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Do individual attitudes towards imprecision survive in experimental asset markets?*

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Abstract

In situations where both the magnitude of gains and losses as well as the probability distribution over these realizations is uncertain, imprecision is an inherent feature of decision-making. While imprecision has been shown to affect *individual* valuations, many decisions are made in *market* settings with potentially different implications. We thus examine the impact of imprecision, first, in an individual decision task, and second, in experimental asset markets—with no imprecision (risk), imprecision in probabilities (ambiguity), imprecision in outcomes, and full imprecision. We find imprecision seeking in outcomes in people's individual attitudes, but these preferences do not withstand market dynamics. Nevertheless, we observe imprecision aversion in probabilities at the end of trading, suggesting that ambiguity aversion, in contrast, prevails in experimental markets.

JEL: G11, G12, C92, D81

Keywords: imprecision attitudes, ambiguity aversion, uncertainty, asset markets, experimental finance

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1 Introduction

Imprecision,[1] in general, is an inherent feature of decision-making under uncertainty coming in number of manifestations. First, we are concerned with *imprecision in probabilities*—i.e., ambiguity—, relating to situations in which the respective probabilities over outcomes are unknown. The second dimension, *imprecision in outcomes*, relates to cases in which probabilities are precisely known but outcomes are not. One intuitive example for such a situation is a common 'Lotto' lottery: the probability of having a winning lottery ticket can easily be calculated, but the size of the prize depends on how many people participate and on how many of them also have a winning ticket—thus, the probability of winning a prize is objectively known, while the outcome realization is not (Schröder, 2020). Combining the two, with *imprecision in probabilities and outcomes*, both the magnitude of outcomes as well as the probability distribution over realizations are only vaguely defined.

Imprecision has been shown to affect *individual* valuations and thus, decisions, in all of these instances; however, many decisions are made in *market* settings with potentially very different implications. In the context of financial markets, uncertainty in general, and imprecision, in particular, play a major role: think about inherently uncertain asset returns, imprecise executive communications with respect to earnings forecasts, or structured financial instruments with a high degree of complexity such that potential outcome realizations are practically imprecise.

In this study, we approach all three forms of imprecision in an experimental setting, disentangling individual and market attitudes. As a baseline, we include *risk*, for which both probabilities and outcomes are precisely defined. In a first step, we elicit participants' individual preferences for risk/imprecision attitudes. In a subsequent market experiment, subjects trade an asset whose fundamental value is governed by imprecision as well. With this design we aim to apply the simplest possible experimental market environment while maintaining a high level of feedback. We therefore use a continuous double auction mechanism, but implement only one trading period, in which each participant faces assets with one of the four types of risk/imprecision (that is, we employ between-subjects treatments; see Sarin and Weber, 1993, for example). Lottery outcomes

[1] We primarily use the terms *imprecision* and *vagueness* but also interchangeably refer to *ambiguity*, as this terminology is common in the decision analysis and economics literature building on Ellsberg (1961). Budescu et al. (1988, p. 282, footnote 1), however, argue that 'a statement, phrase, or event is *ambiguous* if it is capable of being understood in two or more different, but precise, ways. It is *vague* if it is not clearly defined or capable of being understood precisely.' The terms *vagueness* and *imprecision* therefore capture our research objective more accurately.

(respective buyback prices in markets) are either risky, imprecise in probabilities, imprecise in outcomes, or a combination of both. This novel setup allows us to document and characterize not only individual preferences towards risk/imprecision, but also how these attitudes influence aggregate behavior and shape the competitive price in the respective market setting.

With the present study we contribute to two main strands of research—see Table 1 for an overview of the different manifestations of imprecision outlined above (treatments) and related experimental literature. We first contribute to previous work on *individual* ambiguity and imprecision attitudes going back to Knight (1921)[2] and later, Ellsberg (1961), who, in the simplest experiment with two-urns, demonstrated that subjects are averse to imprecise probabilities, i.e. people tend to be ambiguity averse.[3] Extending imprecision to the outcome dimension has resulted in mixed evidence, however. Kunreuther et al. (1995), Gonzalez-Vallejo et al. (1996), and Kuhn and Budescu (1996) report aversion to vagueness in probabilities and in outcomes. On the contrary, Budescu et al. (2002) find evidence for vagueness seeking in outcomes, suggesting the greater salience of the outcome dimension in a pricing task as a potential cause. While Du and Budescu (2005) find similar patterns in eliciting certainty equivalents, their results are not robust to changing the response mode (from pricing to choice), and the domain of the outcomes (losses or gains). In a recent experiment, Onay et al. (2013) also find evidence for imprecision seeking in outcomes in pricing tasks. Thus, with regard to the individual decision task, we see the present study as a conceptual replication of experiments examining imprecision attitudes with comparable elicitation procedures. These replications act as a baseline for the second part of this experiment and are important building blocks for a more comprehensive examination of imprecision.

Moreover, we contribute to the comparatively scarce literature on ambiguity attitudes in experimental market environments,[4] for which previous evidence paints a mixed picture. In a seminal study, Camerer and Kunreuther (1989) find hardly any effects of ambiguity on experimental prices for insurance coverage. Weber (1989) and Sarin and Weber (1993) go on to compare risk and ambiguity in asset markets employing various experimental designs with trading in simultaneous and separately conducted markets. Their findings indicate that market prices for ambiguous as-

[2]Knight (1921) distinguished between *risk*, which is described by known and precise probabilities, and *uncertainty*, where probabilities of events are unknown. This separation has been resumed by the seminal experimental work of Ellsberg (1961), among others.

[3]Trautmann and Van De Kuilen (2015) provide a comprehensive overview on ambiguity attitudes.

[4]A comprehensive overview of (mostly) the theoretical economics literature can be found in Barberis and Thaler (2003), whereas Guidolin and Rinaldi (2013) provide a detailed review of related literature in finance.

Table 1: **Overview of the different treatments and related literature.** This table shows the different treatments (stimuli)—i.e., different types of imprecision (no imprecision, imprecision in probabilities, in outcomes, or in outcomes and probabilities)—and related experimental literature in the domain of individual decision making and in market environments. For cells with a checkmark (✓), there is literature available and we provide a conceptual replication; for cells with an empty square (□) there is no literature available yet and the present study is the first to explore this topic.

		Unit of observation (task)	
		Individual (elicit certainty equivalent or willingness to accept/pay)	Market (continuous double auction)
Treatment (stimulus; type of imprecision	no imprecision ('risk')	✓[a]	✓[e]
	imprec. in probabilities ('ambiguity')	✓[b]	✓[f]
	imprecision in outcomes	✓[c]	□
	imprec. in outcomes and probabilities	✓[d]	□

[a] See, e.g., Eisenberger and Weber (1995), Chow and Sarin (2001), Budescu et al. (2002), Du and Budescu (2005), Borghans et al. (2009), Onay et al. (2013);
[b] See, e.g., Eisenberger and Weber (1995), Chow and Sarin (2001), Budescu et al. (2002), Du and Budescu (2005), Borghans et al. (2009), Onay et al. (2013);
[c] Budescu et al. (2002), Du and Budescu (2005), Onay et al. (2013);
[d] Budescu et al. (2002), Du and Budescu (2005), Onay et al. (2013);
[e] Camerer and Kunreuther (1989), Weber (1989), Sarin and Weber (1993), Bossaerts et al. (2010), Corgnet et al. (2013), Füllbrunn et al. (2014), Corgnet et al. (2020);
[f] Camerer and Kunreuther (1989), Weber (1989), Sarin and Weber (1993), Bossaerts et al. (2010), Corgnet et al. (2013), Füllbrunn et al. (2014), Corgnet et al. (2020).

sets are consistently below prices for risky assets and identify a robust 'ambiguity premium'. In attempting a more exhaustive analysis, Füllbrunn et al. (2014) compare ambiguity in two market institutions—call markets and continuous double auction markets—to incorporate the effects of market dynamics and transparency, and to explore whether ambiguity aversion holds in either of the two institutions. They report significant ambiguity premia in low-feedback call markets for assets which provoke high ambiguity aversion but no effects of ambiguity in high-feedback continuous double auction markets.[5] We extend this research strand by providing the first account of imprecision in outcomes and of 'full' imprecision—i.e., imprecision in outcomes and probabilities—in a market environment. Also, we add to this literature by conceptually replicating previous experiments on imprecision in probabilities (ambiguity) in experimental markets.

Summarising our results, we observe imprecision seeking in outcomes but no statistically significant preferences for or against risk, imprecision in outcomes, or imprecision in outcomes and probabilities for individual decisions. This might potentially be explained by the comparative ig-

[5]Recent contributions to the experimental asset pricing literature with regard to ambiguity also include Bossaerts et al. (2010), whose findings suggest significant ambiguity effects in the context of portfolio choice; as well as Corgnet et al. (2013), who analyze trader reaction to ambiguity when dividend information is only revealed sequentially over three experimental periods. Their results suggest only a limited role of ambiguity in explaining financial market anomalies. Corgnet et al. (2020), in contrast, report lower asset prices with an ambiguous fundamental value than in a risky one in a market experiment designed to examine bubble formation.

norance hypothesis (Fox and Tversky, 1995) as each subject posts a reservation price for only one type of imprecision (in contrast to a comparative setting). In continuous double auction markets, however, imprecision aversion in probabilities (ambiguity) as well as an aversion to the combination of imprecision in outcomes *and* probabilities tend to prevail at the end of trading (that is, we observe an imprecision premium as market prices are significantly below expected fundamentals), whereas market dynamics wash out imprecision seeking attitudes in the outcome dimension.

2 The Experiment

We conduct a laboratory experiment consisting of two main parts: (Part I) an individual decision task to measure subjects' preferences for imprecision by eliciting reservation prices, and (Part II) a continuous double auction market to explore trading behavior and aggregate market outcomes in the face of imprecision. In both parts we aim to analyze the effects of either imprecise probabilities, imprecise outcomes, or both, in comparison to precise probabilities and outcome realizations, respectively. We thus apply a 2×2 between-subjects experimental treatment design.

