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Preferences for the resolution of risk and ambiguity

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ABSTRACT

Generalized recursive utility models often imply that agents have a preference over the timing of uncertainty resolution. Laboratory elicitations of subjects' preferences generally provide direct evidence in support of this implication, but only in the domain of risk. We provide the first experimental examination of uncertainty resolution with respect to ambiguity, in addition to risk. The modal subject exhibits a preference for both early resolution of risk and ambiguity, but with only a minimal willingness to pay to realize either over late resolution. While preferences in both domains are positively correlated, the strength of that correlation varies based on ambiguity attitudes. Among ten commonly used representative recursive utility models, we identify the models that most efficiently explain observed subject preferences under two alternative assumptions: treating a subject's token willingness to pay as either a true preference or indifference.

1. Introduction

Unlike discounted expected utility theory, many models of generalized recursive utility relax the assumption of a direct linkage between preferences of objective uncertainty and intertemporal substitutability (e.g., Kreps and Porteus, 1978; Chew and Epstein, 1989; Epstein and Zin, 1989; Weil, 1990). These models have consequential implications in empirical macroeconomics and finance literature, explaining several empirical anomalies in applications.[2] In many cases, these models also require that agents have a preference over when uncertainty is to be resolved, independent of instrumental concerns. Ongoing debates concern whether such preferences are plausible, and, if plausible, whether people prefer early or late resolution of uncertainty. Experimental evidence is generally divided, and elicitation of these preferences may be complicated by other factors (see Brown and Kim, 2013; Nielsen, 2020, for surveys).

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

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As conventionally defined, “uncertainty” includes both elements of “risk” and “ambiguity” (Knight, 1921). The objective domain of uncertainty, risk, describes a situation where the result is not known, but the underlying probability could be theoretically or empirically determined; the subjective domain of uncertainty, ambiguity, describes a situation where people do not know the basis for objective probability. Notably, all aforementioned experimental studies that elicit preferences for uncertainty resolution have focused only on risk. However, recent theoretical studies have begun to consider environments with subjective uncertainty exclusively (Strzalecki, 2013; Li, 2020; Marinacci et al., 2026); the models they examine build in strict preferences for ambiguity resolution, but not risk.

This paper provides the first experimental elicitation of preferences for uncertainty resolution in the subjective domain as well as in the objective domain. We elicit separate preferences over ambiguity and risk resolution and examine their interrelation with ambiguity attitude. In particular, we find that a plurality of the subjects (47.4%) prefer early resolution of risk and a majority (63.7%) prefer early resolution of ambiguity. However, most subjects do not display a willingness to pay 5 cents or more for their preferred form of resolution. Beyond the aggregate averages, individual subject profiles are correlated across preferences in non-random ways. While resolution preferences are positively correlated across domains, ambiguity attitude separately affects the likelihood of preferring early resolution of ambiguity.

To best characterize the heterogeneities across these individual subject preference profiles, we investigate ten representative recursive utility models under uncertainty. We include the canonical discounted expected utility model (henceforth the DEU model), the dynamic maxmin expected utility model of Gilboa and Schmeidler (1989) and Epstein and Schneider (2003) (henceforth the MEU model), the dynamic smooth ambiguity model of Klibanoff et al. (2005, 2009) and Seo (2009) (henceforth the KMM model), the dynamic multiplier preference model of Hansen and Sargent (2001) and Strzalecki (2011) (henceforth the DMP model), the dynamic variational preference model of Maccheroni et al. (2006a) (henceforth the DVP model), the generalized recursive utility model of Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990) (henceforth the EZ model), the generalized recursive maxmin expected utility model of Hayashi (2005) (henceforth the H model), the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) (henceforth the HM model), the generalized recursive multiplier preference model (henceforth the RMP model), and the generalized recursive variational preference model (henceforth the RVP model).[3]

Consistent with past precedent and for mathematical tractability (see Section 4.2 for more detail), we analyze the ten models under constant relative risk aversion (CRRA) and constant elasticity of substitution (CES) restrictions. We use EZ as the baseline model; it can only accommodate ambiguity-neutral attitudes and predicts consistent preferences over risk and ambiguity resolution. Four models—the H, HM, RMP, and RVP—can simultaneously accommodate non-indifferent preferences for risk resolution, non-indifferent preferences for ambiguity resolution, and non-neutral ambiguity attitudes. Of the four, the HM model implies that ambiguity attitudes affect the connection between these two preferences, with specific comparative statics that align with our data.

In our penultimate section, we investigate which model under the CRRA-CES restriction fits our observed data best using an objective function that penalizes models for being able to rationalize a broader set of action profiles. A key interpretation is whether we should consider subjects that only display a token willingness to pay for their preferred form of resolution as having strict preferences or being indifferent. Under the former view, which we refer to as the “strong” interpretation, the baseline EZ model fares substantially worse than the H, HM, RMP, and RVP models. The HM model performs best, significantly outperforming all other models over 100,000 bootstrapped samples of our data. Under the latter, “weak” interpretation, the modal subject is indifferent over both forms of resolution but ambiguity averse. Hence, the MEU model and its generalizations (DVP, H, and RVP)—the only models that can rationalize this preference profile—are the four best-performing models, with RVP and H the best overall. Because the DEU model cannot accommodate ambiguity aversion, it performs the worst.

While the specific model we endorse is left open for the reader, a few key findings are robust to either the strong or weak interpretation. First, models that allow for both neutral and averse ambiguity attitudes tend to perform well, as those preferences are exhibited by most of our subjects. Second, models that account for strict preferences in both risk and ambiguity resolution also perform well. Third, permitting divergent preferences in risk and ambiguity resolution among ambiguity-averse agents improves explanatory power, as these profiles were observed in a few subjects. Fourth, no model under the CRRA-CES assumption could accommodate the specific preference profiles for gradual resolution of both risk and ambiguity exhibited by a sizable minority of our subjects.

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

Among the studies that do not provide instrumental information, those where the risk has yet to be determined generally find preferences for late or gradual resolution (Budescu and Fischer, 2001). Those where the risk is determined but yet to be resolved for the subject generally find preferences for early resolution (Eliaz and Schotter, 2010; Ganguly and Tasoff, 2016; Falk and Zimmermann, 2024). Nielsen (2020) is the first to note this relationship and demonstrates this result in a unified, non-instrumental framework.

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

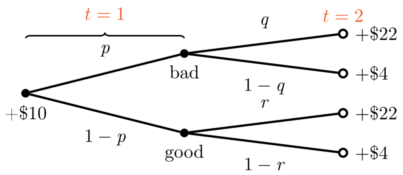

Fig. 1. A general consumption process in risk-resolution preference elicitation.

Table 1
Options used in the risk-resolution preference elicitation.

Options	Information Structure
One-Shot Early (E)	($p = 0.5$, $q = 0$, $r = 1$)
Gradual (Non-Skewed) (G)	($p = 0.5$, $q = 0.25$, $r = 0.75$)
Gradual (Positively-Skewed) (Gp)	($p = 0.8$, $q = 0.4$, $r = 0.9$)
Gradual (Negatively-Skewed) (Gn)	($p = 0.2$, $q = 0.1$, $r = 0.6$)
One-Shot Late (L)	($p = 0.5$, $q = 0.5$, $r = 0.5$)

That is, she finds a preference for early resolution with the pre-determined risk and late or gradual resolution with the isomorphic future-determined risk.

We borrow heavily from Nielsen (2020) in eliciting subjects' preference over risk resolution with non-instrumental information, though we are not explicit about whether the risk is pre-determined or future-determined. Our ambiguity resolution elicitation is a unique design. All choice sets include gradual resolution of information options (non-skewed, positively-skewed, and negatively-skewed) in addition to early and late options.[4]

2. Experimental design and procedures

The experiment consists of two parts: the risk-resolution preference elicitation and the ambiguity-resolution preference elicitation. Each part utilizes four questions to elicit subject preferences on the timing of risk/ambiguity resolution, yielding eight questions in total. 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, we follow the general framework of Nielsen (2020) (see Fig. 1 therein). Subjects participate in a two-period consumption process. At the beginning of $t = 1$, subjects receive an advance payment.[5] At $t = 2$, a lottery is drawn and the additional payoff is realized. Ex-ante, the lottery has a 50/50 chance of a "high" ($22) or "low" ($4) prize. At the end of $t = 1$, subjects receive either a piece of "good" or "bad" news (see Fig. 1) on the underlying probability of the lottery.

