Preferences for the Resolution of Risk and Ambiguity*

Alexander L. Brown† Huiyi Guo‡ Hyundam Je§

Department of Economics, Texas A&M University, College Station, TX 77843

April 16, 2022

Abstract

Models of generalized recursive utility are becoming increasingly common as alternatives to discounted expected utility theory. These models have successfully explained many so-called, "anomalies" in field data, but often imply that agents have a preference over the timing of uncertainty resolution. Laboratory elicitations of subject preferences generally provide direct evidence in support of this implication. However, all previous experimental studies have only elicited preferences over uncertainty resolution in the domain of objective uncertainty, i.e., risk. By definition, uncertainty includes both objective and subjective domains. Further, not all generalized recursive utility models can accommodate preferences over uncertainty in both domains. For these reasons, we provide the first experimental examination of uncertainty resolution with respect to subjective uncertainty, i.e., ambiguity, in addition to risk. We find that subjects most frequently exhibit a preference for early resolution of both risk and ambiguity and these preferences are positively correlated. Additionally, being ambiguity-seeking decreases the probability of preferring early resolution of ambiguity. Of six, commonly-used, representative recursive utility models, only the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) can plausibly explain the entirety of these experimental findings.

*We thank Han Bleichrodt, Ralph Boleslavsky, Eugen Dimant, Russell Golman, Takashi Hayashi, Shaowei Ke, Hwagyun Kim, Jian Li, Jianjun Miao, Kirby Nielsen, Jacob Sagi, Adam Sanjurjo, Kyoungwon Seo, Ran Shorrer, Sarah Zubairy, seminar participants at Peking University, the 2021 ESA Global Online Around-the-Clock Meetings, University of Alicante, MiddExLab Seminar, and the European Winter Meetings of the Econometric Society 2021 for helpful comments. All errors are our own.

†alexbrown@tamu.edu; http://people.tamu.edu/∼alexbrown.

‡huiyiguo@tamu.edu; http://guohuiyi.com.

§hje@tamu.edu; https://sites.google.com/view/hyundamje.

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; Epstein and Zin, 1989; Weil, 1990). Applications of these models explain a wide variety of anomalies regarding asset prices, trade, and inflation (see below). An added implication of these models is that many of them require agents to have a preference over when uncertainty is to be resolved, independent of instrumental concerns. Initial debates concerned whether such preferences were plausible, and, if plausible, whether people prefer early or late resolution of uncertainty. Experimental work is generally divided and elicitation of these preferences may be complicated by other factors (see Brown and Kim, 2013; Nielsen, 2020, for surveys).

As conventionally defined, "uncertainty" includes both elements of "risk" and "ambiguity" (Knight, 1921). The objective domain of uncertainty, risk, describes a situation where the result is not known, but the underlying probability could be theoretically, or empirically determined; the subjective domain of uncertainty, ambiguity, describes a situation where people do not know any basis for objective probability. Interestingly, all aforementioned experimental studies that elicit preferences for uncertainty resolution have focused entirely on the domain of risk. That is, a determination of preferences for early resolution of uncertainty is only finding preferences for early resolution of risk, without establishing individuals' preferences over the removal of ambiguity. By considering environments with subjective uncertainty exclusively, the theoretical studies of Strzalecki (2013) and Li (2020) examine uncertainty resolution where ambiguity is considered. Since these papers focus on the subjective domain of uncertainty, the models examined by them may explain strict preferences for ambiguity resolution, but not risk.

This current paper provides the first experimental elicitation of preferences of uncertainty resolution in the subjective domain as well as in the objective domain. We elicit separate preferences over ambiguity and risk resolution and examine their interrelation with ambiguity attitude. In particular, we find that 47.4% of the subjects prefer early resolution of risk and 63.7% prefer early resolution of ambiguity, and the two preferences are positively correlated.

Controlling for risk resolution preference, being ambiguity seeking decreases the likelihood of preferring early resolution of ambiguity by 25.6%.