Each of the four treatments is defined by a distinct lottery. Treatment RISK represents what is commonly referred to as *risk* and what is, among other applications, the basis of seminal models in economics and finance (e.g. Arrow, 1965; Pratt, 1964; Markowitz, 1952; Sharpe, 1964): in this lottery, subjects have precise information about the outcome realizations as well as about the respective probabilities over outcome realizations. For IP (Imprecise Probabilities) and IO (Imprecise Outcomes), either the respective probabilities or the corresponding realizations are *imprecise*, i.e. they lie within a given interval but are not precisely known with certainty. In IOP, the lottery consists of both, imprecise probabilities and imprecise outcomes. We essentially operationalize imprecision in outcomes (IO and IOP) using compound lotteries with unknown probabilities over the second-stage payoffs (see below).

2.1 Part I: Individual Decision Task

In Part I, we elicit risk or imprecision preferences, respectively, by asking each subject for her reservation price (willingness to accept, *WTA*; i.e., a certainty equivalent) using a Becker-DeGroot-Marschak (BDM, 1964) mechanism. One of the features of this incentive-compatible BDM procedure is that subjects should apply a very similar reasoning in assessing their willingness to accept in the individual task of Part I as in posting orders to buy and/or sell in the market experiment of Part II.

The BDM mechanism works as follows. Subjects are offered a distinct lottery depending on their randomly assigned treatment and are asked to enter the Taler (experimental currency unit) amount they are demanding in order to forego the lottery. The posted reservation price should thus represent the amount at which a subject is indifferent between entering and foregoing the lottery. After each subject has entered their reservation price (*WTA*), a number between 8 and 208 is randomly drawn. If this random number is greater than a subject's *WTA*, she receives the randomly drawn number in Taler. If the random number is smaller than a subject's *WTA*, she enters the respective lottery.

In this individual decision task, we operationalize precise and imprecise outcomes and probabilities as follows. For *precise outcomes* (RISK and IP), there are two possible realizations: either 58 or 158 Taler. In contrast, *imprecise outcomes* (IO and IOP) are operationalized by realizing a randomly distributed Taler value either in the range $[8, 108]$ or in the range $[108, 208]$ (in steps of 5). Regarding the respective probabilities we define *precision* as assigning probabilities $p = 0.50$ and $1 - p = 0.50$ to each of the two outcomes or outcome ranges, respectively. *Imprecise probabilities* are then characterized by randomly determined probabilities $p \in \{0.00, 0.05, 0.10, ..., 0.90, 0.95, 1.00\}$ and $1 - p$. Note that p is randomly distributed and can lie anywhere between 0 and 1 (in steps of 0.05). Similarly, any distribution of outcome realizations within each of the two outcome ranges is possible. The lotteries for imprecise outcomes can therefore be interpreted as compound (two-stage) lotteries (see Gonzalez-Vallejo et al., 1996; Budescu et al., 2002; Du and Budescu, 2005, for example). The first lottery determines whether the outcomes are drawn from a 'low' outcome space in the interval $[8, 108]$ or from a 'high' outcome space in the interval $[108, 208]$. The second lottery determines which of the outcomes within the respective interval is obtained.[6] Both imprecise outcome realizations and imprecise probabilities are drawn from random distributions at the end of the experiment. Thus, with imprecision, sub-

[6]For feasibility, outcome spaces are defined in steps of 5. Hence, we have 21 outcomes in the 'low' outcome space and 21 outcomes in the 'high' outcome space, respectively. We thereby match the analogous implementation of the probability space, for which we allow only a discrete number of probabilities as well.

jects are unaware of the distribution of p (in IP and IOP) or of outcome realizations (in IO and IOP), respectively.[7] Table 2 summarizes the lottery parameters for each of the four treatments.

Table 2: **Treatment overview and parameterization.** This table shows the parameters of the four lotteries each corresponding to one particular treatment. Outcome realizations are either 58 or 158 in treatments RISK and IP, or a randomly drawn value from either the range $[8, 108]$ or $[108, 208]$ in treatments IO and IOP. The probability p corresponding to the lower outcome or outcome range, respectively, is either .5 (RISK and IO), or takes a randomly drawn value from the range $[0, 1]$ (IP and IOP).

Treatment	Possible Outcome Realizations	Possible Probabilities
RISK	58 158	50% otherwise
IP (Imprecise Probabilities)	58 158	[0%; 100%] otherwise
IO (Imprecise Outcomes)	$[8, 108]$ $[108, 208]$	50% otherwise
IOP (Imprecise Outcomes and Probabilities)	$[8, 108]$ $[108, 208]$	[0%; 100%] otherwise

2.2 Part II: Market Experiment

Part II employs an experimental asset market in which subjects trade one of four distinct types of assets, each corresponding to one of the four treatments. In each market there are eight subjects trading for a period of three minutes in a standard computerized continuous double auction environment with single-unit trading. Each trader is endowed with 5 units of the asset and 800 Taler in cash holdings. At the end of trading, the experimenter buys back each unit of the asset for a liquidating, state-dependent buyback price to be determined by drawing balls from one or more non-computerized, opaque Ellsberg-type urns (Ellsberg, 1961). Thus, for each treatment the asset's buyback price is the result of a lottery as depicted in Table 2.

[7] In particular, we use the Random Integer Generator from www.random.org. For imprecise outcome realizations, we draw a series of 21 integers between 0 and 20, multiply each of them with 5 and add 8 for the outcome range $[8, 108]$ and 108 for the outcome range $[108, 208]$. For imprecise probabilities, we draw a series of 20 integers of either 0 or 1 to determine p as the sum of the 20 integers over 20. Samples are independently drawn by research assistants such that neither subjects nor the experimenters know the distribution of p (in IP and IOP) or of outcome realizations (in IO and IOP), respectively. The randomly drawn samples for each experimental session are available upon request.

In each treatment one urn is filled with two types of balls—yellow or white—corresponding to two precise outcomes (RISK and IP) or to two outcome ranges (imprecise outcomes, IO and IOP), respectively, as shown in Table 2. Before trading begins, subjects decide by majority voting which color, if drawn, leads to which of the two possible (precise) outcome realizations or (imprecise) ranges of outcomes, respectively.

In this market experiment, we operationalize precise and imprecise probabilities as follows. For precise probabilities (RISK and IO) the urn is filled with exactly 10 yellow and 10 white balls. With imprecise probabilities (IP and IOP) the urn contains a randomly determined composition of balls.[8] Thus, the urn might contain only white balls, only yellow balls, or a mixture of both, whereas subjects do not know the actual composition.

In treatments with precise outcome realizations (RISK and IP), the yellow or white ball drawn from the urn strictly determines the realization of the buyback price to be either 58 or 158 Taler. Conversely, in treatments IO and IOP—for which outcome realizations are imprecise—, there are two additional urns each of which are filled with 21 balls labelled with possible buyback prices, one with realizations in the range $[8, 108]$ and one with realizations in the range $[108, 208]$ (in steps of 5).[9] Again, the distribution of buyback prices in the urns is unknown. The yellow or white ball then determines from which of the two additional urns—the one with realizations less than or equal to the expected value or the one with realizations greater than or equal to the expected value—the buyback price for the asset is drawn. Finally, a randomly determined participant draws one of the randomly distributed outcome realizations from the relevant urn to determine the buyback price of the asset.

2.3 Experimental Implementation

We ran 17 experimental sessions with a total of 320 students from different fields of study, who were recruited using hroot (Bock et al., 2014). 46.6% of participants are female and their mean age is 23; subjects' demographics, on average, do not differ across treatments (see Table C1 in the

[8] We use the Random Integer Generator from www.random.org once more to draw series of 20 numbers of either 0 or 1 from a random distribution, which determine the number of yellow (0) and white (1) balls in the urn.

[9] For each of the two urns we draw 21 integers between 0 and 20 using the Random Integer Generator from www.random.org prior to each experimental session. The possible realizations written on the balls are then the drawn integers multiplied by 5 plus 8 for the outcome range $[8, 108]$ and plus 108 for the outcome range $[108, 208]$. Samples are independently drawn by research assistants such that neither subjects nor the experimenters know the distribution. The randomly drawn samples for each urn of each session are available upon request.

Appendix). All sessions were completed between March and October 2018 at Innsbruck EconLab at the University of Innsbruck. The experiment was conducted with z-Tree 3.6.7 by Fischbacher (2007) and employs the continuous double auction market environment of GIMS (Palan, 2015).

In total, each experimental session lasted approximately one hour. Experimenters read aloud the written instructions of the individual decision task and allowed sufficient time to study them. Subjects could only continue with the experiment after having had correctly answered three control questions checking their understanding of the respective lottery (RISK, IP, IO, or IOP) and the BDM mechanism. Subjects were then asked to privately enter their respective reservation price (willingness to accept, *WTA*s). Next, subjects received written and read-aloud instructions on the trading environment of the market experiment. After having had the possibility to familiarize themselves with the market institution by trading in a neutral trial period of four minutes, an additional set of instructions on how the buyback price is determined was handed out and read aloud. Subjects then voted on which ball—yellow or white—should pay which of the two outcomes or outcome ranges, respectively. After revealing the majority decision, the three-minute trading period started. After trading concluded, one randomly chosen participant randomly draws one ball (yellow or white) from the urn relating to the asset's type (all treatments), and also draws a ball labelled with a buyback price from the urn relating to the previously determined outcome range of the respective asset type (only treatments IO and IOP).[10] The experimental instructions as well as screenshots of both experimental parts are available in Appendices A and B.

After the two main parts of the experiment, participants complete a four-item cognitive reflection test (CRT Frederick, 2005; Toplak et al., 2014), three financial literacy items (Lusardi and Mitchell, 2007), as well as general questions on their demographics.

Subjects' payouts comprise their earnings from the individual decision task and from the market experiment. For the latter, the buyback price determined by drawing balls from (an) opaque urn(s) was multiplied by a subject's number of shares held at the end of the trading period and added to her end holdings of Taler. Finally, the Taler holdings from the market experiment were exchanged for euros at a rate of 180:1. Earnings from the individual decision task were exchanged for euros at a rate of 30:1. In total, subjects earned between 5 and 28 euros with a mean of 13.1 euros.

