Preferences for the Resolution of Risk and Ambiguity*

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Abstract

Generalized recursive utility models often imply that agents have a preference over the timing of uncertainty resolution. Laboratory elicitations of subject preferences generally provide direct evidence in support of this implication, but only in the domain of risk. We provide the first experimental examination of uncertainty resolution with respect to ambiguity, in addition to risk. The modal subject exhibits a preference for both early resolution of risk and ambiguity, but with only a minimal willingness to pay to realize either over late resolution. While preferences in both domains are positively correlated, the strength of that correlation varies based on ambiguity attitudes. Of ten, commonly used, representative recursive utility models, either the generalized recursive smooth ambiguity model or the generalized recursive variational preference model best explains our findings. The distinction depends on whether we consider subjects' token willingness to pay as a true preference or indifference, respectively.

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1 Introduction

Unlike discounted expected utility theory, many models of generalized recursive utility relax the assumption of a direct linkage between preferences of objective uncertainty and intertemporal substitutability (e.g., Kreps and Porteus, 1978; Chew and Epstein, 1989; Epstein and Zin, 1989; Weil, 1990). These models have consequential implications in empirical macroeconomics and finance literature, explaining several empirical anomalies in applications.[1] In many cases, these models also require that agents have a preference over when uncertainty is to be resolved, independent of instrumental concerns. Ongoing debates concern whether such preferences are plausible, and, if plausible, whether people prefer early or late resolution of uncertainty. Experimental evidence is generally divided, and elicitation of these preferences may be complicated by other factors (see Brown and Kim, 2013; Nielsen, 2020, for surveys).

As conventionally defined, "uncertainty" includes both elements of "risk" and "ambiguity" (Knight, 1921). The objective domain of uncertainty, risk, describes a situation where the result is not known, but the underlying probability could be theoretically or empirically determined; the subjective domain of uncertainty, ambiguity, describes a situation where people do not know the basis for objective probability. Notably, all aforementioned experimental studies that elicit preferences for uncertainty resolution have focused only on risk. However, recent theoretical studies have begun to consider environments with subjective uncertainty exclusively (Strzalecki, 2013; Li, 2020a; Marinacci et al., 2023); the models they examine build in strict preferences for ambiguity resolution, but not risk.

This paper provides the first experimental elicitation of preferences for uncertainty resolution in the subjective domain as well as in the objective domain. We elicit separate preferences over ambiguity and risk resolution and examine their interrelation with ambiguity attitude. In particular, we find that a plurality of the subjects (47.4%) prefer early resolution of risk and a majority (63.7%) prefer early resolution of ambiguity. However, we caution the reader on interpretation as most subjects do not display a willingness to pay 5 cents or more for their preferred form of resolution. Beyond the aggregate averages, individ-

[1] For example, the generalized recursive utility models in Bansal and Yaron (2004), Epstein et al. (2014), Collard et al. (2018), Drechsler (2013), Jeong et al. (2015), and Ju and Miao (2012) can better explain the equity premium, the risk-free rate, and/or the volatility puzzles, etc.

ual subject profiles are correlated across preferences in non-random ways. While resolution preferences are positively correlated across domains, ambiguity attitude separately affects the likelihood of preferring early resolution of ambiguity.

To best characterize the heterogeneities across these individual subject preference profiles, we investigate ten representative recursive utility models under uncertainty. We include the canonical discounted expected utility model (henceforth the DEU model), the dynamic maxmin expected utility model of Gilboa and Schmeidler (1989) and Epstein and Schneider (2003) (henceforth the MEU model), the dynamic smooth ambiguity model of Klibanoff et al. (2005, 2009) and Seo (2009) (henceforth the KMM model), the dynamic multiplier preference model of Hansen and Sargent (2001) and Strzalecki (2011) (henceforth the DMP model), the dynamic variational preference model of Maccheroni et al. (2006a) (henceforth the DVP model), the generalized recursive utility model of Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990) (henceforth the EZ model), the generalized recursive maxmin expected utility model of Hayashi (2005) (henceforth the H model), the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) (henceforth the HM model), the generalized recursive multiplier preference model (henceforth the RMP model), and the generalized recursive variational preference model (henceforth the RVP model).[2]

We analyze the ten models under constant relative risk aversion (CRRA) and constant elasticity of substitution (CES) restrictions. Only the H, HM, RMP, and RVP models can simultaneously accommodate non-indifferent preferences for risk resolution, non-indifferent preferences for ambiguity resolution, and non-neutral ambiguity attitudes. The baseline EZ model can only accommodate ambiguity-neutral attitudes and predicts consistent behaviors in the risk- and ambiguity-resolution experiments. A deductive examination reveals that the HM model not only has the flexibility of accommodating divergent strict preferences for risk resolution and ambiguity resolution, but also allows ambiguity attitudes to affect the connection between risk- and ambiguity-resolution preferences, as found in our data. Under the H model, the ambiguity-resolution preference that is rationalizable globally (i.e., for all consumption processes) is either indifferent or inherited from the risk-resolution preference.

[2] We use the term "recursive utility model" to refer to both the canonical discounted expected utility model and the other more general models.

There exist parameter values under which the RMP model with ambiguity aversion can accommodate an indifferent or early risk-resolution preference as well as an early ambiguity-resolution preference. The RVP model nests the H and the RMP models and accommodates preference profiles rationalizable by either.

In our penultimate section, we investigate which model under the CRRA-CES restriction fits our observed data best using an objective function that penalizes models for being able to rationalize a broader set of action profiles. A key interpretation is whether we should consider subjects that only display a token willingness to pay for their preferred form of resolution as having strict preferences or being indifferent. Under the former view, which we refer to as "optimistic," the baseline EZ model fares substantially worse than the H, HM, RMP, and RVP models. The HM model performs best, outperforming all other four models in global rationalization. Under the latter, "pessimistic" view, the modal subject is indifferent over both forms of resolution but ambiguity averse. Hence, the MEU model and its generalizations (DVP, H, and RVP models)—the only models that can rationalize such a preference profile—are the four best-performing models, with RVP best overall. Because the DEU model cannot accommodate ambiguity aversion, it performs the worst.

While the exact model we endorse—the HM or RVP model—is left open to interpretation, a few key findings are robust to either view. First, models that allow for both neutral and averse ambiguity attitudes tend to perform well, as those preferences are exhibited by most of our subjects. Second, models that account for strict preferences in both risk and ambiguity resolution also perform well. Third, both the HM and RVP allow multiple forms of divergent preferences in risk and ambiguity resolution among ambiguity-averse agents, which is not true for most other models that we examine.

There have been several previous experimental studies on uncertainty resolution in the domain of risk. Nielsen (2020) provides a thorough review, categorizing and summarizing findings in studies with or without incentivized choices, as well as whether the risk is pre-determined or future-determined. Early studies surveyed participants on their preferences and did not incentivize choice (Chew and Ho, 1994; Ahlbrecht and Weber, 1996, 1997; Lovallo and Kahneman, 2000). Later studies incentivized choice but were potentially confounded by the fact that the information revealed is instrumental (Von Gaudecker et al., 2011; Brown and Kim, 2013; Kocher et al., 2014; Zimmermann, 2015; Meissner and Pfeiffer, 2022). That is, learning the information early may pose an additional benefit to an individual outside of these non-instrumental preferences. In both categories, the literature often, but not always, finds a preference for the early resolution of uncertainty in the risk domain.

Among the studies that do not provide instrumental information, those rely on the future-determined risk—where the risk has yet to be determined—generally find preferences for late or gradual resolution (Budescu and Fischer, 2001). Those rely on the pre-determined risk—where the risk is determined but yet to be resolved for the subject—generally find preferences for early resolution (Eliaz and Schotter, 2010; Ganguly and Tasoff, 2016; Falk and Zimmermann, 2017). Nielsen (2020) is the first to note this relationship and demonstrates this result in a unified, non-instrumental framework. That is, she finds a preference for early resolution with the pre-determined risk and late or gradual resolution with the isomorphic future-determined risk.

We borrow heavily from Nielsen (2020) in eliciting subjects' preference over risk resolution with non-instrumental information, though we are not explicit about whether the risk is pre-determined or future-determined. Our ambiguity resolution elicitation is a unique design. All choice sets include gradual resolution of information options (non-skewed, positively-skewed, and negatively-skewed) in addition to early and late options.[3]

2 Experimental Design and Procedures

This paper investigates ten representative recursive utility models, the DEU, MEU, KMM, DMP, DVP, EZ, H, HM, RMP, and RVP models, which are briefly introduced in Section 1 and will be formally defined in Section 4.

Our experiment elicits preferences over risk and ambiguity resolution, as well as ambiguity attitudes. As a first step, we will characterize these preferences on the aggregate. The existence of strict preferences or non-neutral ambiguity attitudes in one of these areas can "falsify" some models as not all models can accommodate strict preferences and a non-neutral

[3]Positive skewness eliminates more uncertainty about the good state and negative skewness is the opposite. Focusing on an environment with objective uncertainty, Masatlioglu et al. (2023) find that subjects prefer a positively-skewed information structure over a symmetric, negatively-skewed one.

	Allows non-indifference over risk resolution?	Allows non-indifference over ambiguity resolution?	Allows non-neutral ambiguity attitudes?
DEU			
MEU		✓	✓
KMM		✓	✓
DMP		✓	✓
DVP		✓	✓
EZ	✓	✓	
H	✓	✓	✓
HM	✓	✓	✓
RMP	✓	✓	✓
RVP	✓	✓	✓

Table 1: Models accommodating non-indifferent resolution preferences and non-neutral ambiguity attitudes.

ambiguity attitude. (Alternatively, one may consider it inappropriate to "test" a model for preferences it cannot accommodate.) In Table 1, a checkmark shows that the theoretical model can incorporate non-indifferent preference regarding risk resolution, non-indifferent preference regarding ambiguity resolution, or non-neutral ambiguity attitude under some parameter values. Technical arguments are provided in Appendix A.

The first column means that the EZ, H, HM, RMP, and RVP models can accommodate non-indifferent preferences in the timing of risk resolution under some parameter values. The second column implies all nine models except for the DEU model support non-indifference in the timing of ambiguity resolution under some parameter values.[4] The last column shows that all eight models except the DEU and EZ models can be used to explain non-neutral ambiguity attitudes. Hence, among these models, only the H, HM, RMP, and RVP models can simultaneously accommodate non-indifferent preferences for the timing of risk resolution and ambiguity resolution, as well as non-neutral ambiguity attitudes.

As a second step, we will investigate theory more thoroughly in Section 4 to identify ranges of parameters under constant relative risk aversion (CRRA) and constant elasticity of substitution (CES) restrictions so that different models can accommodate different ambiguity attitudes and uncertainty-resolution preferences. As will be detailed in Section 4.2, we impose the CRRA-CES restriction for multiple reasons. The restriction is prevalent in applied works, it has well-known implications in the risk-resolution literature, and without it, a decision

[4]Proposition 2 shows that under the (i)MEU model to be defined in Section 4.2, a subcategory of the MEU model, the DM is indifferent between early and late but may prefer one-shot resolution of ambiguity.

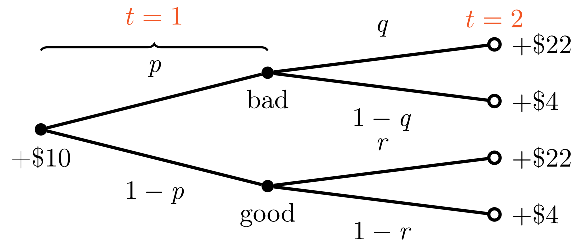


Figure 1: A general consumption process in risk-resolution preference elicitation.

Options	Information Structure
One-Shot Early (E)	(p=0.5, q=0, r=1)
Gradual, non-skewed (G)	(p=0.5, q=0.25, r=0.75)
Gradual, positively skewed (Gp)	(p=0.8, q=0.4, r=0.9)
Gradual, negatively skewed (Gn)	(p=0.2, q=0.1, r=0.6)
One-Shot Late (L)	(p=0.5, q=0.5, r=0.5)

Table 2: Options used in the risk-resolution preference elicitation.

maker may exhibit different resolution preferences for different consumption processes.

This process will culminate in Section 4.4 where we determine which of these models under the CRRA-CES restriction most efficiently and parsimoniously capture the distribution of individual preferences found for subjects in our experiment.

2.1 Risk-Resolution Preference Elicitation

In the risk-resolution preference elicitation, we follow the general framework of Nielsen (2020) (see Figure 1 therein). Subjects participate in a two-period consumption process. At the beginning of $t = 1$, subjects receive an advance payment.[5] At $t = 2$, a lottery is drawn and the additional payoff is realized. Ex-ante, the lottery has a 50/50 chance of a "high" ($22) or "low" ($4) prize. At the end of $t = 1$, subjects receive either a piece of "good" or "bad" news (see Figure 1) on the underlying probability of the lottery.

We follow Nielsen (2020) in viewing a vector (p, q, r) satisfying $pq + (1 - p)r = 0.5$ as an information structure, where the value p is the probability of receiving bad news, $q \leq 0.5$ is the probability of winning the high prize conditional on receiving bad news, and $r \geq 0.5$ is the probability of winning the high prize conditional on receiving good news.[6]

Subjects complete three choice tasks, selecting their most preferred information structure from a set of multiple options listed in Table 2.[7] The **One-Shot Early** (E) option resolves

[5] We interpret the $10 participation payment as the advance payment.

[6] As the focus of the paper is not on the treatment effect between the pre-determined risk and the future-determined risk, which has been thoroughly studied in Nielsen (2020), we do not explicitly mention if the risk is pre-determined or future-determined to the subjects.

[7] By focusing on five options, we depart from past precedent in the literature and fall into what we hope is a "sweet spot" between two extremes. At one end, Nielsen (2020) allows subjects to select resolution anywhere on the continuum between early and late. While this allows a much finer elicitation of gradual

all risk in the first stage. In contrast, the **One-Shot Late** (L) option resolves all risk in the second stage. The three other options gradually resolve risk. In the **Gradual, non-skewed** (G) option, good news and bad news are equally likely to arrive. In the **Gradual, positively skewed** (Gp) option, subjects are more likely to receive bad news ($p = 0.8$). However, the good news is highly informative; upon receiving it, the conditional probability of winning the high prize is 0.9 ($r = 0.9$). In the **Gradual, negatively skewed** (Gn) option, there is a higher likelihood of receiving good news ($p = 0.2$), but the informativeness of this good news is lower ($r = 0.6$) compared to the Gradual, positively skewed option. None of the gradual options is ex-ante more informative than others according to the Blackwell criterion.[8]

There is a 30-minute delay after subjects receive a piece of news at the end of $t = 1$ and before they observe the realization of the lottery in $t = 2$. A 30-minute time delay is considered a minimum, but appropriate, time delay in existing studies for determining preferences over resolution of uncertainty (Nielsen, 2020; Masatlioglu et al., 2023). To minimize the chances of an instrumental information issue (where subjects adjust their future consumption due to any early information), subjects completed Raven's Progressive Matrices.[9]

2.2 Ambiguity-Resolution Preference Elicitation

The ambiguity-resolution preference elicitation is similar to the risk-resolution preference elicitation. Subjects are involved in a two-period consumption process. At the beginning of $t = 1$, subjects receive an advance payment. In $t = 2$, a lottery is drawn and the payoff is realized. Subjects could earn a "high" ($22) or "low" prize ($4) from this lottery. However,

preferences, we instead discretize choice and provide three gradual risk-resolution options to allow for easier subject comprehension. At the other end, Masatlioglu et al. (2023) examine preferences over positively- and negatively-skewed gradual information structures by focusing solely on binary choices. While that method may eliminate concerns about violations of independence of irrelevant alternatives (IIA) (e.g., the "decoy" effect, see Huber et al., 1982), our approach allows subjects to express their most preferred information structure among a broader set of options, allowing us to test the theories more rigorously. For example, when a subject has a strict preference for early resolution of risk, she must prefer the early resolution option to all other information structures (i.e., both gradual and late), making our conclusions more robust.

[8] A Blackwell more-informative information structure has posteriors that are a mean-preserving spread of the posteriors under the Blackwell less-informative one. In our context, information structure (p_A, q_A, r_A) is said to resolve risk earlier (or be Blackwell more-informative) than (p_B, q_B, r_B) if $q_A < q_B$ and $r_A > r_B$.

[9] The Raven test is one of the most widely used methods to measure abstract reasoning and analytic intelligence. Previous studies have found that people with high Raven test scores more accurately predict others' behavior (Burks et al., 2009), and update their beliefs with fewer errors (Charness et al., 2011). In our study, the main purpose of this test is to make subjects stay focused during the time delay.

Options	Information Structure
One-Shot Early (E)	$\{\{0.1\}, \{0.4\}, \{0.6\}, \{0.9\}\}$
Gradual, non-skewed (G)	$\{\{0.1, 0.4\}, \{0.6, 0.9\}\}$
Gradual, positively skewed (Gp)	$\{\{0.1, 0.4, 0.6\}, \{0.9\}\}$
Gradual, negatively skewed (Gn)	$\{\{0.1\}, \{0.4, 0.6, 0.9\}\}$
One-Shot Late (L)	$\{\{0.1, 0.4, 0.6, 0.9\}\}$

Table 3: Options used in ambiguity-resolution preference elicitation.

subjects do not know the probability of winning the high prize, which is denoted by $\mathbf{p}$, at the beginning of $t = 1$.[10] Instead, subjects are given the following description:

> You will draw a ping pong ball out of a bag. The bag contains 60 ping pong balls, and each ball is either red or yellow. If you draw a red ping pong ball, then you will receive a high prize ($22). If you draw a yellow ball, then you will receive a low prize ($4). However, the precise composition of red ping pong balls versus yellow ones in the bag is unknown, although already determined. The only information now is that the proportion of red ping pong balls in the bag, denoted by $\mathbf{p}$, can only be one of the following numbers: 10%, 40%, 60%, and 90%. So the probability for you to win the high prize is one of the following four numbers: 0.1, 0.4, 0.6, or 0.9.

As the proportion of each color is unknown, the probability of drawing each color is unknown at the beginning of $t = 1$. It is not necessarily the case that 0.1, 0.4, 0.6, and 0.9 are drawn uniformly at random.[11] At the end of $t = 1$, subjects receive a piece of news about the value of $\mathbf{p}$. We view a partition of $\{0.1, 0.4, 0.6, 0.9\}$ as an information structure. Depending on the information structure, this news provides no, partial, or complete information about the winning probability. In three choice tasks, subjects choose their most preferred option from a set of information structures listed in Table 3.

The **One-Shot Early** (E) option resolves all ambiguity at $t = 1$. If a subject chooses One-Shot Early, she will be informed of the exact winning chance $\mathbf{p}$ at the end of $t = 1$. **One-Shot Late** (L) resolves no ambiguity until $t = 2$. Only a message that the value of $\mathbf{p}$ is 0.1, 0.4, 0.6, or 0.9 is given at $t = 1$, conveying no new information to the subject. The three gradual ambiguity-resolution information structures are partially revealing. **Gradual, non-skewed** (G) either reveals $\{0.1, 0.4\}$ or $\{0.6, 0.9\}$ at $t = 1$ with unknown probabilities.

[10]Notice that meaning of notation $\mathbf{p}$, i.e., the probability of winning the high prize, is different from the meaning of notation p, i.e., the probability of receiving the bad news in the risk-resolution experiment.

[11]If the distribution over winning probabilities is objectively given, then the information structure is a compound lottery. Halevy (2007), Abdellaoui et al. (2015), and Chew et al. (2017) find a positive correlation between ambiguity aversion and the inability to reduce compound lotteries. What would happen if one formulated the ambiguity-resolution experiment in the language of compound lotteries is an open question.

Elicitation Type	Choices	Available Options	Description
Risk Resolution	RR1	E, G, Gp, Gn, L	Unrestricted
	RR2	G, Gp, Gn, L	One-Shot Early is removed
	RR3	E, G, Gp, Gn	One-Shot Late is removed
	MPLRR	Multiple Price List Questions	
Ambiguity Resolution	AR1	E, G, Gp, Gn, L	Unrestricted
	AR2	G, Gp, Gn, L	One-Shot Early is removed
	AR3	E, G, Gp, Gn	One-Shot Late is removed
	MPLAR	Multiple Price List Questions	

Table 4: Choice sets used in the experiment.

Ambiguity exists in both periods but is resolved gradually. **Gradual, positively skewed** (Gp) option either reveals $\{0.9\}$ or $\{0.1,\ 0.4,\ 0.6\}$: ambiguity is fully resolved when the message is good news, but still exists in the other case. Similarly, the **Gradual, negatively skewed** (Gn) option either reveals $\{0.1\}$ or $\{0.4, 0.6, 0.9\}$. Hence, ambiguity is fully resolved when the message is bad news, but still exists in the other case.

As before, there is a 30-minute delay after subjects receive a piece of news at the end of $t = 1$ and before they observe the realization of the lottery in $t = 2$.

