Preferences for the Resolution of Risk and Ambiguity*

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Abstract

Generalized recursive utility models are becoming increasingly common alternatives to discounted expected utility theory. Such models can explain many so-called, "anomalies" in field data, but 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 objective uncertainty, i.e., risk. We provide the first experimental examination of uncertainty resolution with respect to subjective uncertainty, i.e., ambiguity, in addition to risk. We find that subjects most frequently exhibit a preference for early resolution of both risk and ambiguity and these preferences are positively correlated. Additionally, being ambiguity seeking decreases the probability of preferring early resolution of ambiguity. Of six, commonly-used, representative recursive utility models, only the generalized recursive smooth ambiguity model (Hayashi and Miao, 2011) can accommodate these main findings. However, when we penalize models for the area of action space they can rationalize, the maxmin expected utility model (Hayashi, 2005) characterizes subject data equally well.

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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). Applications of these models explain a wide variety of anomalies regarding asset prices, trade, and inflation (see below). An added implication of these models is that many of them require agents to have a preference over when uncertainty is to be resolved, independent of instrumental concerns. Initial debates concerned whether such preferences were plausible, and, if plausible, whether people prefer early or late resolution of uncertainty. Experimental work 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 any basis for objective probability. Interestingly, all aforementioned experimental studies that elicit preferences for uncertainty resolution have focused entirely on the domain of risk. That is, a determination of preferences for early resolution of uncertainty is only finding preferences for early resolution of risk, without establishing individuals' preferences over the removal of ambiguity. By considering environments with subjective uncertainty exclusively, the theoretical studies of Strzalecki (2013), Li (2020a), and Marinacci et al. (2023) examine uncertainty resolution where ambiguity is considered. Since these papers focus on the subjective domain of uncertainty, the models examined by them may explain strict preferences for ambiguity resolution, but not risk.

This paper provides the first experimental elicitation of preferences of 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, and the two preferences are positively correlated. Controlling for risk resolution preference, being ambiguity seeking decreases the likelihood of preferring early resolution of ambiguity by 25.6 percentage points.

The examination this paper provides is important for two separate reasons, one theoretical and one methodological. The main (theoretical) reason is that there are a variety of models of generalized recursive utility, many with different implications about preferences towards the timing of risk resolution and ambiguity resolution. Scholars began using these models, because the best-fitting discounted expected utility models required unrealistic parameter values.[1] While this specific determination of what is "unrealistic" can be done through introspection, anecdotal observation, or study of actual data, as models become more complex, it becomes more difficult to determine what is "realistic" through the former two methods. Since these generalized recursive utility models have different implications on an individual's preference for risk and ambiguity resolution, this paper investigates the full reasonableness of these theoretical implications. At a basic level, certain models of generalized recursive utility can only account for uncertainty resolution in the form of risk resolution and some can only account for uncertainty resolution in the form of ambiguity resolution. More complex relations exist as well. While the mean subject holds a preference for the early resolution of ambiguity, variation in this preference is positively correlated with variation in the preference for risk resolution. Further, the attitude toward ambiguity affects this relationship. Conclusions drawn about the validity of such models must necessarily include an investigation of both preferences over risk resolution and ambiguity resolution.

To understand what features are important for a model to have strict and differential preferences for risk and ambiguity resolution, we review six representative recursive utility models that have been axiomatized by decision theorists and are commonly applied to field data: the discounted expected utility model, the dynamic maxmin expected utility model of Gilboa and Schmeidler (1989) and Epstein and Schneider (2003), the dynamic smooth ambiguity model of Klibanoff et al. (2005, 2009) and Seo (2009), the generalized recursive utility model of Kreps and Porteus (1978), Epstein and Zin (1989), etc., the generalized

[1]For instance, to explain the equity premium puzzle, the risk-aversion parameter would need to be implausibly large (Mehra and Prescott, 1985).

recursive maxmin expected utility model of Hayashi (2005), and the generalized recursive smooth ambiguity model of Hayashi and Miao (2011).[2] Among these six models, only the generalized recursive maxmin expected utility model of Hayashi (2005) and the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) can simultaneously accommodate non-indifferent preferences for risk resolution, non-indifferent preferences for ambiguity resolution, and non-neutral ambiguity attitudes. A deductive examination reveals that the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) has the flexibility of accommodating divergent strict preferences for risk resolution and ambiguity resolution. According to this model, ambiguity attitudes affect the connection between risk and ambiguity resolution preferences. Our empirical findings support this model as the best explanatory framework for the observed correlation between risk and ambiguity resolution preferences. On the other hand, the generalized recursive maxmin expected utility model of Hayashi (2005) predicts that any strict ambiguity resolution preference between early and late resolution must be inherited from the risk resolution preference. The model of Hayashi (2005) possesses the capability to accommodate a preference for one-shot ambiguity resolution, which cannot be accommodated by the model of Hayashi and Miao (2011). When we penalize models for being able to rationalize a broader range of choice profiles theoretically, the performance of the generalized recursive maxmin expected utility model (Hayashi, 2005) and generalized recursive smooth ambiguity model (Hayashi and Miao, 2011) becomes similar, because they can both explain the most expressed consistent choice profile, i.e., preference for early resolution of risk, preference for early resolution of ambiguity, and ambiguity aversion. We thus conclude that the two models have similar predictive efficiency, and both outperform the generalized recursive utility model of Epstein and Zin (1989).

[2] In the paper, the term "recursive utility model" refers to both the canonical discounted expected utility model and the other more general models. These models have consequential implications in many applications in empirical macroeconomics and finance literature. For example, Bansal and Yaron (2004), Kim et al. (2009), and Epstein et al. (2014) assume that a representative agent has Epstein and Zin (1989) preference; Collard et al. (2018) adopt the dynamic smooth ambiguity model; Trojani and Vanini (2002, 2004) follow a continuous-time version of the dynamic maxmin expected utility model; Drechsler (2013) and Jeong et al. (2015) essentially adopt the model axiomatized by Hayashi (2005); Ju and Miao (2012) follow the generalized recursive smooth ambiguity model axiomatized by Hayashi and Miao (2011). In spite of differences in modeling details, these calibrated models are able to better explain the equity premium, the risk-free rate, and/or the volatility puzzles among others, to different degrees. See also Colacito and Croce (2013), Backus and Smith (1993), and Lee (2019) for further applications of generalized recursive utility models in explaining puzzles in international economics and inflation.

Our paper also provides a methodological contribution to experimental economics. Until this study, there has been no experimental elicitation of individuals' preferences over the resolution of ambiguity. All previous experimental studies have elicited preferences of risk resolution. Our experimental environment provides the first elicitation of ambiguity resolution; the elicitation procedure could be useful to inform future studies of ambiguity resolution preference. Further, our within-subjects design provides the means to tie these preferences to previously used mechanisms for risk resolution preferences and ambiguity attitudes.

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 in the information structure framework and the multi-stage lotteries framework. 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 preferences. In both categories, the literature often, but not always, finds a preference for the early resolution of uncertainty.

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

There are several additional key features of our experimental design. Our experiment follows the general structure of Nielsen (2020) in the risk domain, eliciting subjects' preference over uncertainty resolution with non-instrumental information. We build upon the design in that we separately elicit risk and ambiguity resolution preferences. We also include gradual resolution of information options (non-skewed, positively-skewed, and negatively-skewed) as well as early and late options. Positive skewness eliminates more uncertainty about the good state and negative skewness is the opposite.[3] Hence, participants express preferences over larger choice sets.

This paper proceeds as follows. Section 2 details the experimental design and procedures on the elicitation of risk resolution preference, ambiguity resolution preference, and ambiguity attitude. Section 3 provides experimental results. Section 4 reviews six representative recursive utility models and examines their implications on the preferences of risk resolution and ambiguity resolution. Section 5 identifies the patterns of subjects' choice profiles which are consistent with each model, penalizes the models that rationalize more choice profiles, and calculates their respective Selten scores (Selten, 1991) to measure the predictive efficiency. Lastly, Section 6 concludes.

2 Experimental Design and Procedures

The experiment consists of two parts: the risk-resolution-preference elicitation part and the ambiguity-resolution-preference elicitation part. Each part utilizes three choice tasks and a set of multiple price list questions to elicit subject preferences on the timing of risk/ambiguity resolution. The order of the two parts and the questions within are randomly ordered for subjects in four ways comprising four separate, within-subjects treatments. Full details of the random ordering are explained in Section 2.3.

2.1 Risk-Resolution-Preference Elicitation

In the risk-resolution-preference elicitation experiment, we adopt the framework of Nielsen (2020) (see Figure 1 therein). Subjects participate in a two-period consumption process (see Figure 1). In $t = 1$, subjects receive an advance payment.[4] In $t = 2$, a lottery is drawn and the additional payoff is realized. The lottery has 50% chance leading to a "high prize ($22)"

[3]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.

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

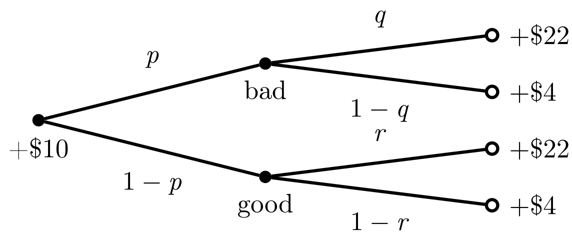


Figure 1: A general consumption process in risk resolution experiment.

Options	**Information Structure**
One-Shot Early	$(p{=}0.5,\ q{=}0,\ r{=}1)$
Gradual (non-skewed)	$(p{=}0.5,\ q{=}0.25,\ r{=}0.75)$
Gradual (positively skewed)	$(p{=}0.8,\ q{=}0.4,\ r{=}0.9)$
Gradual (negatively skewed)	$(p{=}0.2,\ q{=}0.1,\ r{=}0.6)$
One-Shot Late	$(p{=}0.5,\ q{=}0.5,\ r{=}0.5)$

Table 1: Options in risk resolution experiment.

and 50% chance leading to a "low prize ($4)" ex-ante, and thus subjects have the same prior belief at the beginning of $t = 1$: the overall probability of winning the high prize is 0.5.

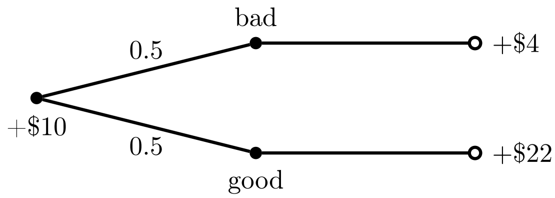
An additional piece of information on the underlying probability of the lottery is realized at the end of $t = 1$. The additional information is either a piece of "good news" or "bad news." Upon receiving the news, subjects update their beliefs on the chance of receiving the "low prize" and the "high prize" in $t = 2$.

We follow Nielsen (2020) in defining an information structure as a vector (p, q, r) satisfying the constraint that $pq + (1 - p)r = 0.5$, 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. Note these parameter choices ensure that the prior belief of winning a high prize is equal to 0.5.[5]

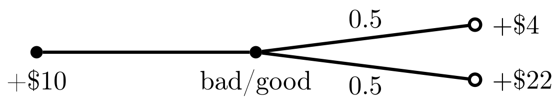
In each of the three choice tasks, subjects are asked to select their most preferred information structure from a set of multiple options listed in Table 1. Under the **One-Shot**

[5]For simplicity, we do not explicitly introduce the language of urns and balls from Nielsen (2020) to the subjects. As the focus of the paper is not on the treatment effect between the information structure framework and the multi-stage lottery framework, which has been thoroughly studied in Nielsen (2020), we also do not explicitly mention if the risk is pre-determined or future-determined to the subjects.

Early option (also denoted as Option E), all the risk is resolved in the first stage. In this scenario, if a subject receives good news, she is guaranteed to receive the high prize ($22) ($r = 1$). Otherwise, she is assured of receiving the low prize ($4) ($q = 0$). Hence, under the One-Shot Early option, the consumption process shown in Figure 1 can be simplified into Figure 2(a).



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



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

Figure 2: Information structures for early and late risk resolution options.

The **One-Shot Late** option (also denoted as Option L) means risk is resolved all at once in the second stage. In this case, the news is not informative: regardless of the news she receives, her conditional probability of winning the high prize remains the same as the prior probability. Hence, one can simplify the consumption process as illustrated in Figure 2(b).

Under the **Gradual (non-skewed)** option (also denoted as Option G), good news and bad news are equally likely to arrive. Under the **Gradual (positively skewed)** option (also denoted as Option Gp), 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 ($r = 0.9$). Under the **Gradual (negatively skewed)** option (also denoted as Option Gn), 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.[6]

[6]While the skewed gradual options can produce positive or negative interim outcomes that are more informative, it is important to note that none of the gradual options are ex-ante more informative than the other at least according to the Blackwell informativeness criterion. 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 structures (p_A, q_A, r_A) is said to resolve risk earlier than in-

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 preferences, we instead discretize choice and provide three gradual risk resolution options to allow for easier subjects' comprehension.[7] At the other end, Masatlioglu et al. (2023) examine preferences over positively- and negatively-skewed gradual information structure 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 conclusion more robust.