[10]Note that subjects were aware from the beginning of the experiment that there would be two main parts. However, it was not announced that the second part would be a related market experiment and that they would be able to earn money in both parts. Lottery outcomes from Part I and II were only revealed and realized at the end of the experiment. Hence, we do not expect subjects to hedge their payoffs in any of the tasks.

3 Results

Across all treatments, the expected value of the lottery is 108. This allows us to compute our primary outcome variable in the individual decision task, the Individual Deviation, as

$$\text{Individual Deviation } ID_i = \frac{WTA_i - EV}{EV} = \frac{WTA_i - 108}{108}, \tag{1}$$

where WTA_i represents the willingness to accept (reservation price) elicited for subject i and EV is the respective lottery's expected value of 108. If the elicited individual WTA_i is above (below) the expected value of 108, the deviation ID_i is thus positive (negative) and we consider this subject to have a preference for (against) the respective combination of precise/imprecise probabilities and outcomes. Hence, a negative price deviation will indicate that individuals value the lottery below its expected value and thus demand a *premium* for entering this gamble.

Result 1. *Individuals are imprecision seeking in outcomes but show no significant preferences towards risk, imprecise probabilities, or a combination of imprecise outcomes and probabilities in the individual decision task.*

Support: Table 3 shows mean Individual Deviations, ID_i, across treatments. We observe that subjects' deviations is on average almost exactly at zero in Treatment RISK (that is, subjects' willingness to accept is almost exactly at the lottery's expected value of 108), whereas they are slightly below zero in treatments IP and IOP, indicating that subjects do not behave particularly risk or ambiguity averse in our individual decision task. However, when it comes to imprecision towards outcomes (Treatment IO), we find a statistically significantly positive Individual Deviation of 5.3% ($p = 0.0145$, two-sided Wilcoxon signed-rank test). In other words, subjects value the lottery with precise probabilities but imprecise outcome realizations significantly higher than its expected value. Notably, we do not find any significant premium for imprecision in probabilities, which adds to the findings of Kocher and Trautmann (2013), Corgnet et al. (2013) and Füllbrunn et al. (2014).

This result of imprecision seeking in outcomes is in line with the findings of Budescu et al. (2002) and Du and Budescu (2005), who report similar observations in a comparable task framework by eliciting certainty equivalents for lotteries with imprecise probabilities and outcomes. Moreover,

Table 3: **Summary statistics and pairwise comparisons of individual and market deviations.** The upper panel of this table shows the mean and standard deviation (S.d.) for both outcome variables: that is, for subjects' Individual Deviation ID_i, and for aggregate markets' Market Deviation MD_m. The column 'p' represents the p-values from Wilcoxon signed-rank tests for the outcome variable to be centered around zero. In the lower panel we report treatment differences ('Diff.') and p-values from pairwise Wilxocon-Mann-Whitney (WMW) tests between treatments. *, **, and *** represent the 10%, 5%, and 1% significance levels from two-sided tests.

	Individual Deviation				Market Deviation			
Treatment	Mean	S.d.	p	Obs.	Mean	S.d.	p	Obs.
RISK	−0.001	(0.345)	0.599	80	0.116	(0.384)	0.625	10
IP	−0.034	(0.309)	0.336	80	−0.028	(0.238)	0.625	10
IO	0.053**	(0.310)	0.015	80	0.112	(0.314)	0.232	10
IOP	−0.031	(0.377)	0.474	80	−0.064	(0.279)	0.432	10
Pairwise WMW tests	Diff.		p		Diff.		p	
RISK vs. IP	0.033		0.273		0.143		0.529	
RISK vs. IO	−0.054		0.575		0.003		0.971	
RISK vs. IOP	0.030		0.185		0.179		0.315	
IP vs. IO	−0.087**		0.025		−0.140		0.218	
IP vs. IOP	−0.003		0.958		0.036		0.796	
IO vs. IOP	0.084***		0.007		0.176		0.248	

comparing individual deviations from the expected value across treatments, we find statistically significantly higher deviations in IO than in IP and IOP, respectively (see Table 3).

Next, we aim to examine whether the patterns we observe in the individual decision task—imprecision seeking in outcomes, i.e. positive deviations from the expected value in IO, in particular—also hold in a high-feedback market environment or whether these individual preferences are washed out by market dynamics. We will thus present the results of the market experiment in the following.

Analogously to the Individual Deviation described above, we can compute an average market deviation as the outcome variable from the market experiment:

$$\text{Market Deviation } MD_m = \frac{P_m - EV}{EV} = \frac{P_m - 108}{108}, \tag{2}$$

where P_m represents the mean price $\frac{1}{T_m}\sum_{t=1}^{T_m} P_t$ for all transactions $t \in \{0, 1, ..., T_m\}$ at which the asset was traded in market m; EV is the respective asset's expected terminal value of 108.

Result 2. *Average market prices are not statistically significantly different from expected fundamentals across all treatments; i.e., on average, neither risky assets nor assets with imprecision in probabilities and/or outcomes reveal a statistically significant deviation from the expected value.*

Support: Table 3 shows mean Market Deviations, MD_m, (i.e., mean percentage market price deviations from the expected value of 108) across treatments. While we observe a similar pattern than in the individual decision task—that is, prices are on average 11.2% higher than the expected value of 108 in Treatment IO—, two-sided Wilcoxon-Mann-Whitney tests against the respective null hypotheses that MD_m is centered around zero show no significant deviations for all four treatments. In addition, we find no statistically significant differences between market deviations across treatments (see 3).

As an interim conclusion, therefore, we find that subjects are imprecision seeking in outcomes in an individual decision task eliciting their willingness to accept, but these individual attitudes do not prevail in a dynamic market environment.

One might now raise the concern that, regarding the market experiment, we have only looked at mean market price deviations, thereby disregarding such a setting's anticipated feature of price convergence towards the rational expectations equilibrium (Plott and Sunder, 1988).[11] Moreover, note that we depart from multi-period trading and require subjects to trade in only one period of three minutes (which is preceded by a training period of four minutes). As subjects might not only be impacted by uncertainty (imprecision) in the asset's fundamental value, but also by uncertainty about others' behavior, we might observe different patterns during different trading phases (subjects naturally learn about others' behavior only during trading; e.g. Corgnet et al., 2018). In the following, we thus examine the price development over the course of the trading period.

We define six intervals of 30 seconds each, representing the full three minutes trading time. Within each interval of each market, we average transaction prices and calculate the respective market deviation analogously to Eq. (2) above. Figure 1 shows these smoothed (that is, averaged per interval) Market Deviations as a function of time for individual markets (grey lines) as well as treatment means and medians (colored, bold lines). First, looking into price evolutions, we observe a declining deviation (i.e., a price decrease) in three out of four treatments (IP, IO, IOP),

[11] See Noussair and Tucker (2013) for an extensive survey of the experimental market literature on asset pricing.

namely those whose terminal value is to be determined by an imprecise lottery. Examining the respective terminal price level, however, reveals that market prices in treatments with imprecise probabilities (IP and IOP) on average converge to a price below the expected value; in Treatment IO, in contrast, prices converge to the expected fundamental value of 108, i.e., the deviation is, on average, not statistically different from zero.

Result 3. *Market prices converge to the expected fundamental value in Treatment* IO*, i.e., with imprecise outcomes, but to a lower level in Treatment* IP *and* IOP*, i.e., with imprecise probabilities.*

Support: Table 4 shows mean market deviations for each of three thirds within the market experiment, i.e. for the first two 30s intervals (1st third), for the second two 30s intervals (2nd third), and for the third two 30s intervals (3rd third) and corresponding test statistics from two-sided Wilcoxon-Mann-Whitney tests.[12] The statistical tests confirm our intuition from the price evolutions depicted in Figure 1: in the last two intervals (3rd third) the market price deviation is statistically significantly different from zero in the imprecise-probabilities treatments IP ($p = 0.049$) and IOP ($p = 0.064$, but not in RISK ($p = 0.193$) and IO ($p = 0.695$).

Table 4: **Market deviations in the first, second, and third third of the market experiment.** This table shows the mean and standard deviation (S.d.) of the Market Deviation MD_m^k across treatments in each of the three thirds of the market experiment. One third corresponds to a 60 second period, i.e., the first third averages transaction prices during the first 60 seconds of trading. 'p' represents the respective p-values from Wilcoxon signed-rank tests for the outcome variable to be centered around zero. *, **, and *** represent the 10%, 5%, and 1% significance levels from two-sided tests. The sample size N for each test is 20.

	1st third			2nd third			3rd third		
Treatment	Mean	S.d.	p	Mean	S.d.	p	Mean	S.d.	p
RISK	0.063	(0.400)	0.846	0.169	(0.558)	0.846	0.132	(0.251)	0.193
IP	0.014	(0.332)	0.919	0.001	(0.222)	1.000	-0.132^{**}	(0.172)	0.049
IO	0.265^{*}	(0.363)	0.084	0.176	(0.401)	0.232	0.030	(0.270)	0.695
IOP	0.076^{*}	(0.440)	0.064	-0.096	(0.268)	0.322	-0.129^{*}	(0.196)	0.064

Comparing the distributions of Individual Deviations represented by orange circles in Figure 1, we observe considerable density in the positive domain in Treatment IO, hinting at imprecision seeking in outcomes, and comparatively symmetric distributions in the other treatments (also see Figure C1 in the Appendix). Market prices, however, converge to a level below individual *WTA*s.

[12] Analogously to Eq. (2) above, market deviations in each of the three thirds are calculated as $MD_m^k = \frac{1}{T_m}\sum_{t=1}^{T_m} P_t$ for all transactions t within the first 60 seconds of trading if $k = 1$ (first third), for all transactions t within the second 60 seconds of trading (i.e., from seconds 60 to 120) if $k = 2$ (second third), and for all transactions t within the third 60 seconds of trading (i.e., from seconds 120 to 180) if $k = 3$ (third third).