2.3 Choice Sets

Each elicitation utilizes three choice tasks and a set of multiple price list questions to determine subjects' preferences. The choice tasks involve subjects picking their most preferred option from subsets of the five options in Table 2 or 3. The first question (RR1/AR1) is an unrestricted choice from the set. The second question (RR2/AR2) removes the One-Shot Early option. The third question (RR3/AR3) removes the One-Shot Late option. The last set of questions (MPLRR/MPLAR) measures the strength of preference for early vs. late resolution by using a multiple price list. Each row presents a mini question that asks the subject to choose from two options "One-Shot Early + \$$x$" and "One-Shot Late + \$$y$." The values of x and y vary among different rows where one term is 0 and the other is a 0.05 increment between 0.00 and 0.50 (see Figure A.5). Table 4 summarizes these procedures.

For each elicitation task, subjects receive news or messages based on their choices of information structures after completing all four sections. They then experience the Raven's

Progressive Matrices test for the next 30 minutes, after which the outcome is revealed. Figure 2 illustrates an example of the timeline of the entire session. The ordering of the questions in the two elicitation tasks was partially randomized in four different ways to reduce ordering effects. The different orders of the experiments are shown in Figure A.4.[12]

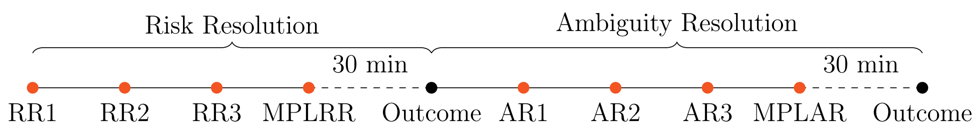


Figure 2: The timeline of the session (Order 1).

2.4 Ambiguity Attitude Elicitation

To elicit their ambiguity attitudes, we also have subjects answer two Ellsberg (1961) questions. Each subject has a small chance to receive an additional $10, depending on their answers to the questions. Subjects are given the following statement.

> Consider a bag containing 90 ping pong balls. 30 balls are blue, and the remaining 60 balls are either red or yellow in unknown proportions. The balls are well mixed so that each individual ball is as likely to be drawn as any other. You will bet on the color that will be drawn from the bag.

Subjects are asked to choose between two lotteries that pay $10 if a blue ball is drawn and if a red ball is drawn, respectively. They are then asked to choose between two lotteries that pay $10 if a blue or yellow ball is drawn and if a red or yellow ball is drawn, respectively. Choosing blue and then red or yellow (red and then blue or yellow) is consistent with ambiguity aversion (seeking). Otherwise, a subject's choices are consistent with ambiguity neutrality.

2.5 Experimental Procedures

Subjects were 135 undergraduate students at Texas A&M University, recruited using the `econdollars.tamu.edu` website, a server based on ORSEE (Greiner, 2015). Subjects sat at computer terminals running zTree software (Fischbacher, 2007). Sessions took place at the Experimental Research Laboratory at Texas A&M University from February to May 2021.

[12] According to Online Appendix G, we find no significant difference across the orders.

Subjects were fully informed about the procedure and the total time of the session at the beginning of the experiment. After the experiment concluded, subjects were paid for money based on one randomly selected decision out of the 48 ($(1+1+1+21)\times 2$) (see Table 4 and Figure A.5).[13] In addition, subjects have another chance to receive an additional \$10 from the bonus ambiguity attitude elicitation task.[14] The average payment for each participant was \$23.33 including a \$10 participation payment.[15]

3 Results

3.1 Revealed Preferences for Risk and Ambiguity Resolution

Table 5 shows the summary of the choices of risk resolution on the three tasks RR1, RR2, and RR3. The modal response of subjects over the unrestricted choice set (RR1) is the preference for early resolution of risk (64 of 135, 47.4%). A similar but smaller portion of subjects indicate a preference for gradual resolution (57, 42.2%).[16] A small remainder prefer late resolution (14, 10.4%). A chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.01$).

Table 6 summarizes the choices of ambiguity resolution on tasks AR1, AR2, and AR3.

[13] Each decision in choice questions RR1, RR2, RR3, AR1, AR2, and AR3 is chosen with probability $\frac{1}{8}$. Each decision in one out of twenty-one MPLRR (or MPLAR) questions is chosen with probability $\frac{1}{8}\times\frac{1}{21}$.

[14] As in Figure A.4, subjects receive the outcome at the end of each uncertainty-resolution elicitation task. On the final screen, subjects see their outcomes for resolution tasks and the bonus task. They are informed which resolution task outcome is selected for payment and whether the bonus task is selected for payment.

[15] We adopt the random incentive scheme, a common payment scheme in the literature, and assume that our non-expected-utility-maximizing subjects either isolate their decisions in different questions, or integrate them but satisfy the statewise monotonicity assumption (Azrieli et al., 2018). In this case, this scheme is incentive compatible. The assumption is justified for subjects in Nielsen (2020), where a treatment with only one question was run and shown to have similar results as those in her main experiments. As our experiments follow the structure of those in Nielsen (2020) and our subjects are also undergraduate students from a similarly large-sized public university, we believe it is reasonable to impose the assumption on many of our subjects. Nevertheless, there may be subjects who do not satisfy the assumption. Their choices under the random incentive scheme may *underestimate* the prevalence of risk and ambiguity aversion (Freeman et al., 2019; Baillon et al., 2022a,b).

[16] Specifically, 36 (26.7%), 6 (4.4%), and 15 (11.1%) prefer the non-skewed, positively-skewed, and negatively-skewed option, respectively (Table A.1). We do not focus on the distinction between these gradual options as they are not Blackwell ordered. For reference, by the entropy informativeness measure (Cabrales et al., 2013), $-\ln(0.5)+p[q\ln(q)+(1-q)\ln(1-q)]+(1-p)[r\ln(r)+(1-r)\ln(1-r)]$, Options E, G, Gp, Gn, and L have entropy levels of 0.69, 0.13, 0.09, 0.09, and 0.00. Among subjects who indicate a preference for gradual resolution, most prefer the option with the higher entropy level (i.e., the non-skewed one). Subjects' preference among the three gradual options is open for further research.

RR1 choice (unrestricted)	RR2 choice (One-Shot Early removed)	RR3 choice (One-Shot Late removed)		Total
		One-Shot Early	Gradual (all forms)	
One-Shot Early	Gradual (all forms)	**38**	10	48
	One-Shot Late	**16**	0	16
	Total	**54**	10	64
Gradual (all forms)	Gradual (all forms)	4	**48**	52
	One-Shot Late	2	3	5
	Total	6	51	57
One-Shot Late	Gradual (all forms)	1	7	8
	One-Shot Late	**1**	**5**	**6**
	Total	2	12	14

Table 5: Revealed preferences for risk resolution in choice tasks RR1, RR2, and RR3. All three forms of gradual resolution of risk are pooled (See Table A.1 for unpooled results). Orange indicates profiles consistent with a strict preference ordering.

The modal response of subjects over the unrestricted choice set (AR1) is the preference for early resolution of ambiguity (86 of 135, 63.7%). A smaller portion of subjects indicate a preference for gradual resolution (42, 31.1%).[17] Very few subjects prefer late resolution of ambiguity (7, 5.2%). As before, a chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.01$).

Our data suggest that most subjects prefer getting some information (either full information or partial information) on the probability of winning the high prize, even if the information has no instrumental value. Comparatively, more subjects prefer early resolution of ambiguity relative to early resolution of risk ($p = 0.01$, Fisher exact test). We will examine these correlations further—along with ambiguity attitude—in Section 3.2.

The restricted choice sets RR2/AR2 and RR3/AR3 allow us to look further at the revealed preference profiles for subjects over risk/ambiguity resolution. A subject with a strict preference ordering that chooses One-Shot Early (resp. One-Shot Late) in the unrestricted set RR1/AR1, will choose One-Shot Early (resp. One-Shot Late) in the restricted set RR3/AR3 (resp. RR2/AR2), and will indicate their second-most preferred option in RR2/AR2 (resp. RR3/AR3). Subject can always select any of the three forms of gradual resolution, so a strict preference ordering would not reveal a second choice.

[17] Specifically, 30 (22.2%), 4 (3.0%) , and 8 (5.9%) prefer the non-skewed, positively-skewed, and negatively-skewed option, respectively. See Table A.2 for more details.

AR1 choice (unrestricted)	AR2 choice (One-Shot Early removed)	AR3 choice (One-Shot Late removed): One-Shot Early	AR3 choice (One-Shot Late removed): Gradual (all forms)	Total
One-Shot Early	Gradual (all forms)	**60**	8	68
	One-Shot Late	**17**	1	18
	Total	**77**	9	86
Gradual (all forms)	Gradual (all forms)	10	**27**	37
	One-Shot Late	1	4	5
	Total	11	31	42
One-Shot Late	Gradual (all forms)	0	2	2
	One-Shot Late	**1**	**4**	**5**
	Total	1	6	7

Table 6: Revealed preferences for ambiguity resolution in choice tasks AR1, AR2, and AR3. All three forms of gradual resolution of ambiguity are pooled (See Table A.2 for unpooled). Orange indicates profiles consistent with a strict preference ordering.

Fifty-four of the 64 (84.4%) subjects that select early resolution in RR1 choose the same option in RR3, consistent with a strict preference for early resolution of risk. Six of the 14 (42.9%) subjects that select late resolution in RR1 select the same option in RR2. Of the 57 subjects that select one of the three gradual options on RR1, 48 (84.2%) also pick gradual options on both RR2 and RR3.[18] Across the entire sample, 54 of 135 (40.0%) of subjects indicate a strict preference for early resolution of risk, 48 (35.6%) indicate a strict preference for gradual resolution, and 6 (4.4%) indicate a strict preference for late resolution. The other 27 (20.0%) give responses that are not consistent with a strict preference ordering.

Similarly, 77 of the 86 (89.5%) subjects that select early in AR1 choose the same option in AR3, consistent with a strict preference for early resolution of ambiguity. Five of the 7 (71.4%) subjects that select late in AR1 select the same option in AR2. Of the 42 subjects that select one of the three gradual options on AR1, 27 (64.2%) also pick gradual options on both AR2 and AR3.[19] Overall, 77 of 135 (57.0%) subjects indicate a strict preference for early resolution of ambiguity, 27 (20.0%) indicate a strict preference for gradual resolution, and 5 (3.7%) indicate a strict preference for late resolution. The other 26 (19.3%) give responses that are not consistent with a strict preference ordering.

[18] Twenty-six of these 48 (54.2%) subjects consistently pick *the same* option (e.g., positively-skewed, negatively-skewed, non-skewed) for gradual resolution of risk over RR1, RR2, and RR3. See Table A.1.

[19] According to Table A.2, 19 of these 27 (70.4%) subjects consistently pick *the same* option for gradual resolution of ambiguity over AR1, AR2, and AR3.

The categorization of subjects by their indicated second-most preferred option is also illuminating. Subjects may prefer both early and late resolution over gradual, or prefer gradual second-most with one of early/late as the most- and least-preferred options. We refer to the former and latter types as having *one-shot* and *monotone* preferences for resolution, respectively. One-shot preferences have been examined theoretically in the domains of risk (Dillenberger, 2010; Cerreia-Vioglio et al., 2015) and ambiguity (Li, 2020a). In total, more subjects display preferences for monotone resolution of risk (60, 44.4%) and ambiguity (74, 54.8%) than one-shot resolution of risk (18, 13.3%) and ambiguity (19, 14.1%).[20]

Subjects also completed two 21-item binary-choice multiple price lists, the MPLRR and MPLAR, to indicate their willingness to pay for one-shot early vs. late resolution of risk and ambiguity, respectively. Implied willingness to pay ranged from −\$0.50 to \$0.50. Figures 3(a) and (b) provide histograms for the 114 and 118 subjects that indicated a single switching point (i.e., a response consistent with preferring more money to less) on the MPLRR and MPLAR. Each figure separates subjects by their choice on the related unrestricted set RR1 or AR1. Responses are centered around 0 in both figures; 86 of the 114 (75.4%) subjects on the MPLRR and 91 of the 118 (77.1%) subjects on the MPLAR do not indicate a willingness to pay more than \$0.05 for their preferred form of one-shot resolution.[21] However, in both figures, groups are ordered in the way one would expect. Separate Cuzick non-parametric trend tests reject the null hypothesis of no trend across groups in both cases ($p < 0.01$).

There is a high degree of consistency between the choice task and multiple price lists for risk and ambiguity resolution. No subject that chose the One-Shot Early (resp. Late) option on RR1/AR1 is willing to pay for late (resp. early) resolution on the MPLRR/MPLAR. Twenty (resp. eight) subjects indicated a *strictly positive* (resp. *negative*) willingness to pay on the MPLRR; 11 (resp. 3) chose One-Shot Early (resp. Late) and 9 (resp. 5) chose a gradual option on RR1 ($p < 0.01$, Fisher's exact test using a 3×3 contingency table). On the MPLAR, 25 (resp. 2) subjects indicate a *strictly positive* (resp. *negative*) willingness to

[20] Of the 64 (resp. 86) subjects that choose One-Shot Early on RR1 (resp. AR1), 48 (resp. 68) choose gradual and 16 (resp. 18) choose One-Shot Late in RR2 (AR2). Of the 14 (resp. 7) that choose One-Shot Late on RR1 (resp. AR1), 12 (resp. 6) choose gradual and 2 (resp. 1) choose One-Shot Early on RR3 (resp. AR3). Note the following calculations: (i) $48 + 12 = 60$ (ii) $68 + 6 = 74$ (iii) $16 + 2 = 18$ (iv) $18 + 1 = 19$.

[21] Importantly, multiple price lists may induce a "compromise effect" where subjects are pushed to switch at the middle option (Beauchamp et al., 2020). This tendency may cause our MPLRR and MPLAR elicitations to *underestimate* the magnitude of resolution preference as subject elicitations are anchored toward 0.

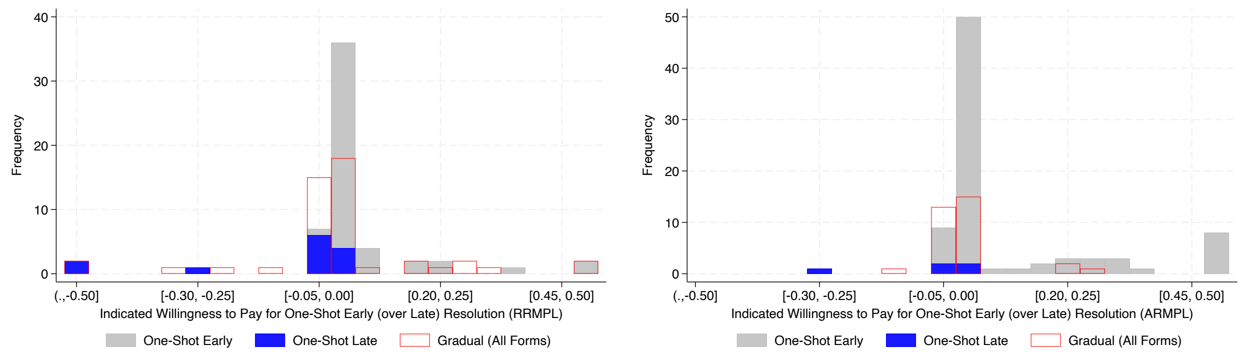


Figure 3: Histogram of implied willingness to pay for early vs. late resolution determined from switching point in RRMPL elicitation (a, left), MPLAR elicitation (b, right). Subjects are separated by unrestricted choice set decision in RR1 (a, single-crossing subjects only, $N = 114$), AR1 (b, single-crossing subjects only, $N = 118$).

pay; 22 (resp. 1) chose One-Shot Early (resp. Late) and 3 (resp. 1) chose a gradual option on AR1 ($p < 0.05$, Fisher's exact test using a 3×3 contingency table).

The 11th choice of each MPL also provides a robustness check of the results: subjects could pick between early or late resolution with no payment each way. Of the 64 subjects that selected the One-Shot Early option on the RR1, 52 (81.3%) chose the early option over late. So do 33 of 57 (57.9%) that selected a gradual option and 5 of 9 (55.6%) that selected the One-Shot Late option. Of the 86 subjects that selected the One-Shot Early option on the AR1, 73 (84.9%) chose the early option over late, 25 of 42 (59.5%) for gradual, 4 of 7 (57.1%) for late. For each form of resolution, we reject the null hypothesis of these results being randomly distributed ($p < 0.01$, Fisher's exact test using a 3×2 contingency table).

Online Appendix H uses interval regression to estimate mean willingness to pay for early vs. late resolution across subjects grouped by their choice on the unrestricted choice set. This regression specification allows the inclusion of subjects that violate single-crossing conditions on the multiple price list if we are willing to assume that one's true preference falls between one's lowest and highest switch point. Tables A.6 and A.7 provide results for risk and ambiguity resolution, respectively. Each table includes two specifications, specification (1) includes all subjects, and specification (2) is restricted to subjects that do not violate single crossing nor strict preference orderings on the choice tasks.

Results are generally consistent across specifications and with previous results. Choosing

RR1 choice	AR1 choice: One-Shot Early	Gradual (all forms)	One-Shot Late	Total
One-Shot Early	57	6	1	64
Gradual (all forms)	22	32	3	57
One-Shot Late	7	4	3	14
Total	86	42	7	135
Fisher's exact test p-value ≈ 0.000				

Table 7: Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1). The three gradual choices are pooled. See Table A.3 for unpooled table.

early (gradual) resolution on RR1 is associated with an expected willingness to pay for early over late resolution of risk of 4.8 to 6.1 (2.0 to 2.2) cents; choosing late resolution is associated with an expected willingness to pay 11.0 to 13.1 cents for late resolution. Choosing early (gradual) resolution on choice task AR1 is associated with an expected willingness to pay for early over late resolution of ambiguity of 10.7 to 12.4 (1.9 to 2.2) cents; choosing late resolution is associated with an expected willingness to pay of 5.5 to 6.2 cents for late resolution. In each specification, a chi-square test rejects the null hypothesis of equality of coefficients across the three groups ($p < 0.01$). See Online Appendix H for more details.

3.2 Ambiguity Attitude, Correlations of Preferences for Resolution

Based on subject responses to Ellsberg's questions, 63 (46.7%) were classified as ambiguity averse, 60 (44.4%) were ambiguity neutral, and 12 (8.9%) were ambiguity seeking. A chi-square test rejects the null hypothesis of responses being randomly distributed ($p < 0.01$).

Table 7 provides counts of subjects based on their joint preferences for risk and ambiguity resolution determined by the unrestricted choice on the RR1 and AR1 elicitation tasks. Unsurprisingly, the modal preference profile (57 of 135 subjects, 42.2%) is early resolution for both risk and ambiguity resolution. However, if preferences for ambiguity and risk resolution were independent, we would only expect about 41 subjects (about 30%) to have this preference (135 subjects $\times\frac{64}{135} \times \frac{86}{135} \approx 41$ subjects). Indeed, a Fisher's exact test rejects the null hypothesis that these joint classifications are due to a random distribution ($p < 0.01$). Further, the preference for early resolution of ambiguity and early resolution of

Ambiguity Attitude (Ellsberg Task)	RR1 Choice	AR1 Choice: One-Shot Early	AR1 Choice: Gradual (all forms)	AR1 Choice: One-Shot Late	Total
Ambiguity Averse	One-Shot Early	28	2	0	30
	Gradual (all forms)	12	11	1	24
	One-Shot Late	4	2	3	9
	Total	44	15	4	63
Ambiguity Neutral	One-Shot Early	24	4	0	28
	Gradual (all forms)	10	16	2	28
	One-Shot Late	3	1	0	4
	Total	37	21	2	60
Ambiguity Seeking	One-Shot Early	5	0	1	6
	Gradual (all forms)	0	5	0	5
	One-Shot Late	0	1	0	1
	Total	5	6	1	12

Table 8: Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1 tasks) separated by revealed ambiguity attitudes on the Ellsberg task.

risk are positively correlated (the correlation coefficient is approximately 0.5, $p < 0.01$).

We also investigate the marginal effect of ambiguity attitude on ambiguity resolution. Table 8 shows the risk resolution and ambiguity resolution from unrestricted choice tasks (RR1/AR1) separated by elicited ambiguity attitude. We run a logistic regression on the binary dependent variable of whether a subject selects early ambiguity resolution on AR1. We use a choice of early risk resolution on RR1 as a control with dummy variables for ambiguity aversion and ambiguity neutrality (ambiguity seeking is the omitted term). Table 9 shows marginal effects of the logistic regression model.[22] Preferring early resolution of risk increases the likelihood of preferring early resolution of ambiguity by 43.5 percentage points ($p < 0.01$). Being ambiguity averse and ambiguity neutral increases the likelihood of preferring early resolution of ambiguity by 29.5 ($p \approx 0.020$) and 21.8 percentage points ($p \approx 0.083$), respectively, relative to an ambiguity seeking subject. The averse and neutral groups are statistically indistinguishable ($p \approx 0.300$) though.

While positively correlated, it appears that there is some variability in the relation of these two preferences of uncertainty resolution that is affected by ambiguity attitude. We examine which models can accommodate this complex relation in the next section.

[22] The full specifications and results of the regression are available in Online Appendix F.

Marginal Effects on Choosing One-Shot Early in AR1			
	Marginal Effect	Standard Error	p-value
One-Shot Early on RR1	0.435	0.045	0.000
Ambiguity Averse	0.295	0.127	0.020
Ambiguity Neutral	0.218	0.127	0.088

Table 9: The average marginal effects in probability points ($N = 135$).