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

Subjects complete three choice tasks, selecting their most preferred information structure from a set of multiple options listed in Table 1.[7] The **One-Shot Early** (E) option resolves all risk in the first stage. In contrast, the **One-Shot Late** (L) option resolves all risk in the second stage. The three other options gradually resolve risk. In the **Gradual (Non-Skewed)** (G) option, good news and bad news are equally likely to arrive. In the **Gradual (Positively-Skewed)** (Gp) option, subjects are more likely to receive bad news ($p = 0.8$). However, the good news is highly informative; upon receiving it, the conditional probability of winning the high prize is

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

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

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

[7] By focusing on five options, we depart from past precedent in the literature and fall into what we hope is a "sweet spot" between two extremes. At one end, Nielsen (2020) allows subjects to select resolution anywhere on the continuum between early and late. While this allows a much finer elicitation of gradual preferences, we instead discretize choice and provide three gradual risk-resolution options to allow for easier subject comprehension. At the other end, Masatlioglu et al. (2023) examine preferences over positively- and negatively-skewed gradual information structures by focusing solely on binary choices. While that method may eliminate concerns about violations of independence of irrelevant alternatives (IIA) (e.g., the "decoy" effect, see Huber et al., 1982), our approach allows subjects to express their most preferred information structure among a broader set of options, allowing us to test theoretical predictions more rigorously. For example, when a subject has a strict preference for early resolution of risk, she must prefer the early resolution option to all other information structures (i.e., both gradual and late), making our conclusions more robust.

Table 2
Options used in ambiguity-resolution preference elicitation.

Options	Information Structure
One-Shot Early (E)	{{0.1}, {0.4}, {0.6}, {0.9}}
Gradual (Non-Skewed) (G)	{{0.1, 0.4}, {0.6, 0.9}}
Gradual (Positively-Skewed) (Gp)	{{0.1, 0.4, 0.6}, {0.9}}
Gradual (Negatively-Skewed) (Gn)	{{0.1}, {0.4, 0.6, 0.9}}
One-Shot Late (L)	{{0.1, 0.4, 0.6, 0.9}}

0.9 ($r = 0.9$). In the **Gradual (Negatively-Skewed)** (Gn) option, there is a higher likelihood of receiving good news ($p = 0.2$), but the informativeness of this good news is lower ($r = 0.6$) compared to the Gradual (Positively-Skewed) option. None of the gradual options is ex-ante more informative than the others according to the Blackwell criterion.[8]

There is a 30-min 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-min time delay is considered a minimum, but appropriate, time delay in existing studies for determining preferences over resolution of uncertainty (Nielsen, 2020; Masatlioglu et al., 2023). To minimize the chances of an instrumental information issue (where subjects adjust their future consumption due to any early information), subjects completed Raven's Progressive Matrices.[9]

2.2. Ambiguity-resolution preference elicitation

The ambiguity-resolution preference elicitation is similar to the risk-resolution preference elicitation. Subjects are involved in a two-period consumption process. At the beginning of $t = 1$, subjects receive an advance payment. In $t = 2$, a lottery is drawn and the payoff is realized. Subjects could earn a "high" ($22) or "low" prize ($4) from this lottery. However, 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 **p**, can only be one of the following numbers: 10%, 40%, 60%, and 90%. So the probability for you to win the high prize is one of the following four numbers: 0.1, 0.4, 0.6, or 0.9.

As the proportion of each color is unknown, the probability of drawing each color is unknown at the beginning of $t = 1$. It is not necessarily the case that 0.1, 0.4, 0.6, and 0.9 are drawn uniformly at random.[11] At the end of $t = 1$, subjects receive a piece of news about the value of $\mathbf{p}$. We view a partition of $\{0.1, 0.4, 0.6, 0.9\}$ as an information structure. Depending on the information structure, this news provides no, partial, or complete information about the winning probability. In three choice tasks, subjects choose their most preferred option from a set of information structures listed in Table 2.

The **One-Shot Early** (E) option resolves all ambiguity at $t = 1$. If a subject chooses One-Shot Early, she will be informed of the exact winning chance $\mathbf{p}$ at the end of $t = 1$. **One-Shot Late** (L) resolves no ambiguity until $t = 2$. Only a message that the value of $\mathbf{p}$ is 0.1, 0.4, 0.6, or 0.9 is given at $t = 1$, conveying no new information to the subject. The three gradual ambiguity-resolution information structures are partially revealing. **Gradual (Non-Skewed)** (G) either reveals {0.1, 0.4} or {0.6, 0.9} at $t = 1$ with unknown probabilities. Ambiguity exists in both periods but is resolved gradually. **Gradual (Positively-Skewed)** (Gp) option either reveals {0.9} or {0.1, 0.4, 0.6}: ambiguity is fully resolved when the message is good news, but still exists in the other case. Similarly, the **Gradual (Negatively-Skewed)** (Gn) option either reveals {0.1} or $\{0.4, 0.6, 0.9\}$. Hence, ambiguity is fully resolved when the message is bad news, but still exists in the other case.

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

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

[9] The Raven test is one of the most widely used methods to measure abstract reasoning and analytic intelligence. In our study, the main purpose of this test is to make subjects stay focused during the time delay.

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

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

Table 3
Choice sets used in the experiment.

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

2.3. Choice sets

Each elicitation utilizes three choice tasks and a set of multiple price list questions to determine subjects' preferences. The choice tasks involve subjects picking their most preferred option from subsets of the five options in Table 1 or 2. The first question (RR1/AR1) is an unrestricted choice from the set. The second question (RR2/AR2) removes the One-Shot Early option. The third question (RR3/AR3) removes the One-Shot Late option. The last set of questions (MPLRR/MPLAR) measures the strength of preference for early vs. late resolution by using a multiple price list. Each row presents a mini question that asks the subject to choose from two options "One-Shot Early + \$$x$" and "One-Shot Late + \$$y$." The values of x and y vary among different rows where one term is 0 and the other is a 0.05 increment between 0.00 and 0.50 (see Fig. H.1). Table 3 summarizes these procedures.

For each elicitation task, subjects receive news or messages based on their choices of information structures after completing all four sections. They then experience the Raven's Progressive Matrices test for the next 30 min, after which the outcome is revealed. Fig. 2 illustrates an example of the timeline of the entire session.[12] The ordering of the questions in the two elicitation tasks was partially randomized in four different ways for robustness. Our data do not appear to exhibit any ordering effects from these randomizations (see Online Appendix F for more detail).

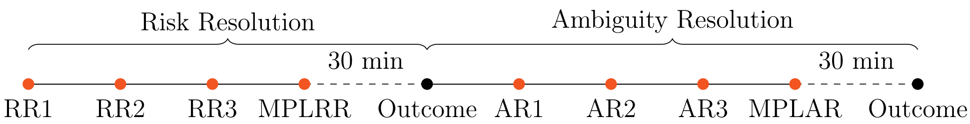

Fig. 2. The timeline of the session (Order 1).

2.4. Ambiguity attitude elicitation

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

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

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

2.5. Experimental procedures

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

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 48 $((1+1+1+21)\times 2)$ (see Table 3)[13].

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[12] The timelines for all four randomization orders are provided in Fig. F.1.

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

Table 4
Revealed preferences for risk resolution in choice tasks RR1, RR2, and RR3. All three forms of gradual resolution of risk are pooled (See Table D.1 for unpooled results). Boldface indicates profiles consistent with a strict preference ordering.