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

To understand what features are important for a model to have strict and differential preferences for risk and ambiguity resolution, we review six representative recursive utility models that have been axiomatized by decision theorists and are commonly applied to field data: the discounted expected utility model, the generalized recursive utility model of Kreps and Porteus (1978), the recursive smooth ambiguity model of Klibanoff et al. (2005, 2009) and Seo (2009), the generalized recursive maxmin expected utility model of Hayashi (2005), and the generalized recursive smooth ambiguity model of Hayashi and Miao (2011).[2] A

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

[2]In the paper, the term "recursive utility model" refers to both the canonical discounted expected utility model and the other five generalized recursive utility models. Models of generalized recursive utility have consequential implications in many applications in empirical macroeconomic and finance literature. For

deductive examination reveals that only the generalized recursive smooth ambiguity model of Hayashi and Miao (2011)—which allows for a three-way separation between the parameter of risk attitude, the parameter of ambiguity attitude, and the elasticity of intertemporal substitution—is consistent with our results. This observation highlights the importance of separating the three parameters in empirical applications.

A secondary (methodological) reason concerns measurement and identification. Until this study, there has been no experimental elicitation of individuals' preferences over the resolution of ambiguity. All previous experimental studies have used preferences of risk resolution as a proxy for the more general, uncertainty resolution. Depending on the correlations between preferences of risk resolution and ambiguity resolution, the conclusions of these studies may vary in their validity. For instance, if preferences of risk and ambiguity resolution are not perfectly correlated, the use of risk-resolution preferences as a proxy for the entirety of one's uncertainty-resolution preferences is problematic.

There have been several previous experimental studies on uncertainty resolution. Nielsen (2020) provides a thorough review, categorizing and summarizing findings in four distinct areas. Early studies surveyed participants on their preferences and did not incentivize choice (Chew and Ho, 1994; Ahlbrecht and Weber, 1996, 1997; Lovallo and Kahneman, 2000). Later studies incentivized choice but were potentially confounded by the fact that the information revealed is instrumental (Von Gaudecker et al., 2011; Brown and Kim, 2013; Kocher et al., 2014; Zimmermann, 2015; Meissner and Pfeiffer, 2022). That is, learning the information early may pose an additional benefit to an individual outside of these preferences. In both categories, the literature often, but not always, finds a preference for the early resolution of uncertainty. Along a related line of experimental literature, there have also been papers studying the association between a subject's attitudes towards ambiguity and compound

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

lotteries (e.g., Halevy, 2007; Abdellaoui et al., 2015).

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

There are several additional key features of our experimental design. Our experiment follows the general structure of Nielsen's, eliciting subjects' preference over uncertainty with non-instrumental information in information structure frames. We build upon the design in that we separately elicit risk and ambiguity resolution preferences. The latter has not previously been elicited in the aforementioned literature. Secondly, we examine more than binary choices, which have been the focus of the literature to date. We also include gradual resolution of information options (non-skewed, positively-skewed, and negatively skewed) as well as early and late options. Positively skewness eliminates more uncertainty about the good state and negatively skewness is the opposite.[3] Hence, participants express preferences over larger choice sets.

This paper proceeds as follows. Section 2 reviews six representative recursive utility models and examines their implications on the preferences of risk resolution and ambiguity resolution. Section 3 details the experimental design and procedures on the elicitation of risk resolution preference, ambiguity resolution preference, and ambiguity attitude. Section 4 provides hypotheses to test the six theoretical models. Section 5 provides results and Section 6 concludes.

[3] Masatlioglu et al. (2017) focus on an environment with (1) objective uncertainty and (2) gradual resolution options only.

2 Theoretical Predictions

This section reviews six representative recursive utility models under uncertainty, including the discounted expected utility model (henceforth the DEU model) which is predominant in applied works, the generalized recursive utility model of Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990) (henceforth the EZ model), the recursive maxmin expected utility model of Gilboa and Schmeidler (1989) and Epstein and Schneider (2003) (henceforth the MEU model), the recursive smooth ambiguity model of Klibanoff et al. (2005, 2009) and Seo (2009) (henceforth the KMM model), the generalized recursive maxmin expected utility model of Hayashi (2005) (henceforth the H model), and the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) (henceforth the HM model). When constant relative risk aversion ex-post utility functions are adopted, the models reviewed here can be easily described with three parameters: risk aversion parameter, ambiguity aversion parameter, and elasticity of intertemporal substitution, which make them particularly tractable in the macroeconomics and finance literature.[4]