4 Theory

Consistent with previous literature, our results so far suggest a large portion of subjects have (i) non-neutral attitudes over ambiguity (generally aversion) and a (ii) preference over the resolution of risk (generally early resolution). Additionally, our new findings indicate that subjects have a (iii) preference over the resolution of ambiguity (generally early), (iv) the preferences over risk and ambiguity resolution are most often correlated. Finally, (v) ambiguity attitude appears to affect the strength of this correlation. In this section, we investigate the implications of different theoretical models and then use individual-level data to evaluate the performance of different models.

4.1 Risk and Ambiguity Resolution

For simplicity, we utilize a two-period dynamic framework with finite state spaces, S_1 and S_2, in both periods, to study preferences for risk and ambiguity resolution theoretically. We restrict attention to consumption processes that are constant and positive in period 1 and s_2-dependent and positive in period 2, i.e., $h = (h_1, h_2)$ such that $h_1 \in \mathbb{R}_{++}$ and $h_2 : S_2 \to \mathbb{R}_{++}$, and let H denote the set of all such consumption processes. The restriction allows us to single out the informational value of period-1 information. Suppose the realization of a period-1 state $s_1 \in S_1$ pins down a unique distribution over S_2 via a publicly known function $f : S_1 \to \Delta(S_2)$. However, the decision maker (DM) may not directly observe s_1 in period 1. Instead, let $\mathcal{Q}^f$ be a publicly known partition of $f(S_1)$ and $\mathcal{S}_1^f$ be the publicly known partition of S_1 such that for each $S_1^k \in \mathcal{S}_1^f$, $f(S_1^k) \in \mathcal{Q}^f$. Hence, observing an event $S_1^k \in \mathcal{S}_1^f$ is equivalent to knowing that the set of possible period-2 distributions is $Q^k \in \mathcal{Q}^f$. We let $\overline{\mathcal{Q}}^f$ and $\underline{\mathcal{Q}}^f$ be the finest and coarsest partitions of $f(S_1)$ respectively, and $\overline{\mathcal{S}}_1^f$ and $\underline{\mathcal{S}}_1^f$ be the corresponding partitions of S_1. Hence, receiving $S_1^k \in \overline{\mathcal{S}}_1^f$ (resp. $S_1^k \in \underline{\mathcal{S}}_1^f$) means that the DM knows precisely (resp. receives no new information about) the period-2 distribution.

Let $\Delta^f(S_1 \times \Delta(S_2))$ be the set of all distributions $\tilde{p} \in \Delta(S_1 \times \Delta(S_2))$ such that for each $s_1 \in S_1$, $\tilde{p}(s_1, \tilde{q}) > 0$ if and only if $\tilde{q} = f(s_1)$. Hence, the realization of each state s_1 with positive probability can only lead to the period-2 distribution $f(s_1)$. For each $\tilde{q} \in \Delta(S_2)$, we further let $\Delta^f(S_1 \times \Delta(S_2))(\tilde{q})$ be the subset of $\Delta^f(S_1 \times \Delta(S_2))$ with mean-$\tilde{q}$ over S_2, i.e., the set of all $\tilde{p} \in \Delta^f(S_1 \times \Delta(S_2))$ such that $\sum_{s_1 \in S_1, \hat{q} \in \Delta(S_2)} \hat{q} \cdot \tilde{p}(s_1, \hat{q}) = \tilde{q}$.

In our risk-resolution experiment, a DM is ex-ante informed of f and an objective distribution $\tilde{p} \in \Delta^f(S_1 \times \Delta(S_2))(\tilde{q})$ where $\tilde{q} \in \Delta(S_2)$ has full support. Her interim information informs her of one $\hat{q} \in f(S_1)$ (equivalently, an element Q^k in $\overline{\mathcal{Q}}^f$, or S_1^k in $\overline{\mathcal{S}}_1^f$). The information structure in a risk-resolution experiment can thus be summarized as a triplet $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$. It resolves risk early if each distribution in $f(S_1)$ degenerates to one state in S_2, and thus, the interim information allows the DM to know for sure the outcome that will be realized. It resolves risk late if $f(S_1) = \{\tilde{q}\}$, where no interim information leads to an updated period-2 distribution. If $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$ neither resolves risk early nor late, then it resolves risk gradually.[23]

In our ambiguity-resolution experiment, a DM is not ex-ante informed of any objective $\tilde{p} \in \Delta^f(S_1, \Delta(S_2))$. Since f is publicly known, she knows how each period-1 state corresponds to a period-2 distribution, and that the set of possible period-2 distributions is $f(S_1)$. A DM's interim information is an element of $\mathcal{S}_1^f$, or equivalently, an element of $\mathcal{Q}^f$. We summarize the information structure in an ambiguity-resolution experiment by $[f, \mathcal{S}_1^f]$, and say it resolves ambiguity early if $\mathcal{S}_1^f = \overline{\mathcal{S}}_1^f$, late if $\mathcal{S}_1^f = \underline{\mathcal{S}}_1^f$, and gradually otherwise.[24]

4.2 Models

As mentioned in Section 2, we review ten representative recursive utility models under uncertainty: the DEU, MEU, KMM, DMP, DVP, EZ, H, HM, RMP, and RVP models. They

[23] In Figure 1 and Table 2, we have $S_1 = \{\text{good}, \text{bad}\}$, $S_2 = \{\text{high prize}, \text{low prize}\}$, and $\overline{\mathcal{S}}_1^f = \{\{\text{good}\}, \{\text{bad}\}\}$. The function f is defined as $f(\text{good}) = (r, 1-r)$, $f(\text{bad}) = (q, 1-q)$. The mean distribution is $\tilde{q} = (0.5, 0.5)$. The joint distribution $\tilde{p} \in \Delta^f(S_1 \times \Delta(S_2))(\tilde{q})$ is given by $\tilde{p}(\text{good}, (r, 1-r)) = 1-p$ and $\tilde{p}(\text{bad}, (q, 1-q)) = p$. In the early resolution case, $f(S_1) = \{(1, 0), (0, 1)\}$. In the late resolution case, $f(S_1) = \{(0.5, 0.5)\}$. For example, in the Gradual (non-skewed) option, $f(S_1) = \{(0.75, 0.25), (0.25, 0.75)\}$.

[24] In Figure A.2, Figure A.3, and Table 3, $S_1 = \{0.1, 0.4, 0.6, 0.9\}$, and $S_2 = \{\text{high prize}, \text{low prize}\}$. Moreover, $f(s_1) = (s_1, 1 - s_1)$. The partitions in Table 3 correspond to different partitions of S_1.

		Atemporal Criterion				
		Subjective Expected Utility	Worst-Case Criterion	Smooth Ambiguity	Multiplier Preference	Variational Preference
Intertemporal Substitution	Depends on risk attitudes	DEU	MEU	KMM	DMP	DVP
	Can be independent of risk attitudes	EZ	H	HM	RMP	RVP

Table 10: A summary of recursive utility models under uncertainty.

differ from each other in two dimensions. First, they describe intertemporal substitution differently. In the two-period framework, the EZ, H, HM, RMP, and RVP models adopt a non-linear time aggregator to add up *certainty equivalents* in two periods for the certainty equivalent of lifetime consumption. The intertemporal substitution can be independent of risk attitudes. However, the DEU, MEU, KMM, DMP, and DVP models sum up *discounted utility flows* across different periods to derive the lifetime utility. Such an approach implies a stringent relationship between the intertemporal substitution and risk attitudes. Second, these models are based on different atemporal decision-making criteria under uncertainty. The DEU and EZ models follow subjective expected utility and only support ambiguity neutrality, but all other models can also accommodate ambiguity aversion. The MEU and H models use the worst-case criterion within each period. The KMM and HM models adopt a smooth ambiguity approach and accommodate a continuum of attitudes ranging from ambiguity aversion to seeking. The DMP and RMP (resp. DVP and RVP) models adopt the multiplier (resp. variational) preference. We summarize the key differences in Table 10.

This paper assumes that utility functions are of the constant relative risk aversion (CRRA) form. In particular, define $u(x) \equiv \frac{x^\alpha}{\alpha}$, where $1-\alpha$ is the risk aversion parameter, and $v(x) \equiv \frac{x^\eta}{\eta}$, where $1-\eta$ is the ambiguity aversion parameter in the KMM and HM models. The time aggregator is assumed to have the constant elasticity of substitution (CES) form: define $W(x,y) = (x^\rho + \beta y^\rho)^{\frac{1}{\rho}}$, where $\frac{1}{1-\rho}$ is the elasticity of intertemporal substitution in the EZ, H, HM, RMP, and RVP models, β is the discount factor, and x and y are certainty equivalents of consumptions in period 1 and period 2. Throughout the paper, we assume that α, η, and ρ are nonzero (for the functions to be well-defined) and finite (to avoid the case that certainty equivalent under u, v, or W reduces to the Leontief case).

The CRRA utility functions u and v and CES time aggregator W are particularly relevant and interpretable in applied works. There is a well-known implication for risk resolution under this restriction (Epstein and Zin, 1989). Moreover, the restriction allows us to focus on the preference for risk resolution in a global sense, which is implicitly assumed by our experimental design. Proposition 1 shows that the strict convexity (resp. strict concavity) of $u(W(h_1, u^{-1}(x)))$ in x characterizes the preference for early (resp. late) resolution of risk in the EZ, H, HM, RMP, and RVP models. Without the restriction, this function may not be convex, concave, or linear, in which case a DM can prefer early resolution of risk for some consumption processes but prefer late resolution for others. For example, suppose $u(x) = -e^{-x}$, and W is of the CES form with $\rho = -0.4$, $\beta = 0.9$, $h_1 = 10$, and period-2 consumption x. In this case, the function $u(W(h_1, u^{-1}(x)))$ with $x \in (-1, 0)$ is not convex, concave, or linear, and thus, the DM has no global risk-resolution preferences.

We review the models by focusing on five of them and viewing the others as special cases.

In the EZ model with subjective expected utility, we assume that the DM forms a belief $\pi \in \Delta(f(S_1)) \subseteq \Delta(\Delta(S_2))$ and reduces compound lotteries within the same period. Given an information structure $[f, \mathcal{S}_1^f]$ and the corresponding $\mathcal{Q}^f$, the certainty equivalent of period-2 consumption conditional on $Q^k \in \mathcal{Q}^f$ (or equivalently, $S_1^k \in \mathcal{S}_1^f$), i.e., $I_2(h|Q^k)$, the certainty equivalent of lifetime consumption conditional on Q^k, i.e., $I_1(h|Q^k)$, and the certainty equivalent of ex-ante lifetime consumption, i.e., $I_1^{ea}(h)$, are given by

$$I_2(h|Q^k) = u^{-1}\Big(\sum_{\hat{q}\in Q^k}\sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k)\Big), \qquad I_1(h|Q^k) = W\big(h_1, I_2(h|Q^k)\big),$$
$$I_1^{ea}(h) = u^{-1}\Big(\sum_{Q^k\in\mathcal{Q}^f} u\big(I_1(h|Q^k)\big)\pi(Q^k)\Big).$$

It is well known that the special case with $\alpha = \rho$ gives us the DEU model. When there is an objective $\tilde{p} \in \Delta^f(S_1, \Delta(S_2))$ as in the risk-resolution experiment, π should coincide with the marginal distribution of $\tilde{p}$ over $\Delta(S_2)$.

In the H model, the DM believes that multiple subjective beliefs $\pi \in \Delta(f(S_1)) \subseteq \Delta(\Delta(S_2))$ are relevant and evaluates a consumption process with the worst-case belief only. Let Π be a convex, non-empty, compact set of such π. By adopting the prior-by-prior updating rule, we have the period-2 certainty equivalent of a consumption process conditional on $Q^k \in \mathcal{Q}^f$, the certainty equivalent of lifetime consumption conditional on Q^k, and the certainty equivalent of ex-ante lifetime consumption given by

$$I_2(h|Q^k) = u^{-1}\Big(\min_{\pi\in\Pi}\sum_{\hat{q}\in Q^k}\sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k)\Big), \quad I_1(h|Q^k) = W\big(h_1, I_2(h|Q^k)\big),$$
$$I_1^{ea}(h) = u^{-1}\Big(\min_{\pi\in\Pi}\sum_{Q^k\in\mathcal{Q}^f} u\big(I_1(h|Q^k)\big)\pi(Q^k)\Big).$$

The special case that $\alpha = \rho$ reduces to the MEU model. When there is an objective $\tilde{p} \in \Delta^f(S_1, \Delta(S_2))$, Π should be a singleton, and the unique element in it should agree with the marginal distribution of $\tilde{p}$ on $\Delta(S_2)$.

Two subcategories in the H model (and the MEU model) are worth mentioning, as they have different yet sharp implications for the ambiguity-resolution experiment. We call the subcategory with $\Pi = \Delta(f(S_1))$ the **Wald-type Hayashi** ((w)H) model. In our experiment, this subcategory corresponds to the case where the DM believes that the probability of winning the high prize can be any number between 0.1 and 0.9 and makes the decision as if the probability is 0.1. When every $\pi \in \Pi$ is fully supported on $f(S_1)$, the model belongs to the **interior Hayashi** ((i)H) model subcategory.[25] The corresponding subcategories of the MEU model are called the (w)MEU model and the (i)MEU model.

Under the HM model, given information structure $[f, \mathcal{S}_1^f]$, a DM knows that $f(S_1) \subseteq \Delta(S_2)$ is the set of possible first-order probabilities and subjectively forms a second-order probability $\mu \in \Delta(f(S_1)) \subseteq \Delta(\Delta(S_2))$. She evaluates the first- and second-order uncertainties with functions u and v, respectively. The period-2 certainty equivalent of a consumption process conditional on Q^k, the certainty equivalent of lifetime consumption conditional on Q^k, and the certainty equivalent of ex-ante lifetime consumption are

$$I_2(h|Q^k) = v^{-1}\Big(\sum_{\hat{q}\in Q^k} v\circ u^{-1}\big(\sum_{s_2\in S_2} u(h_2(s_2))\hat{q}(s_2)\big)\mu(\hat{q}|Q^k)\Big), \quad I_1(h|Q^k) = W\big(h_1, I_2(h|Q^k)\big),$$
$$I_1^{ea}(h) = v^{-1}\Big(\sum_{Q^k\in\mathcal{Q}^f} v\big(I_1(h|Q^k)\big)\mu(Q^k)\Big).$$

[25]The H model includes cases that do not fit into either subcategories: for example, suppose $\Pi = \{\pi\}$ where π imposes probability 1 to one $\hat{q} \in f(S_1)$. In these other cases, the ambiguity-resolution preference is the same as that under either the (i)H model or the (w)H model.

When $\alpha < \eta$ (resp. $\alpha > \eta$, or $\alpha = \eta$), i.e., when v is less (resp. more, or equally) concave than u, the subject is ambiguity seeking (resp. averse, or neutral). The special case that $\alpha = \eta$ (resp. $\alpha = \rho$) yields the EZ model (resp. the KMM model).

By integrating the multiplier preference model of Hansen and Sargent (2001) and Strzalecki (2011) with the time aggregator W, we obtain the RMP model. The DM has a full-support reference belief $\pi' \in \Delta(f(S_1))$. For every other distribution $\pi \in \Delta(f(S_1))$, there is a "punishment" term assigned to the belief π due to its departure from π', which is equal to $\theta \cdot R(\pi|\pi')$. Expression $R(\pi|\pi') = \sum_{\hat{q}\in f(S_1)} \pi(\hat{q}) \ln \frac{\pi(\hat{q})}{\pi'(\hat{q})}$ is the relative entropy that measures the "distance" between the two beliefs. The coefficient $\theta \in (0, +\infty]$ measures the DM's confidence in the reference belief: $\theta \in (0, +\infty)$ (resp. $= +\infty$) reflects ambiguity aversion (resp. neutrality). The DM takes into account the worst-case belief after adjusting for the punishment term. Given a gradual ambiguity-resolution information structure $[f, \mathcal{S}_1^f]$ and the corresponding $\mathcal{Q}^f$,

$$I_2(h|Q^k) = u^{-1}\Big(\min_{\pi\in\Delta(f(S_1))} \{ \sum_{\hat{q}\in Q^k} \sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k) + \theta \sum_{\hat{q}\in Q^k} \pi(\hat{q}|Q^k) \ln \frac{\pi(\hat{q}|Q^k)}{\pi'(\hat{q}|Q^k)} \} \Big),$$

$$I_1(h|Q^k) = W\big(h_1, I_2(h|Q^k)\big),$$

$$I_1^{ea}(h) = u^{-1}\Big(\min_{\pi\in\Delta(f(S_1))} \{ \sum_{Q^k\in\mathcal{Q}^f} u\big(I_1(h|Q^k)\big)\pi(Q^k) + \theta \sum_{Q^k\in\mathcal{Q}^f} \pi(Q^k) \ln \frac{\pi(Q^k)}{\pi'(Q^k)} \} \Big).$$

The special case with $\alpha = \rho$ reduces to the DMP model.

The RVP model has a nonparametric "punishment" term captured by a convex, lower semi-continuous, and grounded cost function $c : \Delta(f(S_1)) \to [0, +\infty]$ (Maccheroni et al., 2006a). Under the RVP model,

$$I_2(h|Q^k) = u^{-1}\Big(\min_{\pi\in\Delta(f(S_1))} \{ \sum_{\hat{q}\in Q^k} \sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k) + c_{Q^k}(\pi(\cdot|Q^k)) \} \Big),$$

$$I_1(h|Q^k) = W\big(h_1, I_2(h|Q^k)\big), \quad I_1^{ea}(h) = u^{-1}\Big(\min_{\pi\in\Delta(f(S_1))} \{ \sum_{Q^k\in\mathcal{Q}^f} u\big(I_1(h|Q^k)\big)\pi(Q^k) + c(\pi) \} \Big),$$

where $c_{Q^k}(\pi(\cdot|Q^k)) = \min_{\hat{\pi}\in\Delta(f(S_1))\text{s.t.}\hat{\pi}(\cdot|Q^k)=\pi(\cdot|Q^k)} \frac{c(\hat{\pi})}{\hat{\pi}(Q^k)}$ (Li, 2020b). The case with $\alpha = \rho$ reduces to the DVP model of Maccheroni et al. (2006b). By Maccheroni et al. (2006a), the

RVP (resp. DVP) model also nests the H and RMP (resp. MEU and DMP) models.

For an ambiguity-neutral DM, the H, HM, RMP, and RVP (resp. MEU, KMM, DMP, and DVP) models reduce to the EZ (resp. DEU) model.

4.3 Summary of Predictions

We consider three ambiguity attitudes: ambiguity aversion, ambiguity neutrality, and ambiguity seeking, and five strict risk-/ambiguity-resolution preferences that can be identified by our individual-level data: a monotone preference for early resolution (denoted by $E \succ G \succ L$), a preference for early and one-shot resolution ($E \succ L \succ G$), a preference for gradual resolution ($G \succ E, L$), a monotone preference for late resolution ($L \succ G \succ E$), and a preference for late and one-shot resolution ($L \succ E \succ G$).[26] Assuming each revealed preference provided by a subject indicates a strict preference, there are 75 possible preference profiles a subject might reveal in our experiment. When we include the possibility of total indifference in the risk-/ambiguity-resolution experiment, denoted by $E \sim G \sim L$, there are 108 possible preference profiles. Table 11 summarizes these preference profiles.

Among the ten models, all but the DEU and EZ models can accommodate ambiguity aversion, but only the KMM and HM models can accommodate ambiguity seeking. The EZ, H, HM, RMP, and RVP models can account for non-indifferent preferences in the timing of risk resolution. In particular, under the CRRA-CES restriction, when $\alpha < \rho$ (resp. $\alpha > \rho$, or $\alpha = \rho$) in these five models, the DM exhibits a preference for early resolution of risk monotonically (resp. a preference for late resolution of risk monotonically, or an indifferent preference to the timing of risk resolution).[27] The other five models degenerate to the DEU model in the risk-resolution experiment and predict indifference in the outcome.

The implications of the ten models on ambiguity resolution are more complicated. We are most interested in global rationalization, i.e., the question of whether there exists a spec-

[26] We abuse notation here by having $E \succ G \succ L$ mean that the second most preferred option is a gradual option, and having $G \succ E, L$ mean that a gradual option is the most preferred option, etc., although we have three gradual options for risk/ambiguity resolution in the experiment.

[27] Although we cannot fully rank all gradual resolution options, Section A.1 provides a ranking between the positively-skewed and negatively-skewed options in our risk-resolution experiment under different parameter values. Similarly, Sections A.2 and A.3 rank the two skewed options in the ambiguity-resolution experiment under the H and the HM models and some assumptions.

ification of parameters α, η, ρ, β, θ, multiple-belief set, reference belief, or cost function c under which a model can rationalize the corresponding preference profile for *all* consumption processes $h \in H$ and *all* early, late, and gradual uncertainty-resolution information structures. We also report results on location rationalization, i.e., the question of whether there exists a specification to rationalize the preference profile for the consumption process and information structures used in our experiments, with the proofs included in Online Appendix B. If a model globally rationalizes a preference profile, it also locally rationalizes the profile, but the reverse may not be true. Whenever we do not specify whether the rationalization is in a global or local sense, global rationalization is the default. We present the key information under the CRRA-CES restriction below and leave the analysis to Appendix A. Table 11 provides a summary—if a cell includes a model without (resp. with) an asterisk, the model can rationalize this preference profile in a global sense (resp. only in a local sense).