		RR3 choice (One-Shot Late removed)		
RR1 choice (unrestricted)	RR2 choice (One-Shot Early removed)	One-Shot Early	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

In addition, subjects have another chance to receive an additional \$10 from the bonus ambiguity attitude elicitation task.[14] The average payment for each participant was \$23.33 including a \$10 participation payment.[15]

3. Results

3.1. Revealed preferences for risk and ambiguity resolution

Table 4 shows the summary of the choices of risk resolution on the three tasks RR1, RR2, and RR3. The modal response of subjects over the unrestricted choice set (RR1) is the preference for early resolution of risk (64 of 135, 47.4%). A similar but smaller portion of subjects indicate a preference for gradual resolution (57, 42.2%).[16] A small remainder prefer late resolution (14, 10.4%). A chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.01$).

Table 5 summarizes the choices of ambiguity resolution on tasks AR1, AR2, and AR3. The modal response of subjects over the unrestricted choice set (AR1) is the preference for early resolution of ambiguity (86 of 135, 63.7%). A smaller portion of subjects indicate a preference for gradual resolution (42, 31.1%).[17] Very few subjects prefer late resolution of ambiguity (7, 5.2%). As before, a chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.01$).

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

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

[14] As shown in Fig. 2, subjects learn the outcome of each uncertainty-resolution elicitation task at its conclusion. The final screen summarizes the outcomes of both resolution tasks, as well as the bonus task. Subjects are then informed which resolution task outcome is selected for payment and whether the bonus task is also paid.

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

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

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

Table 5
Revealed preferences for ambiguity resolution in choice tasks AR1, AR2, and AR3. All three forms of gradual resolution of ambiguity are pooled (See Table D.2 for unpooled). Boldface 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 (all forms)	Total
One-Shot Early	Gradual (all forms)	**60**	8	68
	One-Shot Late	**17**	1	18
	Total	**77**	9	86
Gradual (all forms)	Gradual (all forms)	10	**27**	37
	One-Shot Late	1	4	5
	Total	11	31	42
One-Shot Late	Gradual (all forms)	0	2	2
	One-Shot Late	**1**	**4**	**5**
	Total	1	6	7

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

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

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

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

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

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

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

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

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

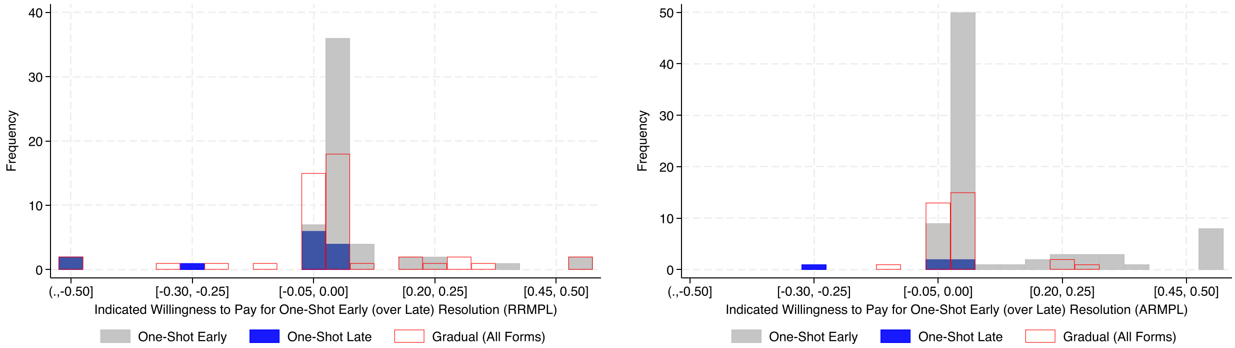

Fig. 3. Histogram of implied willingness to pay for early vs. late resolution determined from switching point in MPLRR elicitation (a, left), MPLAR elicitation (b, right). Subjects are separated by unrestricted choice set decision in RR1 (a, single-crossing subjects only, $N = 114$), AR1 (b, single-crossing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

Table 6
Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1). The three gradual choices are pooled. See Table D.3 for unpooled table.

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

MPLAR, 25 (resp. 2) subjects indicate a *strictly positive* (resp. *negative*) willingness to pay; 22 (resp. 1) chose One-Shot Early (resp. Late) and 3 (resp. 1) chose a gradual option on AR1 ($p < 0.05$, Fisher's exact test using a 3×3 contingency table).

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

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

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

3.2. Correlations of preferences for resolution and ambiguity attitudes

Table 6 provides counts of subjects based on their joint preferences for risk and ambiguity resolution determined by the unrestricted choice on the RR1 and AR1 elicitation tasks. Unsurprisingly, the modal preference profile (57 of 135 subjects, 42.2%) is early resolution for both risk and ambiguity resolution. However, if preferences for ambiguity and risk resolution were independent, we would only expect about 41 subjects (about 30%) to have this preference (135 subjects $\times \frac{64}{135} \times \frac{86}{135} \approx 41$ subjects). Indeed, a Fisher's exact test rejects the null hypothesis that these joint classifications are due to a random distribution ($p < 0.01$). Further, the preference

Table 7
Choices of risk resolution and ambiguity resolution from unrestricted choice tasks (AR1 and RR1 tasks) separated by revealed ambiguity attitudes on the Ellsberg task.

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

Table 8
Logistic regression of choosing one shot early in AR1 on choosing one shot early in RR1 and eliciited ambiguity attitude. Reported values are average marginal effects in probability points ($N = 135$). See Online Appendix E for full details.

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

for early resolution of ambiguity and early resolution of risk are positively correlated (the correlation coefficient is approximately 0.5, $p < 0.01$).

We also investigate the marginal effect of ambiguity attitude on ambiguity resolution. Table 7 characterizes subjects by their elicited risk resolution and ambiguity resolution preferences from unrestricted choice tasks (RR1/AR1) separated by ambiguity attitude. Ambiguity attitude is determined based on subject responses to Ellsberg's questions (see Section 2.4): 63 (46.7%) were classified as ambiguity averse, 60 (44.4%) were ambiguity neutral, and 12 (8.9%) were ambiguity seeking. A chi-square test rejects the null hypothesis of responses being randomly distributed ($p < 0.01$).

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

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

4. Theory

Consistent with previous literature, our results so far suggest a large portion of subjects have (i) non-neutral attitudes over ambiguity (generally aversion) and a (ii) preference over the resolution of risk (generally early resolution). Additionally, our new findings indicate that subjects have a (iii) preference over the resolution of ambiguity (generally early), (iv) the preferences over risk and ambiguity resolution are most often correlated. Finally, (v) ambiguity attitude appears to affect the strength of this correlation. In this section, we investigate how well the implications of ten representative recursive utility models—DEU, MEU, KMM, DMP, DVP, EZ, H, HM, RMP, and RVP—briefly introduced in Section 1 can explain these findings.

The existence of strict risk- or ambiguity-resolution preferences or non-neutral ambiguity attitudes can "falsify" some models as not all models can accommodate these preferences. (Alternatively, one may consider it inappropriate to "test" a model for preferences it

22 The full specifications and results of the regression are available in Online Appendix E.

Table 9
Models accommodating non-indifferent resolution preferences and non-neutral ambiguity attitudes.

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

cannot accommodate.) In Table 9, a checkmark shows that the theoretical model can incorporate non-indifferent preference regarding the timing of risk resolution, non-indifferent preference regarding the timing of ambiguity resolution, or non-neutral ambiguity attitude under some parameter values. Technical arguments are provided in Appendix A.

The first column means that the EZ, H, HM, RMP, and RVP models can accommodate non-indifference to the timing of risk resolution under some parameter values. The second column implies all nine models except the DEU model support non-indifference to the timing of ambiguity resolution under some parameter values.[23] The last column shows that all eight models except the DEU and EZ models can be used to explain non-neutral ambiguity attitudes. Hence, among these models, only the H, HM, RMP, and RVP models can simultaneously accommodate non-indifferent preferences regarding the timing of risk resolution and ambiguity resolution, as well as non-neutral ambiguity attitudes.