These models differ from each other in two dimensions. First, they take two approaches to describe intertemporal substitution: to derive the ex-ante utility of a consumption process, the DEU, MEU, and KMM models use a linear aggregator to sum up the flow of utilities across different periods; the other three models adopt a non-linear aggregator. In addition, the models are based on three intratemporal decision-making criteria under uncertainty: the DEU model and the EZ model follow the subjective expected utility and do not support ambiguity aversion behaviors; the MEU model and the H model use the worst-case criterion to capture ambiguity aversion behaviors; the KMM model and the HM model permit a separation between ambiguity and ambiguity aversion and accommodate a richer class of ambiguity attitudes. We summarize the key differences of these models in Table 1.

For simplicity, we focus on two-period problems and finite state spaces in each period. Let

[4] Strzalecki (2013) has provided a more complete review of recursive utility models with linear time aggregators and ambiguity aversion. A wide class of models reviewed there have been shown to capture preferences for early resolution of uncertainty in the subjective domain, e.g., the recursive smooth ambiguity model, the dynamic variational preference of Maccheroni et al. (2006), and the multiplier preference of Hansen and Sargent (2001). However, due to the linear time aggregators, these models cannot capture strict preferences for risk resolution. We hence only review the smooth ambiguity model as a representative one among this class.

		Intratemporal Criterion		
		Expected Utility	Worst-case Scenario	Smooth Ambiguity
Intertemporal Aggregator	Linear	DEU	MEU	KMM
	Non-linear	EZ	H	HM

Table 1: A summary of recursive utility models under uncertainty

S_1 and S_2 denote the state space in period 1 and period 2 respectively. Let $p \in \Delta(S_1 \times S_2)$ be a joint distribution over the state space and P be a set of such joint distributions representing ambiguity. Consistent with our experiment design, we assume for simplicity that the set of possible distributions P is finite. To define risk and ambiguity resolution, we focus on consumption processes that are constant in period 1 and s_2-dependent in period 2. Let H denote the set of all $h = (h_1, h_2)$, where $h_1 \in \mathbb{R}_+$ and $h_2 : S_2 \to \mathbb{R}_+$. The restriction allows us to focus on the informational value of s_1 without making it payoff-relevant.

For tractability, this paper assumes that utility functions are of the constant relative risk aversion form. In particular, define $u(x) \equiv \frac{x^\alpha}{\alpha}$, where $1 - \alpha$ is the risk aversion parameter; define $v(x) \equiv \frac{x^\eta}{\eta}$, where $1 - \eta$ is the ambiguity aversion parameter in the KMM and HM models; define $W(x, y) = (x^\rho + \beta y^\rho)^{\frac{1}{\rho}}$, where $\frac{1}{1-\rho}$ is the elasticity of intertemporal substitution in the EZ, H, and HM models, and β is the discount factor. Throughout the paper, we assume that α, η, $\rho \neq 0$ for the functions to be well-defined.

The DEU, MEU, and KMM models adopt linear time aggregators. The period-1 utility of a consumption process h after s_1 is realized is given by

$$V_1(h|s_1) = u(h_1) + \beta V_2(h|s_1) = \frac{h_1^\alpha}{\alpha} + \beta V_2(h|s_1),$$

where $V_2(h|s_1)$ is the continuation utility when s_1 is realized in period 1.

In the DEU model, the subject forms a unique subjective probability p over uncertainty and follows the expected utility to derive the continuation utility:

$$V_2(h|s_1) = \sum_{s_2 \in S_2} u(h_2(s_2)) p(s_2|s_1) = \sum_{s_2 \in S_2} \frac{h_2^\alpha(s_2)}{\alpha} p(s_2|s_1).$$

In the MEU model, the decision maker believes that multiple distributions are relevant and evaluates a consumption process by considering the worst-case distribution. By adopting the prior-by-prior updating rule, the continuation utility is given by

$$V_2(h|s_1) = \min_{p\in P} \sum_{s_2\in S_2} u(h_2(s_2))p(s_2|s_1) = \min_{p\in P} \sum_{s_2\in S_2} \frac{h_2^\alpha(s_2)}{\alpha} p(s_2|s_1).$$

