Ambiguity aversion: experimental modeling, evidence, and implications for pricing*

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Abstract

This paper provides a systematic analysis of individual attitudes towards ambiguity, based on laboratory experiments. The design of the analysis captures different degrees of ambiguity in various settings, and it allows to disentangle attitudes towards risk and attitudes towards ambiguity. In addition to individual attitudes, the experiments also elicit expectations about other participants' attitudes, allowing us to relate own behavior to expectations about others. New measures are introduced for both, the degree of ambiguity in a situation and ambiguity aversion. Ambiguity is embedded in standard utility theory and a parameter of ambiguity aversion is estimated and contrasted to the parameter of risk aversion. The analysis provides a test of theoretical models of ambiguity aversion. The main findings are that ambiguity aversion on average is much more pronounced than human aversion against risk and that it is very different across individuals. Moreover, while most theoretical work on ambiguity builds on maxmin expected utility, our results provide evidence that MEU does not adequately capture individual attitudes towards ambiguity.

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1 Introduction

Despite its presumed significant influence on markets, in terms of liquidity and pricing, financial economics has largely sidestepped the presence and potential importance of ambiguity and ambiguity aversion in markets. This is understandable, given that finance as it is taught in school is primarily concerned with well-functioning asset markets - where the moments of the return distributions are well defined, and therefore ambiguity is rather low. In fact, un-ambiguous specification of asset price dynamics is required to price derivative assets, according to existing models. However, the formative experiences in the past few years, as the financial crisis reached ever larger segments of the industry, has underscored the need for a broader analytical basis of asset pricing models, incorporating/embedding ambiguity of return distributions. Equipped with metrics for the level of ambiguity in a particular market, and measures of individual ambiguity aversion, it will be possible to trace the impact of a given level of ambiguity on relative prices in financial markets.

In this paper, we use laboratory evidence to analyze the implications of ambiguity on the asset valuation by individuals and how ambiguity, suitably measured, can be incorporated in a decision theoretic framework. In contrast to concurrent studies, we systematically analyze different levels of ambiguity. Reservation prices are elicited using the Becker-DeGroot-Marschak (BDM) mechanism, thereby avoiding strategic considerations in the subjects' bidding process. The robustness of this approach is analyzed with binary-choice lists. The experiment provides, to the best of our knowledge, the first systematic attempt to derive the impact of ambiguity on individual reservation prices. To this end we define and experimentally test a metric capturing individual behavior towards ambiguity, net of risk aversion. The systematic nature of the setup allowing a variation of the level of ambiguity opens the door to a full-fledged valuation model of ambiguity. Several properties of pure ambiguity aversion are analyzed.

First, the functional form of pure ambiguity aversion is estimated from observed individual data, and it is compared to different models of ambiguity aversion proposed in the literature. One such model predicts a kinked shape of the ambiguity aversion function (Gilboa and Schmeidler, 1989). Another prominent formalization assumes a smooth functional form, as in Klibanoff, Marinacci, and Mukerji, 2005 (KMM). We find that for the majority of subjects, pure ambiguity aversion is increasing in ambiguity as captured by our metric. In absolute terms, ambiguity aversion is increasing almost universally. In relative terms, we find increasing ambiguity aversion to prevail most of the time. In particular, we find decreasing-to-constant relative ambiguity aversion for the median bidder in all sessions. The impact of ambiguity is quite substantial, as the median valuation discount amounts to 25-30% in situations with maximum ambiguity as compared to situations with no ambiguity.

Second, we explore whether a systematic relationship between pure ambiguity aversion and pure risk aversion can be found in the cross section. The literature is heterogeneous and shows no clear effect. To estimate the determinants of ambiguity, we use a panel specification, and regress the observed pure ambiguity discount on the pure risk discount, controlling for the ambiguity level and the risk level.

Third, we elicit participants' estimation of other participants' decisions. Requiring participants to make own decision and to express estimates of the median decision of others substantially enriches our data set. This requirement automatically involves positioning oneself relative to the pool. Thus, we can evaluate individual decisions under ambiguity (controlled for risk), the estimation of others' decisions, the relation between own decisions and estimations, and finally, the relation between estimations and actual decision of others. We can evaluate rational expectations of subjects with respect to both, pure risk aversion and pure ambiguity aversion. Comparing the distribution of estimated median values with true medians, we find that across all experimental sessions, subjects have rational expectations with respect to both risk aversion and ambiguity aversion.

Our results have a number of implications for financial markets and regulation. First, since ambiguity aversion is an individual trait of character, and the degree of ambiguity is a characteristic of a decision situation, our analysis opens the perspective on specific features of financial contracts and market structures that directly determine the level of perceived ambiguity. Thus, reducing ambiguity, for instance by increasing transparency, is conjectured to raise the price of the relevant asset. Conversely, an increase in ambiguity, for instance by issuing financial instruments with hard-to-quantify moments of the return distribution will eventually suppress its market price. Only recently, in their paper presented at the annual conference of leading central bankers at Jackson Hole, Wyoming, Caballero and Kurlat (2009) emphasized the source of the surprise that defines the current financial crisis, namely the repercussions the bursting house price bubble produced inside the global financial system rather than the fall in house prices per se. Caballero and Kurlat (2009) see Knightian uncertainty at work, when suddenly critical links within the financial system are exposed that earlier on went unnoticed (and apparently had functioned smoothly).

Second, a change in ambiguity, due to sudden clouding of information, for instance, will also increase the average risk premium required by market participants. Thus, ambiguity aversion reinforces risk aversion.

Third, the observed bias in ambiguity estimation may bias downward the expected price impact of a given change in ambiguity, thereby increasing the (negative) surprise factor for the average investor. Put differently, people are much better trained to deal with risk and its impact on market outcome, than they are with respect to ambiguity. This raises the case for increased transparency in financial markets, as it lowers ambiguity levels. Put differently, during an acute financial crisis, a possible strategy to reduce the price impact and to restore market liquidity is the provision of detailed information about asset quality - a conclusion that has not been drawn in the years 2007-2009.

Fourth, we find the effect of a change in ambiguity level to be more relevant in low ambiguity environments than in high ambiguity environments. Note that the same is not true for risk aversion, pointing to a relatively prominent role of ambiguity in the high ambiguity environment.

The remainder of the paper is structured as follows. First, the modeling of ambiguity in the literature is surveyed (Section 2), followed by a description of the experimental design chosen in the paper (Section 3). Results are contained in Section 4, distinguishing between (discrete) binary choices and (continuous) monetary bids. These bids are used to estimate individual parameters of risk and ambiguity aversion and to analyze how the attitudes towards risk and ambiguity interrelate. Section 5 summarizes and discusses the findings.

2 Ambiguity in the Theoretical and Experimental Literature

Starting with Knight (1921) and Keynes (1921), there is an exponentially growing literature on decisions under risk and uncertainty. Savage (1954) and von Neumann and Morgenstern (1944) lay the foundation on modern decision theory. Their system of axioms clarify, under which conditions subjective probabilities and a Bernoulli risk adjusted utility function exist. Ellsberg (1961) shows in a simple thought experiment that human decisions are more complex than implied by the Savage axiom system. The so-called Ellsberg Paradox is the flash of inspiration for new developments in economic decision theory, empirical and experimental research. The literature will be summarized briefly.

2.1 Theory

There are many different theories of rational decision making under ambiguity. The axiomatic approach of all theories make some changes of the original axioms of Savage (1954) (subjective) expected utility Theory (SEU), especially on the independence axiom (IA).

Axiom 1 (IA) *for all acts f, g, h: $f \succeq g \Leftrightarrow \alpha f + (1-\alpha)h \succeq \alpha g + (1-\alpha)h$*

If, for the preference relation, the usual axioms hold, including the above independence axiom (IA), then there exists a utility function u and a unique subjective probability distribution p (a priori) with:

$$f \succeq g \Leftrightarrow u(f) \geq u(g) \tag{1}$$

where

$$u(f) = E_p[u \circ f], \tag{2}$$

i.e. the total utility is given as expected value of individual utility values u of possible outcomes f, weighted with the corresponding probability p. Rational decision making then involves choosing the act f that maximizes utility, i.e. $\max_f u(f)$.

The Ellsberg (1961) paradox provides evidence that in the presence of ambiguity, the Savage (1954) utility theory does not work. Assuming that the validity of the independence axiom does not hold unconditionally, but is limited to certain conditions, leads to a different theory of rational decision making.

Gilboa and Schmeidler (1989) consider a setting where IA only holds for sure h. They replace IA by C-IA where h is restricted to sure gambles and add a new axiom called uncertainty aversion, i.e. if $f \sim g$ then $\alpha f + (1-\alpha)g \succeq f$. They obtain maxmin-expected utility (MEU), where the set C of possible probability distributions (a priori) is given exogenously:

$$u(f) = \min_{p \in C} E_p[u \circ f]. \tag{3}$$

Maxmin-expected utility (MEU) involves choosing the act f that maximizes utility while assuming the worst possible probability distribution. Thus, MEU involves extremely negative attitudes towards ambiguity.

Translating the concept of Laplace (1820) to situations involving ambiguity, subjects have a neutral attitude towards uncertain outcomes, i.e. they will treat all possible outcomes equally. Thus, we will refer to neutrality towards ambiguity as Laplace-expected utility (LEU), i.e. SEU with Laplace (1820) attitudes. The corresponding utility can be represented as follows:

$$u(f) = E[E_p[u \circ f]]. \tag{4}$$

There exist some generalizations of the MEU model. A more flexible model of ambiguity than MEU is the α-MEU model (see Ghirardato et al., 2004). According to this theory, subjects value uncertain alternatives by the minimum expected utility with weight α and by the maximum expected utility with weight $1-\alpha$:

$$u(f) = \alpha(\min_{p \in C} E_p[u \circ f]) + (1-\alpha)(\max_{p \in C} E_p[u \circ f]) \tag{5}$$

A generalization of MEU is the concept of Variational Preferences, defined by Maccheroni, Marinacci and Rustichini (2006):

$$\min_{p \in C}(E_p[u \circ f] + c(p)), \tag{6}$$

where c is an ambiguity index on the set of probabilities and can be interpreted as a cost function.

Klibanoff, Marinacci, and Mukerji (2005) introduce "Smooth Preferences" (SP) where μ is a subjective probability on the set of (objective) probability measures p. Thus, μ can be regarded as a second order probability. The normal linear reduction is not possible because KMM postulate a concave function:

$$\int_C \phi(E_p[u \circ f])d\mu(p) \tag{7}$$

In contrast to the other theories, the indifference curves are not kinked at the sure state ($45°$ degree line).

Schmeidler (1989) introduces Choquet expected utility (CEU) with capacity v, a nonadditive measure. This allows the sum of the probabilities to deviate from one. In general, CEU differs from MEU, but with a suitable choice of v, CEU gives the same decision rule:

$$\int E_p[u \circ f] dv \tag{8}$$

Siniscalchi (2009) presents vector expected utility (VEU) with an ambiguity adjustment function A. The adjustment factors ζ_i represent different sources of ambiguity:

$$E_p[u \circ f] + A\left((E[\zeta_i \cdot u \circ f])_{0 \leq i < n}\right) \tag{9}$$

The above models can be considered as special cases of VEU.

Bewley (2002) chooses a different point of view. Following Aumann (1962), he composes a system of axioms without the completeness axiom, i.e. allowing incomplete preferences. Alternatives are then incomparable and an inertia assumption is needed. Gilboa et al. (2010) shows the connection between the approach of Bewley (2002) and MEU theory.

The theoretical discussion is actively going on, as evidenced by Galaabaatar and Karni (2013).

2.2 Ambiguity in experimental economics

Epstein and Schneider (2008) provide a broad overview of the literature. The empirical works on ambiguity can be classified in three categories: tests of ambiguity aversion on the individual level (in line with the original Ellsberg thought experiment), studies on psychological causes of ambiguity, and applied studies with market data.

Becker and Brownson (1964), Sovic and Tversky (1974), MacCrimmon and Larson (1979), Einhorn and Hogarth (1986), and Curley and Yates (1989) support the Ellsberg Paradox and find an ambiguity discount. Furthermore, they find that the ambiguity discount increases with the range of possible outcomes, and there is only little correlation between ambiguity aversion and (normal) risk aversion. Subjects show more ambiguity aversion if the gamble they choose was revealed in front of others. Einhorn and Hogarth (1985) propose a model where subjects anchor ambiguous probability on a focal point and adjust upward or downward. A good overview on experimental and theoretical papers is given by Camerer and Weber (1992).

Halevy (2007) designs an experiment with 4 urns containing red and black balls. Urn 1 contains 5 red and 5 black balls. The composition of Urn 2 is unknown and the composition of Urn 3 is drawn from a uniform distribution. Urn 4 contains either 0 or 10 red balls with equal probability. The subjects have to evaluate the urns by a BDM mechanism. Urn 1 and 2 is the original Ellsberg (1961) two-urn experiment, with Urn 2 involving ambiguity. Urn 3 and 4 represent compound lotteries, where the composition of the urns is determined by a lottery with known probabilities. The experiment demonstrates that attitudes towards ambiguity and compound objective lotteries are tightly associated. Subjects who are ambiguity-neutral correctly compound subjective and objective probabilities. The other subjects show different forms of association between preferences over compound lotteries and ambiguity.