We formalize the theoretical framework of risk and ambiguity resolution in Section 4.1, introduce the ten models in Section 4.2, and investigate their theoretical predictions under the constant relative risk aversion (CRRA) and constant elasticity of substitution (CES) restrictions more thoroughly in Section 4.3. As detailed in Section 4.2, we impose the CRRA-CES restriction for tractability purposes. This process will culminate in Section 4.4 where we determine which of these models under the CRRA-CES restriction most efficiently and parsimoniously capture the distribution of individual preferences found for subjects in our experiment.

4.1. Risk and ambiguity resolution

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

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

In our risk-resolution experiment, a DM is ex-ante informed of f and an objective distribution $\tilde{p} \in \Delta^f(S_1 \times \Delta(S_2))(\tilde{q})$ where $\tilde{q} \in \Delta(S_2)$ has full support. Her interim information informs her of one $\hat{q} \in f(S_1)$ (equivalently, an element Q^k in $\overline{\mathcal{Q}}^f$, or S_1^k in $\overline{\mathcal{S}}_1^f$). The information structure in a risk-resolution experiment can thus be summarized as a triplet $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$. It resolves risk early if each distribution in $f(S_1)$ degenerates to one state in S_2, and thus, the interim information allows the DM to know for sure the outcome that will be realized. It resolves risk late if $f(S_1) = \{\tilde{q}\}$, where no interim information leads to an updated period-2 distribution. If $[f, \tilde{p}, \overline{\mathcal{S}}_1^f]$ neither resolves risk early nor late, then it resolves risk gradually.[24]

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

[24] In Fig. 1 and Table 1, we have $S_1 = \{\text{good}, \text{bad}\}$, $S_2 = \{\text{high prize}, \text{low prize}\}$, and $\overline{\mathcal{S}}_1^f = \{\{\text{good}\}, \{\text{bad}\}\}$. The function f is defined as $f(\text{good}) = (r, 1-r)$, $f(\text{bad}) = (q, 1-q)$. The mean distribution is $\tilde{q} = (0.5, 0.5)$. The joint distribution $\tilde{p} \in \Delta^f(S_1 \times \Delta(S_2))(\tilde{q})$ is given by $\tilde{p}(\text{good}, (r, 1-r)) = 1 - p$

Table 10
A summary of recursive utility models under uncertainty.

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

In our ambiguity-resolution experiment, a DM is not ex-ante informed of any objective $\tilde{p} \in \Delta^f(S_1, \Delta(S_2))$. Since f is publicly known, she knows how each period-1 state corresponds to a period-2 distribution, and that the set of possible period-2 distributions is $f(S_1)$. A DM's interim information is an element of S_1^f, or equivalently, an element of Q^f. We summarize the information structure in an ambiguity-resolution experiment by $[f, S_1^f]$, and say it resolves ambiguity early if $S_1^f = \overline{S}_1^f$, late if $S_1^f = \underline{S}_1^f$, and gradually otherwise.[25]

4.2. Models

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

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

We impose the restriction of CRRA utility functions u and v and CES time aggregator W mainly because they are highly tractable and widely used in applied work. For example, Epstein and Zin (1989) impose the CRRA-CES restriction to study risk-resolution preferences. Under this restriction, clean and sharp predictions that give rise to various risk-resolution preferences can be obtained—a DM prefers early resolution of risk (resp. is indifferent to the timing of risk resolution, or prefers late resolution of risk) if $\alpha < \rho$ (resp. $\alpha = \rho$, or $\alpha > \rho$).[26] This elegant benchmark on risk-resolution preferences provides a strong foundation for studying ambiguity-resolution preferences. Without the CRRA-CES restriction, even the analysis of risk-resolution preferences becomes much more complicated. For instance, Online Appendix B provides an example beyond the CRRA-CES restriction, where the DM may exhibit a preference for gradual risk resolution under the EZ model. Extending the analysis without the CRRA-CES restriction to ambiguity-resolution preferences becomes even less tractable, although richer preference profiles may be accommodated.

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

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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, $f(S_1) = \{(0.75, 0.25), (0.25, 0.75)\}$. The corresponding early and late risk-resolution information structures are illustrated in Fig. C.1.

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

[26] For completeness, the current paper presents and proves this result in Proposition 1. Specifically, the strict convexity (resp. linearity, or strict concavity) of $u(W(h_1, u^{-1}(x)))$ in x is first shown to imply the preference for early resolution of risk (resp. indifference to the timing of risk resolution, or the preference for late resolution of risk) in the EZ, H, HM, RMP, and RVP models for all consumption processes. Then, under the CRRA-CES restriction, it is shown that $u(W(h_1, u^{-1}(x))) = \frac{1}{\alpha}[h_1^\rho + \beta(\alpha x)^{\frac{\rho}{\alpha}}]^{\frac{\alpha}{\rho}}$ is strictly convex (resp. linear, or strictly concave) in x if $\alpha < \rho$ (resp. $\alpha = \rho$, or $\alpha > \rho$). Without the CRRA-CES restriction, $u(W(h_1, u^{-1}(x)))$ may be neither convex, concave, nor linear. For example, when $u(x) = -e^{-x}$ and W is of the CES form with $\rho = -0.4$, $\beta = 0.9$, and $h_1 = 10$, the function $u(W(h_1, u^{-1}(x)))$ with $x \in (-1, 0)$ is neither convex, concave, nor linear.

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

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

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

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

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

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

Two subcategories in the H model (and the MEU model) are worth mentioning, as they have different yet sharp implications for the ambiguity-resolution experiment. We call the subcategory with $\Pi = \Delta(f(S_1))$ the **Wald-type Hayashi** ((w)H) model. In the (w)H model, not every $\pi \in \Pi$ is fully supported on $f(S_1)$. In fact, a $\pi \in \Pi$ attaining the minimum operator can impose the full weight on one distribution.[27] When every $\pi \in \Pi$ is fully supported on $f(S_1)$ instead, the model belongs to the **interior Hayashi** ((i)H) model subcategory.[28] As is shown in Proposition 2, the lack of full support under the (w)H model results in a different prediction from that under the (i)H model in the ambiguity-resolution experiment. Even if a DM follows the H model to assess her payoff, researchers do not observe what her Π looks like, and thus, do not know if she follows the (w)H model or the (i)H model. Because of this, researchers should consider both subcategories. Similarly, the corresponding subcategories of the MEU model are called the (w)MEU model and the (i)MEU model.

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

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

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

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

$$I_2(h|Q^k) = u^{-1}\Big(\min_{\pi\in\Delta(f(S_1))}\{\sum_{\hat{q}\in Q^k}\sum_{s_2\in S_2} u\big(h_2(s_2)\big)\hat{q}(s_2)\pi(\hat{q}|Q^k) + \theta\sum_{\hat{q}\in Q^k}\pi(\hat{q}|Q^k)\ln\frac{\pi(\hat{q}|Q^k)}{\pi'(\hat{q}|Q^k)}\}\Big),$$
$$I_1(h|Q^k) = W\big(h_1, I_2(h|Q^k)\big),$$

[27] For example, in our ambiguity-resolution experiment, $f(S_1) = \{(0.1, 0.9), (0.4, 0.6), (0.6, 0.4), (0.9, 0.1)\}$. The (w)H subcategory corresponds to the case where the DM believes that the probability of winning the high prize can be any number between 0.1 and 0.9 and makes the decision as if the probability is 0.1, i.e., imposes the full weight on the distribution $(0.1, 0.9)$ and zero weight on $(0.4, 0.6)$, $(0.6, 0.4)$, and $(0.9, 0.1)$.