- The MEU, KMM, DMP, and DVP (resp. H, HM, RMP, and RVP) models reduce to the DEU (resp. EZ) model for an ambiguity-neutral DM, in which case the DM is indifferent to the timing of ambiguity resolution (resp. the DM's ambiguity-resolution preference is inherited from her risk-resolution preference).
- In the MEU model, an ambiguity-averse DM can be indifferent to the timing of ambiguity resolution, or indifferent between early and late yet preferring one-shot ambiguity resolution.
- In the KMM model, an ambiguity-averse (resp. -seeking) DM prefers early (resp. late) resolution of ambiguity monotonically.[28]
- In the DMP model, an ambiguity-averse DM prefers early resolution of ambiguity monotonically.
- The DVP model can only globally rationalize preference profiles that are rationalizable under the MEU and DMP models. It can also locally rationalize a preference for one-shot or gradual ambiguity resolution that at least weakly prefers early to late.

[28]Under the CRRA-CES restriction, if $\alpha > 0$, u is positive-valued. In this case, Corollary 2(i) of Strzalecki (2013) has shown that an ambiguity-averse DM with KMM preference prefers early resolution of ambiguity over late. Strzalecki (2013) is silent about the $\alpha < 0$ case, which is covered by the current paper. As our u cannot take both positive and negative values, Corollary 2(ii) therein does not apply to our setup.

- In the H model with $\alpha \neq \rho$, a DM's global ambiguity-resolution preference is either indifferent (e.g., in the (w)H model) or inherited from her risk-resolution preference. This model can also locally rationalize a preference for one-shot resolution.

- In the HM model with $\alpha \neq \rho$, an ambiguity-averse (resp. -seeking) DM preferring early (resp. late) resolution of risk must prefer early (resp. late) resolution of ambiguity monotonically.[29]

- The RMP model with $\alpha \neq \rho$ under ambiguity aversion can only globally rationalize a preference for early risk and ambiguity resolution monotonically. This model can also locally rationalize more preference profiles reported in Table 11.

- The RVP model can only globally rationalize preference profiles that are rationalized by the H and RMP models. This model can also locally rationalize more preference profiles reported in Table 11.

As is previewed in Table 1, only the H, HM, RMP, and RVP models can simultaneously accommodate a non-neutral ambiguity attitude, a non-indifferent preference for the timing of risk resolution, and a non-indifferent preference for the timing of ambiguity resolution.

Note that under the CRRA-CES restriction, among the five strict uncertainty-resolution preferences that can be identified by our experiments, only the monotone ones are globally rationalizable.[30] This restriction ensures that a DM's risk-resolution preference is always global, but it also rules out interesting preferences for one-shot or gradual uncertainty resolution. As an initial attempt to accommodate these preferences, we point out two approaches. If we keep the CRRA-CES restriction, Table 11 has shown that some models can locally rationalize some profiles involving preferences for one-shot or gradual ambiguity resolution. Moreover, Online Appendix C provides one example beyond the CRRA-CES restriction, where the DM may exhibit a preference for gradual risk resolution locally. Such a practice can also locally rationalize profiles involving other uncertainty-resolution preferences.

[29] As we discuss in Appendix A.3, this observation relies crucially on the CRRA-CES restriction.

[30] The preference for one-shot ambiguity resolution with indifference between early and late can be globally rationalized by the MEU model, but it is not one of these five strict uncertainty-resolution preferences that can be identified by our experiments.

Ambiguity Attitude	Risk Resolution Preference	Ambiguity-Resolution Preference $E \succ G \succ L$	$E \succ L \succ G$	$G \succ E, L$	$L \succ G \succ E$	$L \succ E \succ G$	$E \sim L \sim G$
Ambiguity Averse	$E \succ G \succ L$	16 (2) H, HM, RMP, RVP	2 (0) H*, RMP*, RVP*	0 (0) RMP*, RVP*	0 (0) RMP*, RVP*	0 (0) RMP*, RVP*	- (2) H, RVP
	$E \succ L \succ G$	3 (0)	3 (0)	1 (0)	0 (0)	0 (0)	- (1)
	$G \succ E, L$	8 (2)	3 (0)	3 (0)	0 (0)	0 (0)	- (2)
	$L \succ G \succ E$	2 (0) HM, RMP*, RVP*	0 (0) RMP*, RVP*	0 (0) RVP*	2 (0) H, HM, RMP*, RVP	0 (0) H*, RMP*, RVP*	- (0) H, HM, RVP
	$L \succ E \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	- (0)
	$E \sim L \sim G$	- (3) KMM, DMP, DVP, HM, RMP, RVP	- (0) DVP*, RVP*	- (0) DVP*, RVP*	- (1)	- (0)	- (21) MEU, DVP, H, RVP
Ambiguity Neutral	$E \succ G \succ L$	13 (3) EZ, H, HM, RMP, RVP	1 (0)	3 (0)	0 (0)	0 (0)	- (0)
	$E \succ L \succ G$	1 (0)	6 (1)	1 (0)	0 (0)	0 (0)	- (0)
	$G \succ E, L$	4 (2)	1 (0)	12 (2)	0 (0)	1 (0)	- (1)
	$L \succ G \succ E$	0 (0)	0 (0)	0 (0)	0 (0) EZ, H, HM, RMP, RVP	0 (0)	- (0)
	$L \succ E \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	- (0)
	$E \sim L \sim G$	- (0)	- (1)	- (1)	- (0)	- (0)	- (18) all
Ambiguity Seeking	$E \succ G \succ L$	3 (0) HM	0 (0)	0 (0)	0 (0) HM	0 (0)	- (0) HM
	$E \succ L \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	- (0)
	$G \succ E, L$	0 (0)	0 (0)	4 (0)	0 (0)	0 (0)	- (1)
	$L \succ G \succ E$	0 (0)	0 (0)	0 (0)	0 (0) HM	0 (0)	- (0)
	$L \succ E \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	- (0)
	$E \sim L \sim G$	- (0)	- (0)	- (0)	- (0) KMM, HM	- (0)	- (4)

* The preference profile can only be rationalized by the model locally.

Table 11: Empirical classification of subjects (93 of 135) that express choices consistent with strict preference orderings on elicitation tasks RR1–RR3 and AR1–AR3, assuming the ambiguity attitude expressed is strict. A similar classification (in parenthesis) is used for the 68 subjects that jointly satisfy single crossing on the MPLRR and MPLAR tasks, assuming zero willingness to pay indicates indifference over all risk-/ambiguity-resolution options. Models in each preference profile cell can rationalize the corresponding profile.

4.4 Empirical Evaluation

We now incorporate individual-level data in our experiments into the cells of Table 11. These data, along with the theoretical predictions summarized in the table, help us evaluate the performance of different theoretical models under the CRRA-CES restriction.

Only 93 of the 135 subjects (68.9%) can be classified as having strict preference profiles over both risk and ambiguity resolution. The other 42 make choices that either violate a strict preference ordering over tasks RR1-RR3 or tasks AR1-AR3. The first number in each cell of Table 11 provides subject counts classifying these 93 subjects over the 75 profiles. A quick look indicates that subjects do not have preference profiles that are uniformly distributed. Early, monotone preferences for both risk and ambiguity resolution combined with ambiguity aversion ($n = 16$) and ambiguity neutrality ($n = 13$) attitudes are the two most commonly found profiles. The third most commonly found profile is a preference for gradual resolution in both domains and neutral ambiguity attitude ($n = 12$). Together these three profiles account for almost half of the subjects in the table (41 of 93, 44.1%).

Of course, the preceding analysis has ignored the MPLRR and MPLAR elicitation tasks. While almost all subjects exhibited preferences on the MPLs that were not inconsistent with their responses on the choice tasks, the modal subject response on both MPLRR and MPLAR was an unwillingness to pay any amount of money for one's preferred form of resolution, even at increments as low as 5 cents (see Section 3.1). It may be overly optimistic to interpret each one of these subjects as having strict preferences for their indicated form of uncertainty resolution. A more pessimistic interpretation is that subjects who are unwilling to pay for their previously-chosen form of resolution are actually indifferent; their selections on the RR1–RR3 and AR1–AR3 tasks simply reflect the fact that they cannot express this indifference. We also characterize subjects at this extreme. To do so, we omit subjects that violate single-crossing on either MPL task, but allow subjects that violate strict preferences on the choice tasks, provided they do not give a positive willingness to pay on the corresponding MPL task. Sixty-eight subjects satisfy these restrictions. Subjects that do not indicate a positive willingness to pay on the MPLRR (MPLAR) task are classified as indifferent over risk (ambiguity) resolution; otherwise, subjects are classified as before.[31] Table 11 also gives a categorization of subjects under this interpretation; results are shown in parentheses.

The interpretation of subjects' preferences is quite different under this pessimistic view. The modal subject ($n = 21$) is indifferent over the resolution of risk and uncertainty but is ambiguity averse. The second most commonly found profile ($n = 18$) is indifferent over risk and ambiguity resolution and also ambiguity neutral, the only profile that can be rationalized by the standard DEU model (and all models). Four other subjects indicate ambiguity seeking and indifference over risk and ambiguity resolution, a profile that cannot be rationalized by any model. Under this pessimistic view, a majority of subjects (43 of 68, 63.2%) are classified

[31] Recall that our MPL tasks only elicited subject's willingness to pay for early over late resolution (and vice versa). It is possible that a subject preferred gradual resolution most/least and was indifferent between early and late. For instance, there were 27 and 24 subjects on the MPLRR and MPLAR, respectively, that expressed no positive willingness to pay for early or late resolution and consistently selected gradual resolution on the choice tasks. As we are focusing on a pessimistic interpretation of our results, we classify all of these subjects as indifferent over the respective form of resolution.

as being indifferent to the timing of risk and ambiguity resolution.

According to Table 11, certain models can accommodate more preference profiles than others: in the pessimistic view, the DEU model only accommodates one preference profile, while at the other extreme, the RVP model locally rationalizes 19 profiles. Moreover, the portion of action space that is rationalizable for a model varies in non-trivial ways.[32]

Which model does the observed data best fit? To discipline the predictive power of the models, we employ a Selten score (Selten, 1991). That is, we calculate the difference between the percentage of subject observations explained by a model and the percentage of the action space covered by a model under the CRRA-CES restriction. Table 12 provides results for both our optimistic and pessimistic interpretations. In Panel A, the optimistic interpretation, only the EZ, H, HM, RMP, and RVP are included; these models are the only ones that can accommodate strict preferences over both risk and ambiguity resolution.

Fourteen percent of subjects can be classified as falling in the two cells predicted by the EZ model, yielding a Selten score of 0.132. The H, HM, RMP, and RVP models do better. While these models make predictions over a greater number of profiles and action space, they also can rationalize more subjects' behavior. The corresponding Selten scores are close together (0.303–0.369) regardless of whether we consider global rationalization or local rationalization. The gain in performance over the EZ model is largely due to the inclusion of the modal profile, that is, early monotone preferences for both risk and ambiguity resolution combined with ambiguity aversion.

To examine how sensitive the Selten scores are to the distribution of subjects, we calculate confidence intervals on the scores using 100,000 bootstrapped draws with replacement from our 135-subject population. The corresponding confidence intervals indicate scores may vary up or down by 10 percentage points. However, these confidence intervals cannot provide an indication of how correlated the scores of the five models are with each bootstrap. Should a bootstrap produce an exceptionally high Selten score for the EZ model, it likely does the same for the other four models, as the only two profiles the EZ model can rationalize are covered by the other models as well. In fact, in none of the 100,000 bootstraps does the EZ model outscore the H, HM, RMP or RVP models in global rationalization, a trivial case

[32] Tables A.8 and A.9 provide a breakdown of the combinatorics of this action space.

model	proportion of subjects categorized	proportion of action profile space covered	Selten score	(95% CI)
Panel A: optimistic view (93 subjects, 4,900 action profiles)				
EZ	0.140	0.007	0.132	(0.068, 0.208)
H	0.333	0.011	0.322	(0.226, 0.430)
HM	0.387	0.018	0.369	(0.261, 0.476)
RMP	0.312	0.009	0.303	(0.206, 0.410)
RVP	0.333	0.011	0.322	(0.226, 0.430)
H*	0.355	0.012	0.343	(0.235, 0.450)
RMP*	0.376	0.034	0.343	(0.235, 0.450)
RVP*	0.376	0.050	0.326	(0.219, 0.434)
Panel B: pessimistic view (68 subjects, 2,433,600 action profiles)				
DEU	0.265	0.021	0.244	(0.141, 0.361)
MEU	0.574	0.032	0.542	(0.395, 0.689)
KMM	0.309	0.025	0.284	(0.166, 0.416)
DMP	0.309	0.023	0.286	(0.168, 0.418)
DVP	0.618	0.034	0.584	(0.437, 0.746)
EZ	0.309	0.023	0.286	(0.169, 0.419)
H	0.676	0.038	0.639	(0.477, 0.801)
HM	0.382	0.033	0.350	(0.217, 0.482)
RMP	0.382	0.025	0.357	(0.225, 0.490)
RVP	0.721	0.040	0.681	(0.519, 0.843)
DVP*	0.618	0.070	0.548	(0.401, 0.710)
H*	0.676	0.038	0.639	(0.477, 0.800)
RMP*	0.382	0.033	0.349	(0.217, 0.482)
RVP*	0.721	0.090	0.630	(0.468, 0.792)

* Evaluated for local rationalization and differ from those for global rationalization.

Table 12: Calculation of Selten scores for strict uncertainty-resolution preferences, the "optimistic" view (Panel A) and where unwillingness to pay a positive amount on the MPLRR and MPLAR tasks is viewed as indifference, the "pessimistic" view (Panel B). 95% confidence intervals taken from 100,000 bootstraps of subject sample ($N = 135$).

of statistical significance (p = 0.000, in each of the 4 comparisons, see Table A.10). The HM model achieves the highest score overall at 0.369 and outperforms the other models in global rationalization (p < 0.02, 4 comparisons). It characterizes 5 more subjects than any other model, 3 who are ambiguity seeking and 2 who are ambiguity averse with early (late) preferences for ambiguity (risk) resolution.[33] When we compare these five models in local rationalization instead, none perform significantly better than the other four, although the EZ model performs the worst (p = 0.000, in each of the 4 comparisons between the EZ entry

[33]Note that the predictive importance of the decoupling of risk and ambiguity resolution in this specific direction was suggested in the regressions in Table 9.

and the H*, HM, RMP*, or RVP* entry, see Table A.10).

Panel B provides results for the pessimistic interpretation. It classifies subjects differently, placing many into profiles with indifference over risk and ambiguity resolution. Nonetheless, the modal profile includes ambiguity aversion which cannot be characterized by the DEU model. As a result, the DEU model achieves the lowest Selten score of the ten models in global rationalization ($p < 0.1$, in each of the 9 comparisons, see Table A.11). The only four models that can classify the modal profile, the MEU model and its generalizations (DVP, H and RVP), are unsurprisingly better performers in this exercise, achieving Selten scores over 0.5. The RVP model is the best performer in global rationalization overall as it significantly outperforms every other model over the 100,000 bootstraps (all $p < 0.1$, in each of the 9 comparisons). Looking back at Table 11, we see the key areas where the model succeeds. For both ambiguity-neutral and ambiguity-averse attitudes, it covers profiles where subjects are both indifferent and prefer early resolution of both risk and ambiguity. Further, it allows profiles where a subject can be indifferent over one form of uncertainty and prefer early resolution for the other, but only with an ambiguity-averse attitude. Interestingly, such preferences for uncertainty resolution were only demonstrated by ambiguity-averse subjects. In terms of local rationalization, the H and RVP models perform better than other models ($p < 0.05$ in all 16 comparisons between H* or RVP* and DEU, MEU, KMM, DMP, DVP*, EZ, HM, and RMP*), but their two performances are statistically identical ($p = 0.705$).

5 Conclusion

Models of generalized recursive utility provide alternatives to the standard DEU model. They are quite useful in explaining various financial and macroeconomic anomalies that cannot be explained by the DEU model without highly dubious parameter choices. An implication of these generalized recursive utility models is a preference for the timing of uncertainty resolution. Since these empirical estimations do not directly elicit preferences for the resolution of uncertainty, a natural question is whether it is reasonable to believe individuals have such preferences. A large number of experimental studies have found evidence of these preferences. However, all have looked at preferences over risk resolution, neglecting whether individuals have preferences over ambiguity resolution. Since different models make different assumptions about the two preferences, it is not clear to what extent models of generalized recursive utility are supported solely by findings based on risk-resolution preferences.

Our study provides the first experimental elicitation of preferences over ambiguity resolution. We elicit these preferences along with risk-resolution preferences. We find that these two preferences are positively, but not perfectly, correlated, and the attitude toward ambiguity affects this relationship. If an individual prefers early resolution of risk, she is 43.5 probability points more likely to prefer early resolution of ambiguity. If she is ambiguity seeking, she is 21.8–29.5 probability points less likely to prefer early resolution of ambiguity.

We review ten representative models of recursive utility widely used in the macroeconomics and finance literature. Among them, the H, HM, RMP, and RVP models can simultaneously accommodate strict risk-resolution preference, strict ambiguity-resolution preference, as well as non-neutral ambiguity attitude. The HM model can accommodate divergent preferences for strict risk resolution and ambiguity resolution globally. Under this model, having non-neutral ambiguity attitudes leads to distinct implications on the connection between risk- and ambiguity-resolution preferences. Our observed correlation between risk- and ambiguity-resolution preferences is consistent with these implications.

To enhance the precision of our analysis, we classify all subjects that display consistent preferences across the preference profile space and penalize models for being able to rationalize a greater percentage of this space, taking into account that certain preference profiles are associated with a larger number of possible actions. Under this approach, the HM model outperforms all the other models in terms of global rationalization. It benefits from accommodating ambiguity-seeking attitudes and divergent preferences for (early) ambiguity and (late) risk resolution among the ambiguity averse. It is worth noting that only a few subjects demonstrate these profiles, and the H, HM, RMP, and RVP models are much closer in performance than they are to the baseline EZ model which they all substantially outperform.

The preceding analysis requires a somewhat optimistic interpretation of our results. While we observe subjects consistently selecting a preferred option for risk and ambiguity resolution, they cannot indicate indifference. The same subjects often do not indicate a willingness to pay for their preferred form of resolution of more than 5 cents. A pessimistic view of such subjects is that they are indifferent to the timing of uncertainty resolution.

We also examine this more pessimistic interpretation of results and a greater class of models that could potentially rationalize our data. Since half of our subjects exhibit ambiguity aversion, the standard DEU model does not characterize our data well. The MEU, DVP, H, and RVP models perform better as they are the only ones that rationalize our modal subject profile, which includes ambiguity aversion with indifference to the timing of both forms of resolution. The RVP model is the best performer among these four in global rationalization. Like the other three models, it can rationalize profiles with indifference to the timing of both forms of resolution for both ambiguity-neutral and ambiguity-averse agents, as well as profiles with early preference to the timing of both forms of resolution for both ambiguity-neutral and ambiguity-averse agents. Unlike any other model, it allows both possible profiles where a subject can be indifferent to the timing of one form of uncertainty resolution and prefer early resolution for the other, among ambiguity-averse agents.

Regardless of interpretation, we note a few general trends. First, the best-performing models allow for ambiguity aversion; both the EZ and DEU models were consistently outperformed. Second, models that account for non-indifference to the timing of both types of uncertainty resolution, risk and ambiguity, also perform well. Third, while these resolution preferences are correlated, it is not always the case that they are the same. The best-performing model under both interpretations accommodated a decoupling of these preferences under ambiguity aversion. Finally, note that we reported local rationalization results of these models in an attempt to more broadly capture subjects that prefer gradual or one-shot resolution. In general, these local rationalization results failed to offer a great deal more explanatory power. Many of these empirically-observed profiles could not be rationalized by any model, whether in the sense of global or local rationalization, at least under the CRRA-CES restriction imposed in the paper. There have been theoretical papers studying a preference for one-shot resolution, but limited work focuses on preferences for gradual resolution. More theoretical work is needed to flexibly accommodate these exhibited preferences.

References

Abdellaoui, M., Klibanoff, P., and Placido, L. (2015). Experiments on compound risk in relation to simple risk and to ambiguity. *Management Science*, 61(6):1306–1322.

Ahlbrecht, M. and Weber, M. (1996). The resolution of uncertainty: An experimental study. *Journal of Institutional and Theoretical Economics (JITE)/Zeitschrift für die gesamte Staatswissenschaft*, pages 593–607.

Ahlbrecht, M. and Weber, M. (1997). An empirical study on intertemporal decision making under risk. *Management Science*, 43(6):813–826.

Azrieli, Y., Chambers, C. P., and Healy, P. J. (2018). Incentives in experiments: A theoretical analysis. *Journal of Political Economy*, 126(4):1472–1503.

Baillon, A., Halevy, Y., and Li, C. (2022a). Experimental elicitation of ambiguity attitude using the random incentive system. *Experimental Economics*, 25(3):1002–1023.

Baillon, A., Halevy, Y., and Li, C. (2022b). Randomize at your own risk: on the observability of ambiguity aversion. *Econometrica*, 90(3):1085–1107.

Bansal, R. and Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *The Journal of Finance*, 59(4):1481–1509.

Beauchamp, J. P., Benjamin, D. J., Laibson, D. I., and Chabris, C. F. (2020). Measuring and controlling for the compromise effect when estimating risk preference parameters. *Experimental Economics*, 23:1069–1099.