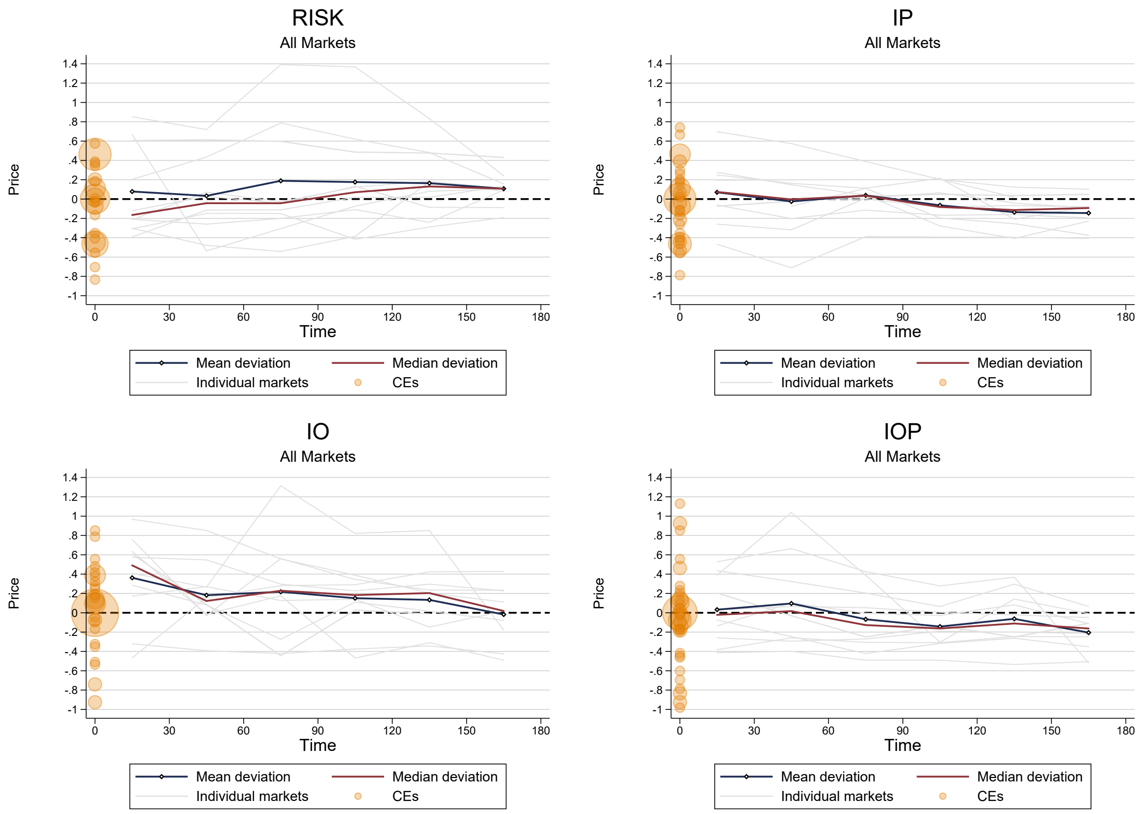

Figure 1: **Market deviations as a function of time and individual deviation densities across treatments.** This figure shows market price deviations averaged over 30s intervals for individual markets (grey lines) as well as treatment means and medians (blue and red bold lines, respectively) as a function of time for each of the four treatments. The orange circles represent the respective distribution of Individual Deviations, ID_i, within a treatment, where larger and darker circles indicate a higher density.

While distributions of market price deviations tend to peak around zero, the respective distributions for treatments with imprecision in probabilities (IP and IOP) have a second mode below zero, between −0.4 and −0.5 (see Figure C2 in the Appendix). Market deviations in Treatment RISK seem to be inflated by extreme values as in the market experiment prices are bounded at a lower limit of zero but unbounded above (prices in RISK increased up to 3.6 times the expected fundamental value).

4 Discussion and Conclusion

We find that individual subjects are significantly imprecision seeking in outcomes in an incentive-compatible task eliciting participants' willingness to accept (a reservation price). In this task, however, we find neither an aversion nor seeking towards risk, imprecision in probabilities, or the combination of imprecision in outcomes and probabilities. Examining whether these individual preferences prevail in a dynamic market environment, we report two striking results: first, we find that, on average, none of the treatments show a statistically significant deviation from the expected value. At a closer look into the last third of the trading period—i.e., after participants have sufficiently learned about and experienced the market framework and the price has potentially aggregated all available beliefs/information—we still encounter no statistically significant deviation from expected fundamentals with imprecision in outcomes alone; however, with imprecision in probabilities or with imprecision in outcomes and probabilities, we observe a significantly negative deviation, i.e. market prices below expected fundamentals, suggesting ambiguity aversion.

Taken together, our results provide mixed evidence with respect to imprecision in laboratory markets. Considering average market prices, we find no statistically significant deviations from the respective expected fundamental value across treatments. However, only considering averages across the whole trading period might provide an insufficient account as trading patterns tend to be much noisier during the beginning of the period (as subjects are not yet used to the market environment or have not yet acquired any information about other participants' expectations and behavior, e.g. through the order book; see Füllbrunn et al., 2014, for example) than towards the end. With regard to *imprecision in probabilities* (i.e., *ambiguity*), we thus find a significantly negative deviation from expected fundamentals during the last third of trading, which confirms results by Weber (1989), Sarin and Weber (1993), and Corgnet et al. (2020), but contrasts with work by, for example, Corgnet et al. (2013) and Füllbrunn et al. (2014).

Our main contribution, however, concerns aggregate market preferences for *imprecision in outcomes*. As we observe a significantly positive deviation from the expected value in an individual decision task, our results corroborate the findings of Budescu et al. (2002) and Du and Budescu (2005), who also report subjects exhibiting imprecision seeking in outcomes in a comparable task eliciting certainty equivalents. They offer a number of potential explanations for this rather counterintuitive result, which relate to both experimental parts of the present study. First, building on Fox and Tversky's (1995) comparative ignorance hypothesis, they suggest that the lack of salience in indirect comparisons in eliciting *WTA*s drives the observed imprecision attitudes, which is potentially also the case in both the individual decision task as well as in the market experiment of this study. Moreover, subjects' strong sensitivity to imprecision in outcomes in comparison with an insensitivity to imprecision in probabilities can be explained by the scale compatibility (Tversky et al., 1988) between responses (*WTA*s) and the salient monetary outcome realizations (Budescu et al., 2002). While this nicely relates to our individual decision task, this notion seems even more relevant in the market experiment, in which monetary outcomes are naturally salient. Nonetheless, the imprecision seeking in outcomes we observed in the individual task did *not* translate into significantly higher market prices; thus, individual attitudes towards imprecision in outcomes tend to vanish in a dynamic market setting such as a continuous double auction.

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Appendix to
'Individual attitudes and market dynamics towards imprecision'

Christoph Huber and Julia Rose

A Experimental Instructions

The following instructions have been translated from German to English. The original instructions are available upon request. Text parts in standard font are identical for all treatments. Text parts in *italics* differ between treatments; margin notes on the left indicate the respective treatment.

Individual decision task

Task

In this part of the experiment you get 1 decision problem on a screen. The decision contains a lottery. You will be asked to enter the exact Taler amount you would have to receive, to forgo the lottery. This Taler amount is equal to the sum, at which entering the lottery gives you the exactly the same utility than receiving this certain Taler amount you choose.

—RISK— *The payment from the lottery amounts to either 58 or 158 Taler with equal probability. That is, with a probability of 50% you receive 58 Taler, and with a complementary probability of 100% - 50% = 50% you receive 158 Taler.*

—IP— *The payment from the lottery amounts to either 58 or 158 Taler. The possible probabilities for the Taler amounts are realized in steps of 5, the possible probabilities for the realization of 58 Taler as a payment are in the range of [0%, 5%, 10%, 15%, ..., 85%, 90%, 95%, 100%]. The exact probability for the Taler amounts is therefore not known, that is, neither you nor the experimenter knows the probability with which each of the two amounts can be drawn.*

—IO— *The payment from this lottery lies, with equal probability, either in the range [8;108] Taler or [108;208] Taler. That is, with a probability of 50% you receive an amount between 8 and 108 Taler, and with the complementary probability of 100% - 50% = 50% you receive an amount between 108 and 208 Taler. The possible Taler amounts are realized in steps of 5, the possible values are therefore either in the range of [8, 13, 18, 23, ..., 93, 98, 103, 108] or in the range of [108, 113, 118, 123, ..., 193, 198, 203, 208]. The distribution of the*

Taler values is not known, that is, neither you nor the experimenter knows the probability with which each of the respective values within the ranges can be drawn. It is possible that all values are equally likely, but it is also possible that only one value occurs; as well as all possible compositions between these two extremes.

IOP

The payment from this lottery lies either in the range [8;108] Taler or [108;208] Taler. The possible Taler amounts are realized in steps of 5, the possible values are therefore either in the range of [8, 13, 18, 23, . . . , 93, 98, 103, 108] or in the range of [108, 113, 118, 123, . . . , 193, 198, 203, 208]. The distribution of the Taler values is not known, that is, neither you nor the experimenter knows the probability with which each of the respective values within the ranges can be drawn. It is possible that all values are equally likely, but it is also possible that only one value occurs; as well as all possible compositions between these two extremes.
The possible probabilities for the Taler amounts are realized in steps of 5, the possible probabilities for the realization of an amount in the range of [8, 13, 18, 23, . . . , 93, 98, 103, 108] Taler are in the range of [0%, 5%, 10%, 15%, . . . , 85%, 90%, 95%, 100%]. The exact probability for the ranges is therefore not known, that is, neither you nor the experimenter knows the probability with which each of the two ranges can be drawn.

The exchange rate from Taler to euros in this part of the experiment is

$$30 \text{ Taler} = €\,1$$

That is, your total payment from this part of the experiment is the Taler amount divided by 30 in euros.

Your decision is only valid when you made a decision and clicked on the OK button in the lower area of the screen.

Payment

Your payment from this part of the experiment will be determined in the following way: the computer generates a random number with equal probability between 8 and 208.

If this number is greater than your entered Taler amount, you will be payed exactly the amount in Taler, which was drawn from the computer. You will get this amount at the end of the experiment in private in cash in addition to your earnings in the other parts of the experiment. Thereby, your payment in Taler will be exchanged for euros with the corresponding exchange rate from above.