In the KMM model, a subject has a subjective second-order belief over potential probabilities and does not reduce compound lotteries. The continuation utility conditional on s_1 being observed in period 1 is given by

$$\begin{aligned} V_2(h|s_1) &= u \circ v^{-1}\Big(\sum_{p\in P} v \circ u^{-1}\big(\sum_{s_2\in S_2} u(h_2(s_2))p(s_2|s_1)\big)\mu(p|s_1)\Big) \\ &= \Big(\sum_{p\in P}\big(\sum_{s_2\in S_2} h_2^\alpha(s_2)p(s_2|s_1)\big)^{\frac{\eta}{\alpha}}\mu(p|s_1)\Big)^{\frac{\alpha}{\eta}}. \end{aligned}$$

When $\eta > \alpha$, i.e., when v is strictly less concave than u, the subject is ambiguity seeking. When $\eta < \alpha$, the subject exhibits ambiguity aversion, and in the limiting case that η goes to $-\infty$, the KMM model converges to the MEU model. When $\eta = \alpha$, the subject is ambiguity neutral and the model reduces to the DEU model.

The EZ, H, and HM models use a non-linear aggregator of the consumption today and the certainty equivalent of the continuation consumption. In particular, a subject's certainty equivalent in period 1, denoted by I_1, is given by

$$I_1(h|s_1) = W\big(h_1, I_2(h|s_1)\big) = \big(h_1^\rho + \beta I_2^\rho(h|s_1)\big)^{\frac{1}{\rho}},$$

where $I_2(h|s_1)$ is the certainty equivalent of continuation consumption conditional on s_1 being observed in period 1.

In the EZ model,

$$I_2(h|s_1) = u^{-1}\Big(\sum_{s_2\in S_2} u\big(h_2(s_2)\big)p(s_2|s_1)\Big) = \big(\sum_{s_2\in S_2} h_2^\alpha(s_2)p(s_2|s_1)\big)^{\frac{1}{\alpha}}. \tag{1}$$

In the H model,

$$I_2(h|s_1) = \min_{p\in P} u^{-1}\Big(\sum_{s_2\in S_2} u\big(h_2(s_2)\big)p(s_2|s_1)\Big) = \min_{p\in P}\big(\sum_{s_2\in S_2} h_2^\alpha(s_2)p(s_2|s_1)\big)^{\frac{1}{\alpha}}.$$

In the HM model,

$$
\begin{aligned}
I_2(h|s_1) =& v^{-1}\Big(\sum_{p\in P} v\circ u^{-1}\big(\sum_{s_2\in S_2} u(h_2(s_2))p(s_2|s_1)\big)\mu(p|s_1)\Big)\\
=&\Big(\sum_{p\in P}\big(\sum_{s_2\in S_2} h_2^{\alpha}(s_2)p(s_2|s_1)\big)^{\frac{\eta}{\alpha}}\mu(p|s_1)\Big)^{\frac{1}{\eta}}.
\end{aligned}
$$

We remark that the HM model is general. When $\alpha = \eta$, the HM model degenerates to the EZ model. When η approaches $-\infty$, the HM model converges to the H model. When $\alpha = \rho$, the HM model yields the KMM model as a special case, and the latter nests the DEU model and can approximate the MEU model in the limit.

In later sections, we mostly rely on the certainty equivalent expressions $I_1(h|s_1)$ and $I_2(h|s_1)$ rather than the continuation utility expressions $V_1(h|s_1)$ and $V_2(h|s_1)$. We denote $I_1(h|s_1)$ by $I_1[p](h|s_1)$ or $I_1[P](h|s_1)$ when necessary to highlight the ex-ante joint distribution p or the set of joint distributions P. Let $I_1[p](h)$ or $I_1[P](h)$ denote the ex-ante certainty equivalent of consumption process h before period-1 state is realized.

2.1 Risk Resolution

The literature has extensively studied preferences on the timing of risk resolution. In Section 2.1, we follow these papers and assume that the only uncertainty that arises in the environment is risk.