Brown, A. and Kim, H. (2013). Do individuals have preferences used in macro-finance models? An experimental investigation. *Management Science*, 60(4):939–958.

Budescu, D. V. and Fischer, I. (2001). The same but different: an empirical investigation of the reducibility principle. *Journal of Behavioral Decision Making*, 14(3):187–206.

Burks, S. V., Carpenter, J. P., Goette, L., and Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. *Proceedings of the National Academy of Sciences*, 106(19):7745–7750.

Cabrales, A., Gossner, O., and Serrano, R. (2013). Entropy and the value of information for investors. *American Economic Review*, 103(1):360–377.

Cerreia-Vioglio, S., Dillenberger, D., and Ortoleva, P. (2015). Cautious expected utility and the certainty effect. *Econometrica*, 83(2):693–728.

Charness, G., Rustichini, A., and Van de Ven, J. (2011). Self-confidence and strategic deterrence. *Working Paper*.

Chew, S. H. and Epstein, L. G. (1989). The structure of preferences and attitudess towards the timing of the resolution of uncertainty. *International Economic Review*, pages 103–117.

Chew, S. H. and Ho, J. L. (1994). Hope: An empirical study of attitude toward the timing of uncertainty resolution. *Journal of Risk and Uncertainty*, 8(3):267–288.

Chew, S. H., Miao, B., and Zhong, S. (2017). Partial ambiguity. *Econometrica*, 85(4):1239–1260.

Collard, F., Mukerji, S., Sheppard, K., and Tallon, J.-M. (2018). Ambiguity and the historical equity premium. *Quantitative Economics*, 9(2):945–993.

Dillenberger, D. (2010). Preferences for one-shot resolution of uncertainty and Allais-type behavior. *Econometrica*, 78(6):1973–2004.

Drechsler, I. (2013). Uncertainty, time-varying fear, and asset prices. *The Journal of Finance*, 68(5):1843–1889.

Eliaz, K. and Schotter, A. (2010). Paying for confidence: An experimental study of the demand for non-instrumental information. *Games and Economic Behavior*, 70(2):304–324.

Ellsberg, D. (1961). Risk, ambiguity, and the Savage axioms. *The Quarterly Journal of Economics*, 75(4):643–669.

Epstein, L. G., Farhi, E., and Strzalecki, T. (2014). How much would you pay to resolve long-run risk? *American Economic Review*, 104(9):2680–97.

Epstein, L. G. and Schneider, M. (2003). Recursive multiple-priors. *Journal of Economic Theory*, 113(1):1–31.

Epstein, L. G. and Zin, S. E. (1989). Risk aversion, and the temporal behavior of consumption and asset returns: a theoretical framework. *Econometrica*, 57(4):937–969.

Falk, A. and Zimmermann, F. (2017). Experimental evidence on preferences for information. *Working Paper*.

Fischbacher, U. (2007). z-tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics*, 10:171–178.

Freeman, D. J., Halevy, Y., and Kneeland, T. (2019). Eliciting risk preferences using choice lists. *Quantitative Economics*, 10(1):217–237.

Ganguly, A. and Tasoff, J. (2016). Fantasy and dread: the demand for information and the consumption utility of the future. *Management Science*, 63(12):4037–4060.

Gilboa, I. and Schmeidler, D. (1989). Maxmin expected utility with non-unique prior. *Journal of Mathematical Economics*, 18(2):141–153.

Greiner, B. (2015). Subject pool recruitment procedures: organizing experiments with orsee. *Journal of the Economic Science Association*, 1(1):114–125.

Halevy, Y. (2007). Ellsberg revisited: An experimental study. *Econometrica*, 75(2):503–536.

Hansen, L. and Sargent, T. J. (2001). Robust control and model uncertainty. *American Economic Review*, 91(2):60–66.

Hayashi, T. (2005). Intertemporal substitution, risk aversion and ambiguity aversion. *Economic Theory*, 25(4):933–956.

Hayashi, T. and Miao, J. (2011). Intertemporal substitution and recursive smooth ambiguity preferences. *Theoretical Economics*, 6(3):423–472.

Huber, J., Payne, J. W., and Puto, C. (1982). Adding asymmetrically dominated alternatives: Violations of regularity and the similarity hypothesis. *Journal of Consumer Research*, 9(1):90–98.

Jeong, D., Kim, H., and Park, J. Y. (2015). Does ambiguity matter? Estimating asset pricing models with a multiple-priors recursive utility. *Journal of Financial Economics*, 115(2):361–382.

Ju, N. and Miao, J. (2012). Ambiguity, learning, and asset returns. *Econometrica*, 80(2):559–591.

Klibanoff, P., Marinacci, M., and Mukerji, S. (2005). A smooth model of decision making under ambiguity. *Econometrica*, 73(6):1849–1892.

Klibanoff, P., Marinacci, M., and Mukerji, S. (2009). Recursive smooth ambiguity preferences. *Journal of Economic Theory*, 144(3):930–976.

Knight, F. H. (1921). *Risk, Uncertainty and Profit*, volume 31. Houghton Mifflin.

Kocher, M. G., Krawczyk, M., and van Winden, F. (2014). 'Let me dream on!' Anticipatory emotions and preference for timing in lotteries. *Journal of Economic Behavior & Organization*, 98:29–40.

Kreps, D. M. and Porteus, E. L. (1978). Temporal resolution of uncertainty and dynamic choice theory. *Econometrica*, 46:185–200.

Li, J. (2020a). Preferences for partial information and ambiguity. *Theoretical Economics*, 15(3):1059–1094.

Li, J. (2020b). Updating variational preferences. *Working Paper*.

Lovallo, D. and Kahneman, D. (2000). Living with uncertainty: Attractiveness and resolution timing. *Journal of Behavioral Decision Making*, 13(2):179–190.

Maccheroni, F., Marinacci, M., and Rustichini, A. (2006a). Ambiguity aversion, robustness, and the variational representation of preferences. *Econometrica*, 74(6):1447–1498.

Maccheroni, F., Marinacci, M., and Rustichini, A. (2006b). Dynamic variational preferences. *Journal of Economic Theory*, 128(1):4–44.

Marinacci, M., Principi, G., and Stanca, L. (2023). Recursive preferences and ambiguity attitudes. *Working Paper*.

Masatlioglu, Y., Orhun, Y., and Raymond, C. (2023). Intrinsic information preferences and skewness. *American Economic Review*, 113(10):2615–44.

Meissner, T. and Pfeiffer, P. (2022). Measuring preferences over the temporal resolution of consumption uncertainty. *Journal of Economic Theory*, 200:105379.

Nielsen, K. (2020). Preferences for the resolution of uncertainty and the timing of information. *Journal of Economic Theory*, 189(105090).

Selten, R. (1991). Properties of a measure of predictive success. *Mathematical Social Sciences*, 21:153–167.

Seo, K. (2009). Ambiguity and second-order belief. *Econometrica*, 77(5):1575–1605.

Strzalecki, T. (2011). Axiomatic foundations of multiplier preferences. *Econometrica*, 79(1):47–73.

Strzalecki, T. (2013). Temporal resolution of uncertainty and recursive models of ambiguity aversion. *Econometrica*, 81(3):1039–1074.

Von Gaudecker, H.-M., Van Soest, A., and Wengstrom, E. (2011). Heterogeneity in risky choice behavior in a broad population. *American Economic Review*, 101(2):664–94.

Weil, P. (1990). Nonexpected utility in macroeconomics. *The Quarterly Journal of Economics*, 105(1):29–42.

Zimmermann, F. (2015). Clumped or piecewise? - Evidence on preferences for information. *Management Science*, 61(4):740–753.

A Theoretical Appendix

A.1 Risk Resolution

For completeness, we present the well-known result on risk resolution under the EZ model.

Proposition 1. In the EZ model with CRRA utility function u and CES time aggregator W, if $\alpha < \rho$ (resp. $\alpha > \rho$), a DM prefers monotone and early (resp. late) resolution of risk globally; if $\alpha = \rho$, a DM is indifferent to the timing of risk resolution globally.

Proof. Fix any $h_1 > 0$, define $\overline{w}(x) \equiv u(W(h_1, u^{-1}(x))) = \frac{1}{\alpha}[h_1^\rho + \beta(\alpha x)^{\frac{\rho}{\alpha}}]^{\frac{\alpha}{\rho}}$. Notice that $\overline{w}'(x) = \beta(h_1^\rho(\alpha x)^{-\frac{\rho}{\alpha}} + \beta)^{\frac{\alpha}{\rho}-1}$ and $\overline{w}''(x) = \beta h_1^\rho(\rho - \alpha)(h_1^\rho + \beta(\alpha x)^{\frac{\rho}{\alpha}})^{\frac{\alpha}{\rho}-2}(\alpha x)^{\frac{\rho}{\alpha}-2}$, which has the same sign with $\rho - \alpha$. Hence, $\overline{w}(x)$ is strictly convex (resp. linear, or strictly concave) in x if $\alpha < \rho$ (resp. =, or >).

Fix a full-support $\tilde{q} \in \Delta(S_2)$. Given $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$ that represents gradual resolution of risk where $\tilde{p} \in \Delta^f(S_1, \Delta(S_2))(\tilde{q})$, the ex-ante certainty equivalent of consumption process h is

$$I_1^{ea}[f, \tilde{p}, \overline{\mathcal{S}}_1^f](h) = u^{-1}\Bigg(\mathbb{E}_{\hat{q}\sim\tilde{p}}\Big[u\Big(W\Big(h_1, u^{-1}\big(\mathbb{E}_{s_2\sim\hat{q}}\big[u(h_2(s_2))\big]\big)\Big)\Big)\Big]\Bigg).$$

Notice that $\mathbb{E}_{\hat{q}\sim\tilde{p}}$ takes expectation over random variable $\hat{q} \in f(S_1)$ following distribution $\tilde{p}$.

When risk is resolved early, every $\hat{q} \in f(S_1)$ degenerates to one state in S_2, and the ex-ante certainty equivalent of h is

$$u^{-1}\Big(\mathbb{E}_{s_2\sim\tilde{q}}\Big[u\big(W\big(h_1, h_2(s_2)\big)\big)\Big]\Big) = u^{-1}\Bigg(\mathbb{E}_{\hat{q}\sim\tilde{p}}\Big[\mathbb{E}_{s_2\sim\hat{q}}\Big[u\big(W\big(h_1, h_2(s_2)\big)\big)\Big]\Big]\Bigg).$$

When risk is resolved late, i.e., $f(S_1) = \{\tilde{q}\}$, the ex-ante certainty equivalent of h is

$$W\Bigg(h_1, u^{-1}\Big(\mathbb{E}_{s_2\sim\tilde{q}}\Big[u\big(h_2(s_2)\big)\Big]\Big)\Bigg) = W\Bigg(h_1, u^{-1}\Bigg(\mathbb{E}_{\hat{q}\sim\tilde{p}}\Big[\mathbb{E}_{s_2\sim\hat{q}}\Big[u\big(h_2(s_2)\big)\Big]\Big]\Bigg)\Bigg).$$

When $\alpha < \rho$, by applying Jensen's inequality, for almost all $h \in H$, we know that

$$u^{-1}\Big(\mathbb{E}_{s_2\sim\tilde{q}}\Big[u\big(W\big(h_1, h_2(s_2)\big)\big)\Big]\Big) > I_1^{ea}[f, \tilde{p}, \overline{\mathcal{S}}_1^f](h) > W\Bigg(h_1, u^{-1}\Big(\mathbb{E}_{s_2\sim\tilde{q}}\Big[u\big(h_2(s_2)\big)\Big]\Big)\Bigg)$$

(an exception happens for a degenerate set of h, for which the three terms are equal), implying a monotone preference for early resolution of risk. Similarly, when $\alpha > \rho$ (resp. $\alpha = \rho$), the DM prefers monotone and late (resp. is indifferent to the timing of) risk resolution. $\square$

The DEU model corresponds to the case that $\alpha = \rho$, thereby implying indifference to the timing of risk resolution. In the risk-resolution experiment where ambiguity is not present, the MEU, KMM, DMP, and DVP models reduce to the DEU model, and the H, HM, RMP, and RVP models reduce to the EZ model. Hence, we have the following corollary.

Corollary 1. Suppose utility functions u and v are of the CRRA form and the time aggregator W is of the CES form. In the DEU, MEU, KMM, DMP, and DVP models, a DM is indifferent to the timing of risk resolution globally. In the EZ, H, HM, RMP, and RVP models, if $\alpha < \rho$ (resp. $\alpha > \rho$), a DM prefers monotone and early (resp. late) resolution of risk globally; if $\alpha = \rho$, a DM is indifferent to the timing of risk resolution globally.

We have a few remarks on the theoretical predictions in the risk-resolution experiment.

1. In all the above models, due to the CRRA-CES restriction, the preference for the timing of risk resolution is indifferent or monotone. Thus, there is no strict preference for gradual resolution or one-shot resolution of risk globally.

2. The three gradual risk-resolution options G, Gp, and Gn are not ranked in Blackwell order. We cannot give a general prediction on their ranking based on the convexity/concavity of the $\overline{w}$ function defined in Proposition 1.

3. Our gradual risk-resolution options Gp and Gn have the same variance and symmetric skewness. Following Masatlioglu et al. (2023), one can make further predictions on the preference between these two based on the sign of the third derivative of $\overline{w}$. Notice that $\overline{w}'''(x) = \beta h_1^\rho(\rho-\alpha)[h_1^\rho + \beta(\alpha x)^{\frac{\rho}{\alpha}}]^{\frac{\alpha}{\rho}-3} \cdot (\alpha x)^{\frac{\rho}{\alpha}-3} \cdot [h_1^\rho(\rho-2\alpha) - (\alpha+\rho)\beta(\alpha x)^{\frac{\rho}{\alpha}}]$, which has the same sign with $(\frac{\rho}{\alpha}-1)[(\frac{\rho}{\alpha}-2)h_1^\rho(\alpha x)^{-\frac{\rho}{\alpha}} - \beta(\frac{\rho}{\alpha}+1)]$. When $\frac{\rho}{\alpha} \in (1,2]$, $\overline{w}'''(\cdot) < 0$, implying a preference for negative over positive skewness in risk resolution; when $\frac{\rho}{\alpha} \in [-1,1)$, $\overline{w}'''(\cdot) > 0$, implying a preference for positive over negative skewness; for $\frac{\rho}{\alpha} > 2$ or < -1, the sign of $\overline{w}'''(\cdot)$ is ambiguous and the preference between skewed options is not global; for $\frac{\rho}{\alpha} = 1$, the DM is indifferent to the timing of risk resolution.

A.2 The MEU and H Models

Proposition 2. 1. In the (w)MEU and (w)H models, a DM is indifferent to the timing of ambiguity resolution globally.

2. In the (i)H model with CRRA utility function u and CES time aggregator W, if $\alpha < \rho$ (resp. $\alpha > \rho$), a DM can prefer monotone and early (resp. late) resolution of ambiguity globally, or one-shot and early (resp. late) resolution of ambiguity locally; if $\alpha = \rho$ (which corresponds to the (i)MEU model), a DM can be indifferent to the timing of ambiguity resolution, or indifferent between early and late ambiguity resolution yet preferring one-shot ambiguity resolution globally.

Proof. In the (w)H model, which nests the (w)MEU model, given an information structure $[f, \mathcal{S}_1^f]$ along with the corresponding $\mathcal{Q}^f$, the ex-ante certainty equivalent of $h \in H$ is

$$I_1^{ea}[f, \mathcal{S}_1^f](h) = \min_{Q^k \in \mathcal{Q}^f} W\big(h_1, \min_{\hat{q} \in Q^k} I_2[\hat{q}](h)\big),$$

where

$$I_2[\hat{q}](h) \equiv u^{-1}\Big(\sum_{s_2 \in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\Big). \tag{1}$$

It is easy to see that under early and late ambiguity-resolution information structures,

$$I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) = \min_{\hat{q} \in f(S_1)} W(h_1, I_2[\hat{q}](h)), \qquad I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h) = W\big(h_1, \min_{\hat{q} \in f(S_1)} I_2[\hat{q}](h)\big).$$

By the monotonicity of W, we can conclude that $I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) = I_1^{ea}[f, \mathcal{S}_1^f](h) = I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h)$.

In the (i)H model, each $\pi \in \Pi$ has full support over $f(S_1)$. Given $\overline{w}(x)$ defined in the proof of Proposition 1 and any gradual ambiguity-resolution information structure $[f, \mathcal{S}_1^f]$ along with the corresponding $\mathcal{Q}^f$, the ex-ante certainty equivalent is given by

$$\begin{aligned} I_1^{ea}[f, \mathcal{S}_1^f](h) =& u^{-1}\Bigg(\min_{\tilde{\pi} \in \Pi} \mathbb{E}_{Q^k \sim \tilde{\pi}}\Bigg[u \circ W\Bigg(h_1, u^{-1}\Big(\min_{\tilde{\pi} \in \Pi} \mathbb{E}_{\hat{q} \sim \tilde{\pi}(\cdot|Q^k)}\Big[u\big(I_2[\hat{q}](h)\big)\Big]\Big)\Bigg)\Bigg]\Bigg) \\ \leq& \min_{\pi \in \Pi} u^{-1}\Bigg(\mathbb{E}_{Q^k \sim \pi}\Bigg[u \circ W\Bigg(h_1, u^{-1}\Big(\mathbb{E}_{\hat{q} \sim \pi(\cdot|Q^k)}\Big[u\big(I_2[\hat{q}](h)\big)\Big]\Big)\Bigg)\Bigg]\Bigg), \end{aligned} \tag{2}$$

where the inequality utilizes the observation that there may not exist a distribution $\pi \in \Pi$ that simultaneously attains the two minimizers in (2). Also, we have

$$I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) = \min_{\pi \in \Pi} u^{-1}\Big(\mathbb{E}_{\hat{q}\sim\pi}\big[u \circ W\big(h_1, I_2[\hat{q}](h)\big)\big]\Big),$$
$$I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h) = \min_{\pi \in \Pi} W\bigg(h_1, u^{-1}\Big(\mathbb{E}_{\hat{q}\sim\pi}\Big[u\big(I_2[\hat{q}](h)\big)\Big]\Big)\bigg).$$

When $\alpha < \rho$, by applying Jensen's inequality, we know that $I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) > I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h)$ for almost all $h \in H$. When Π is "rectangular" (Epstein and Schneider, 2003), the weak inequality after expression (2) holds as equality, and it is easy to see that $I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) > I_1^{ea}[f, \mathcal{S}_1^f](h) > I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h)$ for almost all $h \in H$. For a "non-rectangular" Π, the ranking between $I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h)$ and $I_1^{ea}[f, \mathcal{S}_1^f](h)$ may depend on the specific h and $\mathcal{S}_1^f$, and the DM may exhibit a preference for one-shot resolution locally. Symmetric results hold for $\alpha > \rho$. When $\alpha = \rho$, $I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) = I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h) \geq I_1^{ea}[f, \mathcal{S}_1^f](h)$. The last inequality holds strictly (resp. as equality) for almost all $h \in H$ in the non-rectangular (resp. rectangular) case. □

In the i(H) model, the three gradual ambiguity-resolution options G, Gp, and Gn are not Blackwell ordered and cannot be ranked based on the convexity/concavity of $\overline{w}$. Since the unobserved multiple-belief set Π can be very general, neither can we follow Masatlioglu et al. (2023) to provide a ranking between Gp and Gn. In the special case that the four minimizers when computing the ex-ante certainty equivalents for the Gp and Gn options are all attained by the uniform distribution over $(0.1, 0.9)$, $(0.4, 0.6)$, $(0.6, 0.4)$, and $(0.9, 0.1)$, we can analyze the ranking between the two in a parallel way as in the risk resolution analysis under the EZ model, i.e., when $\frac{\rho}{\alpha} \in (1, 2]$ (resp. $\frac{\rho}{\alpha} \in [-1, 1)$), $\overline{w}'''(\cdot) < 0$ (resp. $\overline{w}'''(\cdot) > 0$), which implies a strict preference for negative over positive (resp. positive over negative) skewness in ambiguity resolution.

A.3 The DEU, KMM, EZ, HM Models

Proposition 3. In the HM model with CRRA utility functions u and v and CES time aggregator W, if $\eta < \rho$ (resp. $\eta > \rho$, or $\eta = \rho$), a DM prefers monotone and early (resp. monotone and late, or is indifferent to the timing of) ambiguity resolution globally.

Proof. Fix any $h_1 > 0$. Define $w(x) \equiv v(W(h_1, v^{-1}(x))) = \frac{1}{\eta}[h_1^\rho + \beta(\eta x)^{\frac{\rho}{\eta}}]^{\frac{\eta}{\rho}}$, which is strictly convex (resp. linear, or strictly concave) in x if $\eta < \rho$ (resp. $=$, or $>$).

Given $[f, \mathcal{S}_1^f]$ that represents gradual resolution of ambiguity and the corresponding $\mathcal{Q}^f$, the ex-ante certainty equivalent of consumption process h can be rewritten as

$$I_1^{ea}[f, \mathcal{S}_1^f](h) = v^{-1}\Big(\mathbb{E}_{Q^k \in \mathcal{Q}^f}\Big[w\big(\mathbb{E}_{\hat{q} \in Q^k}\big[v(I_2[\hat{q}](h)|Q^k)\big]\big)\Big]\Big),$$

where $I_2[\hat{q}](h)$ is defined in expression (1) and $\hat{q} \in f(S_1)$ follows distribution μ.