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

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

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

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

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

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

where $c_{Q^k}(\pi(\cdot|Q^k)) = \min_{\hat{\pi}\in\Delta(f(S_1))\text{s.t.}\hat{\pi}(\cdot|Q^k)=\pi(\cdot|Q^k)}\frac{c(\hat{\pi})}{\hat{\pi}(Q^k)}$ (Li, 2023). The case with $\alpha=\rho$ reduces to the DVP model of Maccheroni et al. (2006b). By Maccheroni et al. (2006a), the RVP (resp. DVP) model also nests the H and RMP (resp. MEU and DMP) models.

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

4.3. Summary of predictions

We consider three ambiguity attitudes—ambiguity aversion, ambiguity neutrality, and ambiguity seeking—and five strict risk-/ambiguity-resolution preferences that can be identified by our individual-level data: a monotone preference for early resolution (denoted by $E \succ G \succ L$), a preference for early and one-shot resolution ($E \succ L \succ G$), a preference for gradual resolution ($G \succ E, L$), a monotone preference for late resolution ($L \succ G \succ E$), and a preference for late and one-shot resolution ($L \succ E \succ G$).[29] Assuming each revealed preference provided by a subject indicates a strict preference, there are 75 possible preference profiles a subject might reveal in our experiment. When we include the possibility of total indifference in the risk-/ambiguity-resolution experiment, denoted by $E \sim G \sim L$, there are six risk-/ambiguity-resolution preferences and 108 possible preference profiles.

Among the ten models, all but the DEU and EZ models can accommodate ambiguity aversion, but only the KMM and HM models can accommodate ambiguity seeking. The EZ, H, HM, RMP, and RVP models can account for non-indifferent preferences regarding the timing of risk resolution. In particular, under the CRRA-CES restriction, when $\alpha<\rho$ (resp. $\alpha>\rho$, or $\alpha=\rho$) in these five models, the DM exhibits a monotone preference for early risk resolution (resp. a monotone preference for late risk resolution, or an indifferent preference regarding the timing of risk resolution).[30] The other five models degenerate to the DEU model in the risk-resolution experiment and predict indifference in outcomes.

Our empirical focus is on how well each of these models can accommodate preference profiles found in our data. We first examine whether a given model can theoretically rationalize a preference profile for the consumption process and information structures adopted in our experiment, i.e., locally. If there exists a specification of parameters α, η, ρ, β, θ, multiple-belief set Π, second-order belief μ, reference belief π', or cost function c under which a model can accommodate the corresponding preference profile, then we say the model rationalizes this preference profile. We present the (local) theoretical results under the CRRA-CES restriction below and leave the analysis to Appendix A.

- The MEU, KMM, DMP, and DVP (resp. H, HM, RMP, and RVP) models reduce to the DEU (resp. EZ) model for an ambiguity-neutral DM, in which case the DM exhibits total indifference to the timing of ambiguity resolution (resp. the DM's ambiguity-resolution preference is inherited from her risk-resolution preference).
- In the MEU model, an ambiguity-averse DM may exhibit total indifference to the timing of ambiguity resolution or be indifferent between early and late but prefer one-shot ambiguity resolution.
- In the KMM model, an ambiguity-averse (resp. -seeking) DM prefers early (resp. late) resolution of ambiguity monotonically.[31]
- In the DMP model, an ambiguity-averse DM prefers early resolution of ambiguity monotonically.
- In the DVP model, among the six ambiguity-resolution preferences (including indifference), an ambiguity-averse DM can have any of the four that at least weakly prefer early to late.
- In the H model, an ambiguity-averse DM with a monotone preference for early (resp. late) risk resolution can have a monotone preference for early (resp. late) ambiguity resolution, a preference for early (resp. late) and one-shot ambiguity resolution, or be indifferent to the timing of ambiguity resolution.
- In the HM model, an ambiguity-averse (resp. -seeking) DM with a monotone preference for early (resp. late) risk resolution must prefer early (resp. late) resolution of ambiguity monotonically, and an ambiguity-averse (resp. -seeking) DM preferring late (resp.

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

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

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

Table 11
Counts of subject preference orderings ($N = 135$) where the top choice is taken from the unrestricted set (RR1/AR1) and the second choice from the corresponding restricted set (RR2/AR2 if E is top, RR3/AR3 if L is top). The first classification assumes the expressed preferences are strict; a second classification (in parenthesis) treats zero willingness to pay on either MPL as indifference over the corresponding option. Preferences are inferred from the number of early choices on MPLs (fewer than $10 \to L \succ E$; 10–11$\to$ $E \sim L$; more than $11 \to E \succ L$, respectively). Models listed in each cell can rationalize the corresponding profile. Table H.5 reports the same analysis restricted to the 80 subjects who satisfy a strict preference ordering across all three choice tasks in each resolution experiment and single crossing on both MPLs.

		Ambiguity-Resolution Preference					
Ambiguity Attitude	Risk Resolution Preference	$E \succ G \succ L$	$E \succ L \succ G$	$G \succ E, L$	$L \succ G \succ E$	$L \succ E \succ G$	$E \sim L \sim G$
Ambiguity Averse	$E \succ G \succ L$	20 (2) H, HM, RMP, RVP	2 (0) H, RMP, RVP	1 (0) RMP, RVP	0 (0) RMP, RVP	0 (0) RMP, RVP	– (2) H, RVP
	$E \succ L \succ G$	3 (0)	3 (0)	1 (0)	0 (0)	0 (0)	– (1)
	$G \succ E, L$	9 (2)	3 (0)	11 (2)	1 (0)	0 (0)	– (4)
	$L \succ G \succ E$	3 (1) HM, RMP, RVP	0 (0) RMP, RVP	2 (0) RVP	2 (0) H, HM, RMP, RVP	0 (0) H, RMP, RVP	– (1) H, HM, RVP
	$L \succ E \succ G$	1 (0)	0 (0)	0 (0)	1 (0)	0 (0)	– (0)
	$E \sim L \sim G$	– (5) KMM, DMP, DVP, HM, RMP, RVP	– (0) DVP, RVP	– (0) DVP, RVP	– (1)	– (0)	– (42) MEU, DVP, H, RVP
Ambiguity Neutral	$E \succ G \succ L$	13 (4) EZ, H, HM, RMP, RVP	3 (0)	3 (0)	0 (0)	0 (0)	– (2)
	$E \succ L \succ G$	2 (1)	6 (2)	1 (0)	0 (0)	0 (0)	– (0)
	$G \succ E, L$	9 (2)	1 (0)	16 (2)	1 (0)	1 (0)	– (4)
	$L \succ G \succ E$	3 (0)	0 (0)	1 (0)	0 (0) EZ, H, HM, RMP, RVP	0 (0)	– (1)
	$L \succ E \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	– (0)
	$E \sim L \sim G$	– (2)	– (1)	– (2)	– (0)	– (0)	– (37) all
Ambiguity Seeking	$E \succ G \succ L$	5 (1) HM	0 (0)	0 (0)	1 (0) HM	0 (0)	– (0) HM
	$E \succ L \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	– (0)
	$G \succ E, L$	0 (0)	0 (0)	5 (0)	0 (0)	0 (0)	– (1)
	$L \succ G \succ E$	0 (0)	0 (0)	1 (0)	0 (0) HM	0 (0)	– (1)
	$L \succ E \succ G$	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	– (0)
	$E \sim L \sim G$	– (0)	– (0)	– (0)	– (1) KMM, HM	– (0)	– (8)

early) resolution of risk may prefer early resolution of ambiguity monotonically, late resolution of ambiguity monotonically, or be indifferent to the timing of ambiguity resolution.[32]

- In the RMP model, an ambiguity-averse DM with a monotone preference for early risk resolution can have any of the five strict ambiguity-resolution preferences. In this model, an ambiguity-averse DM with a monotone preference for late risk resolution can have any of the strict ambiguity-resolution preferences except the one for gradual ambiguity resolution.
- In the RVP model, an ambiguity-averse DM with a monotone preference for early or late risk resolution can have any of the six ambiguity-resolution preferences (including indifference).