Whatever option a subject chooses, it is important to reiterate that the choice of information structure does not affect the ex-ante probability of winning the high prize, which is equal to 0.5, or the timing of the payment of the lottery, which takes place in $t = 2$.

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 occupy their time by completing Raven's Progressive Matrices.[8]

formation structure (p_B, q_B, r_B) if $q_A < q_B$ and $r_A > r_B$. Thus, the One-Shot Early option is Blackwell more informative than any of the gradual options, and any of the gradual options is Blackwell more informative than the One-Shot Late option. As the Blackwell order is an incomplete order, we include the calculation of the entropy informativeness measures in Footnote 14 to showcase one way to complete the Blackwell order.

[7] Nielsen (2020) points out that "Budget sets (which correspond to having subjects choose among all vectors (p, q, r) satisfying $pq + (1 - p)r = 0.5$ in the context of the current paper) are more demanding on subjects' attention and understanding."

[8] The Raven test is one of the most widely used methods to measure abstract reasoning and analytic intelligence, by non-verbal multiple choice questions. Each question consists of a visual pattern with a missing piece, and the subjects are asked to pick the right element to fill in. 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

2.2 Ambiguity-Resolution-Preference Elicitation

The ambiguity-resolution-preference elicitation experiment is similar to the aforementioned risk-resolution experiment. Subjects are involved in a two-period consumption process. In $t = 1$, subjects receive an advance payment.[9] In $t = 2$, a lottery is drawn and the payoff is realized. Subjects could earn a "high prize ($22)" or a "low prize ($4)" from this lottery. However, 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, at the beginning of $t = 1$, the probability of drawing each color is unknown. Notice that it is not necessary that 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 $\mathbf{p}$ from the ball they draw. Depending on the information structure, this news provides no information, partial information, or complete information about the winning probability.

An information structure is a partition of the set $\{0.1, 0.4, 0.6, 0.9\}$. In each of the three choice tasks, subjects are asked to choose their most preferred option from a set of multiple information structures listed in Table 2.

The **One-Shot Early** option (i.e., Option E) represents a fully revealing information structure. If a subject chooses One-Shot Early, she will be informed of the exact winning

to make subjects stay focused during the time delay.

[9]As before, we interpret the $10 participation payment as the advance payment.

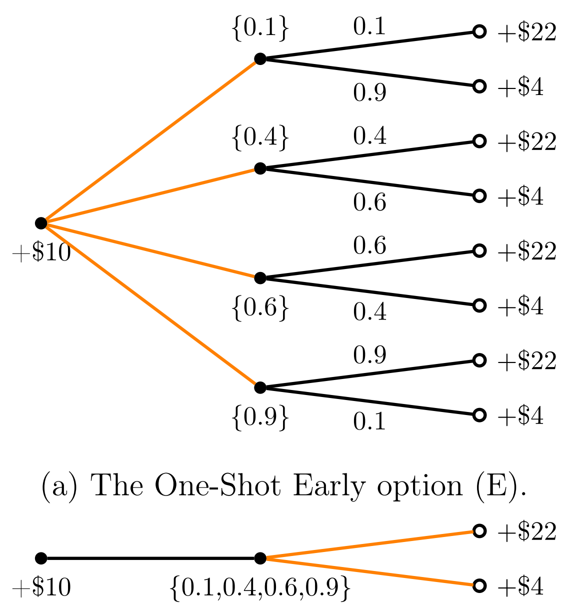
[10]Notice that meaning of notation $\mathbf{p}$, i.e., the probability of winning the high prize, is different from the meaning of notation p, i.e., the probability of receiving the bad news in the risk-resolution experiment.

[11]If the probability over the different winning probabilities is objectively given, then the information structure can be viewed as a compound lottery. Halevy (2007), Abdellaoui et al. (2015), and Chew et al. (2017) have pointed out a positive correlation between ambiguity aversion and the inability to reduce compound lotteries. It remains an open question to explore what would happen if one were to formulate the ambiguity-resolution experiment in the language of compound lotteries instead.

Options	Information Structure
One-Shot Early	{{0.1}, {0.4}, {0.6}, {0.9}}
Gradual (non-skewed)	{{0.1, 0.4}, {0.6, 0.9}}
Gradual (positively skewed)	{{0.1, 0.4, 0.6}, {0.9}}
Gradual (negatively skewed)	{{0.1}, {0.4, 0.6, 0.9}}
One-Shot Late	{{0.1, 0.4, 0.6, 0.9}}

Table 2: Options in ambiguity resolution experiment.

chance $\mathbf{p}$ at the end of $t = 1$. Consequently, ambiguity is resolved in $t = 1$. The consumption process has been summarized in Figure 3(a). The yellow edges starting from the $t = 1$ node are realized with unknown probability. Conditional on a message that has been received, the black edges starting from the corresponding node are realized with known probabilities.



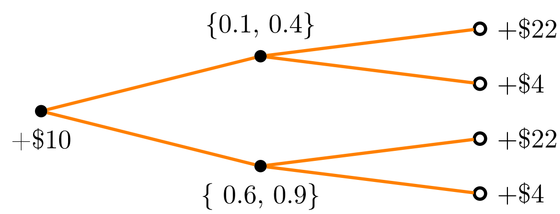
(a) The One-Shot Early option (E).

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

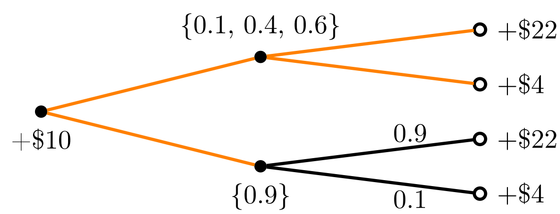
Figure 3: Information structures for early and late ambiguity resolution options.

The **One-Shot Late** option (i.e., Option L) leads to a non-revealing information structure. The only possible message received at the end of $t = 1$ conveys no new information and the subject knows that the value of $\mathbf{p}$ is 0.1, 0.4, 0.6, or 0.9. All uncertainty, including the value of $\mathbf{p}$ and the outcome, is resolved in $t = 2$. We illustrate this consumption process in Figure 3(b).

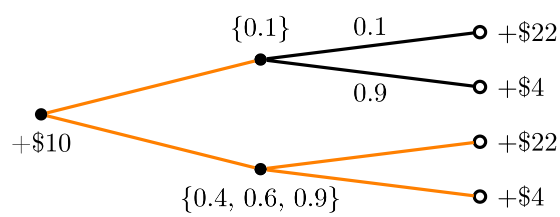
The three gradual ambiguity resolution information structures are partially revealing. If choosing the **Gradual (non-skewed)** option (i.e., Option G), the subject will either receive the message $\{0.1,\ 0.4\}$ or $\{0.6,\ 0.9\}$ at the end of $t = 1$ with unknown probabilities. If the winning chance is 0.1 or 0.4, she will receive the message $\{0.1,\ 0.4\}$. Otherwise, she will receive $\{0.6,\ 0.9\}$. A subject is not disclosed the exact probability of the lottery upon receiving either message. Hence, ambiguity exists in both periods but is resolved gradually. The consumption process is illustrated in Figure 4(a).



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



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



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

Figure 4: Information structures for three gradual ambiguity resolution options.

A subject choosing the **Gradual (positively skewed)** option (i.e., Option Gp) will either receive the message $\{0.9\}$ or $\{0.1,\ 0.4,\ 0.6\}$ at the end of $t = 1$. Hence, a subject will know if the true winning probability is 0.9 or not. Upon receiving $\{0.1,\ 0.4,\ 0.6\}$, the subject knows the winning probability in $t = 2$ is 0.1, 0.4, or 0.6, but she is not informed of the likelihood of each realization, and thus ambiguity still exists in $t = 2$. If $\{0.9\}$ is received, then ambiguity is dissolved immediately and only risk exists in $t = 2$. The consumption

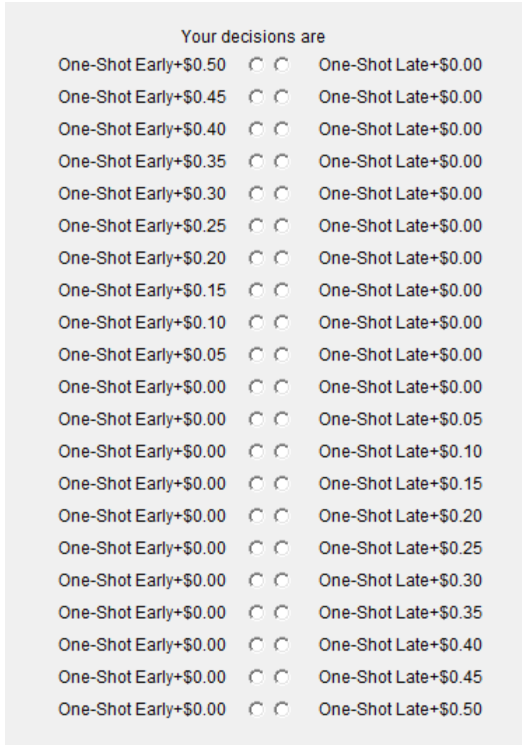


Figure 5: Multiple price list questions.

process is summarized in Figure 4(b).

Similarly, under the **Gradual (negatively skewed)** option (i.e., Option Gn), one of the two messages will be realized at the end of $t = 1$: $\{0.1\}$ and $\{0.4, 0.6, 0.9\}$. It tells the individual whether the winning chance is 0.1 or not. We illustrate the process in Figure 4(c).

The remaining steps are the same as in risk-resolution-preference elicitation experiment. Subjects encounter another set of questions from the Raven test during the 30-minute delay. After 30 minutes have elapsed, all risk and ambiguity are resolved.

2.3 Choice Set

The risk-resolution-preference/ambiguity-resolution-preference elicitation experiment utilizes three choice tasks and a set of multiple price list questions to determine subjects' preferences. The first three involve subjects picking their most preferred option from subsets of the five options in Table 1/Table 2. The first question, denoted by RR1/AR1, is an unrestricted choice from the risk-resolution-preference/ambiguity-resolution-preference choice set. The

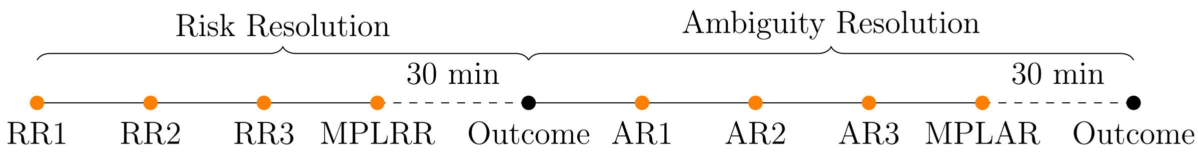
	Choices	Available Options	Description
RR	RR1	E, G, Gp, Gn, L	Unrestricted
	RR2	G, Gp, Gn, L	One-Shot Early is removed
	RR3	E, G, Gp, Gn	One-Shot Late is removed
	MPLRR	Multiple Price List Questions	
AR	AR1	E, G, Gp, Gn, L	Unrestricted
	AR2	G, Gp, Gn, L	One-Shot Early is removed
	AR3	E, G, Gp, Gn	One-Shot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

Table 3: Choice sets used in the experiment.

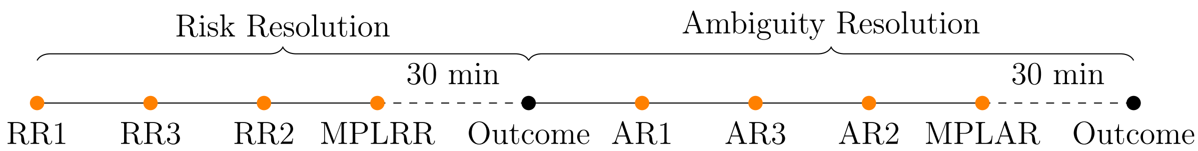
second question, denoted by RR2/AR2 removes the One-Shot Early option. The third question, denoted by RR3/AR3 removes the One-Shot Late option. The last set of questions, denoted by MPLRR/MPLAR, aims to measure the strength of preference for early resolution or late resolution by using the multiple price 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 (see Figure 5). For example, if a subject is indifferent to the timing of resolution, she will always choose the option with additional payment. However, if she strictly prefers early resolution, then she might give up some additional payment to choose One-Shot Early. These multiple price list questions rule out the potential problem that subjects are indifferent between One-Shot Early and One-Shot Late. Table 3 provides a summary of these procedures.