Danan and Ziegelmeyer (2006) test experimentally the completeness axiom (see Bewley (1986/2002)) and state empirical evidence that most subjects show incomplete preferences.

Ahn et al. (2009) test several theories of ambiguity in a portfolio choice experiment. They find support for the α-Maxmin Expected Utility model.

Bossaerts et al. (2009) study the impact of ambiguity and ambiguity aversion on equilibrium asset prices and portfolio holdings in competitive financial markets. They find that ambiguity aversion matters for portfolio choices and indirectly for prices. This is in contrast to the standard theory on asset prices. The theoretical results are supported by an experiment. In contrast to earlier studies, they find that there is a correlation between risk aversion and ambiguity aversion.

Bleaney and Humphrey (2006) run an experiment where subjects have to evaluate lotteries where they know the exact probabilities in a first treatment, and in a second treatment they get additionally information on frequencies. The authors state that the second treatment contains less ambiguity because human cognitive process better information on frequencies than pure mathematical probability information. In the experiment, they find that subjects evaluate lotteries significantly higher in the second treatment than in the first. This points to the importance of framing in the context of ambiguity.

There is also support from the brain and cognition science for ambiguity aversion. We learn that there are different regions in the brain involved when humans take decisions under risk or under uncertainty. Hsu et al. (2005) support in an fMRI (functional magnetic resonance imagine) study that ambiguity aversion is a fundamental part of human decision making.

2.3 The relevance of ambiguity in applied economics

Several papers discuss how ambiguity and ambiguity aversion directly affect market prices of assets. Previous research already established that the equity premium consists of both, a premium for risk and a premium for ambiguity (Chen and Epstein, 2002, and Cao et al., 2005).

There is a lot of theoretical research on the impact of ambiguity on asset prices, in most cases built on maxmim expected utility (MEU) preferences, i.e. the minimum of a set of priors is maximized by agents. Caskey (2009) shows that ambiguity can lead to persistent pricing anomalies, such as under-reaction, over-reaction, and price momentum. It has been shown that ambiguity may lead to agents not participating in markets (Dow and Werlang, 1992). Dow and Werlang (1992) examine a model where portfolio managers can buy or sell (go short) an asset. The value of the asset depends on the future state with unknown probability. They show that there is a positive gap in the price range where the managers take a zero position, in contrast to the standard model. Further studies show that ambiguity can affect asset prices and also their volatility (Epstein and Wang, 1994). Epstein and Wang (1994) introduce ambiguity in an equilibrium model with infinite horizon, based on MEU. In the model, agents act dynamically. They show that there is a large set of equilibrium prices depending on the degree of ambiguity.

The model is extended to continuous time by Chen and Epstein (2002). They show that the excess return of a security can be expressed as a sum of a risk premium and an ambiguity premium. That the return is not only determined by risk aversion but also by ambiguity aversion may in part explain the equity premium puzzle as well as the home-bias puzzle. Easley and O'Hara (2009, 2010) show how microstructure features and market regulation can mitigate the adverse effects of ambiguity on market participation, risk premia, and market performance. Ambiguity is accounted for by MEU preferences. Some research deals with the connection between ambiguity and currency exchange rates. In this line of research, Ilut (2010) provides an explanation of the uncovered interest rate parity puzzle based on signals with uncertain precision. In this setting, market participants are assumed to deal with ambiguity by maxmin optimization, assuming worst-case scenarios. In macroeconomic model building we observe a corresponding development. The model of Hansen and Sargent (2001) on robust control and uncertainty about the right model is built on MEU.

Several studies empirically investigate the impact of ambiguity with real market data. Anderson et al. (2009) find that ambiguity, measured by the dispersion of forecasts, has a higher impact on asset returns than risk. Leippold, Trojani, and Vanini (2008) propose and empirically test a model that accounts for ambiguity (and Bayesian learning) and is able to match the observed equity premium, interest rate, and volatility of stock returns. In this paper, ambiguity aversion is accounted for in the form of maxmin expected utility optimization. There is evidence that a substantial part of bond premia can be attributed to inflation ambiguity (Ulrich, 2011a) and uncertainty regarding government policy (Ulrich, 2011c). Pástor and Veronesi (2011) show that uncertainty regarding government policy increases volatility, risk premia, and correlations among stocks. Further evidence suggests that the volatility smile of interest rate options is driven by macro uncertainty premia (Ulrich, 2011b). Several studies investigated the role of ambiguity in the 2007-2008 financial crisis. Boyarchenko (2011) relates the sudden increases of CDS spreads and the drops of equity prices in the years 2007-2008 to increasing uncertainty about the validity of pricing models and the quality of signals available to market participants. Moreover, it is shown that ambiguity may serve as an explanation for break-downs of markets with collateralized assets (Rinaldi, 2011).

A main challenge for theoretical and empirical studies is the issue how ambiguity can be defined and how it can be captured. So far, it is largely unclear how to operationalize the concept of ambiguity in the context of real economic applications. Most theoretical and empirical studies on ambiguity in applied economics apply rough measures of ambiguity. Most theoretical models, on the one hand, apply the concept of MEU which implies an extreme treatment of ambiguity, i.e. maximum aversion against ambiguity. Most empirical studies, on the other hand, struggle with quantifying the degree of ambiguity in real-world situations. Moreover, there are different possible techniques to measure the degree of ambiguity. Thus, a main challenge is how to measure ambiguity in empirical settings and how a distinction between risk aversion and ambiguity aversion can be found.

Almost all real-world situations involve ambiguity, since the true probabilities of events are generally not known. Moreover, ambiguity is always accompanied by risk - it is the second order of risk. Thus, real-world situations typically involve both risk and ambiguity - two concepts that hardly can be disentangled in practice. One main advantage of laboratory experiments is that the degree of ambiguity can be varied in a controlled way so that it is always known. This allows a distinction between the *degree* of risk and ambiguity in each setting, and it also allows to disentangle *attitudes* towards risk and ambiguity.

3 Experiment Design

This experiment is designed in a different way than in previous research, as the degree of ambiguity in different situations is varied systematically, a broad range of settings or stimuli involving ambiguity is captured, and different ways to extract attitudes towards ambiguity are applied (binary choices and valuations via BDM). The broad setting applied allows us to detect the effect of framing, as some situations occur repeatedly and are presented in different ways.

Table 1 shows how the experiment is organized. The experiment consists of two parts with a total of 6 lists. Each list involves a number of situations (mostly 11) of similar type, where only one parameter is varied in one dimension. In each situation, the participants of the experiment are required to make a decision. Throughout the experiment, these situations are lotteries, presented to the participants as a draw of a ball out of an urn containing 100 balls, each of which is of a particular color. The situations differ with respect to the composition of the urn, the information given to participants about the urn, and the possible choices to be made.

Part 1 has two lists with 11 situations each. In Part 1, the subjects are given binary choices. In particular, they have to choose between a lottery (alternative A) with unsure payoffs of either 0 or 10 Euros and a sure payoff of 6 Euros (alternative B). Each ball in the urn is either black or white. A subject deciding to participate in the lottery wins 10 Euros if a white ball is drawn. In List 1 (situations $i = 1$ to $i = 11$), the subjects are informed about the *exact* number of white balls in the urn, ranging from 0 to 100. Since it is known that the remaining balls are all black, the subjects know the exact composition of the urn.

List 2 contains situations as similar as possible to those in List 1, but the composition of the urns is now uncertain. Subjects only know the *minimum* number of winning white balls is the urns, ranging from a minimum number of 0 white balls in Situation 12 to a minimum number of 100 white balls in Situation 22. In each case, there may be more white balls in the urn, but the exact number is unknown. Again, subjects have to make a choice between a lottery (here with unknown probability) and the sure payoff of 6 Euros. The columns labeled List 1 and List 2 in Table 1 give an overview of the configuration of the urns in Part 1.

This design is called *ordered binary choice list.* A similar design has previously been used by Holt and Laury (2002) for measuring risk aversion. However, in contrast to Holt and Laury (2002), we do not alter the sure payoff, but the probability of success of the lottery. In the risk-only setting of List 1, a subject only deciding based on his risk aversion will opt for the sure payoff (alternative B) for Situation 1 to k, and for Situation $(k + 1)$ to 11 he will choose

Table 1: Experiment Design

This table shows the design of the experiments. In particular, it shows what the subjects know about the composition of the urns. In Part 1, the subjects could choose whether they participate in the lottery or rather choose a sure payment of 6 Euros. In Part 2, the subjects should indicate their reservation price at which they are willing to sell the lotteries. The experiment is organized in six lists, where each list consists of several urns in a particular setting. All urns contain 100 balls. The balls may be of white or black color, except for List 6, where balls also may be red. In List 1 and 3, the *exact* number of white balls is known to the subjects. In List 2 and 4, the *minimum* number of white balls in the urns is known, and the remaining balls may be of white or black color. In List 5, the *minimum* number of white *and* black balls in the urns is known, and the remaining balls may be of white or black color. In List 6, the *exact* number of white balls in the urns is known, and the remaining balls may be of black or red color. In the case of Lists 4, 5, and 6, the subjects have to choose the winning color.

Part 1				**Part 2**								
Binary Choices				**Valuing lotteries**								
List 1		**List 2**		**List 3**		**List 4**		**List 5**			**List 6**	
No.	*white* =	No.	*white* ≥	No.	*white* =	No.	*white* ≥	No.	*white* ≥	*black* ≥	No.	*white* =
1	0	12	0	23	0	34	0	45	50	50	56	0
2	10	13	10	24	10	35	10	46	45	45	57	5
3	20	14	20	25	20	36	20	47	40	40	58	10
4	30	15	30	26	30	37	30	48	35	35	59	15
5	40	16	40	27	40	38	40	49	30	30	60	20
6	50	17	50	28	50	39	50	50	25	25	61	25
7	60	18	60	29	60	40	60	51	20	20	62	30
8	70	19	70	30	70	41	70	52	15	15	63	35
9	80	20	80	31	80	42	80	53	10	10	64	40
10	90	23	90	32	90	43	90	54	5	5	65	45
11	100	22	100	33	100	44	100	55	0	0	66	50
											67	55

the gamble. As soon as the number of white balls in the urn surpasses a certain level, the lottery becomes attractive in the sense that the benefits from the potential gain outweigh the disadvantages of the risks involved. The threshold $T_1 = k$ for List 1, i.e. the number of decisions in favor of alternative B before switching to alternative A, depends on a subject's risk aversion and thus can be interpreted as a measure of risk aversion. A risk-neutral player would choose $T_1 = 6$ or $T_1 = 7$, a risk lover takes $T_1 \leq 6$, and a risk-averse player takes $T_1 \geq 7$.

Similar to List 1, for Situation 12 to m in the setting of List 2 involving both risk and ambiguity, a subject would opt for the sure payoff and for $(m + 1)$ to 22, he would choose the uncertain gamble. We measure ambiguity by the number of B-decisions and call $T_2 = m - 11$ the ambiguity-threshold of a subject.

It is possible to relate the thresholds of List 1 and List 2 to establish general relations for extreme ambiguity aversion and neutrality towards ambiguity. If a subject is ambiguity-averse according to MEU, we will observe $T_2 = T_1$. We assume that an ambiguity-neutral decision maker has an unbiased second-order belief about the number of white balls in the ambiguous urn. Thus, a subject that is ambiguity-neutral will choose the same decision in Situation 2i as in Situation i (i=6,7,...,11). For example, the decision in Situation 12 (the minimum number of white balls is 0, i.e. every composition of the 100 balls is possible) corresponds to the decision in Situation 6 where the composition is 50 white balls and 50 black balls. More generally, an ambiguity-neutral decision maker will choose the same option in List 2 where the minimum number of white balls is $M \in \{0, 20, 40, ...100\}$ and in List 1 where the exact number of white balls is $N = (100 + M)/2$. So we can relate the thresholds of an ambiguity-neutral decision maker for List 1 and List 2: $\hat{T}_2 = max[0, 2T_1 - 10]$. $\hat{T}_2$ is the threshold an ambiguity-neutral subject would choose given a particular level of risk aversion as represented by T_1. The difference $T_2 - \hat{T}_2$ of the observed threshold and the risk-adjusted benchmark is a measure ambiguity aversion, after controlling for risk.

Eliciting risk aversion by an ordered binary choice list is a very robust method because subjects only have to make binary choices. Using the same method for eliciting and measuring ambiguity aversion will have the same advantage. So Part 1 gives a robust but rough estimation of ambiguity aversion. The key advantage of the binary-choice setting is that it does not rely on utility theory, and utility functions do not play any role. Instead, pure preferences can be measured in their basic form. In Part 2, we measure risk aversion and ambiguity aversion in a more sophisticated way, applying ordered valuation lists. Subjects have to provide valuations for lotteries involving both risk and ambiguity. In Part 2, there are 4 lists containing 45 situations in total. The configuration of the urns for Situation 23 to 44 follows the same rule as for Part 1; the configuration of the urns 45 to 67 is specified later. Table 1 contains the information about the urns given to the subjects. In all situations involving ambiguity, i.e. List 4, 5, and 6, subjects also have to choose the winning color.