Table 11 summarizes the previous analysis; it shows which models can rationalize the corresponding preference profile for the consumption processes and information structures used in our experiments. While we only require predictions to hold at this local level, certain models can rationalize a preference profile over all consumption processes and information structures, that is, globally. For the other models that cannot rationalize a profile globally, the predictions necessarily require different preferences to be displayed elsewhere.[33] Therefore, we caution that these predictions must be reconsidered when evaluating data over multiple consumption processes and information structures; in such cases, the distinction between global and local predictions becomes more meaningful. Since our experiment involves only a single consumption process and a small set of information structures over a single state space $S_1 \times S_2$, this distinction matters less in the interpretation of our results, which we present next.

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

[33] For example, there exist parameters α, η, ρ, and β in the HM model such that the model can rationalize the corresponding preference profiles globally; in contrast, the RVP model can rationalize the preference profiles in Table 11 for the specific consumption process and information structures in the experiment, but necessarily requires different preferences to be displayed elsewhere.

4.4. Empirical evaluation

Table 11 also characterizes the preference profiles exhibited by individual subjects in our experiments. These data, along with the theoretical predictions summarized in the table, help us evaluate the performance of different theoretical models under the CRRA-CES restriction.

We categorize all 135 subjects to make the best use of our data. We "approximate" a strict preference ordering for each subject to include subjects who do not exhibit a consistent strict preference ordering in resolution tasks RR1–RR3 and AR1–AR3. We take the option selected from the unrestricted set (RR1/AR1) as a subject's most preferred resolution option. Then we examine the corresponding choice set where that most preferred option is removed (RR2/AR2 if E is top, RR3/AR3 if L is top) to determine a subject's second most preferred option. Note that under this approximation, we do not concern ourselves with whether a subject follows a consistent strict preference ordering over all three choice tasks in each resolution experiment, that is, by selecting the most preferred option again in the other restricted set (42 of 135 subjects, or 31.1%, do not).

The first number in each cell of Table 11 provides subject counts classifying the 135 subjects over the 75 profiles. A quick look indicates that subjects do not have preference profiles that are uniformly distributed. Early, monotone preferences for both risk and ambiguity resolution combined with ambiguity aversion ($n = 20$) and ambiguity neutrality ($n = 13$) attitudes are two of the four most commonly found profiles. The other two profiles involve gradual resolution in both domains combined with ambiguity aversion ($n = 11$) and ambiguity neutrality ($n = 16$). Together these four profiles account for almost half of the subjects in the table (60 of 135, 44.4%).

Of course, the preceding analysis has ignored the MPLRR and MPLAR elicitation tasks. While almost all subjects exhibited preferences on the MPLs that were consistent with their responses on the choice tasks, the modal subject response on both MPLRR and MPLAR was an unwillingness to pay any amount of money for one's preferred form of resolution, even at increments as low as 5 cents (see Section 3.1). It may be too strong an interpretation of our results to think of each one of these subjects as having strict preferences for their indicated form of uncertainty resolution.[34] A weaker interpretation is that subjects who are unwilling to pay for their previously-chosen form of resolution are actually indifferent; their selections on the RR1–RR3 and AR1–AR3 tasks simply reflect the fact that they cannot express this indifference. We also classify all subjects in this manner. To do so, we must accommodate the 24 (17.8%) subjects that fail single crossing in at least one of the MPLRR and MPLAR tasks. We characterize these subjects by approximating their willingness to pay by the number of early choices they select: fewer than 10 indicates a positive willingness to pay for late (over early) resolution; 10 or 11 indicates indifference, and more than 11 indicates a positive willingness to pay for early (over late) resolution. Note this rule also accurately characterizes subjects who exhibit a single switch point.[35]

Table 11 also gives a categorization of subjects under this "weak" interpretation, shown in parentheses. Results are quite different. The modal subject ($n = 42$) is indifferent over the resolution of risk and ambiguity but is ambiguity averse. The second most commonly found profile ($n = 37$) is indifferent over risk and ambiguity resolution and also ambiguity neutral, the only profile that can be rationalized by the standard DEU model (and all models). Eight other subjects indicate ambiguity seeking and indifference over risk and ambiguity resolution, a profile that cannot be rationalized by any model. Under this weak interpretation, a majority of subjects (87 of 135, 64.4%) are classified as being indifferent to the timing of risk and ambiguity resolution.

As Table 11 shows, certain models can accommodate more preference profiles than others. For instance, under the weak interpretation, the DEU model only accommodates one preference profile, but the RVP model rationalizes 19 profiles. Moreover, the portion of action space that is rationalizable for a model varies in non-trivial ways.[36]

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

Roughly ten percent of subjects can be classified as falling in the two cells predicted by the EZ model, yielding a Selten score of 0.089. The H, HM, RMP, and RVP models do better. While these models make predictions over a greater percentage of the action space, they can also rationalize more subjects' behavior. The corresponding Selten scores are close together (0.262–0.308). The gain in performance over the EZ model is largely due to the inclusion of the modal profile, that is, early monotone preferences for both risk and ambiguity resolution combined with ambiguity aversion.

To examine how sensitive the Selten scores are to the distribution of subjects, we calculate confidence intervals on the scores using 100,000 bootstrapped draws with replacement from our 135-subject population. The corresponding confidence intervals indicate

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

[35] Online Appendix Tables H.5 and H.6 provide analogues to Tables 11 and 12 restricted to only the 80 subjects who satisfy a strict preference ordering across all three choice tasks in each resolution experiment and single crossing on both MPLs. The results are qualitatively similar. For full bootstrap results, see Tables H.7 and H.8.

[36] Tables H.1 and H.2 provide a breakdown of the combinatorics of the action space assuming that subjects satisfy a strict preference ordering across all three choice tasks in each resolution experiment and single crossing on both MPLs.

Table 12
Calculation of Selten scores for strict uncertainty-resolution preferences, the "strong" interpretation of our results (Panel A), and where unwillingness to pay a positive amount on the MPLRR and MPLAR tasks is viewed as indifference, the "weak" interpretation (Panel B). Preference orderings are determined where the top choice is taken from the unrestricted set (RR1/AR1) and the second choice from the corresponding restricted set (RR2/AR2 if E is top, RR3/AR3 if L is top). Willingness to pay is inferred from the number of early choices on MPLs (fewer than $10 \to L \succ E$; 10–11$\to E \sim L$; more than $11 \to E \succ L$, respectively). 95% confidence intervals taken from 100,000 bootstraps of subject sample. Table H.6 provides similar analysis restricted to only the 80 subjects who satisfy a strict preference ordering across all three choice tasks in each resolution experiment and single crossing on both MPLs.

model	proportion of subjects categorized	proportion of action profile space covered	Selten score	(95% CI)
Panel A: strong interpretation (135 subjects, 4900 action profiles)				
EZ	0.096	0.007	0.089	(0.045, 0.141)
H	0.274	0.012	0.262	(0.188, 0.336)
HM	0.326	0.018	0.308	(0.233, 0.389)
RMP	0.304	0.034	0.270	(0.196, 0.352)
RVP	0.319	0.050	0.268	(0.194, 0.350)
Panel B: weak interpretation (135 subjects, 2,433,600 action profiles)				
DEU	0.274	0.021	0.253	(0.179, 0.327)
MEU	0.585	0.032	0.554	(0.472, 0.635)
KMM	0.319	0.025	0.294	(0.219, 0.375)
DMP	0.311	0.023	0.288	(0.214, 0.370)
DVP	0.622	0.070	0.553	(0.471, 0.634)
EZ	0.304	0.023	0.281	(0.207, 0.363)
H	0.652	0.038	0.614	(0.532, 0.695)
HM	0.385	0.033	0.353	(0.271, 0.434)
RMP	0.363	0.033	0.330	(0.248, 0.411)
RVP	0.696	0.090	0.606	(0.524, 0.680)

scores may vary up or down by 5–10 percentage points. However, these confidence intervals cannot provide an indication of how correlated the scores of the five models are with each bootstrap. Should a bootstrap produce an exceptionally high Selten score for the EZ model, it likely does the same for the other four models, as the only two profiles the EZ model can rationalize are covered by the other models as well. In fact, in none of the 100,000 bootstraps does the EZ model outscore the H, HM, RMP or RVP model, a trivial case of statistical significance ($p = 0.000$, in each of the 4 comparisons, see Table H.3). The HM model, which achieves the highest score overall at 0.308, also significantly outperforms the other models over the 100,000 bootstraps ($p < 0.100$, all 4 comparisons). Interestingly, it gains on the other models by accommodating profiles that include ambiguity seeking attitudes, which the other models do not accommodate. The other three models, H, RMP, and RVP do not significantly differ in performance ($0.468 < p < 0.882$).