After finishing all four sections on the risk-resolution-preference/risk-resolution-preference elicitation task, subjects receive news/messages based on their choices of information structures, conduct Raven's Progressive Matrices test for the next 30 minutes, and then the outcome is revealed. The ordering of the questions in the two elicitation tasks was partially randomized in four different ways to reduce ordering effects (see Figure 6).[12]

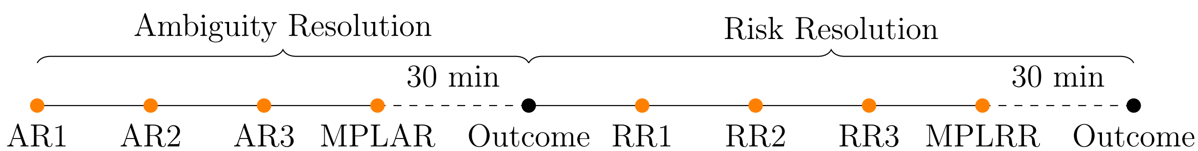
[12] Appendix A.2 provides analysis of subject elicited preferences by order and finds no significant difference across the four orders.



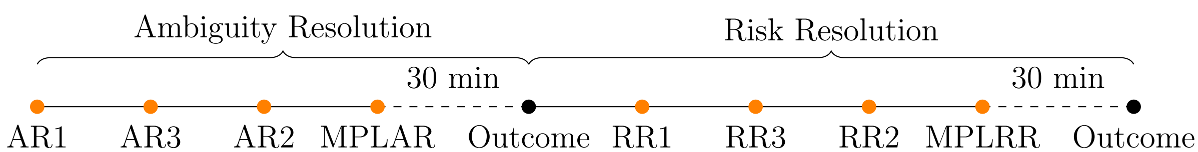
(a) Order 1.



(b) Order 2.



(c) Order 3.



(d) Order 4.

Figure 6: Timeline of the experiment under different orders.

2.4 Ellsberg Questions

Subjects also answered two Ellsberg (1961) questions in the ambiguity-resolution-preference elicitation task section. 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 their preferred options between A & B and between C & D. The four options are listed in Table 4.

A subject that prefers A to B and D to C demonstrates a traditional representation of ambiguity aversion. A subject that prefers B to A and C to D demonstrates the attitude

	Options
Option A	receiving a payment of \$10, if a blue ball is drawn.
Option B	receiving a payment of \$10, if a red ball is drawn.
Option C	receiving a payment of \$10, if a blue ball or a yellow ball is drawn.
Option D	receiving a payment of \$10, if a red ball or a yellow ball is drawn.

Table 4: Ellsberg questions.

of ambiguity seeking. In these two cases, there is no formulation of subjective probabilities that can rationalize the two decisions. Beyond the two cases, the two decisions are consistent with the use of subjective probabilities.

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 and made decisions using zTree software (Fischbacher, 2007). Sessions took place at the Experimental Research Laboratory at Texas A&M University from February to May 2021.

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 based on one randomly selected decision out of the forty-eight $((1 + 1 + 1 + 21) \times 2)$ that they made (see Table 3 and Figure 5).[13] In addition, subjects have another chance to receive an additional \$10 from the "bonus" question in the Ellsberg task. The average payment for each participant was \$23.33 including a \$10 participation payment.

We adopt the random incentive scheme, which is a common payment scheme in the experimental literature. By adopting this scheme, our underlying assumption is that our non-expected-utility-maximizing subjects either isolate their decisions in different questions, i.e., evaluate different choices condition on the question that is used for payment, or integrate their decisions in different questions but satisfy a statewise monotonicity assumption established

[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 $\frac{1}{8} \times \frac{1}{21}$.

by Azrieli et al. (2018). Under such an assumption, the random incentive scheme is incentive compatible. This assumption is justified for subjects in Nielsen (2020), where a control treatment with only one question was run and shown to have to similar results as those in the main experiments thereof. 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. It is, nevertheless, worth mentioning that there may be subjects who do not satisfy the assumption, and in that case, their choices under the random incentive scheme may underestimate the prevalence of risk aversion (for non-expected-utility maximizers) and ambiguity aversion (Freeman et al., 2019; Baillon et al., 2022a,b).

3 Results

3.1 Revealed Preferences for Risk Resolution

Table 5 shows the summary of the choices of risk resolution on the three choice tasks RR1, RR2, and RR3. Consistent with previous literature, 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, 42.4%).[14] A small remainder prefer late resolution (14, 10.3%). A chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.01$).

The restricted choice sets RR2 and RR3 allow us to look further at the revealed preference profiles for subjects over risk resolution. A subject with a strict preference ordering that

[14] Specifically, 36 (26.7%) prefer the non-skewed option, 6 (4.4%) prefer the positively-skewed one, and 15 (11.1%) prefer the negatively-skewed one (see Supplemental Table A.4). We do not focus on the distinction between the three gradual options because they are not Blackwell ordered. Instead, we may calculate the entropy informativeness measure, $-\ln(0.5)+p[q\ln(q)+(1-q)\ln(1-q)]+(1-p)[r\ln(r)+(1-r)\ln(1-r)]$ (Cabrales et al., 2013). Options E, G, Gp, Gn, and L have entropy informativeness levels of 0.69, 0.13, 0.09, 0.09, and 0.00, respectively. Among subjects who indicate a preference for gradual resolution, most prefer the option with the higher entropy informativeness measure (i.e., the non-skewed one). The question on subjects' preference among three gradual options is open for further research. Note that we are not aware of an equivalent or comparable entropy informativeness measure for the gradual options in the ambiguity resolution elicitations.

chooses One-Shot Early in the unrestricted set RR1, will choose One-Shot Early in the restricted set RR3, and will indicate their second-most preferred option in RR2. Similarly, under a strict preference ordering, a subject that chooses One-Shot Late in the unrestricted set RR1 will choose the One-Shot Late option in the restricted set RR2, but must indicate their second-most preferred option in RR3. A subject can select any of the three forms of gradual resolution in any of the choice sets, so we would not observe a second-most preferred option under a strict choice ordering for those subjects.

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. 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 3 gradual options on RR1, 48 (84.2%) also pick one of the three gradual options on both RR2 and RR3.[15] Taking these proportions across the entire sample we can say that 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.

The categorization of subjects by their indicated second-most preferred option is also illuminating. Of the 64 subjects that indicate a preference for the One-Shot Early option on RR1, 48 prefer gradual and 16 prefer One-Shot Late in RR2. We refer to the former and latter subjects as having a preference for *monotone* and *one-shot* resolution of risk, respectively. Note that the latter preference has been studied theoretically by Dillenberger (2010). Of the 14 subjects that indicate a preference for the One-Shot Late option on RR1, 12 prefer gradual and 2 prefer One-Shot Early on RR3. In total, we observe more subjects with preferences for monotone resolution (60, 44.4%) than one-shot resolution (18, 13.3%).

Subjects also completed a 21-item binary-choice multiple price list (MPLRR) to indicate their willingness to pay for one-shot early resolution of risk vs. late. Implied willingness to pay ranged from −\$0.50 to \$0.50. Figure 7 provides a histogram for the 114 subjects that indicated a single switching point (i.e., a response consistent with preferring more money

[15] However, only 26 of these 48 (54.2%) subjects consistently pick *the same* option (e.g., positively-skewed, negatively-skewed, non-skewed) for gradual resolution over all three choices. See Supplemental Table A.4.

RR1 choice (unrestricted)	RR2 choice (One-Shot Early removed)		RR3 choice (One-Shot Late removed): One-Shot Early	RR3 choice (One-Shot Late removed): Gradual (all forms)	Total
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 resolution of risk in choice tasks RR1, RR2, and RR3. All three forms of gradual resolution of risk are pooled (Supplemental Appendix Table A.4 for unpooled results). Yellow indicates profiles consistent with a strict preference ordering.

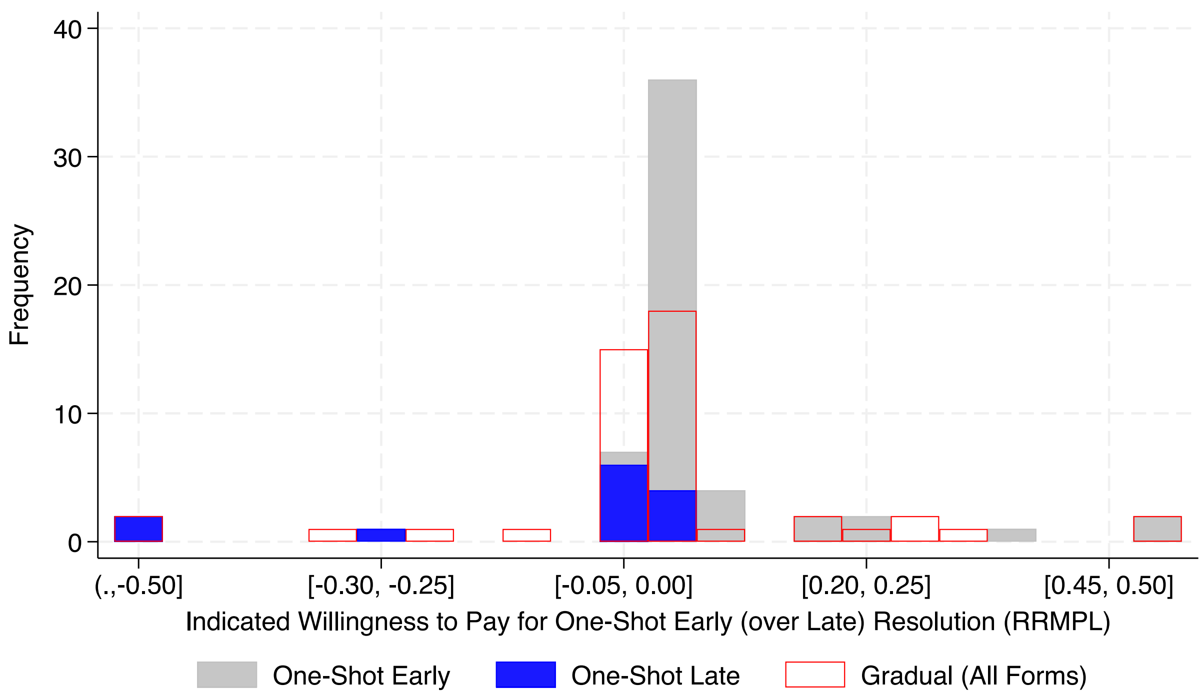


Figure 7: Histogram of implied WTP from interval switching point in RRMPL elicitation by unrestricted choice set decision (RR1) (single-crossing subjects only, $N = 114$).

to less) broken down by indicated choice on the unrestricted choice set RR1. Responses are centered around 0, 86 of the 114 (75.4%) subjects do not indicate a willingness to pay more than \$0.05 for their preferred form of one-shot resolution.[16] However, the direction of the three distributions of subjects is consistent with what we would expect. The Cuzick non-parametric trend test conducted across ordered groups rejects the null hypothesis of no trend across groups ($p < 0.01$).

Further, we observe no subject that chose the One-Shot Early (Late) option on RR1 is willing to pay for late (early) resolution. Of the 20 subjects that indicate a *strictly positive* willingness to pay, 11 chose the One-Shot Early option on RR1 and 9 chose a gradual option. Of the 8 subjects that indicate a *strictly negative* willingness to pay, 3 chose the One-Shot Late option on RR1 and 5 chose a gradual option ($p < 0.01$, chi-square test using a 3×3 contingency table).

The 11th option of the MPL also provides a check on the robustness 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 (81.2%) chose the early option over late, 33 of 57 (57.9%) for gradual, 5 of 9 for late (55.5%) ($p < 0.01$, chi-square test using a 3×2 contingency table).

To provide point estimates in monetary terms we apply interval regression techniques. Consider a the highest row number (1 to 21, see Figure 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)

[16]It is important to note that multiple price lists such as this one 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 list elicitations to *underestimate* the magnitude of resolution preference as subject elicitations are anchored toward 0.

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

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,

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

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 6 provides results over all subjects (specification 1) and 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 (specification 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 ($p < 0.01$).

3.2 Revealed Preferences for Ambiguity Resolution

Table 7 shows the summary of the choices of ambiguity resolution on the three choice tasks AR1, AR2, and AR3. The modal response of subjects over the unrestricted choice set (AR1) is the preference for early resolution of risk (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, 5.18%). 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. Interestingly, a greater proportion of subjects prefers early resolution of ambiguity relative to early resolution of risk. We will examine this relationship further when we consider correlations in Section 3.4.

As with RR2 and RR3, the restricted choice sets AR2 and AR3 allow us to look further at the revealed preference profiles for subjects over ambiguity resolution. A subject with a strict preference ordering that chooses One-Shot Early in AR1, would pick the same on AR3, and reveals their second-most preferred option in AR2. Similarly, a subject that prefers One-Shot Late in AR1, would pick the same on AR2, and reveals their second-most preferred option in AR3. Seventy-seven of the 86 (89.5%) subjects that select early resolution in AR1 choose

[17] Specifically, 30 (22.2%) prefer the non-skewed option, 4 (3.0%) prefer the positively-skewed option, and 8 (5.9%) prefer the negatively-skewed option. See Supplemental Table A.5 for more detail.

the same option in AR3, consistent with a strict preference for early resolution. Five of the 7 (71.4%) subjects that select late resolution in AR1 select the same option in AR2. Of the 42 subjects that select one of the 3 gradual options on AR1, 27 (64.2%) also pick one of the three gradual options on both AR2 and AR3.[18] Taking these proportions across the entire sample we can say that 77 of 135 (57.0%) of 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.