We use the mechanism of Becker, DeGroot, and Marschak (1964) (BDM-mechanism) to elicit the participating subjects' valuations of the lotteries. In line with the BDM-mechanism, the subjects are endowed with a lottery and they are given the opportunity to sell it to an unbiased virtual buyer who randomly values the lottery at $y \in [0, 10]$ according to a uniform distribution. Before knowing y, the subjects have to set a sales price x for the lottery. If the sales price x is higher than the amount y the virtual buyer is willing to pay for the lottery, then there is no transfer and the subject plays the lottery. In the other case, the lottery is sold and the subject receives the buyer's price y. In the instruction, we explain the mechanism in detail and provide a simple graphical explanation clarifying that it is optimal for the subjects to choose as sales price their personal reservation price for the lottery.

List 3 of Part 2 is very similar to List 1 of Part 1. There are 11 situations which differ with respect to the number of white balls in the urns. The number of white balls is known exactly. In situations $i = 23$ to $i = 33$, the number of white balls ranges from 0 to 100. A risk-neutral subject would value (and ask in the BDM-mechanism) the urn of each situation in List 3 by the expected value. A risk-averse subject would ask for a lower price and a risk lover would demand a higher price.

In List 4 of Part 2, subjects have to provide valuations in a context involving ambiguity. In particular, they have to value urns where only the *minimum* number of white balls in the urn is known. Similar to List 2 in Part 1, the minimum number of white balls in situations $i = 34$ to $i = 44$ ranges from 0 to 100. Besides stating a reservation price, the subjects also have to choose the winning color for the lottery. This was done to minimize the subjects' fears that the urns have an adverse composition. In the case of an urn with a minimum number of m white balls, a subject with a neutral attitude towards ambiguity will treat the urn as if it contains $P_m = m + 0.5(100 - m)$ white balls in expectation. And if he is risk-neutral, he will ask for the price $\hat{x}_m = P_m/10$. The attitudes of a subject towards ambiguity are reflected by the direction and the size of the valuation discount. The valuation discount is given by $x(white \geq m) - x(white = 0.5(100 - m))$. Thus, the responses in the risk-and-ambiguity setting of List 4 can be controlled for the responses in the risk-only setting of List 3 to obtain the valuation discount that is due to ambiguity only.

List 5 of Part 2 contains Situations 45 to 55. The minimum number of white *and* black balls are known to the decision makers, ranging from 50 in Situation 45 to 0 in Situation 55. While the degree of ambiguity increases with each situation, the unbiased expected number of white and black balls is always 50. For this reason, the valuation difference of a particular situation from List 5 and Situation 28 from List 3 measures ambiguity aversion.

In List 6, urns with balls of three different colors have to be priced. The exact number of white balls in each urn is known, ranging from 0 to 55. The remaining balls of the 100 balls in the urn are black or red. Again, the subjects have to choose a winning color for the lottery. The decision maker wins 10 Euro if his color is drawn and 0 otherwise.

The Situations 34, 55, and 56 differ only in framing. In all three cases, the urns contain balls of two colors and nothing is known about the composition. This allows us to control the stability of the evaluation. Similarly, Situation 28 corresponds to Situation 45, since in both cases the number of white and black balls is equal to 50.

Throughout the entire experiment, in addition to the participants' own decisions regarding the individual lotteries, the subjects have to provide an estimation on the decision/valuation of the other participants in each situation. In Part 1, subjects have to provide an estimate on the decision of the majority of participants regarding playing the lottery or choosing the fixed payment. The incentive for a correct response is a payoff of 3.00 Euros. For the situations in Part 2, subjects have to estimate the median valuations provided by the participants. The estimation is rewarded with $5 - |s - m|/2$ Euros, where s is a particular subject's estimation and m is the median of all valuations.

The Experiment is set up with the software ztree (see Fischbacher, 2007) and is arranged at the Frankfurt Laboratorium of Experimental Economics (FLEX). Participants are recruited by email and by announcements in lectures at Goethe University Frankfurt. No subject has earlier participated in similar decision experiments. In total, 10 sessions are conducted, with 138 subjects participating in the experiment in total. Given 67 different settings, this leads to a total of 9246 own decisions and the same amount of observed estimations. The average payout to the subjects amounts to 25.73 Euros, ranging from 5.30 Euros to 37.50 Euros.

Each session is organized in the same manner. After being assigned to computer places, the subjects obtain written instructions. Part 1 is read loudly. Questions are answered privately. Before taking decisions in Part 1, the subjects have to pass a test in which they have to prove that they understand the instructions. After subjects have completed all 22 decisions of Part 1, one situation is chosen by chance to be played. All situations have the same probability to be chosen. Practically, we draw one card out of a deck of 22 cards. The chosen card reports the number of the situation to be played and, in the case of a situation involving ambiguity, also the actual composition of the urn. Afterwards, we simulate the draw out of an urn by drawing a card out of a deck containing cards for all numbers from 0 to 100. If the obtained number is smaller or equal to the number of white balls in the urn as reported on the situation card, we treat it as a draw of a white ball. Otherwise, it is assumed to be black. The result of the draw is applied to the decisions of the subjects and money is credited to their account accordingly. After completing Part 1, Part 2 is managed in the same manner: After all decisions are made for Part 2, one situation is selected randomly, a ball is drawn in the same manner as described above, and money is credited to each subject´s account according to his decision and the outcome of the lottery. At the end, the subjects have to complete a questionnaire and are privately payed in cash. The duration of a session is about two hours.

Throughout the entire experiment, big effort is put in creating an environment that represents real ambiguity and that gives the participants exactly the information as indicated. Several measures are taken to accomplish this. The urns are assembled before the experiment and all urns are documented in form of a deck of cards as mentioned above. Naturally, this fact is communicated to the participants before they make their decisions. Moreover, in all situations involving ambiguity, subjects are given the choice of the winning color in order to minimize strategic considerations.

4 Results

4.1 Measuring ambiguity aversion by simple binary choices

Table 2 presents summary statistics of the decisions taken in List 1, a setting only with risk and without any ambiguity. The composition of the urn is known in each situation, as the exact number of white balls is given. The numbers in the table show that the fraction of subjects choosing the lottery instead of the fixed payment tends to increase with the number of white balls in the urn. In most situations, the numbers for actual decision and estimation are similar, indicating that the subjects' own behavior does not differ substantially from the estimated behavior for the other participants. However, in the range of 20 white balls to 50 white balls, there is a substantial deviation, with a larger fraction of subjects actually choosing the lottery than estimating the other participants to do so. This indicates that the individual subjects are less risk-averse themselves than they think others to be.

The risk-only setting in List 1 serves as a benchmark case for the setting of List 2 which has a similar setup, but includes ambiguity in addition to risk. In this case, the subjects only have incomplete information on the composition of each urn. Instead of knowing the exact number of white balls, they only have information on the *minimum* number of white balls in each urn. Summary statistics for List 2 are given in Table 3. The numbers show that the fraction of subjects choosing the lottery instead of the fixed payment tends to increase with the known minimum number of white balls in the urn. This result holds for the actual decisions taken and also for the estimation. However, for almost all urns, the fraction of subjects actually choosing the lottery is larger than the fraction of subjects choosing the lottery as estimated by themselves. This indicates that the individual subjects are less risk- and ambiguity-averse than they think others to be. This effect is most pronounced in the range of minimum 10 to minimum 40 white balls.

Table 2: Summary Statistics, List 1

This table displays summary statistics for List 1, a setting only with risk, but no ambiguity. Panel A displays the actual decisions taken by the subjects, aggregated over the subjects. Panel B displays the estimates of the subjects concerning the median actual decision over all subjects. Panel C displays the difference between a subject's decision and his estimation. Panel D displays the quality of the estimation, represented as difference between a subject's estimation and the median decision. Each column represents a different situation with a different composition of the urn, ranging from exactly 0 white balls to exactly 100 white balls. *Lottery* indicates the fraction of subjects choosing to participate in the lottery, and *Payment* indicates the fraction of subjects choosing the fixed payment instead of the lottery. *Obs.* shows the number of subjects. $Pct > 0$, $Pct = 0$, and $Pct < 0$ show the share of subjects for which the corresponding value is larger than zero, equal to zero, and smaller than zero, respectively.

Panel A: Decision											
#white =	0	10	20	30	40	50	60	70	80	90	100
Lottery	0.0217	0.0290	0.0362	0.0217	0.0797	0.2246	0.5217	0.8478	0.9420	0.9710	0.9928
Fix payment	0.9783	0.9710	0.9638	0.9783	0.9203	0.7754	0.4783	0.1522	0.0580	0.0290	0.0072
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel B: Estimation											
#white =	0	10	20	30	40	50	60	70	80	90	100
Lottery	0.0290	0.0290	0.0217	0.0145	0.0435	0.2101	0.5652	0.8551	0.9493	0.9710	0.9710
Fix payment	0.9710	0.9710	0.9783	0.9855	0.9565	0.7899	0.4348	0.1449	0.0507	0.0290	0.0290
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel C: Decision minus Estimation											
#white =	0	10	20	30	40	50	60	70	80	90	100
Mean	0.0072	0.0000	-0.0145	-0.0072	-0.0362	-0.0145	0.0435	0.0072	0.0072	0.0000	-0.0217
Std	0.1478	0.1208	0.1199	0.0851	0.2537	0.4980	0.5108	0.2833	0.2562	0.2093	0.1464
Pct >0	0.0145	0.0072	0.0000	0.0000	0.0145	0.1159	0.1522	0.0435	0.0362	0.0217	0.0000
Pct =0	0.9783	0.9855	0.9855	0.9928	0.9348	0.7536	0.7391	0.9203	0.9348	0.9565	0.9783
Pct <0	0.0072	0.0072	0.0145	0.0072	0.0507	0.1304	0.1087	0.0362	0.0290	0.0217	0.0217
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel D: Quality of Estimation											
#white =	0	10	20	30	40	50	60	70	80	90	100
Mean	-0.0290	-0.0290	-0.0217	-0.0145	-0.0435	-0.2101	0.4348	0.1449	0.0507	0.0290	0.0290
Std	0.1684	0.1684	0.1464	0.1199	0.2047	0.4089	0.4975	0.3533	0.2202	0.1684	0.1684
Pct >0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.4348	0.1449	0.0507	0.0290	0.0290
Pct =0	0.9710	0.9710	0.9783	0.9855	0.9565	0.7899	0.5652	0.8551	0.9493	0.9710	0.9710
Pct <0	0.0290	0.0290	0.0217	0.0145	0.0435	0.2101	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	138	138	138	138	138	138	138	138	138	138	138

A typical strategy for the settings in List 1 and 2 is a threshold strategy. This implies that with increasing (minimum) number of white balls in the urn, at a particular point, a participant switches from choosing the fixed payment to choosing the lottery. For each participant, this switching point is an individual threshold T_i for List $i = 1$ or $i = 2$. A subject who chooses $T_1 = k$ in List 1 has decided for the sure alternative for all urns where the *exact* number of white balls is $K \leq (k-1)10$. A subject who chooses $T_2 = k$ in List 2 has decided for the sure alternative for all urns where the *minimum* number of white balls is $K \leq (k-1)10$. An ambiguity-neutral subject will opt for the sure alternative in List 1 if the number of white balls is $K' \leq \frac{K+100}{2}$, i.e. the subject will apply equal probabilities to the unknown balls. In total, 123 out of the 138 participants followed threshold strategies and switched once from fixed payment to lottery. Figure 1 shows the results of these participants. The left diagram

Table 3: Summary Statistics, List 2

This table displays summary statistics for List 2, a setting with risk and ambiguity. Panel A displays the actual decisions taken by the subjects, aggregated over the subjects. Panel B displays the estimates of the subjects concerning the median actual decision over all subjects. Panel C displays the difference between a subject's decision and his estimation. Panel D displays the quality of the estimation, represented as difference between a subject's estimation and the median decision. Each column represents a different situation with a different composition of the urn, ranging from a minimum number of 0 white balls to a minimum number of 100 white balls. *Lottery* indicates the fraction of subjects choosing to participate in the lottery, and *Payment* indicates the fraction of subjects choosing the fixed payment instead of the lottery. *Obs.* shows the number of subjects. $Pct > 0$, $Pct = 0$, and $Pct < 0$ show the share of subjects for which the corresponding value is larger than zero, equal to zero, and smaller than zero, respectively.