If this number is smaller than your entered Taler amount, you will enter the lottery, your payment will be determined by the respective rules of the lottery. This lottery will be simulated and you get this amount at the end of the experiment in private in cash in addition to your earnings in the other parts of the experiment. Thereby, your payment in Taler will be exchanged for euros with the corresponding exchange rate from above.

If this number is equal to your entered Taler amount, a computer-simulated fair coin toss will determine, whether you enter the lottery or get your entered Taler amount. If the lottery is relevant for your payment, it will be simulated and you get this amount at the end of the experiment in private in cash in addition to your earnings in the other parts of the experiment. If your entered Taler amount is relevant for your payment, you will get this amount at the end of the experiment in private in cash in addition to your earnings in the other parts of the experiment. Thereby, your payment in Taler will be exchanged for euros with the corresponding exchange rate from above.

Therefore, note that it is in your interest to enter the amount in Taler, for which entering the lottery gives you exactly the same utility than receiving the Taler amount you chose with certainty.

Before the start of this part, please enter a couple of comprehension questions. In the following, you will see the decision screen in the program. You can get detailed information for this decision by clicking on the "Help" button.

Market experiment

Background of the experiment

The current experiment replicates an asset market in which 8 market participants can trade shares of a fictitious company over one period of 180 seconds. You receive an initial endowment of 5 units of the asset and 800 Taler when entering the market. Your asset and Taler holdings cannot drop below zero.

The exchange rate from Taler to euros in this part of the experiment is

$$180 \text{ Taler} = € \, 1$$

That is, your total payment from this part of the experiment is the Taler amount divided by 180 in euros.

To familiarize you with the software and the trading mechanism there will be a trial period which is not relevant for your payment.

Information on the market architecture and your task as a trader

1) Trading

As a trader you can buy and sell assets. Trade is accomplished in form of a continuous double auction. That is, every trader can buy and sell assets. You can submit as many buy and sell orders (with at most 2 decimal places) as you like. Each order is for one unit of the asset.

If you buy assets, your Taler holdings will be decreased by the respective expenditures and the num ber of assets will be increased by one. Conversely, if you sell assets, your Taler holdings will be increased by the respective revenues and the number of assets will be decreased by one. Please note that you can only buy (sell) as many assets as are covered by your Taler (asset) holdings—this includes also your active offers in the market.

2) Payment

At the end of trading a buyback price for the asset is realized. This buyback price determines the value of the assets, which you hold at the end of the trading period. These assets are bought back by the experimenter at this buyback price (price = buyback price). You receive the respective earnings, converted to euros, at the end of the experiment in cash. Before the start of the trading period you will get the information on how the respective buyback price will be determined. In addition, this information is displayed on the upper area of the screen during the trading period.

Thus, this buyback price is relevant for your payment. Your final wealth (= your Taler holdings plus the unites of the asset multiplied with the respective buyback price) will be divided by 180 to determine your payment for this part of the experiment.

3) Short overview

- The price of the asset is determined by supply and demand, that is, through the sell and buy orders entered by yourself and by the other traders in the market (each market consists of 8 market participants).
- In the following you will receive detailed information on how the buyback price at the end of the period will be calculated. This information is also displayed during the trading period.

4) Determination of the buyback price

RISK

The buyback price determines the value of the asset and thereby also your earnings, which you get at the end of the experiment. For each asset you are holding at the end of this period, you will receive the respective buyback price. This buyback price is either 58 or 158 Taler with equal probability. That is, with a probability of 50% you receive 58 Taler per unit of the asset, and with a complementary probability of 100% - 50% = 50% you receive 158 Taler per unit of the asset. The randomly determined buyback price is the same for all assets in this period. Thus, at the end of the period the assets you hold will be bought back from the experimenter at this buyback price, which will be determined as described above.

Short overview of the payment:

1. *In the front of the laboratory you see an urn.*
2. *This urn is filled with 20 balls. 10 balls are white, 10 balls are yellow.*
3. *Before the beginning of the trading period all participants of this experiment vote which color stands for a buyback price of 58 Taler. The other color then stands for a buyback price of 158 Taler. The decision is made by majority vote. If the same number of participants votes for white than for yellow, the computer randomly selects the color which stands for 58 Taler with equal probability.*
4. *Then, participant in cubicle number 1 will be asked to draw a ball from the urn.*

5. *If the ball drawn from the participant is of color with the majority of votes, the buyback price is 58 Taler; otherwise 158 Taler.*

IP

The buyback price determines the value of the asset and thereby also your earnings, which you get at the end of the experiment. For each asset you are holding at the end of this period, you will receive the respective buyback price. This buyback price is either 58 or 158 Taler. The possible probabilities for the buyback prices are realized in steps of 5, the possible probabilities for the realization of 58 Taler as the buyback price are in the range of [0%, 5%, 10%, 15%, . . . , 85%, 90%, 95%, 100%]. The exact probability for the buyback prices are therefore not known, that is, neither you nor the experimenter knows the probability with which each of the two amounts can be drawn. The randomly determined buyback price is the same for all assets in this period. Thus, at the end of the period the assets you hold will be bought back from the experimenter at this buyback price, which will be determined as described above.

Short overview of the payment:

1. *In the front of the laboratory you see an urn.*
2. *This urn is filled with 20 yellow or white balls. Neither you nor the experimenter know the exact composition of balls in this urn.*
3. *Before the beginning of the trading period all participants of this experiment vote which color stands for a buyback price of 58 Taler. The other color then stands for a buyback price of 158 Taler. The decision is made by majority vote. If the same number of participants votes for white than for yellow, the computer randomly selects the color which stands for 58 Taler with equal probability.*
4. *Then, participant in cubicle number 1 will be asked to draw a ball from the urn.*
5. *If the ball drawn from the participant is of color with the majority of votes, the buyback price is 58 Taler; otherwise 158 Taler.*

IO

The buyback price determines the value of the asset and thereby also your earnings, which you get at the end of the experiment. For each asset you are holding at the end of this period, you will receive the respective buyback price. This buyback price lies, with equal probability, either in the range [8;108] Taler or [108;208] Taler. That is, with a probability of 50% you receive an amount between 8 and 108 Taler per unit of the asset, and with the complementary probability of 100% - 50% = 50% you receive an amount between 108 and 208 Taler per unit of the asset. The possible buyback prices are realized in steps of 5, the possible values are therefore either in the range of [8, 13, 18, 23, . . . , 93, 98, 103, 108] or in the range of [108, 113, 118, 123, . . . , 193, 198, 203, 208]. The distribution of the buyback prices is not known, that is, neither you nor the experimenter knows the probability with which each of the respective values within the ranges can be drawn. It is possible that all values are equally likely, but it is also possible that only one value occurs; as well as all possible compositions between these two extremes. The randomly determined buyback price is the same for all assets in this period. Thus, at the end of the period the assets you hold will be bought back from the experimenter at this buyback price, which will be determined as described above.

Short overview of the payment:

1. *In the front of the laboratory you see three numbered urns.*
2. *Urn 1 is filled with 20 balls. 10 balls are white, 10 balls are yellow.*
3. *Before the beginning of the trading period all participants of this experiment vote which color stands for a buyback price in the range between 8 and 108 Taler. The other color then stands for a buyback price in the range between 108 and 208 Taler. The decision is made by majority vote. If the same number of participants votes for white than for yellow, the computer randomly selects the color which stands for a buyback price in the range between 8 and 108 Taler with equal probability.*
4. *Then, participant in cubicle number 1 will be asked to draw a ball from Urn 1.*
5. *If the ball drawn from the participant is of color with the majority of votes, the buyback price is in the range between 8 and 108 Taler; otherwise in the range between 108 and 208 Taler.*
6. *To determine the exact buyback price, the same participants will draw a ball from Urn 2 or Urn 3.*
7. *Urn 2 is filled with 21 balls. The balls are labeled with buyback prices in the range from 8 to 108. Neither you nor the experimenter know the exact composition of balls in this urn.*
8. *Urn 3 is also filled with 21 balls. The balls are labeled with buyback prices in the range from 108 to 208. Neither you nor the experimenter know the exact composition of balls in this urn.*
9. *Depending on the drawn color from the first urn the participant will draw a ball from the urn with the relevant range and thereby determine the exact buyback price.*

IOP

The buyback price determines the value of the asset and thereby also your earnings, which you get at the end of the experiment. For each asset you are holding at the end of this period, you will receive the respective buyback price. The payment from this lottery lies either in the range [8;108] Taler or [108;208] Taler. The possible buyback prices are realized in steps of 5, the possible values are therefore either in the range of [8, 13, 18, 23, …, 93, 98, 103, 108] or in the range of [108, 113, 118, 123, …, 193, 198, 203, 208]. The distribution of the buyback prices is not known, that is, neither you nor the experimenter knows the probability with which each of the respective values within the ranges can be drawn. It is possible that all values are equally likely, but it is also possible that only one value occurs; as well as all possible compositions between these two extremes. The possible probabilities for the buyback prices are realized in steps of 5, the possible probabilities for the realization of an amount in the range of [8, 13, 18, 23, …, 93, 98, 103, 108] Taler are in the range of [0%, 5%, 10%, 15%, …, 85%, 90%, 95%, 100%]. The exact probability for a buyback price in the range [8, 108] is therefore not known, that is, neither you nor the experimenter knows the probability with which each of the two ranges can be drawn. The randomly determined buyback price is the same for all assets in this period. Thus, at the end of the period the assets you hold will be bought back from the experimenter at this buyback price, which will be determined as described above.