Notice that each $Q^k \in \overline{\mathcal{Q}}^f$ is a singleton. Hence, early resolution of ambiguity leads to ex-ante certainty equivalent of

$$I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) = v^{-1}\left(\mathbb{E}_{\hat{q} \in f(S_1)}\Big[w\Big(v\big(I_2[\hat{q}](h)\big)\Big)\Big]\right) = v^{-1}\left(\mathbb{E}_{Q^k \in \mathcal{Q}^f}\left[\mathbb{E}_{\hat{q} \in Q^k}\Big[w\Big(v\big(I_2[\hat{q}](h)\big)\Big)\Big]\right]\right),$$

where the second equality uses the law of iterated expectations.

Also, notice that the only element of $\underline{\mathcal{Q}}^f$ is the set $f(S_1)$. Hence, late resolution of ambiguity leads to ex-ante certainty equivalent of

$$I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h) = v^{-1}\left(w\Big(\mathbb{E}_{\hat{q} \in f(S_1)}\big[v(I_2[\hat{q}](h))\big]\Big)\right) = v^{-1}\left(w\Big(\mathbb{E}_{Q^k \in \mathcal{Q}^f}\Big[\mathbb{E}_{\hat{q} \in Q^k}\big[v(I_2[\hat{q}](h))\big]\Big]\Big)\right).$$

When $\eta < \rho$, by Jensen's inequality, we know that $I_1^{ea}[f, \overline{\mathcal{S}}_1^f](h) > I_1^{ea}[f, \mathcal{S}_1^f](h) > I_1^{ea}[f, \underline{\mathcal{S}}_1^f](h)$ for almost all $h \in H$, due to the strict convexity of w. Hence, the DM prefers early resolution of ambiguity monotonically. Similarly, when $\eta > \rho$ (resp. $\eta = \rho$), the DM prefers monotone and late (resp. is indifferent to the timing of) ambiguity resolution. □

We cannot provide a general ranking among G, Gp, and Gn options in the ambiguity-resolution experiment, and neither can we rank Gp and Gn options in general. However, if there is a good reason to believe that the second-order belief μ is uniform over the four first-order beliefs, the two skewed options have the same variance and symmetric skewness, and their ranking can be analyzed from the third derivative of w: when $\frac{\rho}{\eta} \in (1, 2]$ (resp. $\frac{\rho}{\eta} \in [-1, 1)$), we have $w'''(\cdot) < 0$ (resp. $w'''(\cdot) > 0$), implying a preference for negative over positive (resp. positive over negative) skewness in the ambiguity-resolution experiment; for

$\frac{\rho}{\eta} > 2$ or < -1, the sign of $w'''(\cdot)$ is ambiguous and the preference between skewed options is not global; for $\frac{\rho}{\eta} = 1$, the DM is indifferent to the timing of ambiguity resolution.

Proposition 3 shows that in the HM model, the preference for the timing of ambiguity resolution is determined by two key factors: ρ and η. Recall the conclusion on risk resolution: α and ρ determine the preference for the timing of risk resolution in the HM model. Also, recall that a DM is ambiguity averse (resp. neutral, or seeking) if $\eta < \alpha$ (resp. $\eta = \alpha$, or $\eta > \alpha$). As such, we have the following corollary.

Corollary 2. In the HM model with CRRA utility functions u and v and CES time aggregator W, if an ambiguity-averse (resp. -seeking) DM weakly prefers early (resp. late) resolution of risk, then she prefers early (resp. late) resolution of ambiguity globally; the ambiguity-resolution preference of an ambiguity-neutral DM (this happens only if the HM model reduces to the EZ model) is inherited from her risk-resolution preference.

Without the CRRA-CES restriction, we cannot make this claim on the connection between the risk-resolution preference (decided by the convexity/concavity of $u(W(h_1, u^{-1}(x))))$, the ambiguity-resolution preference (decided by the convexity/concavity of $v(W(h_1, v^{-1}(x))))$, and ambiguity attitude (decided by convexity/concavity of $v \circ u^{-1}$). For example, suppose $v(x) = -e^{-u(x)}$, $u(x)$ is of the CRRA form with $\alpha = -1$, and W is of the CES form with $\rho = -0.4$, $\beta = 0.9$, period-1 consumption $h_1 = 10$, and period-2 consumption x. In this case, function $u(W(h_1, u^{-1}(x)))$ is strictly convex, and thus, the DM prefers early resolution of risk, and the DM is ambiguity averse. But the function $v(W(h_1, v^{-1}(x)))$ is neither convex nor concave for $x \in (-\infty, -1)$. Thus, the DM has no global ambiguity-resolution preference.

Under the CRRA-CES restriction, the DEU (resp. KMM, or EZ) model is equivalent to the HM model with $\alpha = \rho = \eta$ (resp. $\alpha = \rho$, or $\alpha = \eta$). Hence, we have the following result.

Corollary 3.

1. In the DEU model with CRRA utility function u, a DM is indifferent to the timing of ambiguity resolution globally.

2. In the KMM model with CRRA utility functions u and v, an ambiguity-averse (resp. -seeking) DM prefers early (resp. late) resolution of ambiguity monotonically globally; an ambiguity-neutral DM is indifferent to the timing of ambiguity resolution globally.

3. In the EZ model with CRRA utility function u and CES aggregator W, a DM's ambiguity-resolution preference is inherited from her risk-resolution preference.

A.4 The DMP and RMP Models

Proposition 4. In the RMP model with CRRA utility function u, CES time aggregator W, and $\theta < \infty$, for $\alpha = \rho$ (corresponding to the DMP model) or $0 < \alpha < \rho$, a DM prefers monotone and early resolution of ambiguity globally; no other ambiguity-resolution preference can be globally rationalized. If $\theta = \infty$ (which does not rule out the DMP model), a DM's ambiguity-resolution preference is inherited from her risk-resolution preference.

Proof. The second statement is trivial. We focus on the $\theta < \infty$ case. Define a function ϕ_θ: $(0, +\infty) \to \mathbb{R}$ by $\phi_\theta(x) \equiv -e^{-\frac{x}{\theta}}$. Fix any gradual ambiguity resolution information structure $[f, S_1^f]$ and the corresponding $\mathcal{Q}^f$. By Strzalecki (2011), the ex-ante certainty equivalents under early, gradual, and late ambiguity-resolution information structures are equal to

$$u^{-1} \circ \phi_\theta^{-1}\Big(\mathbb{E}_{Q^k \in \mathcal{Q}^f \sim \pi'}\big[\mathbb{E}_{\hat{q} \sim \pi'(\cdot|Q^k)}\big[\phi_\theta \circ u \circ W\big(h_1, u^{-1}(\mathbb{E}_{s_2 \sim \hat{q}}[u(h_2(s_2))])\big)\big]\big]\Big), \tag{3}$$

$$u^{-1} \circ \phi_\theta^{-1}\Big(\mathbb{E}_{Q^k \in \mathcal{Q}^f \sim \pi'}\big[\phi_\theta \circ u \circ W\big(h_1, u^{-1} \circ \phi_\theta^{-1}\big(\mathbb{E}_{\hat{q} \sim \pi'(\cdot|Q^k)}\big[\mathbb{E}_{s_2 \sim \hat{q}}[\phi_\theta \circ u(h_2(s_2))]\big]\big)\big)\big]\Big), \tag{4}$$

$$W\Big(h_1, u^{-1} \circ \phi_\theta^{-1}\Big(\mathbb{E}_{Q^k \in \mathcal{Q}^f \sim \pi'}\big[\mathbb{E}_{\hat{q} \sim \pi'(\cdot|Q^k)}\big[\mathbb{E}_{s_2 \sim \hat{q}}[\phi_\theta \circ u(h_2(s_2))]\big]\big]\Big)\Big). \tag{5}$$

Define $\tilde{w}(x) \equiv \phi_\theta \circ u \circ W(h_1, u^{-1} \circ \phi_\theta^{-1}(x))$, or equivalently $\phi_\theta \circ \overline{w} \circ \phi_\theta^{-1}(x)$, where $x \in (-1, 0)$ for $\alpha > 0$, $x \in (-\infty, -1)$ for $\alpha < 0$, and $\overline{w}$ is defined in the proof of Proposition 1.

It can be shown that $\tilde{w}''(x)$ is given by

$$\frac{\phi_\theta'(\overline{w}(\phi_\theta^{-1}(x)))\overline{w}'(\phi_\theta^{-1}(x))}{(\phi_\theta'(\phi_\theta^{-1}(x)))^2} \cdot \Big(-\frac{1}{\theta}\overline{w}'(\phi_\theta^{-1}(x)) + \frac{\overline{w}''(\phi_\theta^{-1}(x))}{\overline{w}'(\phi_\theta^{-1}(x))} + \frac{1}{\theta}\Big),$$

which has the same sign with

$$-\frac{1}{\theta}\beta[h_1^\rho(\alpha\phi_\theta^{-1}(x))^{-\frac{\rho}{\alpha}} + \beta]^{\frac{\alpha}{\rho}-1} + \frac{(\rho - \alpha)h_1^\rho}{(h_1^\rho + \beta(\alpha\phi_\theta^{-1}(x))^{\frac{\rho}{\alpha}})\alpha\phi_\theta^{-1}(x)} + \frac{1}{\theta}.$$

When $0 < \alpha < \rho$ or $\alpha = \rho$, $\tilde{w}''(x) > 0$ for all $x > 0$ and thus, $\tilde{w}$ is strictly convex; for any other parameter range, $\tilde{w}$ is not globally convex/concave. Notice that (4) is higher/lower than (5) for all h if and only if $\tilde{w}$ is convex/concave. Hence, beyond the range $0 < \alpha < \rho$ or $\alpha = \rho$, there is no global ambiguity-resolution preference.

When $0 < \alpha < \rho$ or $\alpha = \rho$, by strict convexity of $\tilde{w}$ and ϕ_θ,

$$
\begin{aligned}
&\mathbb{E}_{\hat{q}\sim\pi'(\cdot|Q^k)}\left[\phi_\theta \circ u \circ W\left(h_1, u^{-1}\left(\mathbb{E}_{s_2\sim\hat{q}}[u(h_2(s_2))]\right)\right)\right] \\
>&\phi_\theta \circ u \circ W\Big(h_1, u^{-1} \circ \phi_\theta^{-1}\left(\mathbb{E}_{\hat{q}\sim\pi'(\cdot|Q^k)}\left[\phi_\theta \circ \left(\mathbb{E}_{s_2\sim\hat{q}}[u(h_2(s_2))]\right)\right]\right)\Big) \\
>&\phi_\theta \circ u \circ W\Big(h_1, u^{-1} \circ \phi_\theta^{-1}\left(\mathbb{E}_{\hat{q}\sim\pi'(\cdot|Q^k)}\left[\mathbb{E}_{s_2\sim\hat{q}}[\phi_\theta \circ u(h_2(s_2))]\right]\right)\Big)
\end{aligned}
$$

for almost all $h \in H$. As a result, (3) dominates (4), i.e., early resolution of ambiguity dominates gradual resolution. In sum, this is the only parameter range with global ambiguity-resolution preference and the preference is for early resolution of ambiguity. □

A.5 The DVP and RVP Models

Proposition 5. In the RVP model with CRRA utility function u and CES time aggregator W, the only ambiguity-resolution preferences that can be rationalized globally are given as follows. If $\alpha \neq \rho$, a DM can be indifferent to the timing of ambiguity resolution or exhibit the monotone ambiguity-resolution preference inherited from the risk-resolution preference; if $\alpha = \rho$ (i.e., in the DVP model), a DM can be indifferent to the timing of ambiguity resolution, indifferent between early and late ambiguity resolution yet preferring one-shot ambiguity resolution, or exhibit a monotone preference for early ambiguity resolution.

Proof. The fact that the above-mentioned preferences can be globally rationalized is trivial since the RVP model nests the H model and the RMP model as special cases.

We still need to show that it is impossible to globally rationalize other preference profiles.

Step 1. Show that there does not exist $\alpha > \rho$ and function c to globally rationalize ambiguity aversion and a preference for early resolution of ambiguity.

Suppose not. Then there exists $\alpha > \rho$ and function c such that

$$\begin{aligned}
&\min_{\pi\in\Delta(f(S_1))}\{\sum_{\hat{q}\in f(S_1)}\overline{w}\big(\sum_{s_2\in S_2}u\big(h_2(s_2)\big)\hat{q}(s_2)\big)\pi(\hat{q})+c(\pi)\}\\
>&\overline{w}\Big(\min_{\pi\in\Delta(f(S_1))}\{\sum_{\hat{q}\in f(S_1)}\sum_{s_2\in S_2}u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q})+c(\pi)\}\Big) \qquad (6)
\end{aligned}$$

for almost all h_2, where $\overline{w}$ is defined in the proof of Proposition 1.

Suppose $f(S_1) = \{q^1 = (0,1), q^2 = (1,0)\}$ and π assigns probability π_1 to q^1. Define $c_0(\pi_1) \equiv c((\pi_1, 1-\pi_1))$. Notice that to have strict ambiguity-resolution preferences, we cannot have $c_0(0) = 0$ or $c_0(1) = 0$. Otherwise, one can easily construct a generic set of consumption processes for which the worst-case π on both sides of the inequality is $(0,1)$ or $(1,0)$, respectively, leading to indifference between early and late resolution for these consumption processes.

For any $\overline{x} < 0$ and $\xi \geq 0$ such that $\overline{x} \pm \xi < 0$ (when $\alpha < 0$), or $\overline{x} > 0$ and $\xi \geq 0$ such that $\overline{x} \pm \xi > 0$ (when $\alpha > 0$), there exists h_2 such that

$$\overline{x}-\xi=\sum_{s_2\in S_2}u\big(h_2(s_2)\big)q^1(s_2),\ \overline{x}+\xi=\sum_{s_2\in S_2}u\big(h_2(s_2)\big)q^2(s_2).$$

Expression (6) leads to (8)>(9) below:

$$\begin{aligned}
&\min_{\pi_1}\{\overline{w}\big((\overline{x}-\xi)\pi_1+(\overline{x}+\xi)(1-\pi_1)\big)+c_0(\pi_1)\} && (7)\\
\geq&\min_{\pi_1}\{\overline{w}(\overline{x}-\xi)\pi_1+\overline{w}(\overline{x}+\xi)(1-\pi_1)+c_0(\pi_1)\} && (8)\\
>&\overline{w}\big(\min_{\pi_1}\{(\overline{x}-\xi)\pi_1+(\overline{x}+\xi)(1-\pi_1)+c_0(\pi_1)\}\big), && (9)
\end{aligned}$$

for all $\xi > 0$, where (7)≥(8) follows from the strict concavity of $\overline{w}$ (due to $\alpha > \rho$).

Let π_1^*, π_2^{**}, and π_3^{***} denote the maximal minimizers in (7), (8), and (9), which all endogenously depend on $\overline{x}$ and ξ. When $\xi = 0$, $\pi_1^* = \pi_1^{**} = \pi_1^{***} = \underline{\pi}_1$, where $\underline{\pi}_1$ is the maximal number in $[0,1]$ that solves $\min_{\pi_1} c_0(\pi_1) = 0$. We have shown $\underline{\pi}_1 \in (0,1)$ two paragraphs before. By the convexity of c_0, if c_0 is not right-continuous at $\underline{\pi}_1$, it must be the case that $\lim_{\pi_1\to\underline{\pi}_{1+}} c_0(\pi_1) = +\infty$, which essentially leads to the same ambiguity-resolution preference as the H model, contradicting with the supposition that one can rationalize the preference for late resolution of risk and early resolution of ambiguity. At last, if $c'_{0+}(\underline{\pi}_1) > 0$, for sufficiently small $\xi > 0$, the left and right derivatives of the braced term in (9) with respect to π_1 evaluated at $\underline{\pi}_1$ are $-2\xi + c'_{0-}(\underline{\pi}_1) < 0$, following from the fact that π_1 is a minimizer of c_0, and $-2\xi + c'_{0+}(\underline{\pi}_1) > 0$. These inequalities imply that $\pi_1^{***} = \underline{\pi}_1$, and thus, $c_0(\pi_1^{***}) = c_0(\underline{\pi}_1) = 0$, leading to

$$\begin{aligned}&\overline{w}\big((\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***})\big) + c_0(\pi_1^{***})\\ \geq &(7) \geq (8) > (9) = \overline{w}\big((\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***}) + c_0(\pi_1^{***})\big).\end{aligned}$$

Notice that the two ends in the sequence of inequalities are equal, leading to a contradiction. Hence, $c'_{0+}(\underline{\pi}_1) = 0$.

We discuss two cases.

Case 1, $\alpha > 0$. It can be shown that for x that is positive and sufficiently small, $\overline{w}'(x) > 1$. Since $\overline{x} - \xi + c_0(\pi_1^{***}) \leq (\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***}) + c_0(\pi_1^{***}) \leq (\overline{x}-\xi)\underline{\pi}_1 + (\overline{x}+\xi)(1-\underline{\pi}_1) \leq \overline{x}+\xi$, we have $c_0(\pi_1^{***}) \leq 2\xi$. Moreover, the observation that $c'_{0+}(\underline{\pi}_1) = 0$ implies that $-2\xi + c'_{0+}(\underline{\pi}_1) < 0$ for all $\xi > 0$, which further implies that $\pi_1^{***} > \underline{\pi}_1$ by taking the first-order condition with respect to π_1 in the minimizing operator of (9). Hence, $c_0(\pi_1^{***}) \in (0, 2\xi]$. As a result, there exists $\overline{x}$ and ξ positive and sufficiently small such that $(\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***}) + c_0(\pi_1^{***})$ is positive and sufficiently small, and thus, $\overline{w}'\big((\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***}) + c_0(\pi_1^{***})\big) > 1$. This contradicts the inequality that

$$\overline{w}\big((\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***})\big) + c_0(\pi_1^{***}) > \overline{w}\big((\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***}) + c_0(\pi_1^{***})\big),$$

which follows from the inequality that (7) > (9) for $\xi > 0$.

Case 2, $\alpha < 0$. It is easy to show that the second-order Taylor approximation of

$$\overline{w}(\overline{x}-\xi)\pi_1^{**} + \overline{w}(\overline{x}+\xi)(1-\pi_1^{**}) + c_0(\pi_1^{**}) - \overline{w}\big((\overline{x}-\xi)\pi_1^{***} + (\overline{x}+\xi)(1-\pi_1^{***}) + c_0(\pi_1^{***})\big)$$

at $\xi = 0$ has the same sign with $\overline{w}''(\overline{x})\underline{\pi}_1(1-\underline{\pi}_1)c''_0(\underline{\pi}_1) - (\overline{w}')^2(\overline{x}) + \overline{w}'(\overline{x})$, which is negative when $\overline{x}$ goes to zero from the left in which case $\overline{w}'(\overline{x}) \to 0$ yet $\overline{w}''(\overline{x})\underline{\pi}_1(1-\underline{\pi}_1)c''_0(\underline{\pi}_1) < 0$.

This contradicts the observation that (8) > (9).

Step 2. Show that there does not exist $\alpha < \rho$ and function c to globally rationalize ambiguity aversion and a preference for late resolution of ambiguity.

Suppose not. Following a similar argument as in Step 1, we have

$$\begin{aligned}
&\overline{w}\big(\min_{\pi_1}\{(\overline{x}-\xi)\pi_1+(\overline{x}+\xi)(1-\pi_1)+c_0(\pi_1)\}\big)\\
>&\min_{\pi_1}\{\overline{w}(\overline{x}-\xi)\pi_1+\overline{w}(\overline{x}+\xi)(1-\pi_1)+c_0(\pi_1)\}\\
\geq&\min_{\pi_1}\{\overline{w}\big((\overline{x}-\xi)\pi_1+(\overline{x}+\xi)(1-\pi_1)\big)+c_0(\pi_1)\},
\end{aligned}$$

for all $\xi > 0$, where the first inequality follows from the preference for late resolution of ambiguity, and the second follows from the strict convexity of $\overline{w}$. As a result,

$$\overline{w}\big((\overline{x}-\xi)\pi_1^*+(\overline{x}+\xi)(1-\pi_1^*)+c_0(\pi_1^*)\big)>\overline{w}\big((\overline{x}-\xi)\pi_1^*+(\overline{x}+\xi)(1-\pi_1^*)\big)+c_0(\pi_1^*),$$

for all $\overline{x}$ and $\xi > 0$ such that $\overline{x} \pm \xi > 0$ (when $\alpha > 0$) or $\overline{x} \pm \xi < 0$ (when $\alpha < 0$). This implies that $\overline{w}'(x) > 1$ for all $x \in (0, +\infty)$ (resp. $x \in (-\infty, 0)$) when $\alpha > 0$ (resp. $\alpha < 0$). However, this is impossible given the close form of $\overline{w}'$. A contradiction.