Panel A: Decision

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Lottery	0.0290	0.0435	0.0870	0.1739	0.4130	0.6304	0.8261	0.9420	0.9710	0.9710	0.9855
Fix payment	0.9710	0.9565	0.9130	0.8261	0.5870	0.3696	0.1739	0.0580	0.0290	0.0290	0.0145
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel B: Estimation

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Lottery	0.0217	0.0362	0.0435	0.1232	0.2826	0.6232	0.8406	0.9203	0.9710	0.9638	0.9710
Fix payment	0.9783	0.9638	0.9565	0.8768	0.7174	0.3768	0.1594	0.0797	0.0290	0.0362	0.0290
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel C: Decision minus Estimation

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Mean	-0.0072	-0.0072	-0.0435	-0.0507	-0.1304	-0.0072	0.0145	-0.0217	0.0000	-0.0072	-0.0145
Std	0.1478	0.1909	0.2377	0.3882	0.4956	0.4600	0.3193	0.1464	0.2093	0.1478	0.1199
Pct >0	0.0072	0.0145	0.0072	0.0507	0.0652	0.1014	0.0580	0.0000	0.0217	0.0072	0.0000
Pct =0	0.9783	0.9638	0.9420	0.8478	0.7391	0.7899	0.8986	0.9783	0.9565	0.9783	0.9855
Pct <0	0.0145	0.0217	0.0507	0.1014	0.1957	0.1087	0.0435	0.0217	0.0217	0.0145	0.0145
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel D: Quality of Estimation

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Mean	-0.0217	-0.0362	-0.0435	-0.1232	-0.2826	0.3768	0.1594	0.0797	0.0290	0.0362	0.0290
Std	0.1464	0.1875	0.2047	0.3299	0.4519	0.4864	0.3674	0.2718	0.1684	0.1875	0.1684
Pct >0	0.0000	0.0000	0.0000	0.0000	0.0000	0.3768	0.1594	0.0797	0.0290	0.0362	0.0290
Pct =0	0.9783	0.9638	0.9565	0.8768	0.7174	0.6232	0.8406	0.9203	0.9710	0.9638	0.9710
Pct <0	0.0217	0.0362	0.0435	0.1232	0.2826	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Obs.	138	138	138	138	138	138	138	138	138	138	138

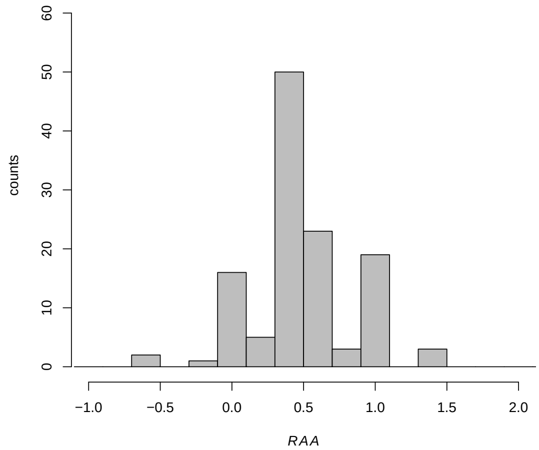
Figure 1: Personal attitudes towards ambiguity

These diagrams display personal attitudes towards ambiguity, controlling for attitudes towards risk. Only individuals following threshold strategies are considered, i.e. individuals choosing the safe payoff for a low number of white balls in the urn and switching once to the lottery at a particular point. The left diagram displays the $(T1, T2)$-combinations of all subjects, i.e. the decisions of all subjects in List 1 ($T1$) and List 2 ($T2$). $T1$ and $T2$ indicate the number of decisions in List 1 and 2 where a subject chooses the sure payoff instead of the lottery. Each threshold stands for the point where a particular subject switches from the risk-free alternative to the lottery. Thus, the thresholds stand for the lottery-equivalent to the safe alternative. The red cells stand for maximum ambiguity aversion, the blue cells stand for neutrality towards ambiguity. The right diagram displays the relative ambiguity aversion RAA of all subjects in form of a histogram. RAA serves as a measure for ambiguity aversion as it describes the horizontal position of a particular subject's $(T1, T2)$-combination in the left diagram. $RAA = 0$ stands for neutrality towards ambiguity, $RAA = 1$ stands for maximum ambiguity aversion. One observation is excluded because RAA is not defined in this case.

Individual thresholds for risk ($T1$) and ambiguity ($T2$)

	T1										
T2	1	2	3	4	5	6	7	8	9	10	Sum
1				1							1
2		1				5	1				7
3				3	2	5	1				11
4				1	11	9	6		1		28
5					3	12	12				27
6						8	17	2	1		28
7						3	4	9	1		17
8								1			1
9									1	1	2
10										1	1
Sum	0	1	0	5	16	42	41	12	4	2	123

Relative Ambiguity Aversion



relates the threshold T_1 of the risk-only setting in List 1 to the threshold T_2 of the risk-and-ambiguity setting in List 2 and counts the number of participants for all (T_1,T_2)-combinations. Thus, naturally, each participant following a threshold strategy is represented once in this diagram. The relation of the two thresholds applied by a particular participant allows to infer her attitude towards ambiguity. In general, perfectly ambiguity-averse participants, as implied by MEU, will treat urns with e.g. *exactly* 20 white balls the same as urns with a *minimum* number of 20 white balls. As a consequence, for these participants, T_1 will be equal to T_2. Thus, in the left diagram, the diagonal cells from top-left to bottom-right, highlighted with red color, denote the extreme case of maximum ambiguity aversion. The other extreme, as implied by Laplace-SEU, is neutrality towards ambiguity. In this case, participants treat urns with a minimum number of 20 white balls the same as urns with exactly 60 white balls, since they treat the probability of the unknown balls being white the same as them being black. The case $(T_1, T_2) = (6, 2)$ and other cases of neutrality towards ambiguity are given in the left diagram by (T_1,T_2)-combinations highlighted blue. These combinations lie on a step function, ranging from the points $(T_1, T_2) = (6, 1)$ to $(T_1, T_2) = (10, 10)$. Taken together, these two lines form a corridor comprising cases ranging from ambiguity neutrality to complete ambiguity aversion. Participants with (T_1,T_2)-combinations located to the right of the corridor exhibit friendliness towards ambiguity. This means that these participants rely on a more favorable outcome than implied by equal probabilities, i.e. that among the unknown balls, there are more white balls than black balls. (T_1,T_2)-combinations located to the left of the corridor indicate inconsistent behavior. In these cases, T_1 is smaller than T_2, i.e. for certain urns, these participants choose the lottery when there are *exactly* x white balls in the urn, but they choose the fixed payment when there are *at least* x white balls in the urn.

As can be seen in the left diagram of Figure 1, while 6 participants lie outside the corridor and 36 are on the border, 81 participants lie within the corridor. It can be seen that of the 123 participants following threshold strategies, 3 can be classified as ambiguity friendly, 16 as ambiguity neutral, 81 as to some extent but not completely ambiguity averse, 19 as completely ambiguity averse, 3 as inconsistent behaviors (since the risk aversion alone is larger than the combined risk-and-ambiguity aversion), and one as indeterminable (since he lies exactly on the intersection of the two boundaries).

The relative position of a participant's (T_1,T_2)-combination compared to the corridor shows her attitudes towards ambiguity. To formally capture an individual's attitude towards ambiguity, we introduce a relative measure of ambiguity aversion RAA which captures the decision taken relative to that in case of ambiguity neutrality and that in case of maximum ambiguity aversion:

$$RAA = \frac{\hat{T}_1 - T_1}{\hat{T}_1 - T_2}, with \tag{10}$$

$$\hat{T}_1 = \begin{cases} \frac{T_2+11}{2} & \text{if } T_2 \text{ is odd} \\ \frac{T_2+10}{2} & \text{if } T_2 \text{ is even} \end{cases} \tag{11}$$

T_1 is the threshold chosen by a particular individual in List 1, and T_2 is the threshold chosen in List 2. $\hat{T}_1$ is the threshold that would apply in List 1 if a particular individual was neutral towards ambiguity for a given choice T_2. The threshold of maximum ambiguity aversion corresponds to T_1, i.e. an individual choosing $T_2 = T_1$ treats an urn with exactly x white balls the same as an urn with a minimum number of x white balls. $RAA = 0$ stands for ambiguity neutrality, $RAA = 1$ stands for maximum ambiguity aversion, and values of $0 < RAA < 1$ indicate intermediate degrees of ambiguity aversion. Negative values for RAA point at ambiguity-friendliness, and values of RAA larger than one indicate an inconsistent behavior of participants.

The right diagram in Figure 1 shows a histogram with individual attitudes towards ambiguity as captured by the measure RAA for relative ambiguity aversion. From the results in the diagram, it can be seen that almost all participants are ambiguity-averse. While the majority of participants has intermediate degrees of ambiguity aversion, two large groups of participants have extreme attitudes towards ambiguity, i.e. neutrality and maximum aversion. A Wilcoxon test independently rejects the hypotheses $RAA = 0$ and $RAA = 1$ with very low p-values ($p \leq 10^{-16}$) in both cases.

Overall, the results of List 1 and List 2 are quite stable and robust. The participants only to a minor extent show inconsistent behavior. This is due to the fact that the experiment design only required simple decisions between a lottery and a fixed payment, rather than more complex decisions, such as e.g. valuations. Already in this simple setting, several properties concerning ambiguity can be observed. The results show that most participants are ambiguity-averse, that the extent of ambiguity aversion varies a lot across individuals, and that ambiguity aversion only in some cases takes extreme values as implied by MEU and Laplace-SEU. On average (and in many cases), ambiguity aversion takes an intermediate value, well between maximum ambiguity (MEU) aversion and no aversion (Laplace-SEU).

4.2 Quantifying ambiguity aversion

In this section, ambiguity aversion is quantified. For this, the treatments in the Lists 3-6 are applied, where the individual subjects were endowed with lotteries that they were allowed to sell. Thus, by applying the BDM-mechanism, we obtain from each subject a reservation price for each lottery. Besides the payoffs of the individual lotteries, this valuation depends on the subjects' attitudes towards risk and ambiguity. Since the experiment is designed to account for both risk and ambiguity in similarly designed treatments, it is possible to extract the effect of risk aversion on the valuations in the ambiguity treatment, thereby isolating the value discount that is due to ambiguity only.

4.2.1 List 3: Risk-only setting

Table 4 and Figure 2 display the results of the risk-only setting where the composition of the urns is known. The numbers in Table 4 show that in all settings, the valuations of the median

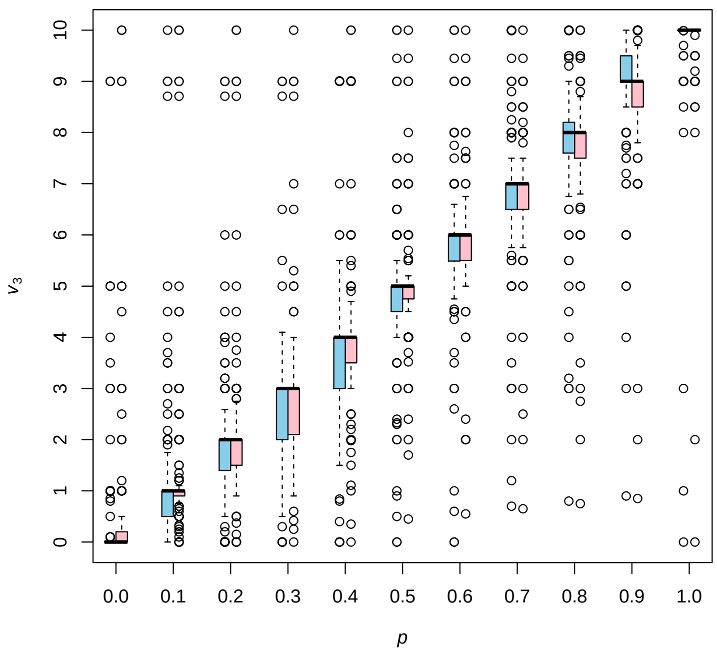
Table 4: Summary Statistics, List 3

This table displays summary statistics for List 3, a setting with risk only. Panel A displays the actual decisions taken by the subjects, aggregated over the subjects. Panel B displays the estimates of the subjects concerning the median actual decision over all subjects. Panel C displays the difference between a subject's decision and his estimation. Panel D displays the quality of the estimation, represented as difference between a subject's estimation and the median decision. Panel E displays the relative risk discount *RRD*. Each column represents a different situation with a different composition of the urn, ranging from exactly 0 white balls to exactly 100 white balls. *Obs.* shows the number of subjects. $Pct > 0$, $Pct = 0$, and $Pct < 0$ show the share of subjects for which the corresponding value is larger than zero, equal to zero, and smaller than zero, respectively. *Q-range* is the difference between the 25th percentile and the 75th percentile.