Short overview of the payment:

1. *In the front of the laboratory you see three numbered urns.*
2. *Urn 1 is filled with 20 yellow or white balls. Neither you nor the experimenter know the exact composition of balls in this urn.*
3. *Before the beginning of the trading period all participants of this experiment vote which color stands for a buyback price in the range between 8 and 108 Taler. The other color then stands for a buyback price in the range between 108 and 208 Taler. The decision is made by majority vote. If the same number of participants votes for white than for yellow, the computer randomly selects the color which stands for a buyback price in the range between 8 and 108 Taler with equal probability.*
4. *Then, participant in cubicle number 1 will be asked to draw a ball from Urn 1.*
5. *If the ball drawn from the participant is of color with the majority of votes, the buyback price is in the range between 8 and 108 Taler; otherwise in the range between 108 and 208 Taler.*
6. *To determine the exact buyback price, the same participants will draw a ball from Urn 2 or Urn 3.*
7. *Urn 2 is filled with 21 balls. The balls are labeled with buyback prices in the range from 8 to 108. Neither you nor the experimenter know the exact composition of balls in this urn.*
8. *Urn 3 is also filled with 21 balls. The balls are labeled with buyback prices in the range from 108 to 208. Neither you nor the experimenter know the exact composition of balls in this urn.*
9. *Depending on the drawn color from the first urn the participant will draw a ball from the urn with the relevant range and thereby determine the exact buyback price.*

B Screenshots of the experimental tasks

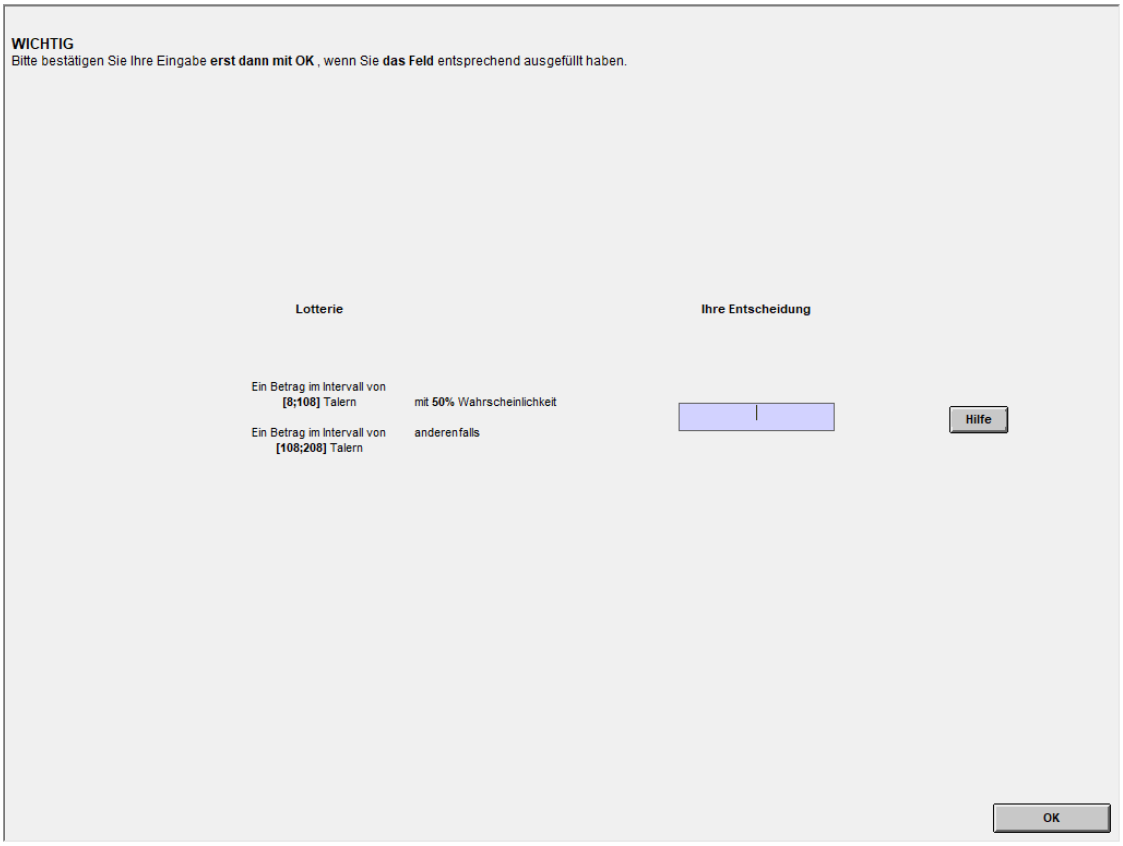

Figure B1: **Screenshot of the Investment Task in Treatment IO.** The text on the top left reads "IMPORTANT: Please confirm your input with 'OK' only if you have filled the respective form." The text in the middle part of the screen outlines the lottery ("A value within the interval $[8, 108]$ with 50% probability" or "A value within the interval $[108, 208]$ otherwise.") Clicking on the middle button ("Help") opens a window explaining the lottery and BDM mechanism in more detail.

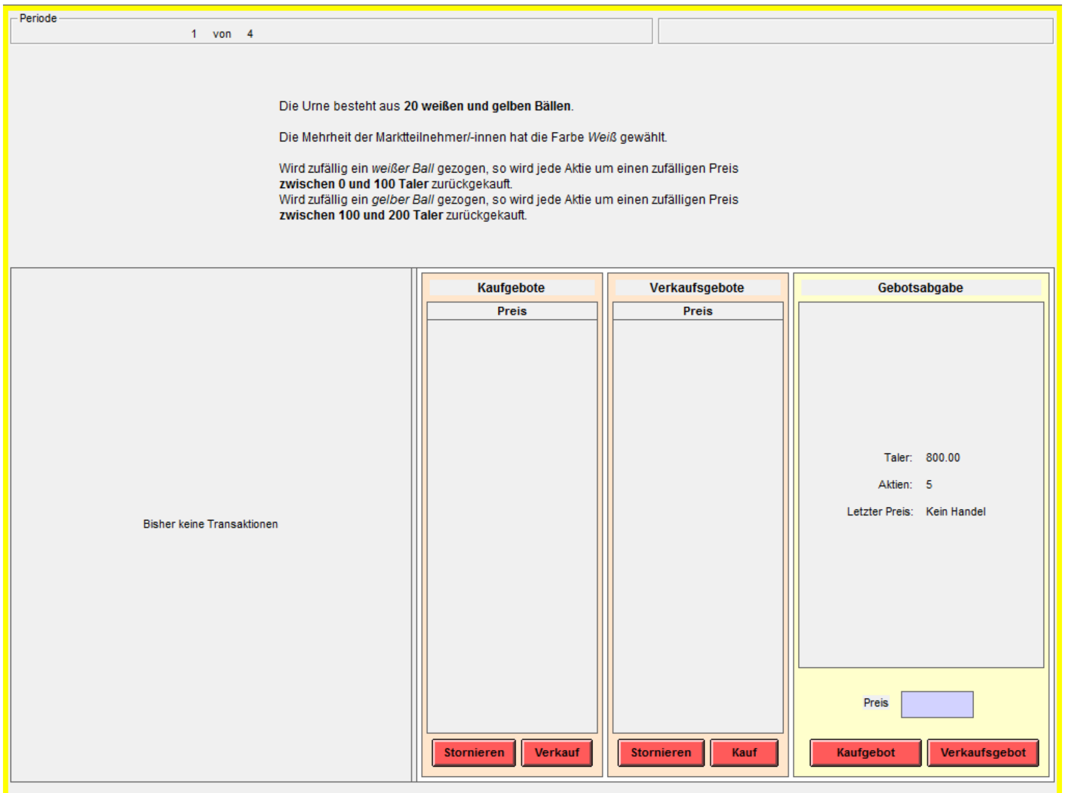

Figure B2: **Screenshot of the Trading Screen in Treatment IO.** The top part of the screen outlines the composition of the urn ("The urn contains 20 white and yellow balls."), the majority voting decision ("The majority has decided on the color 'white.'"), and the respective payouts ("If a white ball is randomly drawn, each asset will be redeemed with a random price between 8 and 108." and "If a yellow ball is randomly drawn, each asset will be redeemed with a random price between 108 and 208.") Orders can be entered on the right-hand side of the screen; the middle part shows the current order book (cf. Palan, 2015). For a pilot experiment we used intervals $[0, 100]$ and $[100, 200]$, respectively, which are shown here.

C Additional figures and tables

Table C1: **Subject demographics across treatments.** This table depicts the averages of demographic variables for each treatment. The last column shows p-values for differences between treatments from Kruskal-Wallis tests.

Treatment	RISK	IO	IOP	IP	p-value
Age	23.49	23.03	23.26	22.88	0.56
Female (in %)	46.25	51.25	45.00	43.75	0.79
Study semester	5.84	5.75	6.28	5.45	0.46
Risk aversion (general)	5.05	4.59	5.14	5.08	0.38
Risk aversion (financial)	4.10	3.89	4.36	4.25	0.53
CRT score (correct out of 4)	1.84	1.71	1.84	2.14	0.16
Financial literacy score (correct out of 3)	2.54	2.46	2.46	2.35	0.23
N	80	80	80	80	

Table C2: **Treatment medians for additional market variables.** This table shows in the upper panel the treatment medians for share turnover (ST)[a], the volatility of log-returns (VOLA)[b], and the bid-ask spread (SPREAD)[c]. In the bottom panel we present the results from pairwise Wilcoxon-Mann-Whitney (WMW) tests between treatments for each variable; the numbers represent the corresponding Z-values. *, **, and *** represent the 10%, 5%, and 1% significance levels from two-sided tests. The sample size N for each test is 20.

Treatment	ST	VOLA	SPREAD
RISK	0.61	0.41	45.50
IP	0.44	0.37	29.56
IO	0.56	0.46	67.73
IOP	0.64	0.35	32.13
Pairwise WMW tests			
RISK vs. IP	0.98	0.68	1.72*
RISK vs. IO	0.19	−1.21	−1.13
RISK vs. IOP	0.04	0.30	1.44
IP vs. IO	−0.87	−1.59	−2.53**
IP vs. IOP	−0.87	−0.15	−0.16
IO vs. IOP	−0.27	1.29	1.81*

[a] ST is defined by the total trading volume normalized by the total number of shares outstanding at the end of the period.
[b] VOLA measures the standard deviation of log-returns on all market prices within the period.
[c] SPREAD is calculated as the mean difference between the best bid and the best ask price.

Table C3: **Completed transactions across treatments.** This table depicts the summary statistics of the number of completed transactions across all treatments. There is no statistically significant difference across treatments ($p = 0.715$, Kruskal-Wallis test).