Step 3. When there is a strict preference between early and late ambiguity-resolution options, we claim that the RVP model cannot globally rationalize a strict preference for gradual or one-shot ambiguity resolution. To see this, think of a sufficiently large set S_1 and a bijection f. When partitioning S_1 differently, we can have different gradual ambiguity-resolution options, some sufficiently "close" to the early option and some sufficiently "close" to late. Due to the strict ranking between early and late options, it is impossible that all the gradual options dominate both early and late options; neither is it possible that all gradual options are dominated by both early and late options. □

B Omitted Proofs for Local Rationalization

The following claim shows that the RMP and RVP models can rationalize many risk- and ambiguity-resolution preferences in a local sense.

Claim 1. Excluding the profile with ambiguity aversion, monotone preference for late risk resolution, and the preference for gradual ambiguity resolution, for any profile with ambiguity aversion, strict monotone risk-resolution preference, and strict ambiguity-resolution preference of any format, there exists $\alpha \neq 0$, $\rho \neq 0$, $\theta \in (0, +\infty)$, $\beta \in (0, 1)$, and full-support $\pi' \in \Delta(f(S_1))$, such that the preference profile can be rationalized locally.

Proof. To establish this claim, we present three groups of parameters and numerically compute the rankings between E, G, Gp, Gn, and L options in our ambiguity-resolution experiment (with period-1 payment \$10 and period-2 payment \$22 or \$4).

Group 1: For uniform π', $\alpha = -3.2$, $\rho = -0.2$, $\beta = 0.9$, the DM is predicted to prefer early resolution of risk monotonically. In the ambiguity-resolution experiment, the predicted preferences can be $L \succ Gp \succ G \succ Gn \succ E$ when $\theta = 1.05$, $Gp \succ L \succ E \succ G \succ Gn$ when $\theta = 16$, and $E \succ Gp \succ G \succ Gn \succ L$ when $\theta = 50$.

Group 2: For $\pi'((0.1, 0.9), (0.4, 0.6), (0.6, 0.4), (0.9, 0.1)) = (0.4, 0.3, 0.2, 0.1)$, where $(0.1, 0.9)$ assigns probability 0.1 to the high prize \$22 and 0.9 to the low prize \$4, $\alpha = -1.2$, $\rho = -0.2$, and $\beta = 0.9$, the DM prefers early resolution of risk monotonically. In the ambiguity-resolution experiment, the predicted preferences can be $L \succ E \succ Gp \succ G \succ Gn$ when $\theta = 3.1$ and $E \succ L \succ Gp \succ G \succ Gn$ when $\theta = 3.2$.

Group 3: For uniform π', $\alpha = 0.8$, $\rho = 0.75$, and $\beta = 0.9$, the DM is predicted to prefer late resolution of risk monotonically. The predicted ambiguity-resolution preferences are $E \succ Gp \succ G \succ Gn \succ L$ when $\theta = 0.1$, $E \succ L \succ Gp \succ G \succ Gn$ when $\theta = 500$, $L \succ E \succ Gp \succ G \succ Gn$ when $\theta = 600$, and $L \succ Gp \succ G \succ Gn \succ E$ when $\theta = 10000$. □

Claim 2. The DVP model can locally rationalize all ambiguity-resolution preferences where early is at least weakly preferred to late. The RVP model with $\alpha \neq \rho$ can locally rationalize every preference profile with ambiguity aversion, strict monotone risk-resolution preference, and any strict ambiguity-resolution preference.

Proof. To establish the first statement, we complement Proposition 5 ($\alpha = \rho$) with two examples.

To see that an RVP model with $\alpha = \rho = 1$, which is also a DVP model, can locally rationalize a preference for gradual ambiguity resolution, we modify Li (2020a)'s example. For each $r \in [0, 0.5]$, let $\pi_r = (r, 0.25, 0.25, 0.5 - r)$ denote a distribution over $f(S_1) = \{q^1 = (0.1, 0.9), q^2 = (0.4, 0.6), q^3 = (0.6, 0.4), q^4 = (0.9, 0.1)\}$, where $(0.1, 0.9)$ assigns probability 0.1 to the high prize (\$22) and 0.9 to the low prize (\$4) (the advance payment is \$10). Denote the class of all π_r by $\hat{\Pi}$ and $\mathcal{Q}^f = \{Q^1 = \{q^1, q^2\}, Q^2 = \{q^3, q^4\}\}$. Define

$$c(\pi) \equiv \begin{cases} |r - 0.25| & \text{if } \pi \in \hat{\Pi}, \\ +\infty & \text{if } \pi \notin \hat{\Pi}. \end{cases}$$

When $\beta = 1$, it is easy to establish that Options E and L lead to ex-ante certainty equivalents of 19.65, and Option G has a certainty equivalent of 20.152. Slightly perturbing it so that $\beta \in (0, 1)$, we can still locally rationalize a preference for gradual ambiguity resolution.

To show that an RVP model with $\alpha = \rho = 1$ can locally rationalize a preference for one-shot and early ambiguity resolution, recall from Maccheroni et al. (2006b) that the mean-variance preference is a special case of the DVP model. Let $\theta \in (0, +\infty]$ be a parameter and $\hat{q}$ be a reference distribution of random variable s_2. For any gradual ambiguity-resolution information structure $[f, S_1^f]$ and corresponding $\mathcal{Q}^f$ whose generic element is denoted by Q^k, the ex-ante certainty equivalents of early, gradual, and late ambiguity resolution are

$$h_1 + \beta \mathbb{E}_{s_2 \sim \hat{q}}[h_2(s_2)] - \frac{\beta^2}{2\theta} \mathrm{Var}_{s_2 \sim \hat{q}}[h_2(s_2)],$$

$$h_1 + \beta \mathbb{E}_{s_2 \sim \hat{q}}[h_2(s_2)] - \frac{\beta}{2\theta} \mathbb{E}_{Q^k \sim \hat{q}}\big[\mathrm{Var}_{s_2 \sim \hat{q}|Q^k}[h_2(s_2)|Q^k]\big] - \frac{\beta^2}{2\theta} \mathrm{Var}_{Q^k \sim \hat{q}}\big[\mathbb{E}_{s_2 \sim \hat{q}|Q^k}[h_2(s_2)|Q^k]\big]$$
$$- \frac{\beta^2}{8\theta^3} \mathrm{Var}_{Q^k \sim \hat{q}}\big[\mathrm{Var}_{s_2 \sim \hat{q}|Q^k}[h_2(s_2)|Q^k]\big] + \frac{\beta^2}{2\theta^2} \mathrm{Cov}_{Q^k \sim \hat{q}}\big[\mathbb{E}_{s_2 \sim \hat{q}|Q^k}[h_2(s_2)|Q^k], \mathrm{Var}_{s_2 \sim \hat{q}|Q^k}[h_2(s_2)|Q^k]\big],$$

$$h_1 + \beta \mathbb{E}_{s_2 \sim \hat{q}}[h_2(s_2)] - \frac{\beta}{2\theta} \mathrm{Var}_{s_2 \sim \hat{q}}(h_2(s_2)).$$

When $\beta \to 1$ from the left, the positive payoff difference between early and late resolution converges to zero, and the payoff difference between early and gradual resolution converges to $\frac{1}{8\theta^3}\mathrm{Var}\left[\mathrm{Var}[h_2(s_2)|Q^k]\right] - \frac{1}{2\theta^2}\mathrm{Cov}\left[\mathbb{E}[h_2(s_2)|Q^k], \mathrm{Var}[h_2(s_2)|Q^k]\right]$, which has the same sign with $\mathrm{Var}\left[\mathrm{Var}[h_2(s_2)|Q^k]\right] - 4\theta\mathrm{Cov}\left[\mathbb{E}[h_2(s_2)|Q^k], \mathrm{Var}[h_2(s_2)|Q^k]\right]$. Given the consumption process and three gradual ambiguity-resolution information structures used in the experiments, by adjusting $\hat{q}$ so that the first variance term is always positive under all three gradual resolution information structures, this expression can be made positive to locally rationalize a preference for one-shot and early ambiguity resolution when $\theta \to 0$.

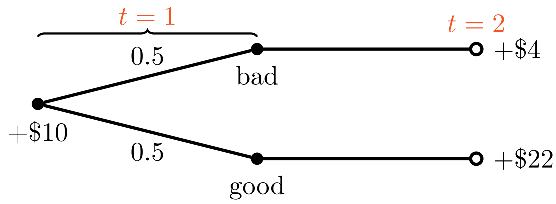
To show that the RVP model with $\alpha \neq \rho$ can locally rationalize every preference profile with ambiguity aversion, strictly monotone risk-resolution preference, and strict ambiguity-resolution preference, it suffices to supplement Claim 1 with our first example in the current proof by slightly perturbing α and ρ so that $\alpha < \rho$ or $\rho < \alpha$. By continuity, the certainty equivalent of G can still be higher than that of E and L. □

C Accommodating Preferences for Gradual Uncertainty Resolution

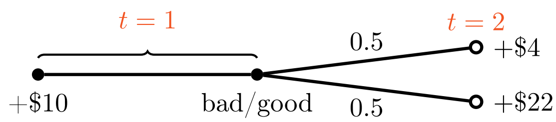
In this section, we show with an example that if one goes beyond the CRRA-CES restriction, the EZ, H, HM, RMP, and RVP models can locally rationalize preference for gradual risk resolution. Similarly, going beyond the CRRA-CES restriction may lead to a local preference for gradual resolution of ambiguity in some models.

Example 1. Let W be the same as the one introduced in the main text, i.e., of the CES form with parameter ρ. Let $u(x) = -e^{-\frac{x}{\theta}}$, which is of the constant absolute risk aversion (CARA) form. For $\rho = -0.2$ and $\beta = 0.9$, the predicted risk-resolution preference under the EZ model (with period-1 payment \$10 and period-2 payment \$22 or \$4) is $Gp \succ L \succ G \succ Gn \succ E$ when $\theta = 17$.

D Information Structure Diagrams in Risk- (RR1-RR3) and Ambiguity-Resolution Tasks (AR1-AR3)

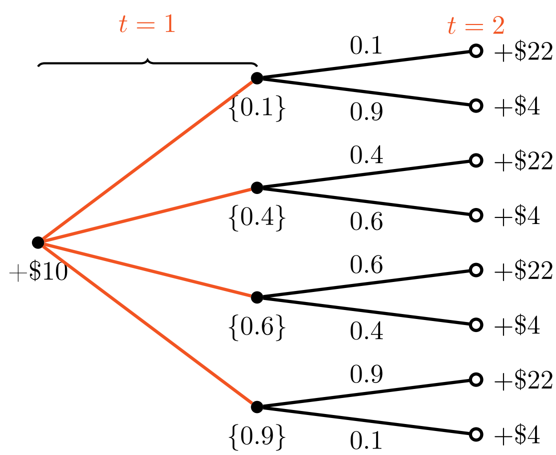


(a) The One-Shot Early option (E).

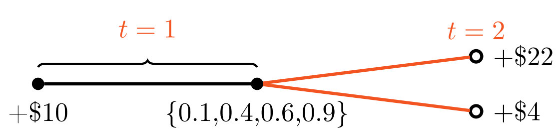


(b) The One-Shot Late option (L).

Figure A.1: Information structures for early and late risk-resolution options.

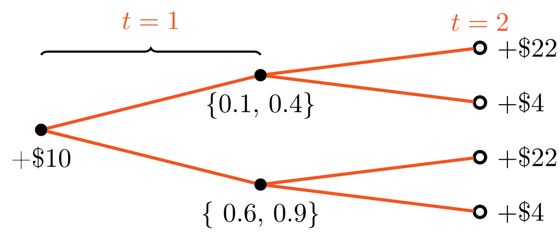


(a) The One-Shot Early option (E).

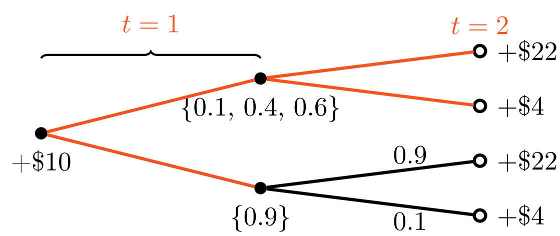


(b) The One-Shot Late option (L).

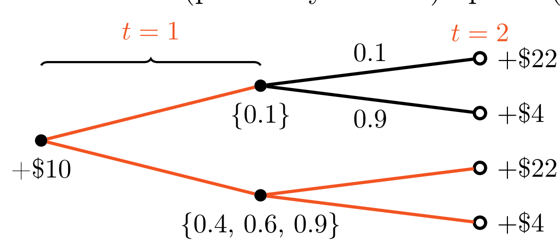
Figure A.2: Information structures for early and late ambiguity-resolution options.



(a) The Gradual (non-skewed) option (G).



(b) The Gradual (positively skewed) option (Gp).



(c) The Gradual (negatively skewed) option (Gn).

Figure A.3: Information structures for three gradual ambiguity-resolution options.

E Unpooled Results of Risk- and Ambiguity-Resolution Decisions

		RR3 choice (One-Shot Late removed)				
RR1 choice (unrestricted)	RR2 choice (One-Shot Early removed)	One-Shot Early	Gradual (Positively-Skewed)	Gradual (Negatively-Skewed)	Gradual (Non-Skewed)	Total
One-Shot Early	Gradual (Positively-Skewed)	**6**	1	2	2	11
	Gradual (Negatively-Skewed)	**10**	0	2	0	12
	Gradual (Non-Skewed)	**22**	1	0	2	25
	One-Shot Late	**16**	0	0	0	16
	Total	**54**	2	4	4	64
Gradual (Positively-Skewed)	Gradual (Positively-Skewed)	0	**4**	0	0	4
	Gradual (Negatively-Skewed)	0	0	0	0	0
	Gradual (Non-Skewed)	0	0	0	1	1
	One-Shot Late	0	0	0	1	1
	Total	0	4	0	2	6
Gradual (Negatively-Skewed)	Gradual (Positively-Skewed)	0	0	0	2	2
	Gradual (Negatively-Skewed)	0	0	**10**	2	12
	Gradual (Non-Skewed)	0	0	1	0	1
	One-Shot Late	0	0	0	0	0
	Total	0	0	11	4	15
Gradual (Non-Skewed)	Gradual (Positively-Skewed)	0	2	1	3	6
	Gradual (Negatively-Skewed)	1	0	3	1	5
	Gradual (Non-Skewed)	3	3	3	**12**	21
	One-Shot Late	2	2	0	0	4
	Total	6	7	7	16	36
One-Shot Late	Gradual (Positively-Skewed)	1	1	0	0	2
	Gradual (Negatively-Skewed)	0	0	1	0	1
	Gradual (Non-Skewed)	0	2	1	2	5
	One-Shot Late	**1**	**0**	**2**	**3**	**6**
	Total	2	3	4	5	14

Table A.1: Revealed preferences for resolution of risk in choice tasks RR1, RR2, and RR3. Orange indicates profiles consistent with a strict preference ordering.

Table A.1 and A.2 describe the revealed preferences for the resolution of risk and ambiguity without pooling gradual resolution options. Of the 48 subjects who chose some form of gradual option in RR1, RR2, and RR3, 26 (54.2%) consistently chose the same option (e.g., positively-skewed, negatively-skewed, non-skewed) for gradual resolution of risk across RR1, RR2, and RR3. Similarly, of the 27 subjects who chose some form of gradual option in AR1, AR2, and AR3, 19 (70.4%) consistently selected the same option for gradual resolution of ambiguity across AR1, AR2, and AR3. Table A.3 shows the unpooled results and correlations from the unrestricted choice sets RR1 and AR1.

AR1 choice (unrestricted)	AR2 choice (One-Shot Early removed)	AR3 choice (One-Shot Late removed): One-Shot Early	Gradual (Positively-Skewed)	Gradual (Negatively-Skewed)	Gradual (Non-Skewed)	Total
One-Shot Early	Gradual (Positively-Skewed)	**15**	1	0	1	17
	Gradual (Negatively-Skewed)	**7**	1	0	0	8
	Gradual (Non-Skewed)	**38**	1	0	4	43
	One-Shot Late	**17**	0	0	1	18
	Total	**77**	3	0	6	86
Gradual (Positively-Skewed)	Gradual (Positively-Skewed)	0	**1**	0	0	1
	Gradual (Negatively-Skewed)	0	1	0	0	1
	Gradual (Non-Skewed)	0	0	0	0	0
	One-Shot Late	1	1	0	0	2
	Total	1	3	0	0	4
Gradual (Negatively-Skewed)	Gradual (Positively-Skewed)	0	0	0	0	0
	Gradual (Negatively-Skewed)	1	0	**3**	1	5
	Gradual (Non-Skewed)	0	1	1	0	2
	One-Shot Late	0	0	0	1	1
	Total	1	1	4	2	8
Gradual (Non-Skewed)	Gradual (Positively-Skewed)	1	0	1	0	2
	Gradual (Negatively-Skewed)	1	0	0	2	3
	Gradual (Non-Skewed)	7	0	1	**15**	23
	One-Shot Late	0	0	0	2	2
	Total	9	0	2	19	30
One-Shot Late	Gradual (Positively-Skewed)	0	0	0	0	0
	Gradual (Negatively-Skewed)	0	0	0	0	0
	Gradual (Non-Skewed)	0	1	1	0	2
	One-Shot Late	**1**	**1**	**1**	**2**	**5**
	Total	1	2	2	2	7

Table A.2: Revealed preferences for resolution of ambiguity in choice tasks AR1, AR2, and AR3. Orange indicates profiles consistent with a strict preference ordering.

RR1 choice	AR1 choice: One-Shot Early	Gradual (Positively-Skewed)	Gradual (Negatively-Skewed)	Gradual (Non-Skewed)	One-Shot Late	Total
One-Shot Early	57	1	1	4	1	64
Gradual (Positively-Skewed)	1	1	2	2	2	6
Gradual (Negatively-Skewed)	9	1	2	3	0	15
Gradual (Non-Skewed)	12	0	2	19	3	36
One-Shot Late	7	1	1	2	3	14
Total	86	4	8	30	7	135
Chi-square test p-value ≈ 0.000						

Table A.3: Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1 tasks).

F Logistic Regression Results

To see the relationship between preferences for ambiguity resolution and risk resolution, we ran the following logistic regression model:

$$P(y = 1) = F(b_1x_1 + b_2x_2 + b_3x_3),$$

where y is the binary dependent variable that equals 1 when a subject chooses the early option in the ambiguity-resolution task, x_1 is a binary variable that equals 1 when a subject chooses the early option in the risk-resolution task, and x_2 and x_3 are binary variables that equal 1 when a subject exhibits ambiguity-averse and ambiguity-neutral behavior, respectively, on the Ellsberg task.

Table A.4 shows the regression results. The first row indicates that the preference for early resolution of risk is strongly correlated with the preference for early resolution of ambiguity. This suggests that subjects who prefer to resolve risk early are significantly more likely to also prefer resolving ambiguity early. Additionally, the results show that ambiguity attitude affects these preferences. Ambiguity-averse subjects (p $\approx$ 0.028) and ambiguity-neutral subjects (p $\approx$ 0.102) are more likely to choose the early option for ambiguity resolution compared to ambiguity-seeking subjects.

	Coefficients	Standard Error	p-value
Early on RR1	2.61	0.50	0.000
Ambiguity Averse	1.76	0.80	0.028
Ambiguity Neutral	1.30	0.79	0.102
LR chi-square test p-value = 0.000			

Table A.4: The results of the logistic regression (pseudo $R^2 \approx 0.2372$, $N = 135$).

G Investigation of Possible Ordering Effects

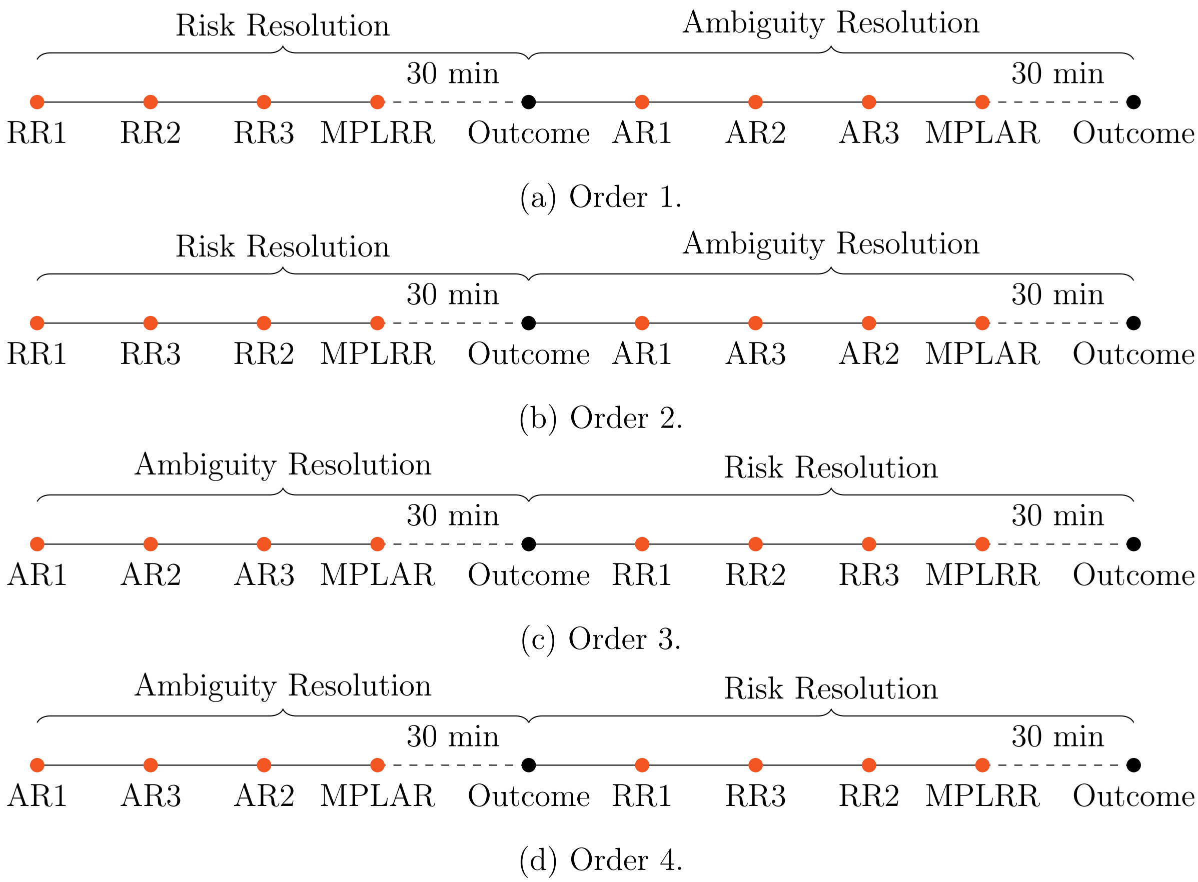


Figure A.4: Timeline of the experiment under different orders.