As with risk-resolution preferences, the second-most preferred option allows us to categorize them as having a preference for either *monotone* or *one-shot* resolution of ambiguity, where the latter preference has been studied by Li (2020a) from a theoretical perspective. Of the 86 subjects that indicate a preference for One-Shot Early in AR1, 68 prefer gradual and 18 prefer One-Shot Late on AR2. Of the 7 subjects that indicate a preference for One-Shot Late on AR1, 6 prefer gradual and 1 prefers One-Shot Early on AR3. In total, we observe more subjects with a preference for monotone resolution (74, 54.8%) than one-shot resolution (19, 14.1%).

Subjects also completed a 21-item binary-choice multiple price list (MPLAR) to indicate their willingness to pay for one-shot early resolution of ambiguity vs. late. Implied willingness to pay ranged from −\$0.50 to \$0.50. Figure 8 provides a histogram for the 118 subjects that indicated a single switching point (i.e., a response consistent with preferring more money to less) broken down by indicated choice on the unrestricted choice set AR1. Responses are centered around 0, 91 of the 118 (77.1%) subjects do not indicate a willingness to pay more than \$0.05 for their preferred form of one-shot resolution. However, the direction of the three distributions of subjects is consistent with what we would expect. The Cuzick non-parametric trend test conducted across ordered groups rejects the null hypothesis of no trend across groups ($p < 0.01$).

As before with risk resolution, we also observe no subject that chose the One-Shot Early (Late) option on AR1 is willing to pay for late (early) resolution. Of the 25 subjects that

[18] However, only 19 of these 42 (45.2%) subjects consistently pick *the same* option (e.g., positively-skewed, negatively-skewed, non-skewed) for gradual resolution over all three choices. See Supplemental Appendix Table A.5.

AR1 choice (unrestricted)			AR3 choice (One-Shot Late removed)		Total
			One-Shot Early	Gradual (all forms)	
One-Shot Early	AR2 choice (One-Shot Early removed)	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 7: Revealed preferences for resolution of ambiguity on choice tasks AR1, AR2, and AR3. All three forms of gradual resolution of risk are pooled (see Supplemental Appendix Table A.5 for unpooled results). Yellow indicates profiles consistent with a strict preference ordering.

indicates a *strictly positive* willingness to pay, 22 chose the One-Shot Early option on AR1 and 3 chose a gradual option. There are only 2 subjects that indicate a *strictly negative* willingness to pay, 1 chose the One-Shot Late option on AR1 and 1 chose a gradual option ($p < 0.01$, chi-square test using a 3×3 contingency table).

The 11th option of the MPLAR also provides a check on the robustness of the results: subjects could pick between early or late resolution with no payment each way. 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, ($p < 0.01$, chi-square test using a 3×2 contingency table).

Table 8 provides the results of an interval regression for revealed preferences of ambiguity resolution using the same form as Table 6; the MLE is calculated using the same technique as in equation (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 risk of \$0.107 (specification 1: $0.088 + 0.019$, $p < 0.01$)

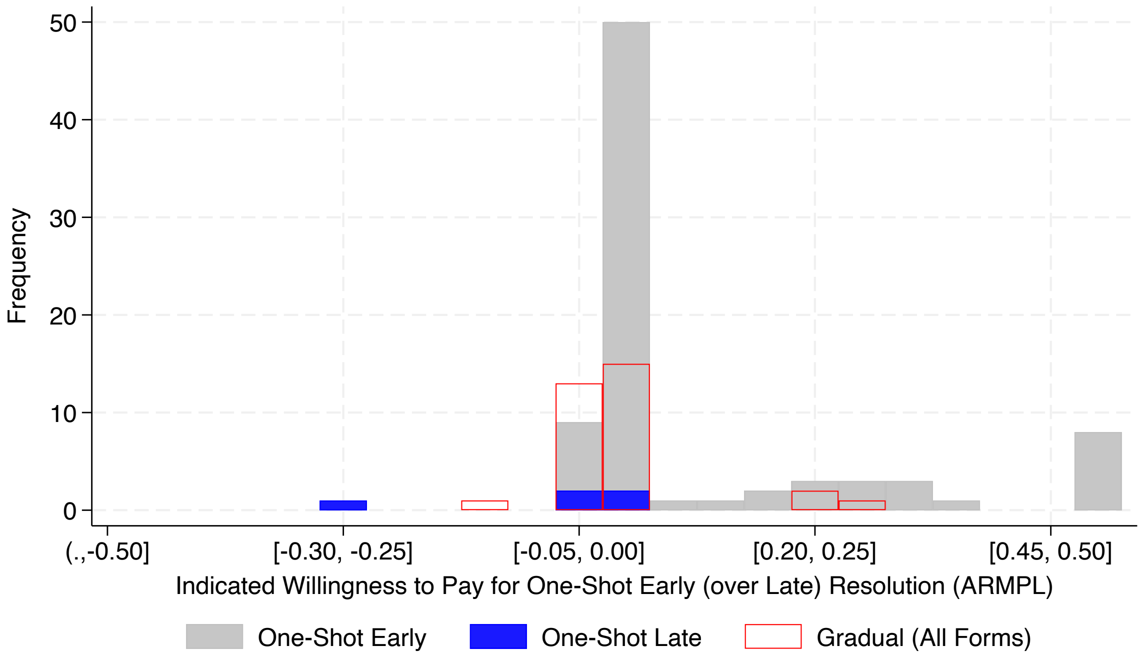


Figure 8: Histogram of implied willingness to pay for early vs. late ambiguity resolution determined from switching point in MPLAR elicitation. Groups are separated by unrestricted choice set decision (AR1) on a previous task (single-crossing subjects only, $N = 118$).

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 risk 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: $0.022 + (-0.077) = -0.055$, $p \approx 0.420$) 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 ($p < 0.01$).

3.3 Ambiguity Attitudes

Based on the responses of Ellsberg's questions in Section 2.4, 63 (46.7%) were ambiguity averse, 60 (44.4%) were ambiguity neutral, and 12 (8.9%) were ambiguity seeking. A chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.001$).

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

3.4 Correlations between Preferences for Resolution and Ambiguity Attitude

Table 9 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 chi-square 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 risk are positively correlated (the correlation coefficient is approximately 0.5, $p < 0.001$).

We also investigate the marginal effect of ambiguity attitude on ambiguity resolution. Table 10 shows the risk resolution and ambiguity resolution from unrestricted choice tasks

		AR1 choice			
		One-Shot Early	Gradual (all forms)	One-Shot Late	Total
RR1 choice	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
Chi-square test p-value ≈ 0.000					

Table 9: Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1 tasks). The three gradual choices are pooled. See Appendix Table A.3 for unpooled table.

Ambiguity Attitude (Ellsberg Task)			AR1 Choice			
			One-Shot Early	Gradual (all forms)	One-Shot Late	Total
Ambiguity Averse	RR1 Choice	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 10: Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1 tasks) separated by revealed ambiguity attitudes on the Ellsberg task.

Marginal Effects on Choosing One-Shot Early in AR1			
	Marginal Effect	Standard Error	p-value
One-Shot Early on RR1	0.436	0.045	0.000
Ambiguity Seeking	−0.256	0.123	0.037

Table 11: The average marginal effects in probability points ($N = 135$).

(AR1 and RR1 tasks) separated by elicited ambiguity attitude on the Ellsberg task. To validate these observations, we utilize the logistic regression below:

$$P(y = 1) = F(b_1 x_1 + b_2 x_2), \tag{2}$$

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 is a binary variable that equals 1 when a subject exhibits ambiguity-seeking behavior on the Ellsberg task.

Table 11 shows marginal effects of the logistic regression model.[19] Preferring early resolution of risk increases the likelihood of preferring early resolution of ambiguity by 43.6 percentage points ($p < 0.001$). Being ambiguity seeking decreases the likelihood of preferring early resolution of ambiguity by 25.6 percentage points ($p \approx 0.037$). We conclude that there is some validity to the idea that ambiguity aversion affects the correlation of these preferences in that a smaller proportion of ambiguity-seeking subjects favor early resolution of ambiguity compared with those who are ambiguity neutral or ambiguity averse.

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)

[19] The full results of the regression are available in Appendix C.

ambiguity-seeking attitudes appear to mitigate preferences for the early resolution of ambiguity. We now look to see which if any theoretical model can accommodate these five findings.

4.1 Risk and Ambiguity Resolution

We utilize a dynamic framework that allows us to study preferences towards risk resolution and ambiguity resolution theoretically.

For simplicity, we focus on two-period problems and finite state spaces, S_1 and S_2, in period 1 and period 2. 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, we do not always assume that the decision maker (DM) directly observes s_1 in period 1. Instead, let $\mathcal{Q}^f$ be a partition of $f(S_1)$ and $\mathcal{S}_1^f$ be the 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, when the partition $\mathcal{Q}^f$ is also publicly known, 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 partition 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 the period-2 distribution (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 (i) $\tilde{p}(s_1, \tilde{q}) > 0$ for each $s_1 \in S_1$ and $\tilde{q} = f(s_1)$, and (ii) $\tilde{p}(s_1, \tilde{q}) = 0$ for each $s_1 \in S_1$ and $\tilde{q} \in \Delta(S_2) \backslash \{f(s_1)\}$. Namely, for any $\tilde{p} \in \Delta^f(S_1 \times \Delta(S_2))$ and $s_1 \in S_1$, the realization of each state s_1 is assigned a positive probability and 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 essentially informs her of one $\hat{q} \in f(S_1)$, or equivalently, an element Q^k in $\overline{\mathcal{Q}}^f$, or an element

S_1^k in $\overline{\mathcal{S}}_1^f$. The information structure in a risk resolution experiment can thus be summarized as a triplet $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$. We say information structure $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$ resolves risk early if $f(S_1)$ is a set of distributions in $\Delta(S_2)$, where each degenerates to one state in S_2, and thus the interim information allows the subject to know for sure the outcome that will be realized. We say $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$ resolves risk late if $f(S_1) = \{\tilde{q}\}$, where no interim information leads to a new period-2 distribution. If $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$ neither resolves risk early nor late, then it is said to resolve risk gradually.[20]

In our ambiguity resolution experiment, a DM is not ex-ante informed of any objective $\tilde{p} \in \Delta^f(S_1, \Delta(S_2))$ although f is publicly known. Hence, she knows how each period-one state corresponds to a period-two distribution, and the set of possible period-2 distributions $f(S_1)$. Let $\mathcal{Q}^f$ be a partition of $f(S_1)$ and $\mathcal{S}_1^f$ be the corresponding partition of S_1. A DM's interim information is an element of $\mathcal{S}_1^f$, or equivalently, an element of $\mathcal{Q}^f$. We thus summarize the information structure in an ambiguity resolution experiment by $[f, \mathcal{S}_1^f]$, and say it resolves ambiguity early if $\mathcal{S}_1^f = \overline{\mathcal{S}}_1^f$, resolves ambiguity late if $\mathcal{S}_1^f = \underline{\mathcal{S}}_1^f$, and resolves ambiguity gradually otherwise.[21]

4.2 Models

This section reviews six representative recursive utility models under uncertainty, including the discounted expected utility model (henceforth the DEU model) which is predominant in applied works, the generalized recursive utility model of Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990) (henceforth the EZ 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

[20]To see how this definition is consistent with the one defined by Figure 1 and Table 1 used in our experiment, we have $S_1 = \{\text{good}, \text{bad}\}$, and $S_2 = \{\text{high prize}, \text{low prize}\}$. The function $f : S_1 \to \Delta(S_2)$ is defined as follows: $f(\text{good}) = (r, 1-r)$, $f(\text{bad}) = (q, 1-q)$. The partition $\overline{\mathcal{S}}_1^f = \{\{\text{good}\}, \{\text{bad}\}\}$. 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, $f(S_1) = \{(0.75, 0.25), (0.25, 0.75)\}$.

[21]To match this definition with the one defined by Figure 3, Figure 4, and Table 2, we have S_1 be the collection of all possible $\mathbf{p}$, i.e., $S_1 = \{0.1, 0.4, 0.6, 0.9\}$, and $S_2 = \{\text{high prize}, \text{low prize}\}$. The function $f : S_1 \to \Delta(S_2)$ is defined as follows: $f(s_1) = (s_1, 1 - s_1)$. The partitions in Table 2 correspond to different partitions of S_1 and thus are associated with different information structures.

Seo (2009) (henceforth the KMM model), the generalized recursive maxmin expected utility model of Hayashi (2005) (henceforth the H model), and the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) (henceforth the HM model). As will be clear in Section 4.3, our focus will be on the H model and the HM model which can simultaneously allow non-indifferent risk resolution preference, non-indifferent ambiguity resolution preference, and non-neutral ambiguity attitude.[22] However, we list the six models here because some of the models here are important and familiar special cases of the other more general models.