Treatment	RISK	IO	IOP	IP
Median	24.50	22.50	25.50	17.50
Mean	26.60	27.10	26.10	22.90
Standard Deviation	(10.52)	(13.74)	(9.28)	(11.77)
N	10	10	10	10

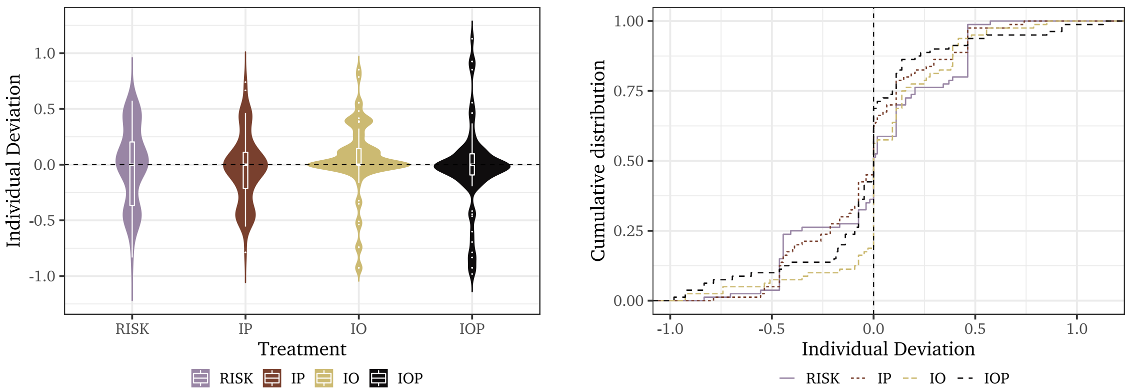

Figure C1: **Individual Deviations, ID_i, across treatments.** This figure shows the distribution of Individual Deviations, ID_i,—that is, the percentage deviation of individual i's reservation price WTA_i from the expected value of 108. The left-hand side depicts the distribution of ID_is using violin charts as well as boxplots where the lower and upper hinges correspond to the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, respectively. The right-hand side shows the cumulative distribution of ID_is.

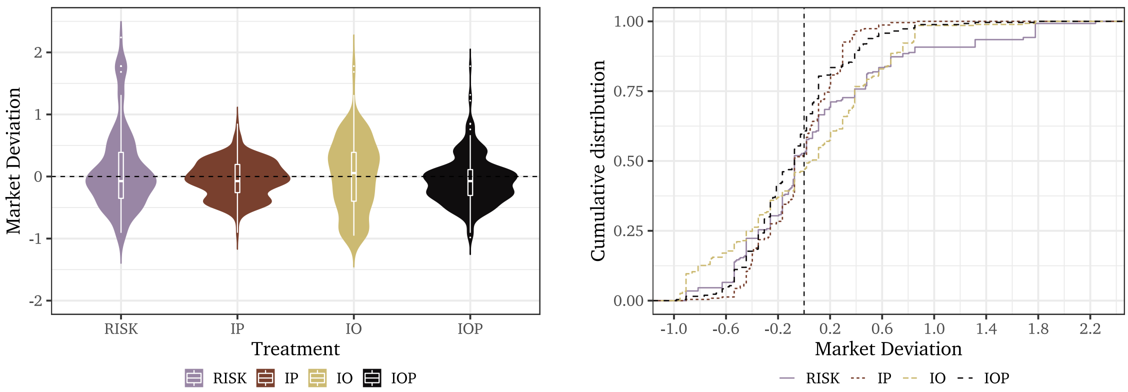

Figure C2: **Price deviations across treatments.** This figure shows the distribution of price deviations—that is, the percentage deviation of each transaction price from the expected value of 108. The left-hand side depicts the distribution of price deviations using violin charts as well as boxplots where the lower and upper hinges correspond to the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles, respectively. The right-hand side shows the cumulative distribution of price deviations.

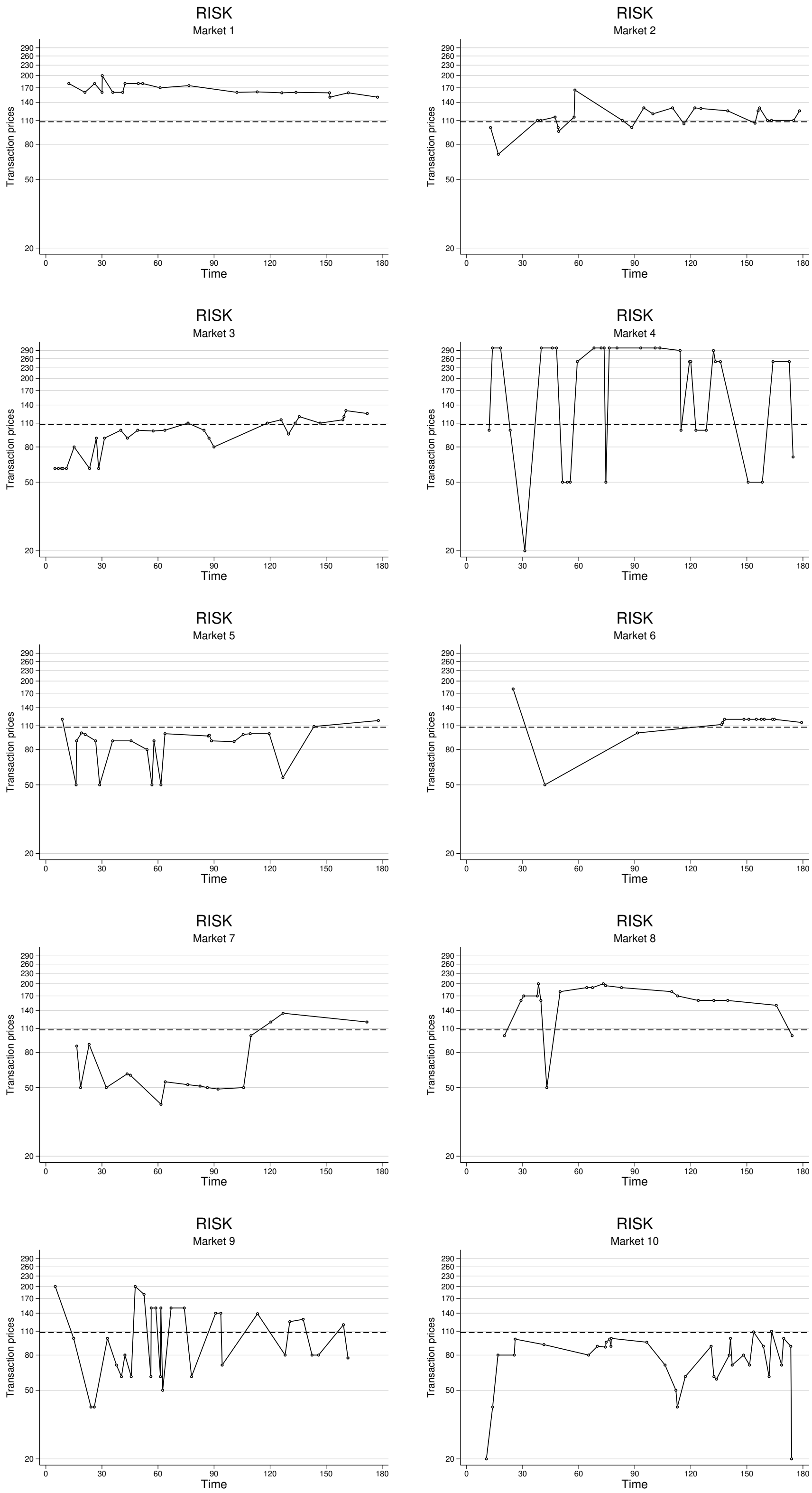

Figure C3: **Individual transaction prices for each market of Treatment RISK.** The dashed line represents the expected value of 108.

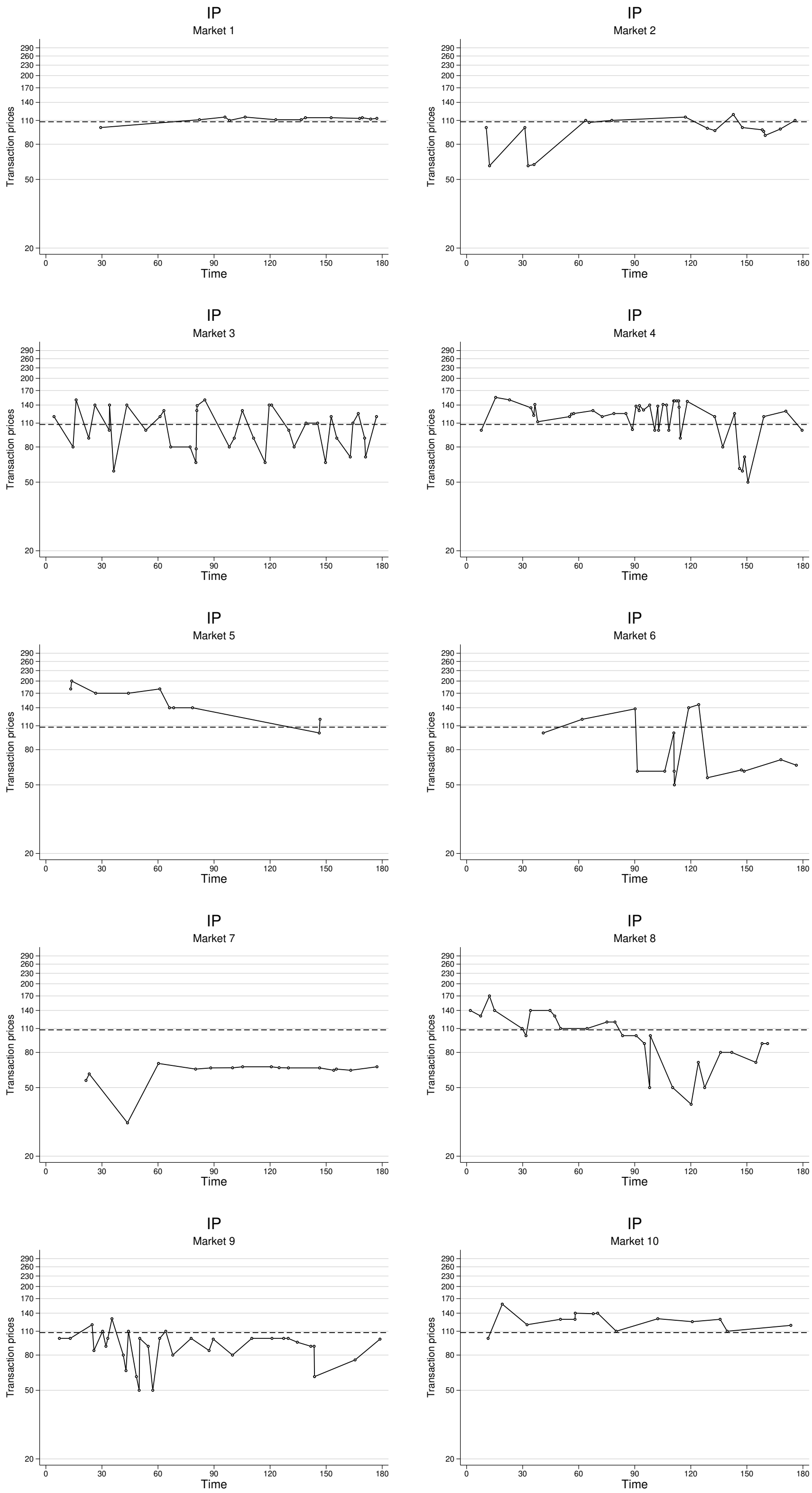

Figure C4: **Individual transaction prices for each market of Treatment IP.** The dashed line represents the expected value of 108.