Panel A: Required Price											
$\#white =$	0	10	20	30	40	50	60	70	80	90	100
Mean	0.44	1.26	1.96	2.74	3.70	4.91	5.84	6.84	7.84	8.79	9.73
Std.	1.36	1.63	1.43	1.42	1.47	1.54	1.49	1.47	1.37	1.31	1.30
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.70	0.80	0.90	0.00
25%	0.00	0.50	1.41	2.00	3.00	4.50	5.49	6.50	7.65	8.99	10.00
Median	0.00	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
75%	0.01	1.00	2.00	3.00	4.00	5.00	6.00	7.01	8.20	9.50	10.00
Max	9.00	10.00	9.00	9.00	9.01	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel B: Estimation of Median Required Price											
$\#white =$	0	10	20	30	40	50	60	70	80	90	100
Mean	0.63	1.40	2.18	2.98	3.99	4.98	5.86	6.79	7.67	8.70	9.76
Std.	1.79	1.74	1.65	1.48	1.46	1.23	1.22	1.18	1.32	1.23	1.12
Min	0.00	0.00	0.00	0.00	0.00	0.45	0.55	0.65	0.75	0.85	0.00
25%	0.00	0.90	1.50	2.18	3.50	4.79	5.50	6.50	7.50	8.50	10.00
Median	0.00	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
75%	0.18	1.00	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel C: Decision minus Estimation											
$\#white =$	0	10	20	30	40	50	60	70	80	90	100
Mean	-0.18	-0.14	-0.22	-0.23	-0.29	-0.08	-0.02	0.05	0.17	0.09	-0.03
Std	1.28	1.01	1.14	1.16	1.36	1.37	1.30	1.37	1.35	1.22	0.79
$Pct > 0$	0.07	0.17	0.20	0.20	0.20	0.22	0.26	0.30	0.30	0.30	0.07
$Pct = 0$	0.80	0.53	0.49	0.46	0.46	0.54	0.49	0.46	0.51	0.55	0.90
$Pct < 0$	0.13	0.30	0.31	0.34	0.33	0.23	0.25	0.25	0.18	0.15	0.04
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel D: Quality of Estimation											
$\#white =$	0	10	20	30	40	50	60	70	80	90	100
Mean	0.63	0.40	0.18	-0.02	-0.01	-0.02	-0.14	-0.21	-0.33	-0.30	-0.24
Std	1.79	1.74	1.65	1.48	1.46	1.23	1.22	1.18	1.32	1.23	1.12
$Pct > 0$	0.36	0.23	0.22	0.20	0.22	0.17	0.17	0.20	0.20	0.19	0.00
$Pct = 0$	0.64	0.49	0.46	0.45	0.45	0.54	0.48	0.44	0.47	0.50	0.87
$Pct < 0$	0.00	0.28	0.32	0.36	0.33	0.29	0.35	0.36	0.33	0.31	0.13
Obs.	138	138	138	138	138	138	138	138	138	138	138
Panel E: Relative Risk Discount											
$\#white =$	0	10	20	30	40	50	60	70	80	90	100
Median		0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	
Q-range		0.50	0.29	0.33	0.25	0.10	0.09	0.07	0.07	0.06	

Figure 2: Summary Statistics, List 3

This figure displays summary statistics for List 3 (risk only, no ambiguity). The graphic contains boxplots showing the distribution of individual valuations (blue color) and estimations about others' valuations (red color) for each setting. Each setting is characterized by p, i.e. the *exactly known* probability that a white ball is drawn. The results are based on observations from 138 participants.



participant equal exactly the expected value of the urn. Thus, the median participant is risk-neutral. In fact, a large fraction of participants are risk-neutral, as can be seen by the fact that the same applies to the 75 percent quantile. The participants at the 25 percent quantile are slightly risk-averse, with valuations only slightly below the expected values of the urns. The minimum and maximum numbers show that the entire range of possible valuations is covered, some of them clearly non-realistic outliers. A comparison of Panel A and Panel B shows that actual prices and estimated prices do not differ substantially in most settings. Panel D shows the quality of the estimation. It can be seen that for settings with low probability of success, participants tend to overestimate the amount of money others are willing to pay, while for settings with high probability of success, participants tend to underestimate it. The highest accuracy is given for urns with 30-50 winning balls. In Figure 2, the blue-colored boxplots stand for valuations, and the red-colored boxplots stand for estimations. The diagram provides several insights: First, the results indicate that a large fraction of participants is risk neutral or slightly risk-averse. The boxes, standing for 75 percent of the observations, are in almost all situations located at and below the expected payoff of that situation. In many cases, median and 75 percent quantile coincide exactly with the expected payoff. Second, the results indicate that own valuations do not differ substantially from estimates about other participants' valuations. Thus, own attitudes towards risk are generally also attributed to the other participants.

4.2.2 List 4: Risk and Ambiguity - asymmetrical case

List 4 is a setting with both risk and ambiguity. It is an asymmetrical setting since the minimum number of balls of one color only (white) is given. The number of black balls in the urn is unknown.

Table 5 and Figure 3 display the results of the setting involving risk and ambiguity. The composition of the urns is only known to some extent, as the participants obtain information on the minimum number of white balls in the urn. The participants of the experiment could select the winning color. The numbers in Table 5 are larger than those of the risk-only setting in Table 4, which is not surprising since these situations clearly dominate. Moreover, there is an almost monotonic increase in mean and median valuations of the urns with rising minimum number of white balls in the urn. This is consistent with SEU theory since a larger number of white balls guaranteed in the urn increases the probability of a good outcome. However, the first urn with a minimum number of 0 white balls is an exception, with valuations larger than that of the next urn with a minimum number of 10 white balls. Panel B shows the estimations of median required prices for each urn. The numbers are similar to the ones in Panel A, showing that the belief about others' valuations does not differ dramatically from own valuations. Panel E shows for each urn the winning color chosen by the participants. For the first urn with a minimum number of 0 white balls in the urn, a similar number of participants chose black and white as winning color. This is a very plausible result, since no information is given about the urn and there is no reason to prefer one color to the other. For the next urns with increasing number of white balls guaranteed, the fraction of participants choosing white as winning color

Table 5: Summary Statistics, List 4

This table displays summary statistics for List 4, a setting with both risk and ambiguity. Panel A displays the actual decisions taken by the subjects, aggregated over the subjects. Panel B displays the estimates of the subjects concerning the median actual decision over all subjects. Panel C displays the difference between a subject's decision and his estimation. Panel D displays the quality of the estimation, represented as difference between a subject's estimation and the median decision. Panel E displays the relative ambiguity discount *RAD*. Panel F displays the percentage number of subjects choosing white or black as winning color. Each column represents a different situation with a different composition of the urn, ranging from a minimum number of 0 white balls to a minimum number of 100 white balls. The other balls in the urn may either be of white or black color. *Obs.* shows the number of subjects. $Pct > 0$, $Pct = 0$, and $Pct < 0$ show the share of subjects for which the corresponding value is larger than zero, equal to zero, and smaller than zero, respectively. *Q-range* is the difference between the 25th percentile and the 75th percentile.

Panel A: Required Price

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Mean	4.12	3.85	3.97	4.46	4.92	5.78	6.65	7.54	8.28	9.07	9.81
Std.	3.21	2.59	2.22	2.04	1.91	1.79	1.69	1.57	1.51	1.25	1.17
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.60	0.70	0.80	0.90	0.00
25%	1.00	1.58	2.00	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
Median	4.26	3.50	4.00	4.50	5.00	6.00	7.00	8.00	8.50	9.50	10.00
75%	5.00	5.50	6.00	6.00	6.24	7.00	8.00	8.50	9.00	9.70	10.00
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel B: Estimation of Median Required Price

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Mean	4.32	4.06	4.24	4.62	5.17	5.74	6.56	7.38	8.16	8.96	9.65
Std.	3.19	2.55	2.15	1.82	1.62	1.51	1.44	1.38	1.36	1.18	1.52
Min	0.00	0.00	0.00	1.00	1.50	0.00	0.00	0.00	0.00	0.00	0.00
25%	2.00	2.00	2.50	3.00	4.00	5.00	6.00	7.00	8.00	9.00	10.00
Median	4.00	3.55	4.00	4.50	5.00	5.50	6.95	7.50	8.22	9.00	10.00
75%	5.89	5.50	6.00	6.00	6.00	6.95	7.50	8.20	9.00	9.50	10.00
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel C: Decision minus Estimation

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Mean	-0.19	-0.21	-0.27	-0.16	-0.25	0.04	0.09	0.15	0.13	0.11	0.16
Std	2.16	1.65	1.73	1.70	1.57	1.49	1.41	1.39	1.33	1.29	1.49
$Pct > 0$	0.22	0.31	0.28	0.31	0.26	0.35	0.36	0.41	0.33	0.36	0.08
$Pct = 0$	0.52	0.38	0.41	0.36	0.43	0.41	0.40	0.40	0.50	0.46	0.89
$Pct < 0$	0.25	0.30	0.32	0.33	0.30	0.25	0.24	0.20	0.17	0.17	0.03
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel D: Quality of Estimation

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Mean	0.06	0.56	0.24	0.12	0.17	-0.26	-0.44	-0.62	-0.34	-0.54	-0.36
Std	3.19	2.55	2.15	1.82	1.62	1.51	1.44	1.38	1.36	1.18	1.52
$Pct > 0$	0.49	0.50	0.46	0.46	0.42	0.34	0.30	0.27	0.38	0.20	0.00
$Pct = 0$	0.00	0.01	0.05	0.04	0.17	0.14	0.20	0.17	0.09	0.20	0.86
$Pct < 0$	0.51	0.49	0.49	0.49	0.41	0.51	0.50	0.57	0.53	0.61	0.14
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel E: Relative Ambiguity Discount

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
Median	0.06		0.47		0.67		0.60		0.50		
Q-range	0.86		0.94		0.77		0.84		1.00		

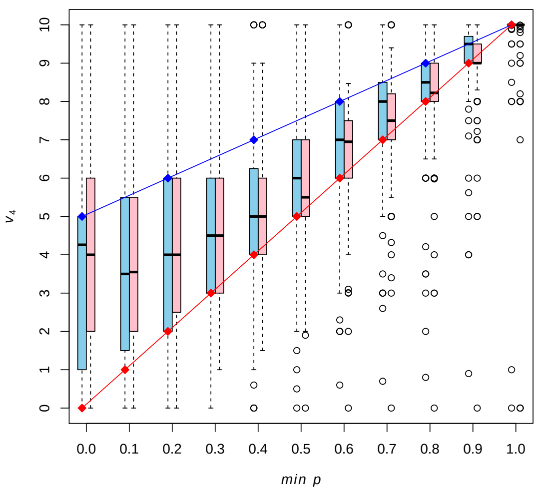
Panel F: Chosen Color

$\#white \geq$	0	10	20	30	40	50	60	70	80	90	100
White	0.514	0.630	0.681	0.703	0.848	0.957	0.986	0.993	1.000	1.000	0.986
Black	0.486	0.370	0.319	0.297	0.152	0.043	0.014	0.007	0.000	0.000	0.014

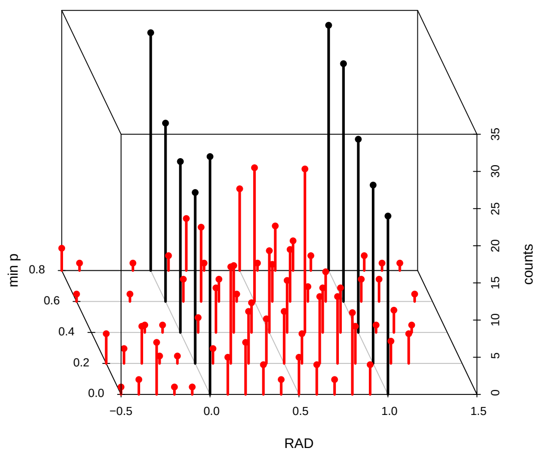
Figure 3: Summary Statistics, List 4

This figure displays summary statistics for List 4 (risk and ambiguity). The left graphic contains boxplots showing the distribution of individual valuations (blue color) and estimations about others' valuations (red color) for each setting. The red line represents the valuation boundary at maximum ambiguity aversion for a participant with median risk attitudes according to List 3. The blue line represents the valuation boundary at neutral attitudes towards ambiguity for a participant with median risk attitudes according to List 3. The right graphic shows the distributions of the relative ambiguity discount *RAD* of individual participants in different settings. Each setting is characterized by *min p*, i.e. the *minimum* probability that a white ball is drawn. The results are based on observations from 138 participants.

Valuations



Relative Ambiguity Discount



increases monotonically. In the urn with at least 50 white balls, 95.7 percent of the participants chose white as winning color. This is plausible, since white clearly dominates black. In the cases of the urns with a minimum of 10 to 40 white balls, a rather large fraction of participants chose black as winning color (between 15.2 percent and 37.0 percent), given the fact that the information given speaks in favor of white, since a certain number of white balls is guaranteed while the number of black balls is unknown.

Figure 3 displays the participants' valuations in two diagrams. The left diagram shows for each urn the distribution of the observations in the form of boxplots. The left, blue-colored boxplots stand for valuations, and the right, red-colored boxplots stand for estimations. In addition, the diagram includes in blue- and red-colored diamonds, representing valuations according to MEU theory (red diamonds) and Laplace-SEU theory (blue diamonds). In both cases, risk attitudes as obtained from List 3 are accounted for. MEU theory implies maximum ambiguity aversion. Thus, experiment participants with maximum ambiguity aversion will treat urns with a certain guaranteed minimum number of white balls as if they contain *exactly* this number of white balls. In addition, they will not consider black as winning color because there is no guarantee at all on the number of black balls. Thus, for completely ambiguity-averse participants, the setting of List 4 is exactly the same as the setting of List 3. As a consequence, the valuations of List 3 can be taken as a reference for List 4. In the diagram, median valuations of List 3 are included as red diamonds to graphically show the extreme case of maximum ambiguity aversion (and still accounting for actual risk attitudes as gathered with the responses in List 3). The second extreme is the case of neutrality towards ambiguity. This case corresponds to SEU theory with Laplace (1820) attitudes. In the case of neutrality towards ambiguity, the balls with unknown color will symmetrically be assumed to be of white or black color. An urn with a guaranteed minimum number of e.g. 20 white balls will correspondingly be assumed to consist of 60 white balls by ambiguity-neutral participants. Again, the risk-only valuation of this urn can be found in List 3. The corresponding median numbers from the risk-only setting of List 3 are included as blue diamonds in the diagram. Taken together, the red and blue diamonds in the left diagram of Figure 3 serve as boundaries, indicating two extreme cases concerning the attitudes towards ambiguity, i.e. maximum ambiguity aversion and ambiguity neutrality. Note that these boundaries account for risk aversion as we employ the valuations of the risk-only setting of List 3.