These six models differ from each other in two dimensions. First, they describe intertemporal substitution differently. In the two-period framework, the EZ, H, and HM models adopt a non-linear time aggregator to add up *certainty equivalents* in two periods to derive the certainty equivalent of life-time consumption. The intertemporal substitution can be independent of risk attitudes. However, the DEU, MEU, and KMM models sum up discounted utility flows across different periods to derive the life-time utility. Such an approach implies an astringent relationship between the intertemporal substitution and risk attitudes. Second, these models are based on three intratemporal decision-making criteria under uncertainty. The DEU model and the EZ model follow the subjective expected utility and do not support ambiguity aversion behaviors. The MEU model and the H model use the worst-case criterion to capture ambiguity aversion behaviors. The KMM model and the HM model adopt a smooth ambiguity approach, which permits a separation between ambiguity and ambiguity aversion and accommodates a richer class of ambiguity attitudes. We summarize the key differences of these models in Table 12.

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 param-

[22]In Appendix B, we discuss two more models that can simultaneously allow these non-indifferent/non-neutral preferences, i.e., the generalized recursive multiplier preference model and the generalized recursive variational preference model. Under the CRRA-CES restriction that we will introduce soon, the implications of these two models are very rich but can be less sharp, because under a wide range of parameters, these models do not exhibit globally consistent ambiguity resolution preferences for all consumption processes. Namely, a DM may have different ambiguity resolution preferences for different consumption processes, which is not a phenomenon that the current experiment looks at. Hence, we only list the six representative models in the main text, under which a DM has global ambiguity resolution preferences given our CRRA-CES restriction.

		Intratemporal Criterion		
		Subjective Expected Utility	Worst-Case Criterion	Smooth Ambiguity
Intertemporal	Depends on risk attitudes	DEU	MEU	KMM
Substitution	Can be independent of risk attitudes	EZ	H	HM

Table 12: A summary of recursive utility models under uncertainty.

eter. Define $v(x) \equiv \frac{x^\eta}{\eta}$, 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, and HM models, β is the discount factor, and x and y are certainty equivalents of consumptions in period 1 and period 2, respectively. 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. Moreover, they allow us to focus on preferences for risk/ambiguity resolution in a global sense. For example, Proposition 1 shows that the convexity (resp. 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, and HM models; Proposition 3 shows that the convexity (resp. concavity) of $v(W(h_1, v^{-1}(x)))$ in x characterizes the preference for early (resp. late) resolution of ambiguity in the HM model. Beyond the CRRA-CES case, these functions may be neither globally convex nor concave (in which case a DM can prefer early resolution of risk/ambiguity 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 $\rho = -0.4$, $\beta = 0.9$, period-1 consumption $h_1 = 10$, and period-2 consumption x. In this case, the function $u(W(h_1, u^{-1}(x)))$ (where $x \in (-1, 0)$) is not convex, concave, or linear and thus the DM has no global risk resolution preferences.

Now we review these recursive utility models under uncertainty.

In the **Epstein-Zin** (EZ) model that incorporates subjective expected utility, there is a subjectively formed belief in $\Delta(S_2)$. To also accommodate period-1 information, we assume that the DM forms a subjective belief $\pi \in \Delta(f(S_1)) \subseteq \Delta(\Delta(S_2))$ and reduces compound lotteries. 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, $S_1^k \in \mathcal{S}_1^f$), the certainty equivalent of life-time consumption conditional on Q^k, and the certainty equivalent of ex-ante life-time consumption are given by

$$\begin{aligned} I_2(h|Q^k) &= u^{-1}\Big(\sum_{\hat{q}\in Q^k}\sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k)\Big), \\ I_1(h|Q^k) &= W(h_1, I_2(h|Q^k)), \\ I_1(h) &= u^{-1}\Big(\sum_{Q^k\in\mathcal{Q}^f} u\big(I_1(h|Q^k)\big)\pi(Q^k)\Big), \end{aligned} \tag{3}$$

where the special case that $\alpha = \rho$ gives us the **discounted expected utility** (DEU) model.[23] 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 **Hayashi** (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 by considering the worst-case belief. 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 $Q^k \in \mathcal{Q}^f$ and the certainty equivalent of ex-ante life-time consumption given by

$$\begin{aligned} I_2(h|Q^k) &= u^{-1}\Big(\min_{\pi\in\Pi}\sum_{\hat{q}\in Q^k}\sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k)\Big), \\ I_1(h) &= u^{-1}\Big(\min_{\pi\in\Pi}\sum_{Q^k\in\mathcal{Q}^f} u\big(I_1(h|Q^k)\big)\pi(Q^k)\Big), \end{aligned}$$

with the certainty equivalent of life-time consumption conditional on Q^k, $I_1(h|Q^k)$, given by expression (3). The special case that $\alpha = \rho$ gives us the dynamic **maxmin expected utility** (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 representative subcategories in the H model (and also the MEU model) are worth mentioning, as the two have different yet sharp implications on the ambiguity resolution

[23] To see this, we illustrate with the case where $\mathcal{Q}^f = \{f(S_1)\}$, i.e., ambiguity is resolved late. The familiar form of life-time utility under the DEU model is given by $u(h_1) + \beta u(I_2(h|f(S_1)))$, which linearly aggregates the utility flows across different periods. Instead, if we impose $\rho = \alpha$ in the EZ model, the certainty equivalent of life-time consumption is given by $(h_1^\alpha + \beta I_2^\alpha(h|f(S_1)))^{\frac{1}{\alpha}} = u^{-1}(u(h_1) + \beta u(I_2(h|f(S_1))))$. By applying utility function u on this certainty equivalent, we get the same form of life-time utility.

experiment. We call the subcategory that $\Pi = \Delta(f(S_1)) \subseteq \Delta(\Delta(S_2))$ the **Wald-type Hayashi** model, i.e., the (w)H model. In our ambiguity resolution experiment, this subcategory corresponds to the simple 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 $f(S_1)$, we put this model into the less extreme subcategory, the **interior Hayashi** model, i.e., the (i)H model.[24] The corresponding subcategories of the MEU model are called the (w)MEU model and the (i)MEU model.

Under the **Hayashi-Miao** (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 all possible first-order probabilities and subjectively forms a second-order probability $\mu \in \Delta(f(S_1)) \subseteq \Delta(\Delta(S_2))$. The DM, however, does not necessarily reduce compound lotteries, but evaluates the first-order uncertainty and second-order uncertainty with functions u and v, respectively. Hence,

$$\begin{aligned}
I_2(h|Q^k) =& v^{-1}\Big(\sum_{\hat{q}\in Q^k} v \circ u^{-1}\big(\sum_{s_2\in S_2} u(h_2(s_2))\hat{q}(s_2)\big)\mu(\hat{q}|Q^k)\Big),\\
I_1(h) =& v^{-1}\Big(\sum_{Q^k\in\mathcal{Q}^f} v\big(I_1(h|Q^k)\big)\mu(Q^k)\Big),
\end{aligned}$$

where $I_1(h|Q^k)$ is given by (3). 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. ambiguity averse, or ambiguity neutral). The special case that $\alpha = \eta$ gives the (subjective) EZ model. The special case that $\alpha = \rho$ yields the dynamic **Klibanoff-Marinacci-Mukerji** (KMM) model, i.e., the dynamic smooth ambiguity model.

Finally, we remark that for an ambiguity-neutral DM, the H model and the HM model both reduce to the EZ model, and the MEU model and KMM model both reduce to the DEU model.

[24]The H model includes cases that do not fit into either subcategories: for example, suppose $\Pi = \{\pi\}$ where π imposes probability 1 to one $\hat{q} \in f(S_1)$. Under these other cases, the ambiguity resolution preference is the same with that under either the (i)H model or the (w)H model. As such, we only list the (w)H model and the (i)H model separately.

	Risk Resolution	Ambiguity Resolution	Ambiguity Attitude
DEU			
MEU		✓	✓
KMM		✓	✓
EZ	✓	✓	
H	✓	✓	✓
HM	✓	✓	✓

Table 13: Models accommodating non-indifferent resolution preferences and non-neutral ambiguity attitudes.

4.3 Summary of Predictions

We now present two tables to summarize the predictions of each model. Technical arguments are provided in Appendix A.

In Table 13, 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. The first column means that the EZ, H, and HM models can accommodate non-indifferent preferences in the timing of risk resolution under some parameter values. The second column implies the MEU, KMM, EZ, H, and HM models support non-indifference in the timing of ambiguity resolution under some parameter values. We complement Table 13 with two observations regarding ambiguity resolution. As is shown in Appendix A, under the (w)MEU and (w)H models, the DM should be indifferent to the timing of ambiguity resolution, and under the (i)MEU model, the DM should be indifferent between early and late resolution of ambiguity, but may prefer one-shot resolution of ambiguity. The last column shows that the MEU, KMM, H, and HM models can be used to explain non-neutral ambiguity attitudes. Hence, among these models, only the H and HM models can simultaneously accommodate non-indifferent preferences for the timing of risk resolution and ambiguity resolution, as well as non-neutral ambiguity attitudes.

Table 14 provides further predictions on "strict" preferences in the risk and ambiguity resolution experiments condition on "strict" ambiguity attitudes. We consider three ambiguity attitudes: ambiguity averse, ambiguity neutral, and ambiguity seeking, and five strict risk/ambiguity resolution preferences that can be identified by our experiments: $E \succ G \succ L$, i.e., a monotone preference for early resolution, $E \succ L \succ G$, i.e., a preference for early resolution and one-shot resolution, $G \succ E, L$, i.e., a preference for gradual resolution, $L \succ G \succ E$, i.e., a monotone preference for late resolution, $L \succ E \succ G$, i.e., a preference for late resolution and one-shot resolution. If a model is placed in a cell, it means that there exist unobserved parameters (e.g., risk parameters, multiple-belief set, etc.) under which the model can rationalize the corresponding "strict" preferences profile. For example, the cell corresponding to (Risk Resolution: $G \succ E, L$, Ambiguity Resolution: $G \succ E, L$, Ambiguity Averse) is empty, because none of the six models can simultaneously rationalize strict preferences for gradual resolution in the two resolution experiments as well as strict ambiguity aversion.

We now summarize some essential theoretical results that underly Table 14.

Among the six theoretical models, the MEU, KMM, H, and HM models can be used to explain non-neutral ambiguity attitudes. In particular, only the KMM model and the HM model can accommodate the ambiguity-seeking attitude.

The EZ, H, and HM models can accommodate non-indifferent preferences in the timing of risk resolution. On the contrary, the DEU, MEU, and KMM models do not appear in any cell in Table 14, because these models degenerate to the DEU model in the risk resolution experiment, and the DEU model predicts total indifference in the risk resolution experiment. In particular, under the CRRA-CES restriction, when $\alpha < \rho$ (resp. $\rho < \alpha$, $\alpha = \rho$) in the EZ, H, and HM models, the DM exhibits a preference for early resolution of risk monotonically (resp. a preference for late resolution of risk monotonically, and an indifferent preference to the timing of risk resolution).[25]

The implications of the six models on ambiguity resolution are more complicated. We summarize the key information under the CRRA-CES restriction below and leave the formal statement of propositions to the Appendix A:

- In the DEU model, a DM is indifferent to the timing of ambiguity resolution.
- In the MEU model, a DM is indifferent between early and late resolution of ambiguity,

[25]Section B.1 in the Appendix shows that without the CRRA-CES restriction, these models may accommodate a preference for one-shot risk resolution or gradual resolution, but only in a local sense. Notice that we are not able to provide a complete ranking between gradual resolution options that are not Blackwell ordered, but Section A.1 in the Appendix provides a ranking between the positively-skewed option and the negatively-skewed one in our risk resolution experiment under different parameter values.

but may prefer one-shot resolution of ambiguity.

- In the KMM model, a DM's ambiguity resolution preference is either indifferent or monotone. An ambiguity-averse (resp. ambiguity-seeking) DM prefers early (resp. late) resolution of ambiguity monotonically.
- In the EZ model, a DM's ambiguity resolution preference is either indifferent (when $\alpha = \rho$) or monotone, and is inherited from her risk resolution preference.
- In the H model, a DM's ambiguity resolution preference can be indifferent (e.g., when the H model reduces to the (w)H case). If it is not indifferent, then her preference between early and late resolution of ambiguity is inherited from the risk resolution preference, but she may prefer one-shot resolution of ambiguity.
- In the HM model, a DM's ambiguity resolution preference is either indifferent (when $\alpha = \rho$) or monotone. In addition, an ambiguity-neutral or ambiguity-averse (resp. ambiguity-neutral or ambiguity-seeking) DM preferring early (resp. late) resolution of risk must prefer early (resp. late) resolution of ambiguity monotonically.[26]
- The MEU model and the KMM model reduce to the DEU model for ambiguity-neutral DM, in which case the DM is indifferent to the timing of ambiguity resolution. The H model and the HM model reduce to the EZ model for ambiguity-neutral DM, in which case the DM's ambiguity resolution preference and risk resolution preference coincide.