Panel B provides results for the weak interpretation. It classifies subjects differently, placing many into profiles with indifference over risk and ambiguity resolution. Nonetheless, the modal profile includes ambiguity aversion which cannot be characterized by the DEU model. As a result, the DEU model achieves the lowest Selten score of the ten models ($p < 0.1$, in each of the 9 comparisons, see Table H.4). The only four models that can classify the modal profile, the MEU model and its generalizations (DVP, H and RVP), are unsurprisingly better performers in this exercise, all achieving Selten scores over 0.5. The H and RVP models are the top two performers overall as they significantly outperform every other model over the 100,000 bootstraps (each model has $p < 0.05$, for the other 8 comparisons). The H model is the more parsimonious of the two: it rationalizes behavior over 5.2 percentage points less of the total action space but accommodates six fewer subjects (4.4%). As a result, it achieves a slightly higher Selten score, though the difference relative to RVP is statistically indistinguishable across the bootstraps.

5. Conclusion

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

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

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

To enhance the precision of our analysis, we classify all subjects across the preference profile space and penalize models for being able to rationalize a greater percentage of this space, taking into account that certain preference profiles are associated with a larger number of possible actions. Under this approach, the HM model outperforms all the other models in predictive power. It benefits from accommodating some, but not all, of divergent preference profiles for risk and ambiguity resolution among the ambiguity averse as well as early monotone preferences for both risk and ambiguity resolution among the ambiguity seeking. Crucially, the baseline EZ model performs worst in this exercise; it is significantly outperformed by all other models.

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

We also examine this weak interpretation of results and a broader class of models that could potentially rationalize our data. Since half of our subjects exhibit ambiguity aversion, the standard DEU model does not characterize our data well. The MEU, DVP, H, and RVP models perform better as they are the only ones that rationalize our modal subject profile, which includes ambiguity aversion with indifference to the timing of both forms of resolution. Among these four, the H and RVP models perform best. Like the other two models, the H and RVP models can rationalize profiles with indifference to the timing of both forms of resolution for both ambiguity-neutral and ambiguity-averse agents. The H and RVP models can also rationalize profiles with an early preference for both forms of resolution for both ambiguity-neutral and ambiguity-averse agents. Finally, the two allow profiles where a subject can be indifferent to the timing of one form of uncertainty resolution and prefer early resolution for the other, among ambiguity-averse agents.

In either interpretation, strong or weak, we note a few general trends. First, the best-performing models allow for ambiguity aversion; both the EZ and DEU models are consistently outperformed. Second, models that account for non-indifference to the timing of both types of uncertainty resolution, risk and ambiguity, also perform well. Third, while these resolution preferences are correlated, it is not always the case that they are the same. The best-performing model under both interpretations accommodates a decoupling of these preferences under ambiguity aversion.

However, many of these empirically observed profiles could not be rationalized by any model, at least under the CRRA-CES restriction imposed in the paper. This finding is especially apparent under the strong interpretation of our results, where the top-performing models can only rationalize observed behavior for about a third of subjects. Of the remaining subjects, most exhibit a preference for gradual resolution of risk, ambiguity, or both. Thus, the data indicate that the greatest explanatory gains would come from models that could explain preferences for gradual resolution. Specifically, under our strong interpretation of results, the predictive power of the best-performing model more than doubles if it could accommodate a preference for gradual resolution for risk or ambiguity. We would emphasize that while there have been theoretical papers studying a preference for one-shot resolution, limited work focuses on preferences for gradual resolution. More theoretical work is needed to accommodate these exhibited preferences flexibly.

Finally, we again note that our experiments only observed a single consumption process and a small set of information structures over a single state space. Several of the models we consider rationalize the preference profiles in Table 11 for the specific consumption process and information structures in the experiment, but require different preferences to be displayed elsewhere. That is, they could not accommodate a given preference profile over uncertainty resolution globally. Future studies are needed to empirically determine under what parameter values these preferences would reverse, if they do at all. We encourage work in this area.

CRediT authorship contribution statement

Alexander L. Brown: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization; **Huiyi Guo:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization; **Hyundam Je:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Declarations of competing interest

None.

Appendix A. Theoretical appendix

A.1. Risk resolution

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

Proposition 1. *In the EZ model with CRRA utility function u and CES time aggregator W, if $\alpha < \rho$ (resp. $\alpha > \rho$), a DM prefers monotone and early (resp. late) resolution of risk; 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 (resp. linear, or strictly concave) in x if $\alpha < \rho$ (resp. $=$, or $>$).

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

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

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

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

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

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

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

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

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

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

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

Corollary 1. *Suppose utility functions u and v are of the CRRA form and the time aggregator W is of the CES form. In the DEU, MEU, KMM, DMP, and DVP models, a DM is indifferent to the timing of risk resolution. In the EZ, H, HM, RMP, and RVP models, if $\alpha < \rho$ (resp. $\alpha > \rho$), a DM prefers monotone and early (resp. late) resolution of risk; 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 the above models, due to the CRRA-CES restriction, the preference for the timing of risk resolution is indifferent or monotone. Thus, there is no strict preference for gradual resolution or one-shot resolution of risk.
2. The three gradual risk-resolution options G, Gp, and Gn are not ranked in Blackwell order. We cannot give a general prediction on their ranking based on the convexity/concavity of the $\overline{w}$ function defined in Proposition 1.
3. Our gradual risk-resolution options Gp and Gn have the same variance and symmetric skewness. Following Masatlioglu et al. (2023), one can make further predictions on the preference between these two based on the sign of the third derivative of $\overline{w}$. Notice that $\overline{w}'''(x) = \beta h_1^\rho(\rho - \alpha)[h_1^\rho + \beta(\alpha x)^{\frac{\rho}{\alpha}}]^{\frac{\alpha}{\rho}-3} \cdot (\alpha x)^{\frac{\rho}{\alpha}-3} \cdot [h_1^\rho(\rho - 2\alpha) - (\alpha + \rho)\beta(\alpha x)^{\frac{\rho}{\alpha}}]$, which has the same sign with $(\frac{\rho}{\alpha} - 1)[(\frac{\rho}{\alpha} - 2)h_1^\rho(\alpha x)^{-\frac{\rho}{\alpha}} - \beta(\frac{\rho}{\alpha} + 1)]$. When $\frac{\rho}{\alpha} \in (1, 2]$, $\overline{w}'''(\cdot) < 0$, implying a preference for negative over positive skewness in risk resolution; when $\frac{\rho}{\alpha} \in [-1, 1)$, $\overline{w}'''(\cdot) > 0$, implying a preference for positive over negative skewness; for $\frac{\rho}{\alpha} > 2$ or < -1, the sign of $\overline{w}'''(\cdot)$ is ambiguous; for $\frac{\rho}{\alpha} = 1$, the DM is indifferent to the timing of risk resolution.

A.2. The MEU and H models

Proposition 2.

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

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

Proof. In the (w)H model, which nests the (w)MEU model, given an information structure $[f, S_1^f]$ along with the corresponding Q^f, the ex-ante certainty equivalent of $h \in H$ is

$$I_1^{ea}[f, S_1^f](h) = \min_{Q^k \in Q^f} W\big(h_1, \min_{\hat{q} \in Q^k} I_2[\hat{q}](h)\big),$$

where

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

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

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

By the monotonicity of W, we can conclude that $I_1^{ea}[f, \overline{S}_1^f](h) = I_1^{ea}[f, S_1^f](h) = I_1^{ea}[f, \underline{S}_1^f](h)$.