For each distribution q over S_2 with $|S_1| \geq |S_2|$, define a set $P(q) \equiv \{p \in \Delta(S_1 \times S_2)|p(s_2) = q(s_2), \forall s_2 \in S_2\}$, which is the set of all joint distributions over $S_1 \times S_2$ with marginal distributions over S_2 identical to q. Let $P^E(q) \subseteq P(q)$ be the set of all joint distributions $p \in P(q)$ that resolve risk early, i.e., p satisfies that $p(s_2|s_1) \in \{0, 1\}$ for all $s_1 \in S_1$ and $s_2 \in S_2$. Let $P^L(q) \subseteq P(q)$ be the set of all joint distributions $p \in P(q)$ that resolve risk late, i.e., p satisfies $p(s_2|s_1) = q(s_2)$ for all $s_1 \in S_1$ and $s_2 \in S_2$. Let $P^G(q) = P(q) \setminus (P^E(q) \cup P^L(q))$ denote all joint distributions that resolve risk gradually.

We consider the following example as an illustration.

Example 1. Let S_1 be given by $\{s_1^1, s_1^2\}$ and S_2 be $\{s_2^1, s_2^2\}$. Consider a distribution over S_2, $q = (0.5, 0.5)$. In Table 2, under each of the three joint distributions over $S_1 \times S_2$, the marginal distribution over S_2 is equal to q. Thus, from an ex-ante perspective, all three joint distributions are equally risky about the period-2 state.

	s_2^1	s_2^2
s_1^1	0.5	0
s_1^2	0	0.5

(a) $p \in P^E(q)$

	s_2^1	s_2^2
s_1^1	0.3	0.2
s_1^2	0.2	0.3

(b) $p \in P^G(q)$

	s_2^1	s_2^2
s_1^1	0.25	0.25
s_1^2	0.25	0.25

(c) $p \in P^L(q)$

Table 2: Three joint distributions with different timings of risk resolution

In Table 2(a), upon receiving s_1, the subject knows the s_2 that will be realized. Thus, the period-2 risk is resolved early. In Table 2(c), receiving each s_1 leads to the same posterior belief about which s_2 will be realized, and thus period-2 risk is resolved late. In Table 2(b), the period-1 state s_1 is neither fully uninformative nor fully informative about which s_2 will be realized, and thus partially, or gradually, resolves period-2 risk.

Definition 1.

1. A subject is indifferent towards the timing of risk resolution if $I_1[p](h) = I_1[p'](h)$ for all $h \in H$, $q \in \Delta(S_2)$, and $p, p' \in P(q)$.

2. A subject prefers early resolution of risk if she is not indifferent towards the timing of risk resolution, and $I_1[p](h) \geq I_1[p'](h)$ for all $h \in H$, $q \in \Delta(S_2)$, $p \in P^E(q)$, and $p' \in P(q)$.

3. A subject prefers late resolution of risk if she is not indifferent towards the timing of risk resolution, and $I_1[p](h) \geq I_1[p'](h)$ for all $h \in H$, $q \in \Delta(S_2)$, $p \in P^L(q)$, and $p' \in P(q)$.

According to the well-known result of Epstein and Zin (1989), a subject with the EZ preference prefers early resolution of risk if $\alpha < \rho$, prefers late resolution of risk if $\alpha > \rho$, and is indifferent towards the timing of risk resolution if $\alpha = \rho$.

When the only uncertainty that arises in the environment is risk, since the H model and the HM model reduce to the EZ model, preferences towards the timing of risk resolution in the H model and the HM model can be characterized in the same way as in the EZ model. Also, when there is no ambiguity, the MEU model and the KMM model reduce to the DEU model which is essentially the EZ model with $\alpha = \rho$. Hence, a subject is indifferent towards the timing of risk resolution in the MEU/KMM/DEU model.

2.2 Ambiguity Resolution

We consider a notion of ambiguity resolution with a partition structure. Let Q be a finite set of possible period-2 distributions over S_2, which captures period-2 ambiguity from an ex-ante view, such that $|Q| = |S_1|$.[5] Let $\mathcal{Q}$ be a partition of Q: a period-1 state informs the subject of an element of $\mathcal{Q}$, i.e., a subset of possible period-2 distributions. Hence, when the partition is the finest one $\mathcal{Q}^E$, any period-1 state resolves period-2 ambiguity early by identifying the unique period-2 distribution. Similarly, the coarsest partition $\mathcal{Q}^L$ corresponds to late resolution of ambiguity, and any other partition $\mathcal{Q}^G$ corresponds to gradual resolution.