The left diagram provides several insights: First, the results indicate that a large fraction of participants is ambiguity-averse. The boxes, standing for 50 percent of the observations, are in almost all situations located well between the two boundaries representing ambiguity-neutrality and maximum ambiguity-aversion. Second, the boxes are wide-spread between the boundaries, indicating that all levels of ambiguity aversion between the two extremes are present among the participants of the experiment. Third, some observations lie above the upper boundary, indicating that there are some individual cases of friendliness towards ambiguity. Fourth, only a few observations lie below the lower boundary. Fifth, the median ambiguity aversion given by the small horizontal line in the individual boxes is well between the two boundaries. However, its relative location between the boundaries varies and depends on the situation. Sixth, the boxplots for own valuations and estimations have a similar shape and location, indicating that own valuations do not differ substantially from estimates about other participants' valuations. Thus, own attitudes towards ambiguity are generally also attributed to the other participants.

To track the attitude towards ambiguity for each participant more in detail, we introduce a measure RAD representing the relative ambiguity discount. The relative ambiguity discount RAD is determined by the location of a particular valuation V_{actual} in relation to the boundaries given by valuations in the case of maximum ambiguity aversion $V_{maximumaversion}$ and valuations in the case of ambiguity neutrality $V_{neutrality}$, i.e.

$$RAD = \frac{V_{neutrality} - V_{actual}}{V_{neutrality} - V_{maximumaversion}} = \frac{V_{0.5(1+p)}^{List3} - V_{p}^{List4}}{V_{0.5(1+p)}^{List3} - V_{p}^{List3}}. \tag{12}$$

A relative ambiguity discount of $RAD = 0$ indicates ambiguity neutrality, and $RAD = 1$ stands for maximum ambiguity aversion. The right diagram of Figure 3 shows the number of participants with a particular relative ambiguity discount for each situation. A situation is represented by an urn with a certain minimum probability of a good outcome, e.g. a guaranteed minimum number of 20 white balls. It can be seen that the participants can be classified into three groups of roughly equal size. The black vertical lines in the diagram stand for participants with extreme types of ambiguity aversion, i.e. maximum ambiguity aversion and ambiguity neutrality. It can be seen that in fact, many participants chose one of the two extremes (around one third of the participants for each extreme). Most remaining participants impose a relative ambiguity discount of $0 < RAD < 1$. They form a third group with intermediate values of ambiguity aversion. To a certain extent, these results can be interpreted in correspondence to Einhorn and Hogarth (1985) in the sense that subjects anchor on focal points. However, we find that correlation of risk and ambiguity aversion depends on the decision situation.

Note that the RAD measure differs from the α-MEU of Ahn et al. (2009) in the sense that it relates the ambiguity discount to the difference of the neutral and the worst case instead of the difference of the best and worst case.

These results indicate that neither SEU with Laplace (1820) attitudes nor MEU or α-MEU are appropriate characterizations of ambiguity aversion that apply in general. Instead, the extent of ambiguity aversion depends on the type of each individual, and each type seems to exist.

4.2.3 List 5: Risk and Ambiguity - symmetrical case

The setting in List 5 also involves both risk and ambiguity. However, in contrast to List 4, a symmetrical case of ambiguity is investigated. In particular, the same information is available concerning the guaranteed minimum number of both white and black balls in the urn. Across the individual urn, the guaranteed minimum number of white and black balls is reduced stepwise from 50 to 0. Thus, while the extent of ambiguity in the different situations increases, the relative attractiveness of choosing white or black as winning color remains the same. Thus,

Table 6: Summary Statistics, List 5

This table displays summary statistics for List 5, a setting with both risk and ambiguity. Panel A displays the actual decisions taken by the subjects, aggregated over the subjects. Panel B displays the estimates of the subjects concerning the median actual decision over all subjects. Panel C displays the difference between a subject's decision and his estimation. Panel D displays the quality of the estimation, represented as difference between a subject's estimation and the median decision. Panel E displays the relative ambiguity discount *RAD*. Panel F displays the percentage number of subjects choosing white or black as winning color. Each column represents a different situation with a different composition of the urn, ranging from minimum numbers of 50 white balls and 50 black balls to minimum numbers of 0 white balls and 0 black balls. The other balls in the urn may either be of white or black color. *Obs.* shows the number of subjects. $Pct > 0$, $Pct = 0$, and $Pct < 0$ show the share of subjects for which the corresponding value is larger than zero, equal to zero, and smaller than zero, respectively. *Q-range* is the difference between the 25th percentile and the 75th percentile.

Panel A: Required Price

$\#white, \#black \geq$	50	45	40	35	30	25	20	15	10	5	0
Mean	4.92	4.60	4.35	4.11	3.92	3.81	3.75	3.56	3.48	3.27	3.35
Std.	1.72	1.65	1.63	1.64	1.71	1.82	1.97	2.05	2.15	2.30	2.60
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	4.50	4.00	3.93	3.50	3.00	2.50	2.03	2.00	2.00	1.03	1.00
Median	5.00	4.80	4.43	4.00	4.00	4.00	3.80	3.60	3.50	3.50	3.65
75%	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel B: Estimation of Median Required Price

$\#white, \#black \geq$	50	45	40	35	30	25	20	15	10	5	0
Mean	4.97	4.70	4.48	4.24	4.08	3.86	3.83	3.66	3.56	3.31	3.45
Std.	1.57	1.50	1.55	1.53	1.57	1.65	1.84	2.01	2.15	2.37	2.59
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	4.73	4.25	4.00	3.50	3.00	2.50	2.29	2.00	2.00	1.00	1.00
Median	5.00	4.60	4.50	4.00	4.00	4.00	4.00	3.80	3.75	3.55	4.00
75%	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel C: Decision minus Estimation

$\#white, \#black \geq$	50	45	40	35	30	25	20	15	10	5	0
Mean	-0.05	-0.11	-0.13	-0.14	-0.16	-0.06	-0.08	-0.10	-0.07	-0.04	-0.10
Std	1.63	1.51	1.68	1.46	1.61	1.47	1.66	1.78	1.80	1.58	1.73
$Pct > 0$	0.23	0.30	0.30	0.24	0.25	0.29	0.27	0.27	0.26	0.27	0.17
$Pct = 0$	0.57	0.44	0.46	0.48	0.50	0.48	0.49	0.49	0.49	0.47	0.59
$Pct < 0$	0.20	0.25	0.25	0.28	0.25	0.23	0.24	0.24	0.25	0.26	0.24
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel D: Quality of Estimation

$\#white, \#black \geq$	50	45	40	35	30	25	20	15	10	5	0
Mean	-0.03	-0.10	0.05	0.24	0.08	-0.14	0.03	0.06	0.06	-0.19	-0.20
Std	1.57	1.50	1.55	1.53	1.57	1.65	1.84	2.01	2.15	2.37	2.59
$Pct > 0$	0.14	0.44	0.51	0.49	0.46	0.41	0.54	0.52	0.51	0.50	0.55
$Pct = 0$	0.59	0.02	0.00	0.12	0.12	0.11	0.00	0.00	0.02	0.01	0.00
$Pct < 0$	0.27	0.54	0.49	0.40	0.42	0.48	0.46	0.48	0.46	0.49	0.45
Obs.	138	138	138	138	138	138	138	138	138	138	138

Panel E: Relative Ambiguity Discount

$\#white, \#black \geq$	50	45	40	35	30	25	20	15	10	5	0
Median			0.40		0.50		0.39		0.34		0.22
Q-range			1.00		0.83		0.83		0.80		0.89

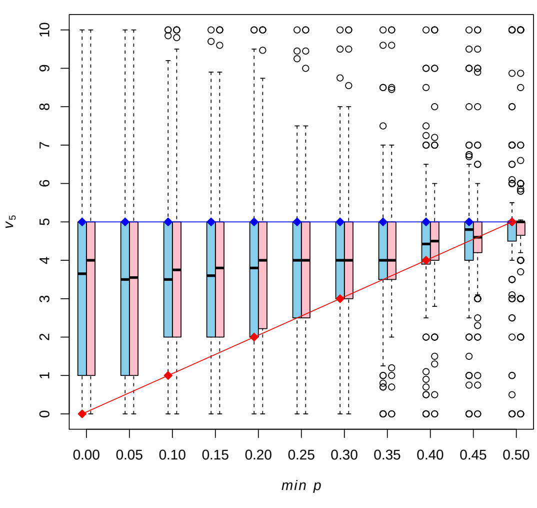
Panel F: Chosen Color

$\#white, \#black \geq$	50	45	40	35	30	25	20	15	10	5	0
White	0.826	0.819	0.833	0.819	0.833	0.812	0.833	0.783	0.812	0.812	0.833
Black	0.174	0.181	0.167	0.181	0.167	0.188	0.167	0.217	0.188	0.188	0.167

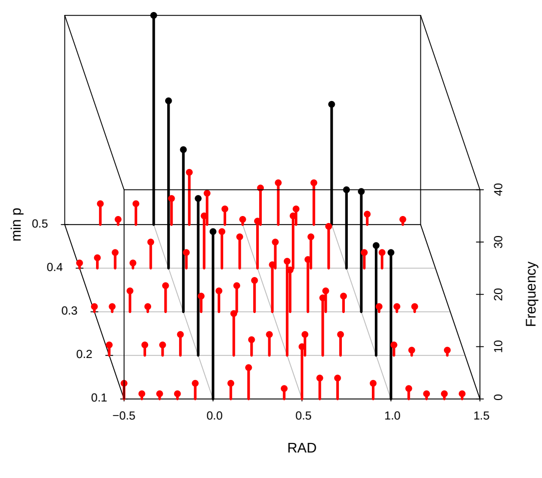
Figure 4: Summary Statistics, List 5

This figure displays summary statistics for List 5 (symmetrical ambiguity). The left graphic contains boxplots showing the distribution of individual valuations (blue color) and estimations about others' valuations (red color) for each setting. The red line represents the valuation boundary at maximum ambiguity aversion for a participant with median risk attitudes according to List 3. The blue line represents the valuation boundary at neutral attitudes towards ambiguity for a participant with median risk attitudes according to List 3. The right graphic shows the distributions of the relative ambiguity discount *RAD* of individual participants in different settings. Each setting is characterized by *min p*, i.e. the *minimum* probability that a white ball is drawn. The results are based on observations from 138 participants.

Valuations



Relative Ambiguity Discount



any obtained valuation difference across the situations is only attributable to attitudes towards risk and ambiguity, and not to a changing expected value due to more white balls in the urn. After extracting the effect of risk, the pure effect of ambiguity can be observed.

Table 6 and Figure 4 display the results of the setting involving risk and ambiguity in the symmetrical case. The first case with minimum numbers of 50 white and 50 black balls is a case with risk only, involving no ambiguity, since the composition of the urn is known completely. The setting of this case corresponds exactly to the urn in List 3 with 50 white and 50 black balls. A comparison of these two cases with respect to mean and median valuations (but also the quantiles) shows that these numbers are essentially the same. This demonstrates that there is some stability of the behavior of experiment participants during the course of the experiment. As mentioned before, the median participant is risk-neutral.

The results in Table 6 demonstrate that both mean and median valuations in almost all settings decrease monotonically as the degree of ambiguity increases and the fraction of balls in the urn with unknown color becomes larger. Only in the last setting, the special case of complete ambiguity, i.e. nothing is known about the number of white or black balls in the urn, there is a slight but remarkable increase in valuations again. But overall, median valuations drop from 5 in the first setting to a low of 3.5 in the next-to-last setting. Since risk and expected return are the same across the settings, this effect is due to ambiguity only. This ambiguity discount is very substantial and it exists although the participants were allowed to choose the winning color, demonstrating the strong valuation impact of ambiguity.

Figure 4 presents boxplots for all the settings of List 5. The results are essentially the same as in List 4: there is wide-spread ambiguity-aversion among participants, all degrees of ambiguity aversion are present, and the median relative ambiguity discount takes values ranging from 22 percent to 50 percent.

4.2.4 List 6: Risk and Ambiguity - multiple states

List 6 presents a final variation of the ambiguity setting. It includes risk and ambiguity in multiple states. There are two changes made to the previous settings. First, the balls in the urns may be of a third color, red, in addition to white and black. Second, the exact number of white balls in the urns is known to the participants, instead of the minimum number, as in the other ambiguity settings. In this setting, ambiguity stems from the fact that the balls with unknown color may be of two specific colors (black and red), for which no information is available.

Table 7 and Figure 5 display the results of the setting involving risk and ambiguity in the case of multiple states. In List 6, participants in general rarely show high degrees of ambiguity aversion. The median ambiguity discounts are 1 percent and 12 percent, reflecting a slight aversion of experiment participants against ambiguity. These discounts are substantially lower than the discounts observed in the other treatments. This suggests that the degree of ambiguity aversion to some extent seems to depend on framing.