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

$$\begin{aligned} I_1^{ea}[f, S_1^f](h) =& u^{-1}\left(\min_{\tilde{\pi} \in \Pi} \mathbb{E}_{Q^k \sim \tilde{\pi}}\left[u \circ W\left(h_1, u^{-1}\Big(\min_{\tilde{\pi} \in \Pi} \mathbb{E}_{\hat{q} \sim \tilde{\pi}(\cdot|Q^k)}\Big[u\big(I_2[\hat{q}](h)\big)\Big]\Big)\right)\right]\right) \\ \leq& \min_{\pi \in \Pi} u^{-1}\left(\mathbb{E}_{Q^k \sim \pi}\left[u \circ W\left(h_1, u^{-1}\Big(\mathbb{E}_{\hat{q} \sim \pi(\cdot|Q^k)}\Big[u\big(I_2[\hat{q}](h)\big)\Big]\Big)\right)\right]\right), \end{aligned} \tag{A.2}$$

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

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

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

When $\alpha < \rho$, by applying Jensen's inequality, we know that $I_1^{ea}[f, \overline{S}_1^f](h) > I_1^{ea}[f, \underline{S}_1^f](h)$ for almost all $h \in H$. When Π is "rectangular" (Epstein and Schneider, 2003), the weak inequality after expression (A.2) holds as equality, and it is easy to see that $I_1^{ea}[f, \overline{S}_1^f](h) > I_1^{ea}[f, S_1^f](h) > I_1^{ea}[f, \underline{S}_1^f](h)$ for almost all $h \in H$. For a "non-rectangular" Π, the ranking between $I_1^{ea}[f, \underline{S}_1^f](h)$ and $I_1^{ea}[f, S_1^f](h)$ may depend on the specific h, S_1^f, and Π, and the DM may exhibit a preference for one-shot resolution. Symmetric results hold for $\alpha > \rho$. When $\alpha = \rho$, $I_1^{ea}[f, \overline{S}_1^f](h) = I_1^{ea}[f, \underline{S}_1^f](h) \geq I_1^{ea}[f, S_1^f](h)$ for all $h \in H$. The last inequality can hold strictly for some $h \in H$ in the non-rectangular case. □

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

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

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

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

Given $[f, S_1^f]$ that represents gradual resolution of ambiguity and the corresponding Q^f, the ex-ante certainty equivalent of consumption process h can be rewritten as

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

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

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

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

where the second equality uses the law of iterated expectations.

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

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

When $\eta < \rho$, by Jensen's inequality, we know that $I_1^{ea}[f, \overline{S}_1^f](h) > I_1^{ea}[f, S_1^f](h) > I_1^{ea}[f, \underline{S}_1^f](h)$ for almost all $h \in H$, due to the strict convexity of w. Hence, the DM prefers early resolution of ambiguity monotonically. Similarly, when $\eta > \rho$ (resp. $\eta = \rho$), the DM prefers monotone and late (resp. is indifferent to the timing of) ambiguity resolution. □

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

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

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

Without the CRRA-CES restriction, we cannot make this claim on the connection between the risk-resolution preference (decided by the convexity/concavity of $u(W(h_1, u^{-1}(x))))$, the ambiguity-resolution preference (decided by the convexity/concavity of $v(W(h_1, v^{-1}(x))))$, and ambiguity attitude (decided by convexity/concavity of $v \circ u^{-1}$). For example, suppose $v(x) = -e^{-u(x)}$, $u(x)$ is of the CRRA form with $\alpha = -1$, and W is of the CES form with $\rho = -0.4$, $\beta = 0.9$, period-1 consumption $h_1 = 10$, and period-2 consumption x. In this case, function $u(W(h_1, u^{-1}(x)))$ is strictly convex, and thus, the DM prefers early resolution of risk, and the DM is ambiguity averse. But the function $v(W(h_1, v^{-1}(x)))$ is neither convex nor concave for $x \in (-\infty, -1)$.

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

Corollary 3.

1. *In the DEU model with CRRA utility function u, a DM is indifferent to the timing of ambiguity resolution.*
2. *In the KMM model with CRRA utility functions u and v, an ambiguity-averse (resp. -seeking) DM prefers early (resp. late) resolution of ambiguity monotonically; an ambiguity-neutral DM is indifferent to the timing of ambiguity resolution.*
3. *In the EZ model with CRRA utility function u and CES aggregator W, a DM's ambiguity-resolution preference is inherited from her risk-resolution preference.*

A.4. The DMP and RMP models

Proposition 4. *In the DMP model with CRRA utility function u and CES time aggregator W, an ambiguity-averse DM prefers early resolution of ambiguity monotonically.*

Proof. Recall that the DMP model is the special case of RMP model with $\alpha = \rho$. In both models, ambiguity aversion correponds to the $\theta < \infty$ case. Fix any gradual ambiguity resolution information structure $[f, S_1^f]$ and the corresponding Q^f.

Define a function ϕ_θ: $(0, +\infty) \to \mathbb{R}$ by $\phi_\theta(x) \equiv -e^{-\frac{x}{\theta}}$. By Strzalecki (2011), the ex-ante certainty equivalents under early, gradual, and late ambiguity-resolution information structures in the RMP model are equal to

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

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

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

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

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

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

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 $\alpha=\rho$ and $\theta<\infty$, $\tilde{w}''(x)>0$ for all $x>0$. Therefore, $\tilde{w}$ is strictly convex. Hence, (A.4) is higher than (A.5) for almost all $h\in H$. By strict convexity of $\tilde{w}$ and ϕ_θ,

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

for almost all $h\in H$. As a result, (A.3) dominates (A.4), i.e., early resolution of ambiguity dominates gradual resolution. In sum, the DM has a monotone preference for early resolution of ambiguity. □

Claim 1. *In the RMP model, an ambiguity-averse DM with a monotone preference for early risk resolution can have any of the five strict ambiguity-resolution preferences. In this model, an ambiguity-averse DM with a monotone preference for late risk resolution can have any of the strict ambiguity-resolution preferences except the one for gradual ambiguity resolution.*

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

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

and $E\succ Gp\succ G\succ Gn\succ L$ when $\theta=50$.

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

and $E\succ L\succ Gp\succ G\succ Gn$ when $\theta=3.2$.

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

$L\succ E\succ Gp\succ G\succ Gn$ when $\theta=600$, and $L\succ Gp\succ G\succ Gn\succ E$ when $\theta=10000$. □

A.5. The DVP and RVP models

Claim 2. *In the DVP model, among the six ambiguity-resolution preferences (including indifference), an ambiguity-averse DM can have any of the four that at least weakly prefer early to late. In the RVP model, an ambiguity-averse DM with a monotone preference for early or late risk resolution can have any of the six ambiguity-resolution preferences.*

Proof. To establish the first statement, first recall that the DVP model nests the MEU model and the DMP model. Therefore, the DVP model can rationalize both a monotone preference for early ambiguity resolution and a total indifference to the timing of ambiguity resolution. We supplement with two examples below to show that the DVP model can rationalize a preference for gradual ambiguity resolution and one for one-shot and early ambiguity resolution.

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

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

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

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

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

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

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

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

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

We now establish that an ambiguity-averse DM with a monotone preference for early or late risk resolution can have any of the six ambiguity-resolution preferences (including indifference). Since the RVP model nests the H and RMP models, it suffices to supplement Proposition 2 and Claim 1 with one example. In the first example of the current proof, we slightly perturb α and ρ so that either $\alpha < \rho$ or $\rho < \alpha$. By continuity, the certainty equivalent of G remains higher than that of E and L. □

Online appendices and supplementary material

Online Appendices B–H as well as experimental instructions associated with this article can be found online at 10.1016/j.jet.2026.106151.

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