Figure A.4 illustrates the timeline of four different orders. Table A.5 verifies that there is no order effect on the timing of resolution, as indicated by the F-test p-value (0.8931).

Group	Number	Early in RR	Early in AR	Ambiguity Aversion
Order 1	35	42.8%	62.9%	37.1%
Order 2	32	43.8%	59.4%	59.4%
Order 3	31	45.2%	67.8%	35.5%
Order 4	37	56.8%	64.9%	54.1%
Total	135	47.4%	63.7%	46.7%
F-test p-value = 0.8931				

Table A.5: Proportions of subjects who revealed ambiguity aversion or preference for early resolution of risk and ambiguity across different orders.

H Interval Regression of WTP for Early Over Late Risk and Ambiguity Resolution

To provide point estimates in monetary terms we apply interval regression techniques. Consider a the highest row number (1 to 21, see Figure A.5) where a subject selects the left option (i.e., One-Shot Early + money) and has not selected the right option (i.e., One-Shot Late + money) on any previous rows. Consider b the lowest row number where a subject selects the right option (i.e., One-Shot Late + money) and will not select the left option on any higher rows. For such subject $j \in \mathcal{I}$, we assume that the amount of money that will make an indifference between late and early resolution, Y_j, falls on the interval $[y_{1j}, y_{2j}] = [\$(-0.50 + 0.05(a-1)), \$(-0.50 + 0.05(b-1))]$. Note that for an observation that satisfies single-crossing, $a + 1 = b$ and the interval length is \$0.05. There are also two special cases. A subject, $j \in \mathcal{L}$, that picks the right option on the first row, will be (left) censored from below, their likelihood contribution will be $Pr\left(Y_j \leq \$(-0.50 + 0.05(b-1))\right)$. Alternatively, a subject, $j \in \mathcal{R}$, that picks the left option on the 21st choice, will be (right) censored from above, their likelihood contribution will be $Pr(Y_j \geq \$(-0.50 + 0.05(a-1))$. We maximize the likelihood function over all subject observations,

$$\ln L = \sum_{j \in \mathcal{L}} \ln \left\{ \Phi\left(\frac{y_{1j} - x_j\beta}{\sigma}\right) \right\} + \sum_{j \in \mathcal{R}} \ln \left\{ 1 - \Phi\left(\frac{y_{2j} - x_j\beta}{\sigma}\right) \right\} + \sum_{j \in \mathcal{I}} \ln \left\{ \Phi\left(\frac{y_{1j} - x_j\beta}{\sigma}\right) - \Phi\left(\frac{y_{2j} - x_j\beta}{\sigma}\right) \right\} \tag{A.1}$$

where x_j are dummy variables indicating a subject's choice on RR1 (i.e., early, gradual, or late resolution), β is the corresponding coefficient, and Φ and σ are CDF and standard deviation of a normal distribution.

Table A.6 provides results over all subjects (specification 1) and is restricted only to subjects that obey both single crossing on the MPLRR and a strict preference ordering over RR1–RR3 (specification 2). The results indicate that subjects that select early resolution on choice task RR1 are associated with an estimated willingness to pay for early over late resolution of risk of roughly \$0.061 (specification 1: $0.041 + 0.020$, $p < 0.01$) or \$0.048 (spec-

RR1 choice	(1) WTP for early over late risk resolution	(2) WTP for early over late risk resolution
One-Shot Early	0.041	0.026
	(0.032)	(0.035)
One-Shot Late	−0.130**	−0.153***
	(0.053)	(0.055)
Constant	0.020	0.022
(Gradual)	(0.023)	(0.024)
Observations	135	95
Left-Censored	6	4
Right-Censored	11	2
Interval-Censored	118	89
Log-Likelihood	−291.68	−240.27

*** p<0.01, ** p<0.05, * p<0.1

Table A.6: Interval regressions of implied willingness to pay for early risk resolution over late (MPLRR) on risk resolution selected on RR1 (all forms of gradual preference omitted).

ification 2: $0.026 + 0.022$, $p < 0.10$). Subjects that select gradual resolution are associated with a \$0.020–0.022 willingness to pay for risk resolution, but the results are not significantly different than 0 ($p \approx 0.394$, $p \approx 0.367$, specifications 1 and 2, respectively). Subjects that select late resolution over early are predicted to pay \$0.110 (specification 1: $0.020+(-0.130)$, $p < 0.05$) to 0.131 (specification 2: $0.022 + (-0.153)$, $p < 0.01$) for late resolution over early. For both specifications, a chi-square test rejects the null hypothesis of equality of coefficients across the three groups under either specification ($p < 0.01$).

Table A.7 provides the results of an interval regression for revealed preferences of ambiguity resolution using the same form as Table A.6; the MLE is calculated using the same technique as in equation (A.1). As before, specification 1 calculates the results over all subjects and specification 2 is restricted only to subjects that obey both single crossing on the MPLAR task and a strict preference ordering over AR1–AR3. The results indicate that subjects that select early resolution on choice task AR1 are associated with an estimated willingness to pay for early over late resolution of ambiguity of \$0.107 (specification 1: $0.088+0.019$,

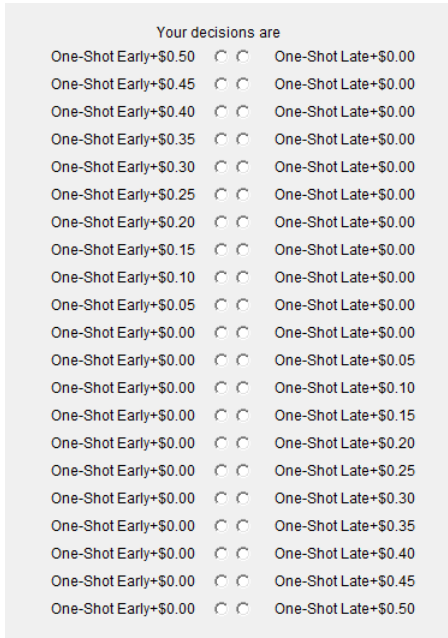
AR1 choice	(1) WTP for early over late ambiguity resolution	(2) WTP for early over late ambiguity resolution
One-Shot Early	0.088***	0.102***
	(0.031)	(0.033)
One-Shot Late	−0.081	−0.077
	(0.069)	(0.073)
Constant	0.019	0.022
(Gradual)	(0.026)	(0.027)
Observations	134	100
Left-Censored	1	0
Right-Censored	12	7
Interval-Censored	121	93
Log-Likelihood	−292.43	−246.19

*** p<0.01, ** p<0.05, * p<0.1

Table A.7: Interval regressions of implied willingness to pay for early ambiguity resolution over late (MPLAR) on ambiguity resolution selected on AR1 (all forms of gradual preference omitted).

$p < 0.01$) to \$0.124 (specification 2: $0.102 + 0.022$, $p < 0.01$). Subjects that select gradual resolution are associated with a \$0.019–0.022 willingness to pay for ambiguity resolution, but the results are not significantly different than 0 ($p \approx 0.453$, $p \approx 0.426$, specifications 1 and 2, respectively). Subjects that select late resolution on AR1 are predicted to pay positive amounts for late resolution over early (specification 1: $0.019 + (-0.081) = -0.062$, specification 2: $0.022 + (-0.077) = -0.055$) but the results are not significantly different from 0 ($p \approx 0.335$, $p \approx 0.420$, specifications 1 and 2, respectively). For both specifications, a chi-square test rejects the null hypothesis of equality of coefficients across the three groups ($p < 0.01$).

I Additional Tables and Figures



Your decisions are

One-Shot Early+$0.50	One-Shot Late+$0.00
One-Shot Early+$0.45	One-Shot Late+$0.00
One-Shot Early+$0.40	One-Shot Late+$0.00
One-Shot Early+$0.35	One-Shot Late+$0.00
One-Shot Early+$0.30	One-Shot Late+$0.00
One-Shot Early+$0.25	One-Shot Late+$0.00
One-Shot Early+$0.20	One-Shot Late+$0.00
One-Shot Early+$0.15	One-Shot Late+$0.00
One-Shot Early+$0.10	One-Shot Late+$0.00
One-Shot Early+$0.05	One-Shot Late+$0.00
One-Shot Early+$0.00	One-Shot Late+$0.00
One-Shot Early+$0.00	One-Shot Late+$0.05
One-Shot Early+$0.00	One-Shot Late+$0.10
One-Shot Early+$0.00	One-Shot Late+$0.15
One-Shot Early+$0.00	One-Shot Late+$0.20
One-Shot Early+$0.00	One-Shot Late+$0.25
One-Shot Early+$0.00	One-Shot Late+$0.30
One-Shot Early+$0.00	One-Shot Late+$0.35
One-Shot Early+$0.00	One-Shot Late+$0.40
One-Shot Early+$0.00	One-Shot Late+$0.45
One-Shot Early+$0.00	One-Shot Late+$0.50

Figure A.5: Multiple price list questions.

Ambiguity Attitude	Risk Resolution Preference	Ambiguity-Resolution Preference				
		$E \succ G \succ L$	$E \succ L \succ G$	$G \succ E, L$	$L \succ G \succ E$	$L \succ E \succ G$
Ambiguity Averse	$E \succ G \succ L$	9	3	81	9	3
	$E \succ L \succ G$	3	1	27	3	1
	$G \succ E, L$	81	27	729	81	27
	$L \succ G \succ E$	9	3	81	9	3
	$L \succ E \succ G$	3	1	27	3	1
Ambiguity Neutral	$E \succ G \succ L$	18	6	162	18	6
	$E \succ L \succ G$	6	2	54	6	2
	$G \succ E, L$	162	54	1,458	162	54
	$L \succ G \succ E$	18	6	162	18	6
	$L \succ E \succ G$	6	2	54	6	2
Ambiguity Seeking	$E \succ G \succ L$	9	3	81	9	3
	$E \succ L \succ G$	3	1	27	3	1
	$G \succ E, L$	81	27	729	81	27
	$L \succ G \succ E$	9	3	81	9	3
	$L \succ E \succ G$	3	1	27	3	1

Table A.8: Counts of combinations of possible actions for each possible exhibited preference profile, ignoring willingness to pay preference profile.

Ambiguity Attitude	Risk Resolution Preference	Ambiguity-Resolution Preference: $E \succ G \succ L$	$E \succ L \succ G$	$G \succ E, L$	$L \succ G \succ E$	$L \succ E \succ G$	$E \sim G \sim L$
Ambiguity Averse	$E \succ G \succ L$	900	300	16,200	900	300	4,800
	$E \succ L \succ G$	300	100	5,400	300	100	1,600
	$G \succ E, L$	16,200	5,400	291,600	16,200	5,400	86,400
	$L \succ G \succ E$	900	300	16,200	900	300	4,800
	$L \succ E \succ G$	300	100	5,400	300	100	1,600
	$E \sim G \sim L$	4,800	1,600	86,400	4,800	1,600	25,600
Ambiguity Neutral	$E \succ G \succ L$	1,800	600	32,400	1,800	600	9,600
	$E \succ L \succ G$	600	200	10,800	600	200	3,200
	$G \succ E, L$	32,400	10,800	583,200	32,400	10,800	172,800
	$L \succ G \succ E$	1,800	600	32,400	1,800	600	9,600
	$L \succ E \succ G$	600	200	10,800	600	200	3,200
	$E \sim G \sim L$	9,600	3,200	172,800	9,600	3,200	51,200
Ambiguity Seeking	$E \succ G \succ L$	900	300	16,200	900	300	4,800
	$E \succ L \succ G$	300	100	5,400	300	100	1,600
	$G \succ E, L$	16,200	5,400	291,600	16,200	5,400	86,400
	$L \succ G \succ E$	900	300	16,200	900	300	4,800
	$L \succ E \succ G$	300	100	5,400	300	100	1,600
	$E \sim G \sim L$	4,800	1,600	86,400	4,800	1,600	25,600

Table A.9: Counts of combinations of possible actions for each possible exhibited preference profile, assuming zero willingness to pay on MPLRR and MPLAR indicates indifference over all risk- and ambiguity-resolution options, respectively.

93 subjects, 4,900 action profiles (see Table A.8)								
	EZ	H	HM	RMP	RVP	H*	RMP*	RVP*
EZ	-	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)
H	100,000\0 (0.000)	-	629\99,371 (0.013)	86,653\13,347 (0.267)	-	13,587\86,413 (0.272)	23,691\76,309 (0.474)	43,387\56,631 (0.868)
HM	100,000\0 (0.000)	99,371\629 (0.013)	-	99,926\74 (0.002)	99,371\629 (0.013)	83,446\16,554 (0.331)	87,656\12,344 (0.247)	94,742\5,258 (0.105)
RMP	100,000\0 (0.000)	13,347\86,653 (0.267)	74\99,926 (0.002)	-	13,347\86,653 (0.267)	1,762\98,238 (0.035)	5,913\94,087 (0.118)	14,551\85,449 (0.291)
RVP	100,000\0 (0.000)	-	629\99,371 (0.013)	86,653\13,347 (0.267)	-	13,587\86,413 (0.272)	23,691\76,309 (0.474)	43,387\56,613 (0.868)
H*	100,000\0 (0.000)	86,413\13,587 (0.272)	16,554\83,446 (0.331)	98,238\1,762 (0.035)	86,413\13,587 (0.272)	-	40,663\59,367 (0.813)	85,903\14,097 (0.282)
RMP*	100,000\0 (0.000)	76,309\23, 691 (0.474)	12,344\87,656 (0.247)	94,087\5,913 (0.118)	76,309\23,691 (0.474)	59,367\40,663 (0.813)	-	100,000\0 (0.000)
RVP*	100,000\0 (0.000)	56,631\43,387 (0.868)	5,258\94,742 (0.105)	85,449\14,551 (0.291)	56,613\43,387 (0.868)	14,097\85,903 (0.282)	0\100,000 (0.000)	-

* Evaluated for local rationalization and differ from those for global rationalization.

Table A.10: Classification of 100,000 bootstraps where row\column achieved a higher Selten score than model found in column\row model for strict uncertainty-resolution preferences using total action space. Equivalent two-tailed p-value given in parentheses.

68 subjects, 2,433,600 action profiles (see Table A.9)														
	DEU	MEU	KMM	DMP	DVP	EZ	H	HM	RMP	RVP	DVP*	H*	RMP*	RVP*
DEU	-	0\100,000 (0.000)	4,910\95,090 (0.098)	4,910\95,090 (0.098)	0\100,000 (0.000)	4,802\95,198 (0.096)	0\100,000 (0.000)	17\99,983 (0.000)	17\99,983 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	17\99,983 (0.000)	0\100,000 (0.000)
MEU	100,000\0 (0.000)	-	99,995\5 (0.000)	99,995\5 (0.000)	4,910\95,090 (0.098)	99,997\3 (0.000)	80\99,920 (0.002)	99,540\460 (0.009)	99,180\820 (0.016)	1\99,999 (0.000)	42,030\57,970 (0.841)	80\99,920 (0.002)	99,540\460 (0.009)	2,483\97,517 (0.050)
KMM	95,090\4,910 (0.098)	5\99,995 (0.000)	-	0\100,000 (0.000)	0\100,000 (0.000)	41,628\58,372 (0.833)	0\100,000 (0.000)	623\99,377 (0.012)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	623\99,377 (0.012)	0\100,000 (0.000)
DMP	95,090\4,910 (0.098)	5\99,995 (0.000)	100,000\0 (0.000)	-	0\100,000 (0.000)	41,628\58,372 (0.833)	0\100,000 (0.000)	623\99,377 (0.012)	623\99,377 (0.012)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	623\99,377 (0.012)	0\100,000 (0.000)
DVP	100,000\0 (0.000)	95,090\4,910 (0.098)	100,000\0 (0.000)	100,000\0 (0.000)	-	100,000\0 (0.000)	13,010\86,990 (0.260)	99,937\63 (0.001)	99,937\63 (0.001)	80\99,920 (0.002)	100,000\0 (0.000)	13,010\86,990 (0.260)	99,937\63 (0.001)	7,530\92,470 (0.151)
EZ	95,198\4,802 (0.096)	3\99,997 (0.000)	58,372\41,628 (0.833)	58,372\41,628 (0.833)	0\100,000 (0.000)	-	0\100,000 (0.000)	615\99,385 (0.012)	615\99,385 (0.012)	0\100,000 (0.000)	9\99,991 (0.000)	0\100,000 (0.000)	615\99,385 (0.012)	0\100,000 (0.000)
H	100,000\0 (0.000)	99,920\80 (0.002)	100,000\0 (0.000)	100,000\0 (0.000)	86,990\13,010 (0.260)	100,000\0 (0.000)	-	99,999\1 (0.000)	99,999\1 (0.000)	4,910\95,090 (0.098)	98,291\1,709 (0.034)	100,000\0 (0.000)	99,999\1 (0.000)	64,728\35,272 (0.705)
HM	99,983\17 (0.000)	460\99,540 (0.009)	99,377\623 (0.012)	99,377\623 (0.012)	63\99,937 (0.001)	99,385\615 (0.012)	1\99,999 (0.000)	-	0\100,000 (0.000)	0\100,000 (0.000)	248\99,752 (0.005)	1\99,999 (0.000)	100,000\0 (0.000)	0\100,000 (0.000)
RMP	99,983\17 (0.000)	820\99,180 (0.016)	100,000\0 (0.000)	99,377\623 (0.012)	63\99,937 (0.001)	99,385\615 (0.012)	1\99,999 (0.000)	100,000\0 (0.000)	-	0\100,000 (0.000)	453\99,547 (0.009)	1\99,999 (0.000)	100,000\0 (0.000)	0\100,000 (0.000)
RVP	100,000\0 (0.000)	99,999\1 (0.000)	100,000\0 (0.000)	100,000\0 (0.000)	99,920\80 (0.002)	100,000\0 (0.000)	95,090\4,910 (0.098)	100,000\0 (0.000)	100, 000\0 (0.000)	-	100, 000\0 (0.000)	95,090\4,910 (0.098)	100, 000\0 (0.000)	100, 000\0 (0.000)
DVP*	100,000\0 (0.000)	57,970\42,030 (0.841)	100,000\0 (0.000)	100,000\0 (0.000)	0\100,000 (0.000)	99,991\9 (0.000)	1,709\98,291 (0.034)	99,752\248 (0.005)	99,547\453 (0.009)	0\100,000 (0.000)	-	1,709\98,291 (0.034)	99,752\248 (0.005)	643\99,357 (0.013)
H*	100,000\0 (0.000)	99,920\80 (0.002)	100,000\0 (0.000)	100,000\0 (0.000)	86,990\13,010 (0.260)	100,000\0 (0.000)	0\100,000 (0.000)	99,999\1 (0.000)	99,999\1 (0.000)	4,910\95,090 (0.098)	98,291\1,709 (0.034)	-	99,999\1 (0.000)	64,728\35,272 (0.705)
RMP*	99,983\17 (0.000)	460\99,540 (0.009)	99,377\623 (0.012)	99,377\623 (0.012)	63\99,937 (0.001)	99,385\615 (0.012)	1\99,999 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	0\100,000 (0.000)	248\99,752 (0.005)	1\99,999 (0.00)	-	0\100,000 (0.000)
RVP*	100,000\0 (0.000)	97,517\2,483 (0.050)	100,000\0 (0.000)	100,000\0 (0.000)	92,470\7,530 (0.151)	100,000\0 (0.000)	35,272\64,728 (0.705)	100,000\0 (0.000)	100,000\0 (0.000)	0\100,000 (0.000)	99,357\643 (0.013)	35,272 \ 64,728 (0.705)	100,000\0 (0.000)	-

* Evaluated for local rationalization and differ from those for global rationalization.

Table A.11: Classification of 100,000 bootstraps where row\column achieved a higher Selten score than model found in column\row model where unwillingness to pay a positive amount on the MPLRR and MPLAR tasks is viewed as indifference, the "pessimistic" view. Total action space used in calculations. Equivalent two-tailed p-value given in parentheses.