Under the CRRA-CES restriction, strict ambiguity resolution preferences that are rationalizable by these models are either monotone or one-shot. Appendix B provides two ways to accommodate a local preference for gradual resolution of ambiguity without going too far from the current framework. First, one can have the EZ, H, or HM model go beyond the CRRA-CES constraint. Alternatively, one can go beyond the intratemporal criteria in Table 12, for example, by considering the multiplier preference or the variational preference model. As in the risk resolution case, we cannot provide a complete ranking between all gradual

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

Ambiguity Attitude			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	Risk Resolution Preference	$E \succ G \succ L$	H, HM	H			
		$E \succ L \succ G$					
		$G \succ E, L$					
		$L \succ G \succ E$	HM			H, HM	H
		$L \succ E \succ G$					
Ambiguity Neutral		$E \succ G \succ L$	EZ, H, HM				
		$E \succ L \succ G$					
		$G \succ E, L$					
		$L \succ G \succ E$				EZ, H, HM	
		$L \succ E \succ G$					
Ambiguity Seeking		$E \succ G \succ L$	HM			HM	
		$E \succ L \succ G$					
		$G \succ E, L$					
		$L \succ G \succ E$				HM	
		$L \succ E \succ G$					

Table 14: Prediction on strict risk and ambiguity resolution preferences condition on (strict) ambiguity attitude.

ambiguity resolution information structures that are not Blackwell ordered. However, we impose some astringent assumptions in Sections A.2 and A.3, which allow us to rank between the two skewed options in the ambiguity resolution experiment.

5 Subject Classification and Predictive Power of Models

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. From Section 4, we know only the EZ, H, and HM models can accommodate such strict preference over both ambiguity resolution and risk resolution. Tables 14 categorizes these predictions, noting that the EZ, H and HM models categorize 2, 6, and 8 of the 75 possible profiles, respectively.

Recall that only 93 of the 135 subjects (68.8%) can be classified into as having these types of strict preference profiles; the other 42 make choices that either violate a strict preference ordering over tasks RR1-RR3 or tasks AR1-AR3. Table 15 provides subject counts classifying these 93 subjects over the 75 profiles. A precursory look at the table indicates subjects are not uniformly distributed over these preference profiles. Early, monotone preferences for both risk and ambiguity resolution combined with ambiguity aversion ($n = 16$) and ambiguity

Ambiguity Attitude			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	Risk Resolution Preference	$E \succ G \succ L$	16	2	0	0	0
		$E \succ L \succ G$	3	3	1	0	0
		$G \succ E, L$	8	3	3	0	0
		$L \succ G \succ E$	2	0	0	2	0
		$L \succ E \succ G$	0	0	0	0	0
Ambiguity Neutral		$E \succ G \succ L$	13	1	3	0	0
		$E \succ L \succ G$	1	6	1	0	0
		$G \succ E, L$	4	1	12	0	1
		$L \succ G \succ E$	0	0	0	0	0
		$L \succ E \succ G$	0	0	0	0	0
Ambiguity Seeking		$E \succ G \succ L$	3	0	0	0	0
		$E \succ L \succ G$	0	0	0	0	0
		$G \succ E, L$	0	0	4	0	0
		$L \succ G \succ E$	0	0	0	0	0
		$L \succ E \succ G$	0	0	0	0	0

Table 15: Empirical classification of subjects (93 of 135) that express choices consistent with strict preference orderings on elicitation tasks RR1–RR3 and AR1–AR3. We assume the preference expressed for ambiguity attitude on the Ellsberg task is strict.

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%).

Because it can accommodate the highest number of preference profiles, it is not that all surprising that the HM can rationalize the highest number of subject observations. To discipline the predictive power of these three 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 75 preference profiles space covered by a model. Table 16, Panel A provides results. Fourteen percent of subjects can be classified as falling in the two cells predicted by the EZ model, yielding a score of 0.113. Both the H and HM model do slightly better. While both models make predictions over a higher number of cells, they also explain more than a third of subject behavior. The corresponding Selten scores are nearly identical (0.275 vs. 0.280). 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 calculate 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 three 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 two models, as the only two profiles the EZ model can rationalize are covered by the H and HM models, as well. In fact, out of the 100,000 bootstraps in only one (none) does the EZ model outscore the HM (H) model. The corresponding p-values are statistically significant ($p < 0.01$ both comparisons). On the other hand, the HM model outperforms the H model in only 56,898 of the 100,000 bootstraps (corresponding p-value≈ 0.862, two-tailed, see Table A.9).

The similar performance in the H and HM models can be explained by the profiles that are rationalizable by only one of the models. The H model has the flexibility over the HM model in being able to accommodating one-shot preferences for ambiguity resolution. The HM model has the flexibility in being able to accommodate ambiguity-seeking attitudes and divergent monotone preferences between risk and ambiguity resolution. These predictions only net another two and five subjects, respectively, suggesting that neither prediction is particularly advantageous in characterizing our data.

One issue with this approach so far is that we have been treating each of the preference profiles as equally likely. A more common convention is to focus on action space—there are $5 \times 4 \times 4 \times 5 \times 4 \times 4 \times 2 \times 2 =$25,600 possible actions in RR1, RR2, RR3, AR1, AR2, AR3, and two Ellsberg questions in our experiment—and certain preference profiles are associated with a larger number of possible actions than others. Table A.7 provides counts for the total number action combinations that could support a given preference profile. Violations of strict preferences account for the largest amount of preference space (20,700 action profiles, 80.8%), then preferences for gradual resolution (2,916 action profiles, 11.4%). The EZ, H and HM models do not make prediction in either area and account for only 36 (0.1%), 60 (0.2%) and 90 (0.4%) action profiles respectively.

Panel B provides revised Selten scores using the space of actions rather than preference profiles. Because each model predicts so little of the action space, the Selten score is essentially a percentage of subjects correctly classified. Here we include all 135 subjects including the 42 that violate a strict preference ranking, as their choices can now be accommodated by the larger action space. As before, the H and HM models outperform the EZ model ($p < 0.01$ both comparisons). However, the slightly higher performance of the HM model is not statistically distinguishable from the H model ($p \approx 0.331$, see Table A.9, Panel B for full bootstrap details).

Taken together, the H and HM models are the apparent winners of this exercise. The differential performance of these two models over the EZ model is due to the fact the two can accommodate specific types of profiles with ambiguity aversion, largely those that contain early preference of risk and ambiguity resolution. Unfortunately, the areas where these models differ in predictions are not observed frequently enough to find a clear difference in predictive performance over 135 subjects.

At this point we may wonder how the HM model cannot outperform the H model given the comparative static observed in Table 11, specifically that ambiguity attitudes appear to affect the correlations between risk and ambiguity resolution. Indeed, Table 10 indicates that 29 ambiguity-averse and ambiguity-neutral subjects that do not prefer early resolution of risk prefer early resolution of ambiguity. There are no ambiguity-seeking subjects that have a similar preference. However, of these 29 subjects, 22 prefer gradual resolution of risk. These 22 subjects, so far, have not been counted as evidence of any of the six models; their gradual preference for risk excludes them from being rationalized by any model.

We might alternatively view a selection of gradual resolution over both early and late resolution as indicative of indifference to the timing of uncertainty resolution. Our MPLRR and MPLAR tasks do provide some support for this assumption. The groups of subjects that select gradual resolution do not have mean willingness to pay for early rather than late resolution that significantly deviates from 0 in either domain (see Tables 6 and 8).

Nonetheless, strict preference for gradual resolution is not theoretically predicted, so we do not really know what an indication of this preference signifies. If we proceed under the assumption that gradual preference indicates indifference, we can rationalize subject choices under any of the six main theoretical models (see Table A.8). For instance, DEU makes one

	proportion of subjects categorized	proportion of profile space covered	Selten score (95% CI)
Panel A: 93 subjects, 75 preference profiles (see Table 14)			
EZ	0.140	0.027	0.113
	(13)	(2)	(0.047, 0.188)
H	0.355	0.080	0.275
	(33)	(6)	(0.179, 0.374)
HM	0.387	0.107	0.280
	(36)	(8)	(0.182, 0.382)
Panel B: 135 subjects, 25,600 action profiles (see Table A.7)			
EZ	0.096	0.001	0.095
	(13)	(36)	(0.050, 0.147)
H	0.244	0.002	0.242
	(33)	(60)	(0.168, 0.316)
HM	0.267	0.004	0.263
	(36)	(90)	(0.189, 0.337)
Panel C: 135 subjects, 25,600 action profiles (see Table A.8)			
DEU	0.089	0.057	0.032
	(12)	(1,458)	(−0.013, 0.084)
MEU	0.111	0.085	0.026
	(15)	(2,187)	(−0.026, 0.085)
KMM	0.148	0.063	0.085
	(20)	(1,620)	(0.026, 0.144)
EZ	0.185	0.058	0.127
	(25)	(1,494)	(0.060, 0.193)
H	0.356	0.094	0.261
	(48)	(2,409)	(0.180, 0.343)
HM	0.415	0.073	0.342
	(56)	(1,872)	(0.260, 0.423)

Table 16: Calculation of Selten scores for strict uncertainty resolution preferences using profile preference space (Panel A), total action space (Panel B), and total action space where a selection of gradual preference indicates indifference (Panel C). 95% confidence intervals taken from 100,000 bootstraps of subject sample ($N = 135$).

prediction, "gradual" options chosen for both risk and ambiguity resolution and ambiguity neutrality on the Ellsberg task.

Panel C provides the results of this alternative specification. Under these new assumptions, the HM model appears to have a substantially greater Selten score than the H model (0.342 vs. 0.261). Of our 100,000 bootstraps, the HM model scores higher than the H in over 99,000 cases, an equivalent two-tailed p-value of $p \approx 0.01$. Table A.10 provides full details. In general, the H and HM model significantly outperform all other models.

6 Conclusion

Models of generalized recursive utility provide alternatives to the standard discounted expected utility model. They are quite useful in explaining various financial and macroeconomic anomalies that cannot be explained by the discounted expected utility model without highly dubious parameter choices. An implication of models of generalized recursive utility 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 such 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 by solely findings based on risk-resolution preferences.

Our study provides the first experimental elicitation of preferences over ambiguity resolution, in addition to eliciting these preferences along with risk-resolution preferences. We also find that these two preferences are positively correlated, and the attitude toward ambiguity affects this relationship. If an individual prefers early resolution of risk, she is 43.6 probability points more likely to prefer early resolution of ambiguity. If she is ambiguity seeking, she is 25.6 probability points less likely to prefer early resolution of ambiguity.

We review six representative models of recursive utility that are widely used in the macroeconomics and finance literature. Among these models, the H model and the HM model can simultaneously accommodate strict risk resolution preference, strict ambiguity resolution preference, as well as non-neutral ambiguity attitude. From a theoretical perspective, the HM model has the flexibility of accommodating divergent preferences for risk resolution and ambiguity resolution. According to this model, being ambiguity averse or ambiguity seeking leads to distinct implications on the connection between risk and ambiguity resolution preferences.

Our empirical findings support the HM model as the best explanatory framework for the observed correlation between risk and ambiguity resolution preferences. On the other hand, the H model predicts that any strict ambiguity resolution preference between early and late resolution options should be inherited from the risk resolution preference. However, the H model possesses the capability to accommodate a preference for one-shot ambiguity resolution which cannot be accommodated by the HM model.

To enhance the precision of our analysis, we further refine our subjects to those who display consistent risk resolution preference as well as consistent ambiguity resolution preference. When we penalize models for accommodating a broader range of choice profiles, the performance of the H model and the HM models becomes similar, because the most expressed consistent choice profile involves preference for early resolution of risk, preference for early resolution of ambiguity, and ambiguity aversion. We thus conclude that the H model and the HM model have similar predictive efficiency, and both outperform the EZ model.

However, our data do contain one anomaly that could prove pivotal in endorsing a single model. We observe a significant proportion of subjects who are ambiguity averse and exhibit the preferences for gradual resolution of risk and early resolution of ambiguity. Under the CRRA-CES restriction, none of our six theoretical models can accommodate such preferences. One possibility is that this "gradual" preference indicated by subjects is an expression of indifference. If subjects are indifferent to the timing of risk resolution but prefer early ambiguity resolution with ambiguity-averse attitude, their preference profiles can fit under the HM model. Making this strong assumption puts the HM model as the best predictive model for this experiment. We cannot think of any similar assumption that would elevate any other model as the best predictive model. However, we are concerned that the exhibition of gradual preferences may indicate something besides indifference for subjects. Until we have a better explanation for what gradual preferences entail, we are hesitant to make this endorsement.

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A Theoretical Appendix

Below we provide technical details on how Tables 13 and 14 are constructed. We first discuss the predictions on risk resolution experiment in Section A.1. Then we discuss predictions on ambiguity resolution experiment in Sections A.2 to A.4.