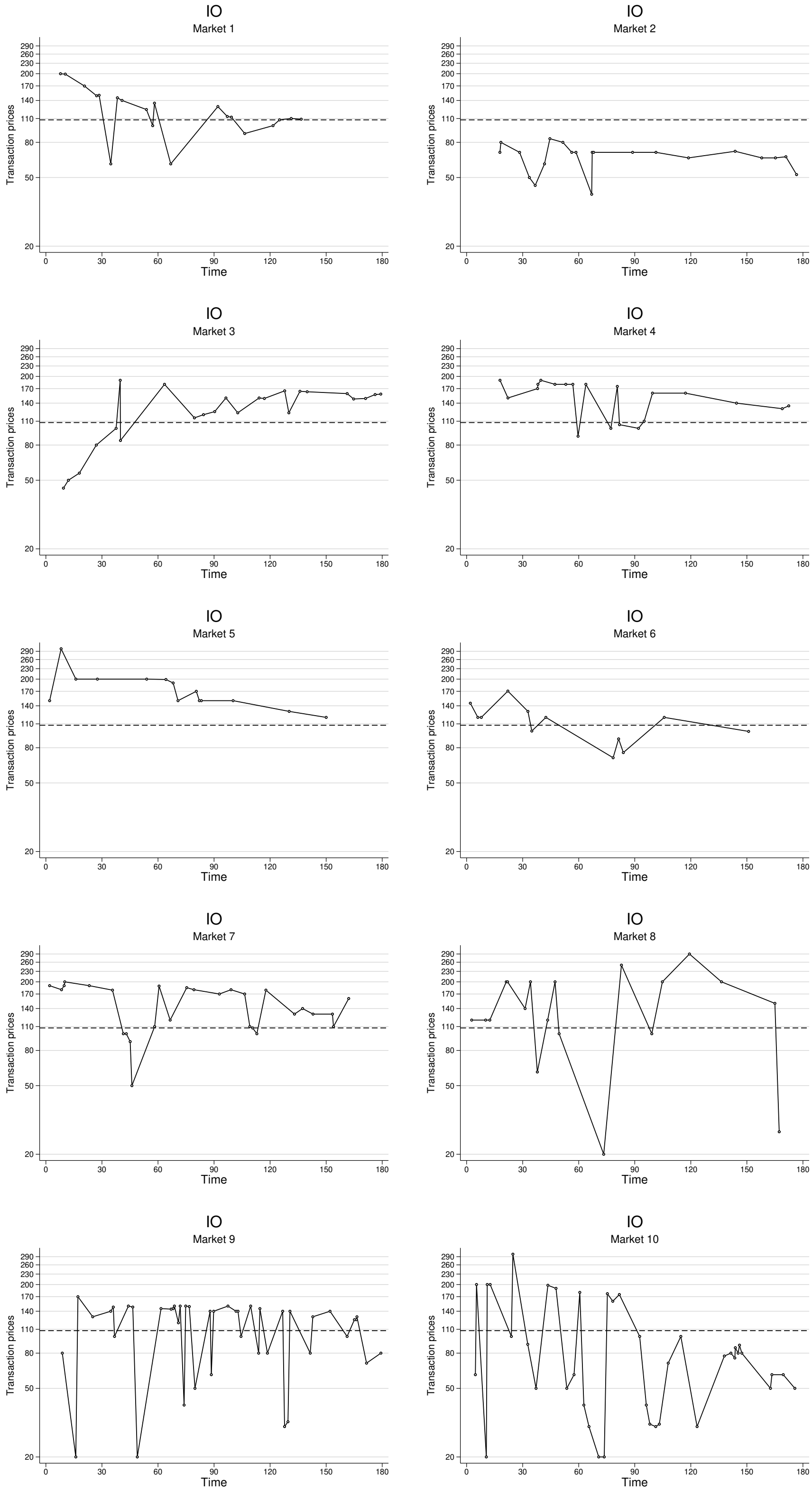

Figure C5: **Individual transaction prices for each market of Treatment IO.** The dashed line represents the expected value of 108.

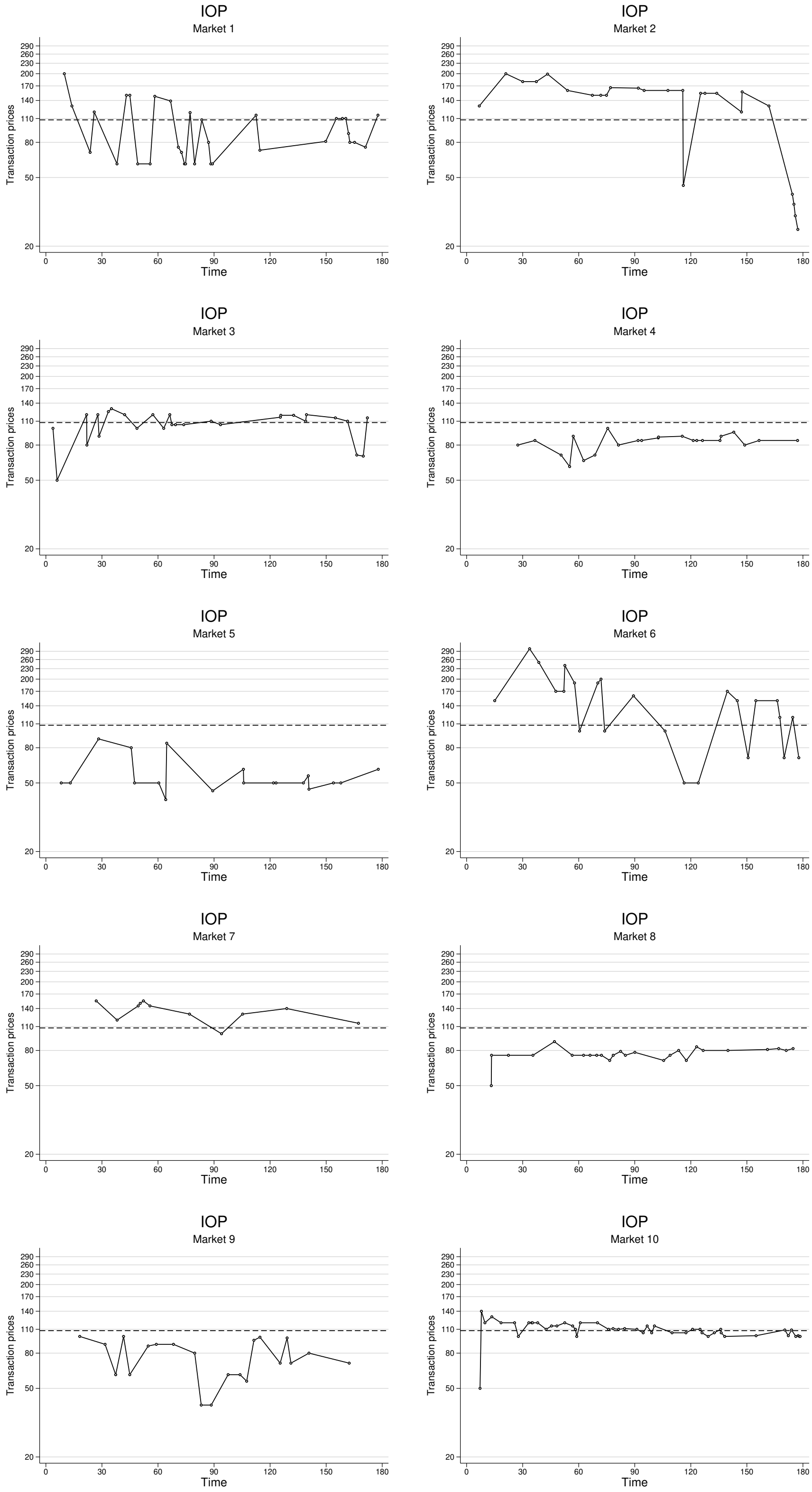

Figure C6: **Individual transaction prices for each market of Treatment IOP.** The dashed line represents the expected value of 108.

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2019-06

Christoph Huber, Julia Rose

Do individual attitudes towards imprecision survive in experimental asset markets?

Abstract
In situations where both the magnitude of gains and losses as well as the probability distribution over these realizations is uncertain, imprecision is an inherent feature of decision-making. While imprecision has been shown to affect individual valuations, many decisions are made in market settings with potentially different implications. We thus examine the impact of imprecision, first, in an individual decision task, and second, in experimental asset markets-with no imprecision (risk), imprecision in probabilities (ambiguity), imprecision in outcomes, and full imprecision. We find imprecision seeking in outcomes in people's individual attitudes, but these preferences do not withstand market dynamics. Nevertheless, we observe imprecision aversion in probabilities at the end of trading, suggesting that ambiguity aversion, in contrast, prevails in experimental markets.

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