The results obtained from the experiments suggest that: 1) ambiguity aversion exists, 2)

Table 7: Summary Statistics, List 6

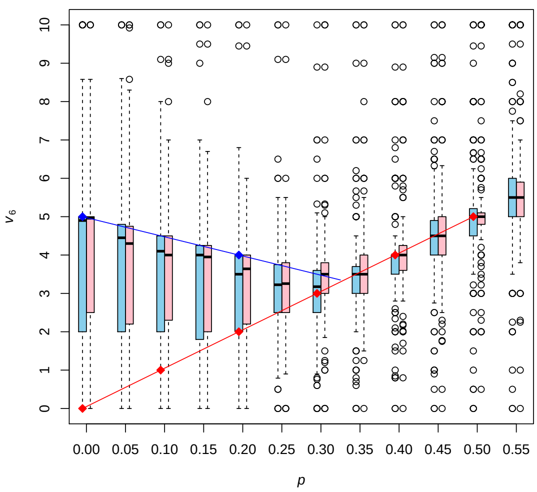
This table displays summary statistics for List 6, a setting with both risk and ambiguity. Panel A displays the actual decisions taken by the subjects, aggregated over the subjects. Panel B displays the estimates of the subjects concerning the median actual decision over all subjects. Panel C displays the difference between a subject's decision and his estimation. Panel D displays the quality of the estimation, represented as difference between a subject's estimation and the median decision. Panel E displays the relative ambiguity discount *RAD*. Panel F displays the percentage number of subjects choosing white, black, or red as winning color. Each column represents a different situation with a different composition of the urn, ranging from exactly 0 white balls to exactly 100 white balls. While the number of white balls in the urn is known, the number of black and red balls is unknown. *Obs.* shows the number of subjects. $Pct > 0$, $Pct = 0$, and $Pct < 0$ show the share of subjects for which the corresponding value is larger than zero, equal to zero, and smaller than zero, respectively. *Q-range* is the difference between the 25th percentile and the 75th percentile.

Panel A: Required Price												
$\#white =$	0	5	10	15	20	25	30	35	40	45	50	55
Mean	4.01	3.85	3.66	3.44	3.30	3.22	3.16	3.45	3.98	4.45	4.96	5.59
Std.	2.56	2.20	1.94	1.85	1.62	1.55	1.47	1.52	1.58	1.67	1.76	1.84
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25%	2.00	2.09	2.00	1.85	2.00	2.50	2.50	3.00	3.50	4.00	4.50	5.00
Median	4.90	4.45	4.10	4.00	3.50	3.23	3.18	3.50	4.00	4.50	5.00	5.50
75%	5.00	4.80	4.50	4.25	4.00	3.75	3.58	3.70	4.00	4.88	5.21	6.00
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138	138
Panel B: Estimation of Median Required Price												
$\#white =$	0	5	10	15	20	25	30	35	40	45	50	55
Mean	4.01	3.88	3.73	3.50	3.39	3.32	3.48	3.72	4.20	4.67	5.21	5.63
Std.	2.29	2.09	1.84	1.61	1.42	1.30	1.51	1.38	1.50	1.59	1.57	1.53
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.50	0.00
25%	2.63	2.24	2.33	2.00	2.21	2.50	3.00	3.00	3.63	4.00	4.83	5.00
Median	4.96	4.30	4.00	3.95	3.64	3.26	3.50	3.50	4.00	4.50	5.00	5.50
75%	5.00	4.75	4.50	4.25	4.00	3.79	3.80	4.00	4.24	5.00	5.08	5.85
Max	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00	10.00
Obs.	138	138	138	138	138	138	138	138	138	138	138	138
Panel C: Decision minus Estimation												
$\#white =$	0	5	10	15	20	25	30	35	40	45	50	55
Mean	-0.01	-0.03	-0.07	-0.06	-0.09	-0.10	-0.31	-0.27	-0.22	-0.22	-0.25	-0.04
Std	1.65	1.66	1.63	1.63	1.62	1.62	1.72	1.66	1.66	1.71	1.68	1.78
$Pct > 0$	0.22	0.24	0.20	0.23	0.21	0.20	0.20	0.20	0.21	0.22	0.23	0.33
$Pct = 0$	0.51	0.44	0.46	0.46	0.50	0.49	0.46	0.50	0.48	0.48	0.51	0.44
$Pct < 0$	0.26	0.32	0.33	0.31	0.29	0.31	0.33	0.30	0.31	0.30	0.25	0.23
Obs.	138	138	138	138	138	138	138	138	138	138	138	138
Panel D: Quality of Estimation												
$\#white =$	0	5	10	15	20	25	30	35	40	45	50	55
Mean	-0.89	-0.57	-0.37	-0.50	-0.11	0.10	0.30	0.22	0.20	0.17	0.21	0.13
Std	2.29	2.09	1.84	1.61	1.42	1.30	1.51	1.38	1.50	1.59	1.57	1.53
$Pct > 0$	0.51	0.49	0.48	0.41	0.51	0.52	0.57	0.33	0.29	0.33	0.25	0.28
$Pct = 0$	0.00	0.00	0.01	0.09	0.04	0.00	0.00	0.33	0.41	0.35	0.48	0.35
$Pct < 0$	0.49	0.51	0.51	0.50	0.45	0.48	0.43	0.34	0.30	0.32	0.27	0.38
Obs.	138	138	138	138	138	138	138	138	138	138	138	138
Panel E: Relative Ambiguity Discount												
$\#white =$	0	5	10	15	20	25	30	35	40	45	50	55
Median	0.01				0.12							
Q-range	0.50				0.50							
Panel F: Chosen Color												
$\#white =$	0	5	10	15	20	25	30	35	40	45	50	55
White	0.138	0.123	0.152	0.188	0.196	0.196	0.333	0.783	0.891	0.935	0.957	0.971
Black	0.551	0.609	0.522	0.536	0.551	0.529	0.428	0.145	0.080	0.051	0.036	0.022
Red	0.312	0.268	0.326	0.275	0.254	0.275	0.239	0.072	0.029	0.014	0.007	0.007

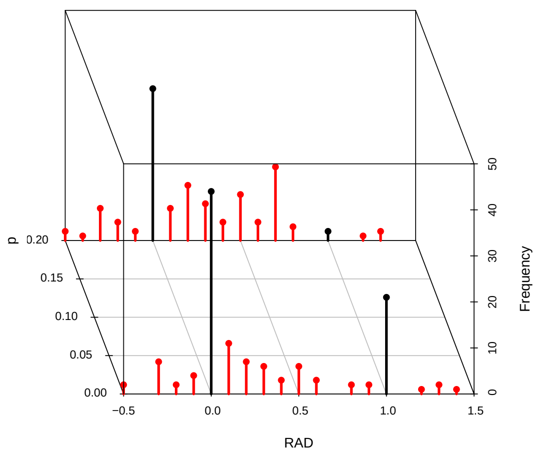
Figure 5: Summary Statistics, List 6

This figure displays summary statistics for List 6 (balls with three colors). The left graphic contains boxplots showing the distribution of individual valuations (blue color) and estimations about others' valuations (red color) for each setting. The red line represents the valuation boundary at maximum ambiguity aversion for a participant with median risk attitudes according to List 3. The blue line represents the valuation boundary at neutral attitudes towards ambiguity for a participant with median risk attitudes according to List 3. The right graphic shows the distributions of the relative ambiguity discount *RAD* of individual participants in different settings. Each setting is characterized by p, i.e. the *exactly known* probability that a white ball is drawn. The results are based on observations from 138 participants.

Valuations



Relative Ambiguity Discount



ambiguity aversion is different from that assumed in several theories, 3) ambiguity aversion is very different across individuals, 4) the attitudes of individual subjects concerning ambiguity correspond to their expectations about others' attitudes, and 5) ambiguity aversion differs substantially from risk aversion. Overall, the obtained results suggest that human aversion against ambiguity exists and that it is much more pronounced than human aversion against risk. This suggests that for model applications, it is important to capture both, attitudes towards risk and attitudes towards ambiguity, having important implications for asset pricing. Finally, while most theoretical work on ambiguity builds on MEU, our results provide evidence that MEU does not adequately capture individual attitudes towards ambiguity.

4.3 Estimating Parameters for Risk Aversion and Ambiguity Aversion

The results as evaluated in the previous sections indicate that there is a widespread aversion against ambiguity and that subjects are imposing a value discount on lotteries involving ambiguity. The value discount due to ambiguity is an additional value discount which is not related to the risks involved, since risk is controlled for. However, the valuation discounts for risk and ambiguity, as investigated in the previous sections, cannot be compared directly, because the discount not only depends on personal attitudes, but also on the amount of risk and ambiguity inherent in a particular situation. This is a problem, since a measure for comparing specific amounts of risk and ambiguity first has to be developed.

This problem can be resolved by estimating the parameters of risk aversion and ambiguity aversion, instead of focussing on valuation discounts. In classical utility theory, the aversion of subjects against risk is typically captured by a specific risk aversion parameter. In a similar manner, this section aims at identifying and estimating a parameter that captures the ambiguity aversion of individual subjects and relating it to the corresponding parameter of risk aversion. Once the parameters for risk aversion and ambiguity aversion are estimated, they can be compared directly with respect to their impact and direction.

Izhakian and Benninga (2008) derive a formal expression relating the uncertainty premium to both risk aversion and ambiguity aversion, assuming a SP-utility function as introduced by Klibanoff, Marinacci, and Mukerji (2005). This allows to jointly estimate the parameters for risk aversion and ambiguity aversion. However, this expression relies on a Taylor-approximation and is found to be too inaccurate for our purpose, since it cannot deal with a variation of ambiguity as large as in the settings of our experiment.

Thus, we refer directly to Klibanoff, Marinacci, and Mukerji (2005). Since a joint estimation of the two parameters is not feasible, we apply a two-stage procedure to estimate the two parameters separately. In the first stage, the parameter of risk aversion γ is estimated in the risk-only setting of List 3. In the second stage, the obtained parameter of risk aversion is used to estimate the parameter of ambiguity aversion η in the risk-and-ambiguity settings of Lists 4-6.

We will now focus on the models for risk/ambiguity and the approach how to extract the parameters. In particular, we consider two types of utility functions capturing the individual preferences towards risk and ambiguity. The first class of functions is power utility for both risk and ambiguity, implying constant relative risk aversion and constant relative ambiguity aversion (CRRA-CRAA). The second class is exponential utility for both risk and ambiguity, implying constant absolute risk aversion and constant absolute ambiguity aversion (CARA-CAAA). We will discuss both classes of utility functions and the extraction method for the parameters of risk aversion and ambiguity aversion in order.

4.3.1 Power Utility Function (Method 1)

As mentioned above, the first stage of obtaining individual attitudes consists of estimating the parameter of risk aversion. Thus, based on the observations from List 3, we can estimate the parameter of risk aversion γ from the utility function in a risk-only situation. We have:

$$V(m,\gamma) = \frac{m}{100}\, 10^{(1-\gamma)}, \tag{13}$$

with m representing the number of white balls in the urn. By the BDM mechanism we observe the (empirical) sure equivalent $S_e(m)$ and so we get:

$$\begin{aligned} S_e^{(1-\gamma)} &= \frac{m}{100}\, 10^{(1-\gamma)} &\quad (14)\\ \log \frac{S_e}{10} &= \frac{1}{1-\gamma} \log \frac{m}{100}. &\quad (15) \end{aligned}$$

From this linear equation for the dependent variable $\log S_e$ and the independent variable $\log \frac{m}{100}$, we can estimate γ form all observations $m > 0$ of a subject.

The second stage consists of estimating the parameter of ambiguity aversion. We follow KKM, according to which ambiguity aversion is represented by a concave deformation of second order beliefs. Since the nature of ambiguity differs in the three treatment involving both risk and ambiguity, the utility functions differ for Lists 4-6. For the setting of List 4, we assume that the utility function is given by:

$$V(m,\gamma,\eta) = \sum_{k=m}^{100} \frac{1}{101-m} \left(\frac{k}{100}\, 10^{(1-\gamma)} \right)^{(1-\eta)}, \tag{16}$$

with m representing the minimum number of white balls in the urn and γ (η) representing the degree of risk (ambiguity) aversion. Correspondingly, the sure equivalent of a decision maker who is characterized by an ambiguity utility function with parameter η in List 4 is given by:

$$
\begin{aligned}
S(m,\gamma,\eta)^{(1-\gamma)(1-\eta)} &= \sum_{k=m}^{100} \frac{1}{101-m} \left(\frac{k}{100}\, 10^{(1-\gamma)} \right)^{(1-\eta)} && (17)\\
S(m,\gamma,\eta) &= 10 \left(\frac{1}{101-m} \sum_{k=m}^{100} \left(\frac{k}{100} \right)^{(1-\gamma)} \right)^{\frac{1}{(1-\gamma)(1-\eta)}} . && (18)
\end{aligned}
$$

We observe $S_e(m)$, and γ is known from List 3. So we estimate η by minimizing the sum of squared errors:

$$
\sum_m \left(S_e(m) - S(m,\gamma,\eta) \right)^2 \tag{19}
$$

For List 5, we estimate η in an analogous way to the above least square method with:

$$
S(m,\gamma,\eta) = 10 \left(\frac{1}{101-2m} \sum_{k=m}^{100-m} \left(\frac{k}{100} \right)^{(1-\gamma)} \right)^{\frac{1}{(1-\gamma)(1-\eta)}} , \tag{20}
$$

where m is the minimum number of white *and* black balls.

