings are reduced by the respective price, while your holdings of the asset are increased by 1. If you ***sell*** an asset your money holdings are increased by the respective price while your asset holdings are reduced by 1. Please note that you can buy (sell) only as many assets as are covered by your money holdings (asset holdings). Negative holdings of money or assets (short selling) are not allowed. The computer automatically deletes orders that are not covered by asset/money holdings.



To familiarize you with the functioning of the trading system, we will now conduct one trial period. Please use this period to train with all the functions. The returns of the trial period are not payout-relevant.

(2) DETAILS OF THE EXPERIMENT:

This experiment consists of a total of **8 Periods**, where you trade units of a different asset each period (8 periods, 8 different assets). The periods and assets are completely independent of each other. Each asset will realize a return (profit or loss) after trading ends. One of the 8 periods will randomly be picked as the payout-relevant one and will be paid out accordingly. The distribution of possible returns and their respective probabilities are shown to you at the beginning of the period and throughout trading.

Every period has the same structure: First you see the return distribution and are asked to assess how risky you perceive the asset to be. Then each of you is endowed with 5 units of the asset and 800 units of money with which you can trade throughout the period by selling to other traders or buying from them.

Details:

- The price of the asset is set through supply and demand, i.e. through the buy and sell orders of you and the other seven traders in your market (each market consists of eight traders).
- At the end of a period each unit of the asset pays the nominal value of 100 plus/minus the return (profit or loss). The return is randomly drawn from the distribution you are shown at the beginning of the period (and throughout trading). The draw is done separately after each of the eight periods.
- The drawn returns are independent of each other, i.e. returns drawn in one period do not have any influence on later returns. You will see all returns only at the very end of the experiment.
- **The expected return for each of the 8 assets is positive and is close to 8%**.

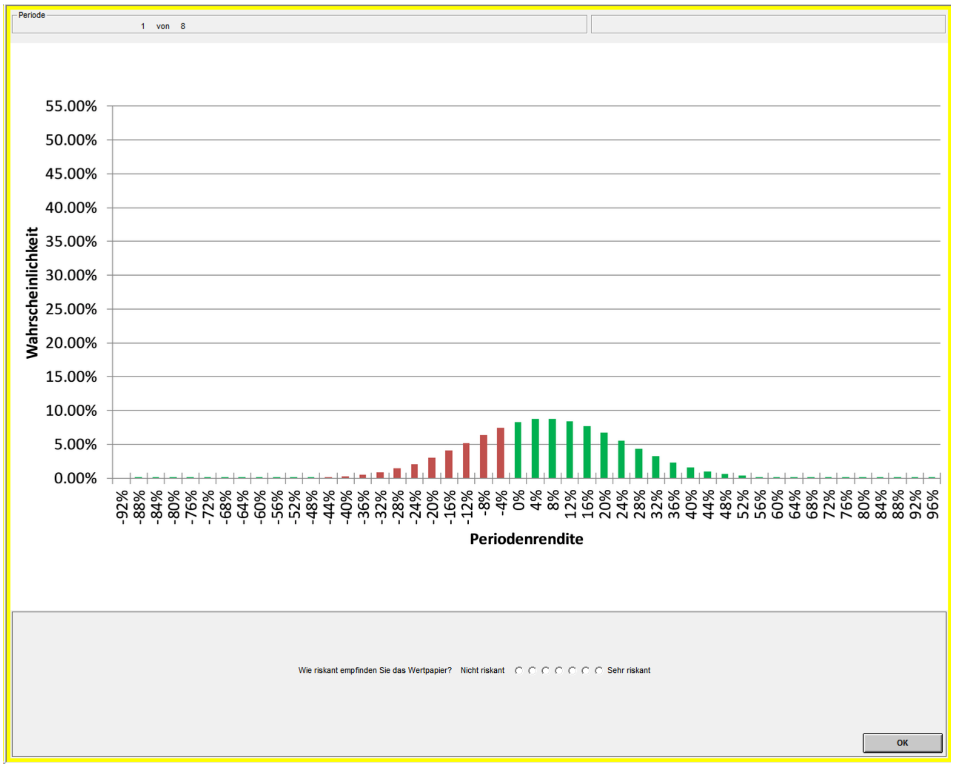
Overview over one period

Each period has the same structure, as you will see three screens each periods: (1) the return distribution (30 sec.), (2) the trading screen (3 min.), and (3) the overview screen showing your final holdings (10 sec.).

(2) RETURN DISTRIBUTION:

Below you see an exemplary return distribution, showing possible return realizations on the horizontal axis and the respective probabilities on the vertical axis. The higher a column, the more likely a return is. Red columns show losses (in percent of the nominal value of 100), while green columns show profits. Each of the 8 assets you will trade has an expected average return of close to +8%.

The randomly drawn return increases or lowers the value of the asset and thus the final payment you receive at the end of the experiment. Starting from the nominal value of 100 a return of 8% means a payout of 108 per asset; a return of 30% means a payout of 130 per asset; and a return of -30% means a payout of 70 per asset.



In the figure above the possible return realizations (between -92% and +96%) are shown on the horizontal axis, while their respective probabilities are shown on the vertical axis. Green columns are positive returns (profits), while red columns show negative returns (losses). The values on the horizontal axis give the lower bound for each column, i.e. 4% mean that returns can be between 4% and 8%. The higher a column is, the more likely it is that the respective return is realized. In the example above returns between 4% and 8% have a likelihood of 12%, i.e. 12% of the draws will result in returns between 4% and 8%.

At the start of each period you will be shown the return distribution for 30 seconds. You are asked to mark on a 7-point scale how risky you perceive the asset to be. The return distribution is also shown on the top left of the trading screen. If you click on the distribution it will be shown enlarged so you can inspect it more closely.

(3) OVERVIEW SCREEN:

After trading you will see your final holdings on the overview screen. The next period you are again endowed with 5 assets and 800 units of money.

(4) PAYOUT:

After all 8 periods are done one of them is randomly drawn (one of the participants will roll an 8-sided die). This (and only this) period is relevant for your payout. For the asset traded in this period a return is drawn from the respective return distribution. This return is relevant for your payout. Your final wealth (=your money holdings plus units of the asset multiplied with the randomly drawn asset value) is divided by 100 to arrive at your payout in euro for this part of the experiment.

Again the most important details of the experiment:

- There are 8 trading periods. Each period consists of the same parts and the periods are independent of each other.
- Each participant starts each period with 5 units of the asset and 800 units of money.
- At the end of the experiment each unit of the asset pays the nominal value of 100 plus/minus the randomly drawn profit/loss. For your payout in euros one of the 8 periods is randomly drawn and only this period will be paid out.
- The returns of all of the 8 assets have a positive expected value of around 8%.