A.1 Risk Resolution

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

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

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 in x (resp. linear, or strictly concave) 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

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

Notice that $\mathbb{E}_{\hat{q}\sim\tilde{p}}$ means taking 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 thus under the early resolution information structure, the ex-ante certainty equivalent of h is

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

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

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

When $\alpha < \rho$, by applying Jensen's inequality, we know that

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

and thus, the DM prefers early resolution of risk monotonically. Similarly, when $\rho < \alpha$, the DM prefers late resolution of risk monotonically. When $\rho = \alpha$, the DM is indifferent to the timing of risk resolution. □

The DEU model corresponds to the case that $\alpha = \rho$, and thus implies indifference to the timing of risk resolution. In the risk resolution experiment where ambiguity is not present, the MEU and KMM models reduce to the DEU model, and the H and HM 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, and KMM models, a DM is indifferent to the timing of risk resolution. In the EZ, H, and HM models, if $\alpha < \rho$ (resp. $\alpha > \rho$), a DM strictly prefers early (resp. late) resolution of risk monotonically; if $\alpha = \rho$, a DM is indifferent to the timing of risk resolution.

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

1. In all above models (under the CRRA-CES restriction), the preference for the timing of risk resolution is indifferent or monotone, and thus there is no strict preference for gradual resolution of risk or for one-shot resolution of risk.

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

3. Following Masatlioglu et al. (2023), gradual risk resolution options Gp and Gn have the same variance and the symmetric skewness, and thus 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 $(\frac{\rho}{\alpha}-1)[(\frac{\rho}{\alpha}-2)h_1^\rho(\alpha x)^{-\frac{\rho}{\alpha}} - \beta(\frac{\rho}{\alpha}+1)]$. Hence, when $\frac{\rho}{\alpha} \in (1, 2]$, $\overline{w}'''(\cdot) < 0$, implying a strict preference for negative over positive skewness in risk resolution; when $\frac{\rho}{\alpha} \in [-1, 1)$, $\overline{w}'''(\cdot) > 0$, implying a strict preference for positive over negative skewness in risk resolution; for $\frac{\rho}{\alpha} > 2$ or < -1, the sign of $\overline{w}'''(\cdot)$ is ambiguous and the preference between skewed options is not global, i.e., depends on the specific vector (h_1, x); for $\frac{\rho}{\alpha} = 1$, the DM is indifferent to the timing of risk resolution.

A.2 The H Model

Proposition 2.

1. In the (w)H model, a DM is indifferent to the timing of ambiguity resolution.

2. In the (i)H model with CRRA utility function u and CES time aggregator W, if $\alpha < \rho$ (resp. $\alpha > \rho$) a DM strictly prefers early (resp. late) resolution of ambiguity, but may

prefer one-shot resolution of ambiguity; if $\alpha = \rho$, a DM is indifferent between early and late resolution of ambiguity, but may prefer one-shot resolution of ambiguity.

Proof. We now establish the first statement.

In the (w)H model, given an information structure $[f, \mathcal{S}_1^f]$ (and also the corresponding $\mathcal{Q}^f$), the ex-ante certainty equivalent of $h \in H$ is given by

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

where

$$I_2[\hat{q}](h) \equiv u^{-1}\Big(\sum_{s_2 \in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\Big). \tag{4}$$

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

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

By the monotonicity of W, we can conclude that $I_1[f, \overline{\mathcal{S}}_1^f](h) = I_1[f, \mathcal{S}_1^f](h) = I_1[f, \underline{\mathcal{S}}_1^f](h)$. Namely, the DM is indifferent to the timing of ambiguity resolution.

We now establish the second statement.

In the (i)H model, given parameters α and ρ as well as a period-1 consumption $h_1 > 0$, we define $\overline{w}(x) \equiv u(W(h_1, u^{-1}(x))) = \frac{1}{\alpha}[h_1^\rho + \beta(\alpha x)^{\frac{\rho}{\alpha}}]^{\frac{\alpha}{\rho}}$, which is strictly convex in x (resp. linear, or strictly concave) if $\alpha < \rho$ (resp. $\alpha = \rho$, or $\alpha > \rho$). Let $\Pi \subseteq \Delta(f(S_1))$ be a convex, compact, and non-empty belief set, such that each $\pi \in \Pi$ is fully supported on $f(S_1)$. Given an information structure $[f, \mathcal{S}_1^f]$, the ex-ante certainty equivalent is given by

$$\begin{aligned} I_1[f, \mathcal{S}_1^f](h) =& u^{-1}\left(\min_{\hat{\pi} \in \Pi} \mathbb{E}_{Q^k \sim \hat{\pi}}\left[u \circ W\left(h_1, u^{-1}\left(\min_{\tilde{\pi} \in \Pi} \mathbb{E}_{\hat{q} \sim \tilde{\pi}(\cdot|Q^k)}\left[u\big(I_2[\hat{q}](h)\big)\right]\right)\right)\right]\right) \\ \leq& \min_{\pi \in \Pi} u^{-1}\left(\mathbb{E}_{Q^k \sim \pi}\left[u \circ W\left(h_1, u^{-1}\left(\mathbb{E}_{\hat{q} \sim \pi(\cdot|Q^k)}\left[u\big(I_2[\hat{q}](h)\big)\right]\right)\right)\right]\right), \end{aligned} \tag{5}$$

where the inequality utilizes the observation that there may not exist a distribution $\pi \in \Pi$

that simultaneoulsly attains the two minimizers in (5). Also, we have

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

When $\alpha < \rho$, by applying Jensen's inequality, we know that $I_1[f, \overline{\mathcal{S}}_1^f](h) > I_1[f, \underline{\mathcal{S}}_1^f](h)$ and $I_1[f, \overline{\mathcal{S}}_1^f](h) > I_1[f, \mathcal{S}_1^f](h)$. Similarly, when $\alpha > \rho$, $I_1[f, \underline{\mathcal{S}}_1^f](h) > I_1[f, \overline{\mathcal{S}}_1^f](h)$ and $I_1[f, \underline{\mathcal{S}}_1^f](h) > I_1[f, \mathcal{S}_1^f](h)$. When $\alpha = \rho$, $I_1[f, \overline{\mathcal{S}}_1^f](h) = I_1[f, \underline{\mathcal{S}}_1^f](h) \geq I_1[f, \mathcal{S}_1^f](h)$. □

We have two remarks regarding gradual ambiguity resolution in the i(H) model:

1. When Π is "rectangular" (Epstein and Schneider, 2003), the weak inequality after expression (5) holds as equality, and it is easy to see that the preference for ambiguity resolution discussed under the (i)H model must be monotone or indifferent.

2. In the i(H) model, the three gradual ambiguity resolution options G, Gp, and Gn are not Blackwell ordered and thus 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 claim that Gp and Gn have the same variance and symmetric skewness and then follow Masatlioglu et al. (2023) to provide a ranking. In the special case that the four minimizers when computing the ex-ante certainty equivalents for the Gp and Gn options can all be 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 the risk resolution analysis under the EZ model, i.e., when $\frac{\rho}{\alpha} \in (1, 2]$, we have $\overline{w}'''(\cdot) < 0$, implying a strict preference for negative over positive skewness in ambiguity resolution; when $\frac{\rho}{\alpha} \in [-1, 1)$, we have $\overline{w}'''(\cdot) > 0$, implying a strict preference for positive over negative skewness in ambiguity resolution.

A.3 The HM Model

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

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 in x (resp. linear, or strictly concave) if $\eta < \rho$ (resp. $=$, or $>$).

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

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

where $I_2[\hat{q}](h)$ is defined in expression (4) 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

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

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

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

When $\eta < \rho$, by applying Jensen's inequality, we know that $I_1[f, \overline{\mathcal{S}}_1^f](h) > I_1[f, \mathcal{S}_1^f](h) > I_1[f, \underline{\mathcal{S}}_1^f](h)$ due to the strict convexity of w. Similarly, when $\eta > \rho$, $I_1[f, \overline{\mathcal{S}}_1^f](h) < I_1[f, \mathcal{S}_1^f](h) < I_1[f, \underline{\mathcal{S}}_1^f](h)$; when $\eta = \rho$, $I_1[f, \overline{\mathcal{S}}_1^f](h) = I_1[f, \mathcal{S}_1^f](h) = I_1[f, \underline{\mathcal{S}}_1^f](h)$. □

Our ambiguity resolution prediction under the HM model is either indifferent or monotone. Hence, there is no strict preference for gradual or one-shot resolution of ambiguity. 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. 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 hence their ranking can be analyzed from the third derivative of w: when $\frac{\rho}{\eta} \in (1, 2]$, we have $w'''(\cdot) < 0$, implying a strict preference for negative over positive skewness in the ambiguity resolution experiment; when $\frac{\rho}{\eta} \in [-1, 1)$, we have $w'''(\cdot) > 0$, implying a strict preference for 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, i.e., may depend on the specific vector (h_1, x); for $\frac{\rho}{\eta} = 1$, the DM is indifferent to the timing of ambiguity resolution.

Proposition 3 shows that 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 timing of risk resolution in the HM model. Also recall that a DM is ambiguity averse (resp. ambiguity neutral, and ambiguity seeking) if $\eta < \alpha$ (resp. $\eta = \alpha$ and $\eta > \alpha$). 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,

1. if an ambiguity-averse DM weakly prefers early resolution of risk, then she strictly prefers early resolution of ambiguity;
2. if an ambiguity-seeking DM weakly prefers late resolution of risk, then she strictly prefers late resolution of ambiguity;
3. an ambiguity-neutral DM strictly prefers early (resp. late) resolution of risk if and only if she strictly prefers early (resp. late) resolution of ambiguity.

Without the CRRA-CES restriction, we cannot make the above claim on the connection between the preference for risk resolution (decided by the convexity/concavity of $u(W(h_1, u^{-1}(x)))$), that for ambiguity resolution (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 convex and thus the DM prefers early resolution of risk, the DM is ambiguity averse, but the function $v(W(h_1, v^{-1}(x)))$ is neither convex nor concave for $x \in (-\infty, -1)$ and thus the DM has no global ambiguity resolution preference.

A.4 The DEU, MEU, KMM, and EZ Models

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

Corollary 3. In the DEU model with CRRA utility function u, a DM is indifferent to the timing of ambiguity resolution.

The KMM model is equivalent to the HM model with $\alpha = \rho$. Hence, in the KMM model, a DM strictly prefers early (resp. late) resolution of ambiguity monotonically if $\eta < \alpha$ (resp. $\eta > \alpha$); she is indifferent to the timing of ambiguity resolution if $\eta = \alpha$. We have the following corollary.

Corollary 4. In the KMM model with CRRA utility functions u and v, an ambiguity-averse (resp. ambiguity-seeking) DM strictly prefers early (resp. late) resolution of ambiguity monotonically; an ambiguity-neutral DM is indifferent to the timing of ambiguity resolution.

Recall that the EZ model is equivalent to the HM model with $\alpha = \eta$.

Corollary 5. In the EZ model with CRRA utility function u and CES aggregator W, a DM strictly prefers early (resp. late) resolution of ambiguity monotonically if and only if she prefers early (resp. late) resolution of risk; she is indifferent to the timing of ambiguity resolution if and only if she is indifferent to the timing of risk resolution.

The MEU model is equivalent to the H model with $\alpha = \rho$. Thus, we have the following corollary.

Corollary 6.

1. In the (w)MEU model with CRRA utility function u, a DM is indifferent to the timing of ambiguity resolution.

2. In the (i)MEU model with CRRA utility function u, a DM is indifferent between early and late resolution of ambiguity, but may prefer one-shot ambiguity resolution.

B Accommodating Preferences for Gradual Uncertainty Resolution

Recall that in our RR1 and AR1 questions respectively, 42.4% and 31.1% subjects choose some form of gradual resolution. However, under the CRRA-CES restriction, none of the six models in the main text can accommodate a preference for gradual resolution of risk or ambiguity. In this section, we discuss two ways that allow a DM to exhibit a preference for gradual resolution of risk or ambiguity without deviating too far from the framework discussed in the current paper.

B.1 Relaxing the CRRA-CES Restriction

According to our analysis in Sections A.1 to A.3, if one goes beyond the CRRA-CES restriction, early resolution of risk in EZ, H, and HM models is still captured by the convexity of $u(W(h_1, u^{-1}(x)))$ function in x, and early resolution of ambiguity in the HM model is captured by the convexity of $v(W(h_1, v^{-1}(x)))$ function in x. These models cannot be used to accommodate a strict preference for gradual resolution of risk or ambiguity for all consumption processes.

However, as is discussed in Sections 4.2 and A.3, without the CRRA-CES restriction, (i) there may not exist a global risk or ambiguity resolution preference for all consumption processes, and (ii) the connection between risk resolution preference, ambiguity resolution preference, and ambiguity attitude specified in Corollary 2 may not hold. Nevertheless, we show with an example that the DM may exhibit preference for gradual resolution of risk/ambiguity at least for some consumption processes.

Example 1. Let W be the same with 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

- $E \succ Gp \succ G \succ Gn \succ L$ when $\theta = 5$,
- $Gp \succ L \succ G \succ Gn \succ E$ when $\theta = 17$,
- $L \succ Gp \succ G \succ Gn \succ E$ when $\theta = 20$.