For decisions in List 6, subjects can choose between a risky lottery (choosing white as the winning color) and a lottery also involving ambiguity. They will maximize $\max\{V(m,\gamma,\eta|color \neq white) V(m,\gamma,\eta = 0, color = white)\}$. An ambiguity-neutral decision maker would choose white only if the number of white balls is greater than 33. If m is now the number of white balls, we get for:

$$
\begin{aligned}
S^{(1-\gamma)(1-\eta)} &= \begin{cases} \frac{m}{100}\, 10^{(1-\gamma)} & \text{if the color is white and } m > 33 \\ \\ \sum_{k=0}^{100-m} \frac{1}{101-m} \left(\frac{k}{100}\, 10^{(1-\gamma)} \right)^{(1-\eta)} & \text{else} \end{cases} \\
S(m,\gamma,\eta) &= \begin{cases} 10 \left(\frac{m}{100} \right)^{\frac{1}{(1-\gamma)}} & \text{if the color is white and } m > 33 \\ 10 \left(\frac{1}{101-m} \sum_{k=m}^{100} \left(\frac{k}{100} \right)^{(1-\gamma)} \right)^{\frac{1}{(1-\gamma)(1-\eta)}} & \text{else} \end{cases}
\end{aligned}
$$

and again we choose η so that $S(\cdot)$ is the best fit to the observed data S_e (in the sense of the least-square method).

Remark: The term $0^{(1-\alpha)}$ is not defined for $\alpha > 1$. Hence, in some cases, $S(\cdot)$ is not defined, and we have to restrict the regression to a subset of observations. The estimation of γ is restricted to the observations $m > 0$ (the number of white balls). In the same way the estimation of η_l in List 4 and 5 is restricted to the observation where the minimum number of unsure white balls is greater then 0. In List 6, the minimum number of winning balls in the ambiguity urn is 0 for all observations. Thus, we have to restrict η_6 to values smaller or equal to 1. For our computation we restricted our search for the best η_l to values in the interval

$[-.99, 10]$ and for List 6 to values in $[-.99, .99]$.

4.3.2 Exponential Utility Function (Method 2)

Let us now try another approach where risk is modeled by constant absolute risk aversion (CARA): $u(x) = \frac{\exp(-\lambda x)}{-\lambda}$ if $\lambda \neq 0$) and $u(x) = x$ if $\lambda = 0$ and ambiguity is modeled by constant absolute ambiguity aversion (CAAA): $\phi(\xi) = \frac{\mu(-\mu\xi)}{-\eta}$ if $\mu \neq 0$) and $\phi(\xi) = \xi$ if $\mu = 0$.

Let $E_k[u]$ be the expected value of an urn with k winning balls.

$$E_k[u] = \begin{cases} \frac{k}{100} \frac{\exp(-\lambda 10)}{-\lambda} + \frac{100-k}{100} \frac{\exp(-\lambda 0)}{-\lambda} & \text{if } \lambda \neq 0 \\ \frac{k}{10} & \text{if } \lambda = 0 \end{cases} \tag{21}$$

and let $E[\phi]$ be the expected value of the set of urns involving ambiguity, assuming that all possible urns have the same probability to be chosen.

$$E[\phi] = \begin{cases} \sum_k \frac{1}{101-m} \frac{\exp(-\mu E_k[u])}{-\mu} & \text{if } \mu \neq 0 \\ \sum_k \frac{1}{101-m} E_k[u] & \text{if } \mu = 0 \end{cases} \tag{22}$$

The sure equivalent of a decision maker who is characterized by a CARA-CAAA-utility function is then given by:

$$E[\phi] = \frac{\exp(-\mu \frac{\exp(-\lambda S)}{-\lambda})}{-\mu} \tag{23}$$

We are now able to compute for any combination of λ and μ the sure equivalent for List 3 to 6. By the least-squares method we can then estimate the best approximation for the parameters to our data set. Since in List 3, there is no ambiguity, we set $\mu = 0$ and compute for every subject the risk parameter λ. We separately estimate the ambiguity parameter for Lists 4 to 6.

4.3.3 Parameter Estimates

An overview of the estimated parameters of risk aversion and ambiguity aversion is given in Table 8. The parameter estimates based on power utility functions are displayed in Panel A, and the parameter estimates based on exponential utility functions are displayed in Panel B. Note that the ambiguity aversion μ will be infinity if a decision maker chose the minimum. The results indicate that the median participant is risk-neutral, but ambiguity-averse. It is worth noting that parameter estimates for ambiguity aversion are similar for List 4 and 5, they differ substantially for List 6, with a much less pronounced ambiguity aversion.

4.4 Relation between risk aversion and ambiguity aversion

The relation between risk aversion and ambiguity aversion is given in Figure 6. Risk and ambiguity aversion are captured in different ways, i.e. based on relative valuation discounts (without assuming a particular class of utility function) and based on different utility functions

Table 8: Estimated parameters of risk aversion and ambiguity aversion

This table displays the estimated parameters of risk aversion and ambiguity aversion in various treatments. Panel A displays the parameter estimates as obtained by using a power utility function (CRRA-CRAA). Panel B displays the parameter estimates as obtained by using an exponential utility function (CARA-CAAA). γ (λ) stands for the estimated risk aversion and η (μ) stands for the estimated ambiguity aversion. The numbers behind η (μ) stand for the corresponding treatment.

Panel A: Power Utility				
	γ	η_4	η_5	η_6
Min	-0.1016	-0.9900	-0.990	-0.9900
25%	-0.0002	-0.1475	0.000	-0.9375
Median	0.0000	2.1500	1.700	0.1900
75%	0.2539	∞	8.275	0.9200
Max	0.9927	∞	∞	0.9900
Panel B: Exponential Utility				
	λ	μ_4	μ_5	μ_6
Min	-1.0000	-1.000	-1.000	-1.0000
25%	-0.0070	0.000	0.000	-0.0055
Median	0.0000	0.551	0.512	0.0850
75%	0.0515	3.120	2.688	0.6985
Max	2.0320	∞	∞	∞

for risk and ambiguity (power utility and exponential utility). The three diagrams are based on the degree of ambiguity aversion estimated from List 4, 5, and 6, respectively. The diagrams confirm the results seen earlier that ambiguity-aversion is u-shaped, with many participants showing either no ambiguity aversion or very high degrees of ambiguity aversion. Moreover, it can be seen that there is no clear relation between risk and ambiguity.

Table 9 displays the results of regressions relating attitudes towards ambiguity to attitudes towards risk to determine whether they are correlated. It can be seen that in three cases, there is a negative relation between attitudes towards risk and ambiguity, while there is a positive relation in one case. However, only in the case of Model (1), there is a significantly negative relation. Thus, overall, if there is any correlation between the risk aversion and the ambiguity aversion of an individual, then it is slightly negative. This stresses the fact that risk and ambiguity are not only two different concepts, but also that individual attitudes towards risk and ambiguity typically differ.

So we conclude: (1) risk and ambiguity are different concepts, (2) they both matter, (3) individual preferences concerning risk and ambiguity are largely unrelated or even negatively related, and (4) the extent of ambiguity aversion depends on the specific decision.

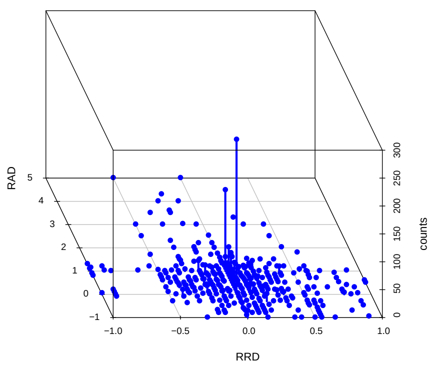
5 Conclusion

We introduce a new measure, the relative ambiguity discount *RAD*, that, after controlling for risk, measures the discount due to ambiguity relative to the possible discount (represented as the difference between the worst case and the case of neutrality towards ambiguity). We find

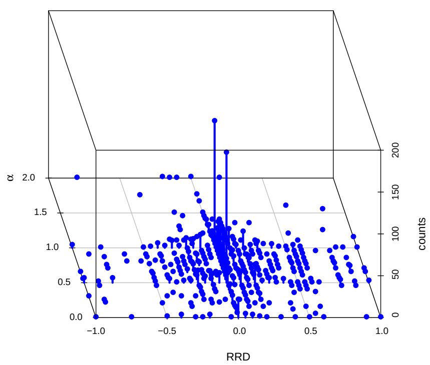
Figure 6: Relation between risk aversion and ambiguity aversion

These diagrams display the relation between risk aversion and ambiguity aversion for the individual participants. Three types of measures are applied, i.e. (1) relative risk discounts RRD and relative ambiguity discounts RAD, (2) relative risk discounts RRD and ambiguity aversion measured by α, (3) estimated coefficients of risk aversion γ and ambiguity aversion η based on power utility, and (4) estimated coefficients of risk aversion λ and ambiguity aversion μ based on exponential utility. In each case, the measure of risk aversion is obtained from the risk-only setting of List 3. The measure of ambiguity aversion is obtained from List 4, 5, and 6, controlling for the risk aversion measured in List 3. While relative discounts and values for α are observed for each setting, coefficients obtained from utility functions are observed for each list. Thus, there are 12 RRD-RAD combinations per participant, while for the coefficients, there are three risk-ambiguity combinations per participant. For power (exponential) utility functions, extreme coefficients of ambiguity aversion are set equal to -1(-1) or 10(5), depending on whether they are very small or very large.

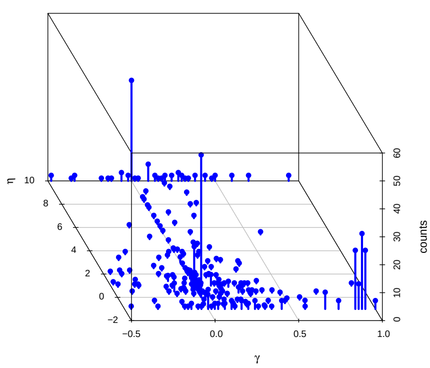
Relative Discounts



α-MEU



Power Utility



Exponential Utility

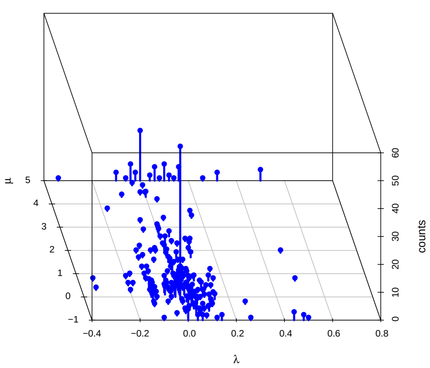


Table 9: Relation between risk aversion and ambiguity aversion

This table displays the results of regressions relating attitudes towards ambiguity to attitudes towards risk. As measures of ambiguity, the relative ambiguity discount RAD and the parameter of ambiguity aversion based on power utility as well as exponential utility are applied. Model (1) is based on relative risk and ambiguity discounts. Model (2) is based on α-MEU. Model (3) displays the results as obtained by using a power utility function (CRRA-CRAA) for both risk and ambiguity. Model (4) displays the results as obtained by using an exponential utility function (CARA-CAAA) for risk and ambiguity. γ (λ) stands for the estimated risk aversion in the power utility (exponential utility) setting.

	(1) Relative Discount	(2) Alpha	(3) Power utility	(4) Exponential utility
RRD	-1.1707*	0.1575		
	(-2.34)	(1.72)		
γ			-0.3642	
			(-1.38)	
λ				-0.3537
				(-1.06)
Constant	-0.0599	0.4570***	2.0413	0.1019
	(-0.29)	(6.22)	(1.27)	(0.18)
Subject dummies	yes	yes	yes	yes
Situation dummies	yes	yes		
List dummies	yes	yes	yes	yes
Observations	1586	1618	414	414
R^2	0.266	0.279	0.633	0.630

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the values of RAD to be quite stable across different settings for individual participants. We find that human aversion against ambiguity exists, and that ambiguity aversion is quite stable for the individual subjects across different treatments. However, ambiguity aversion differs substantially across individuals: About one third of the subjects showed no ambiguity aversion, one third showed maximum aversion against ambiguity, and one third showed intermediate values of ambiguity aversion. Thus, the extreme cases of MEU and Laplace-SEU are not consistent with the data as a general rule: Although many individuals lie on the extremes, the median degree of ambiguity aversion is well between the extremes of no aversion and maximum aversion.

Moreover, we find that ambiguity aversion differs from risk aversion. The obtained results also suggest that human aversion against ambiguity is even more pronounced than human aversion against risk. This suggests that for model applications, attitudes towards ambiguity are more relevant than attitudes towards risk. Finally, we find that the own ambiguity discount imposed by individual subjects corresponds closely to the subjects' expectations regarding the ambiguity discount of others. Since expectations correspond to own actions and perceptions, a stable ambiguity discount can be expected in market prices. Since heterogeneity among subjects with respect to their attitudes towards ambiguity is quite large, future research on how ambiguity influences equilibrium market prices seems very promising.

Overall, the presented findings have tremendous implications for asset pricing, since huge price discounts are possible due to the ambiguity aversion of market participants in combination with the existence of ambiguity in many situations and for many assets. Moreover, the mechanics outlined in this paper suggest that indeed, sudden shifts in ambiguity in line with Caballero and Kurlat (2009) may lead to substantial price movements. Overall, the presented findings call for a broadened attention to ambiguity in all pricing contexts.

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