Hence, there are function forms u and W in the EZ model (and thus H and HM models), under which some format of gradual resolution is the most preferred choice in the risk resolution experiment. Similarly, we can show that going beyond the CRRA-CES restriction may lead to a local preference for gradual resolution of ambiguity in the EZ, H, and HM models. Since local resolution preference is not the focus of our paper, we do not aim to exhaustively search for non-CRRA-CES functions to identify all locally rationalizable choice patterns.

B.2 Other Theoretical Models

Another approach to accommodate local preference for gradual ambiguity resolution without explicitly adopting non-CRRA-CES framework is by going beyond the six models. The literature has introduced other popular ambiguity models with nontrivial implication on ambiguity resolution, e.g., the multiplier preference model (Hansen and Sargent, 2001; Strzalecki, 2011) and its nonparametric generalization, the variational preference model (Maccheroni et al., 2006a,b).

In this section, we integrate the multiplier preference model (a special case of the variational preference model) with the time aggregator W and call this model the generalized recursive multiplier preference model. There is a parameter range under which the DM prefers early resolution of ambiguity monotonically and globally; it is also the only range where the ambiguity resolution preference is global. Beyond this range, we demonstrate with an example that the model can accommodate various local preferences including preference for one-shot resolution of ambiguity and preference for gradual resolution of ambiguity.

In the generalized **recursive multiplier preference** (RMP) model, the DM has a reference belief $\pi' \in \Delta(f(S_1))$. For every other distribution $\pi \in \Delta(f(S_1))$, there is a "punishment" to the belief π due to its departure from π'. The punishment is the multiplication of two expressions. First, 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. Second, the coefficient $\theta \in (0, +\infty]$ measures the DM's confidence in the reference belief: $\theta = (0, +\infty)$ reflects ambiguity aversion, and $\theta = +\infty$ represents full confidence in π' and reflects ambiguity neutrality. The DM takes into account the worst-case belief after adjusting for the punishment term.

Formally, in the RMP model, given a gradual ambiguity resolution information structure $[f, \mathcal{S}_1^f]$ and the corresponding $\mathcal{Q}^f$,

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

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

where $I_1(h|Q^k)$ is defined in (3) and uses the aggregator W.

Proposition 4. In the RMP model with CRRA utility function u and CES time aggregator W, (i) if $\alpha = \rho$ or $0 < \alpha < \rho$, a DM prefers early resolution of ambiguity monotonically and globally and the preference is strict for all full-support π'; (ii) otherwise, the DM's ambiguity resolution preference cannot be global.

Proof. Define a function ϕ_θ: $(0, +\infty) \to \mathbb{R}$,

$$\phi_\theta(x) = \begin{cases} -e^{-\frac{x}{\theta}} & \text{if}\, \theta \in (0, +\infty), \\ x & \text{if}\, \theta = +\infty. \end{cases}$$

Fix any gradual ambiguity resolution information structure $[f, S_1^f]$ and corresponding $\mathcal{Q}^f$. By Strzalecki (2011), the ex-ante certainty equivalents under early, gradual, and late ambiguity resolution information structures can be respectively written as

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

$$u^{-1} \circ \phi_\theta^{-1}\big(\mathbb{E}_{Q^k\in\mathcal{Q}^f\sim\pi'}\big[\phi_\theta \circ u \circ W\big(h_1, u^{-1} \circ \phi_\theta^{-1}\big(\mathbb{E}_{\hat{q}\sim\pi'(\cdot|Q^k)}\big[\mathbb{E}_{s_2\sim\hat{q}}[\phi_\theta \circ u(h_2(s_2))]\big]\big)\big)\big]\big), \tag{A.2}$$

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

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

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

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 globally strictly convex. For any other parameter range, $\tilde{w}$ is not globally convex/concave.

Notice that (A.2) is higher/lower than (A.3) for all h if and only if $\tilde{w}$ is convex/concave, because switching the order of operators $\mathbb{E}_{Q^k \in \mathcal{Q}^f \sim \pi'}$ and $\tilde{w}$ in (A.2) obtains (A.3). 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 convexity of $\tilde{w}$ and weak concavity of ϕ_θ, we know that for each $Q^k \in \mathcal{Q}^f$,

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

for all $h \in H$ and the first inequality holds strictly for some $h \in H$. As a result, (A.1) is strictly higher than (A.2), i.e., early solution of ambiguity dominates gradual resolution. In sum, this is the only parameter range with global ambiguity resolution preference and the global preference is for early resolution of ambiguity. □

Hence, only when $\alpha = \rho$ or $0 < \alpha < \rho$, there is a global ambiguity resolution preference. This range covers the most expressed preferences in the RR experiment, the AR experiment, and the Ellsberg task. The caveat is, it may not be fair to directly compare the Selten scores from the EZ, H, and the HM models with the ones from the RMP model, because the Selten

Ambiguity Attitude			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	Risk Resolution Preference	$E \succ G \succ L$	RMP				
		$E \succ L \succ G$					
		$G \succ E, L$					
		$L \succ G \succ E$					
		$L \succ E \succ G$					
Ambiguity Neutral		$E \succ G \succ L$	RMP				
		$E \succ L \succ G$					
		$G \succ E, L$					
		$L \succ G \succ E$				RMP	
		$L \succ E \succ G$					
Ambiguity Seeking		$E \succ G \succ L$					
		$E \succ L \succ G$					
		$G \succ E, L$					
		$L \succ G \succ E$					
		$L \succ E \succ G$					

Table A.1: Rationalizable strict and global resolution preferences condition on (strict) ambiguity attitude by the RMP model.

scores of the former models are computed based on the entire parameter space, but the RMP model does not have global ambiguity resolution preferences on the entire parameter space. As such, we do not provide the computation of Selten scores of the RMP model in the paper. They are available upon request.

Although the only global ambiguity resolution preference supported by the RMP model is early resolution of ambiguity, Example 2 shows that the model can rationalize many more ambiguity resolution preferences in a local sense. The preferences can be complicated in a few ways. First, regardless of the DM's risk resolution preferences, the DM can prefer early or late resolution of ambiguity. Also, there may be preferences for gradual ambiguity resolution, one-shot ambiguity resolution, and monotone ambiguity resolution. Moreover, under the same group of parameters, some gradual ambiguity resolution options can be better than one-shot options and some can be worse.

Example 2. We present two groups of parameters specification and the 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 with the h specified therein, the predicted ambiguity resolution 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 $\theta = 16$,
- $Gp \succ E \succ L \succ G \succ Gn$ when $\theta = 17.9$,
- $E \succ Gp \succ G \succ Gn \succ L$ when $\theta = 50$.

Group 2: 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

- $E \succ Gn \succ Gp \succ G \succ L$ when $\theta = 0.1$,
- $E \succ L \succ Gp \succ Gn \succ G$ when $\theta = 500$,
- $L \succ E \succ Gp \succ Gn \succ G$ when $\theta = 600$,
- $L \succ Gp \succ G \succ Gn \succ E$ when $\theta = 10000$.

By replacing the punishment term in the RMP model (which adopts an aggregator W) with the nonparametric c function of Maccheroni et al. (2006a,b) and following the updating rule of Li (2020b), one can define a generalized **recursive variational preference** (RVP) model. Li (2020a) has constructed such an example with $\alpha = \rho$ that accommodates local preference for gradual resolution of ambiguity as well as local preference for one-shot ambiguity resolution. Hence, because the c function can be very general, there may not exist a globally optimal information structure for the RVP model, but the model can accommodate rich local resolution preferences. In fact, the punishment terms in the RMP model and the RVP model implicitly go beyond the CRRA-CES framework, which is essentially the reason why they can accommodate local preference for gradual resolution of ambiguity.

C Additional Tables and Figures

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.2: Proportions of subjects who revealed ambiguity aversion or preference for early resolution of risk and ambiguity across different orders. The p-value of F-test provides the evidence that there is no order effect on the timing of resolution.

		AR1 choice					
		One-Shot Early	Gradual (Positively-Skewed)	Gradual (Negatively-Skewed)	Gradual (Non-Skewed)	One-Shot Late	Total
RR1 choice	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).

RR1 choice (unrestricted)	RR2 choice (One-Shot Early removed)		RR3 choice (One-Shot Late 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.4: Revealed preferences for resolution of risk in choice tasks RR1, RR2, and RR3. Yellow indicates profiles consistent with a strict preference ordering.

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

	Coefficients	Standard Error	p-value
Early on RR1	2.59	0.49	0.000
Ambiguity Seeking	-1.53	0.77	0.046
LR chi-square test p-value = 0.000			

Table A.6: The results of the logistic regression shown in equation (2) (pseudo $R^2 \approx 0.2310$, $N = 135$).

Ambiguity Attitude			Ambiguity Resolution Preference					
			$E \succ G \succ L$	$E \succ L \succ G$	$G \succ E, L$	$L \succ G \succ E$	$L \succ E \succ G$	not strict
Ambiguity Averse	Risk Resolution Preference	$E \succ G \succ L$	9	3	81	9	3	135
		$E \succ L \succ G$	3	1	27	3	1	45
		$G \succ E, L$	81	27	729	81	27	1215
		$L \succ G \succ E$	9	3	81	9	3	135
		$L \succ E \succ G$	3	1	27	3	1	45
		not strict	135	45	1215	135	45	2025
Ambiguity Neutral		$E \succ G \succ L$	18	6	162	18	6	270
		$E \succ L \succ G$	6	2	54	6	2	90
		$G \succ E, L$	162	54	1458	162	54	2430
		$L \succ G \succ E$	18	6	162	18	6	270
		$L \succ E \succ G$	6	2	54	6	2	90
		not strict	270	90	2430	270	90	4050
Ambiguity Seeking		$E \succ G \succ L$	9	3	81	9	3	135
		$E \succ L \succ G$	3	1	27	3	1	45
		$G \succ E, L$	81	27	729	81	27	1215
		$L \succ G \succ E$	9	3	81	9	3	135
		$L \succ E \succ G$	3	1	27	3	1	45
		not strict	135	45	1215	135	45	2025

Table A.7: Counts of combinations of possible actions for each possible exhibited preference profile.

Ambiguity Attitude			Ambiguity Resolution Preference				
			$E \succ G \succ L$	$E \succ L \succ G$	$E \sim L$	$L \succ G \succ E$	$L \succ E \succ G$
Ambiguity Averse	Risk Resolution Preference	$E \succ G \succ L$	H, HM	H	H		
		$E \succ L \succ G$					
		$E \sim L$	KMM, HM		MEU, H		
		$L \succ G \succ E$	HM		H, HM	H, HM	H
		$L \succ E \succ G$					
Ambiguity Neutral		$E \succ G \succ L$	EZ, H, HM				
		$E \succ L \succ G$					
		$E \sim L$			all		
		$L \succ G \succ E$				EZ, H, HM	
		$L \succ E \succ G$					
Ambiguity Seeking		$E \succ G \succ L$	HM		HM	HM	
		$E \succ L \succ G$					
		$E \sim L$				KMM, HM	
		$L \succ G \succ E$				HM	
		$L \succ E \succ G$					

Table A.8: Prediction on strict risk and ambiguity resolution preferences condition on (strict) ambiguity attitude. Preferences for gradual resolution are considered indifference between early and late.

Panel A: 93 subjects, 75 preference profiles (see Table 14)			
	EZ	H	HM
EZ	-	0/100,000 (0.000)	1/99,999 (0.000)
H	100,000/0 (0.000)	-	43,102/56,898 (0.862)
HM	99,999/1 (0.000)	56,898/43,102 (0.862)	-
Panel B: 135 subjects, 25,600 action profiles (see Table A.7)			
	EZ	H	HM
EZ	-	0/100,000 (0.000)	0/100,000 (0.000)
H	100,000/0 (0.000)	-	16,554/83,446 (0.331)
HM	100,000/0 (0.000)	83,446/16,554 (0.331)	-

Table A.9: Classification of 100,000 bootstraps where row/column model achieved a higher Selten score than column/row model for strict uncertainty resolution preferences using profile preference space (Panel A) and total action space (Panel B). Equivalent two-tailed p-value given in parentheses.

135 subjects, 25,600 action profiles (see Table A.8)						
	DEU	MEU	KMM	EZ	H	HM
DEU	-	64,622/35,378 (0.708)	28/99,972 (0.001)	0/100,000 (0.000)	0/100,000 (0.000)	0/100,000 (0.000)
MEU	35,378/64,622 (0.708)	-	966/99,034 (0.019)	10/99,990 (0.000)	0/100,000 (0.000)	0/100,000 (0.000)
KMM	99,972/28 (0.001)	99,034/966 (0.019)	-	11,196/88,804 (0.224)	2/99,998 (0.000)	0/100,000 (0.000)
EZ	100,000/0 (0.000)	99,990/10 (0.000)	88,804/11,196 (0.224)	-	0/100,000 (0.000)	0/100,000 (0.000)
H	100,000/0 (0.000)	100,000/0 (0.000)	99,998/2 (0.000)	100,000/0 (0.000)	-	505/99,495 (0.010)
HM	100,000/0 (0.000)	100,000/0 (0.000)	100,000/0 (0.000)	100,000/0 (0.000)	99,495/505 (0.010)	-

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