To compare ex-ante payoffs a subject receives under different timings of ambiguity resolution, i.e., from different partitions of Q, we construct a set of joint distributions over $S_1 \times S_2$ for each partition $\mathcal{Q}$, denoted by $P[\mathcal{Q}](Q)$. This set can be understood as possible beliefs over $S_1 \times S_2$ from an ex-ante perspective. The details of the construction are relegated to Appendix A.1. As an illustration, we look at the following example.

Example 2. Let S_1 be given by $\{s_1^1, s_1^2, s_1^3, s_1^4\}$ and S_2 be $\{s_2^1, s_2^2\}$. Let $Q = \{q^1 = (0.1, 0.9), q^2 = (0.4, 0.6), q^3 = (0.6, 0.4), q^4 = (0.9, 0.1)\}$ represent possible period-2 distributions over S_2 from an ex-ante perspective. Table 3 shows three sets of joint distributions over $S_1 \times S_2$. The second set of joint distributions, $P[\mathcal{Q}^G](Q)$, is generated by Let $\mathcal{Q}^G = \{\{q^1, q^2\}, \{q^3, q^4\}\}$. Again, $\mathcal{Q}^E$ and $\mathcal{Q}^L$ are the finest and coarsest partitions of Q respectively.

For each partition $\mathcal{Q}$ above, we can label the elements of $P[\mathcal{Q}](Q)$, from left to right, by p^1 to p^4 respectively. Elements of $P[\mathcal{Q}](Q)$ have a one-to-one correspondence with those in Q: upon receiving any $s_1 \in S_1$ that occurs with positive probability under $p^k \in P[\mathcal{Q}](Q)$, the updated belief of p^k over S_2 coincides with q^k, i.e., $p^k(\cdot|s_1) = q^k(\cdot) \in \Delta(S_2)$ for all $k \in \{1, 2, 3, 4\}$ and $s_1 \in S_1$ such that $p^k(s_1) > 0$.

Suppose a subject's ex-ante ambiguous beliefs over $S_1 \times S_2$ are given by Table 3(a). When $s_1^k \in S_1$ is realized, the only joint distribution in $P[\mathcal{Q}^E](Q)$ generating s_1^k with positive probability is p^k, and the subject knows that the true distribution over S_2 is q^k immediately. In this sense, receiving a period-1 state resolves ambiguity about period-2 distribution early.

Suppose a subject's ex-ante ambiguous beliefs over $S_1 \times S_2$ are given by Table 3(c). Since

[5] We restrict Q to be finite and to satisfy $|Q| = |S_1|$ so that it is feasible to fully resolve ambiguity in period 1 by having a one-to-one relationship between states in S_1 and distributions in Q.

	s_2^1	s_2^2		s_2^1	s_2^2		s_2^1	s_2^2		s_2^1	s_2^2
s_1^1	0.1	0.9	s_1^1	0	0	s_1^1	0	0	s_1^1	0	0
s_1^2	0	0	s_1^2	0.4	0.6	s_1^2	0	0	s_1^2	0	0
s_1^3	0	0	s_1^3	0	0	s_1^3	0.6	0.4	s_1^3	0	0
s_1^4	0	0	s_1^4	0	0	s_1^4	0	0	s_1^4	0.9	0.1

(a) $P[\mathcal{Q}^E](Q)$

	s_2^1	s_2^2		s_2^1	s_2^2		s_2^1	s_2^2		s_2^1	s_2^2
s_1^1	0.05	0.45	s_1^1	0.2	0.3	s_1^1	0	0	s_1^1	0	0
s_1^2	0.05	0.45	s_1^2	0.2	0.3	s_1^2	0	0	s_1^2	0	0
s_1^3	0	0	s_1^3	0	0	s_1^3	0.3	0.2	s_1^3	0.45	0.05
s_1^4	0	0	s_1^4	0	0	s_1^4	0.3	0.2	s_1^4	0.45	0.05

(b) $P[\mathcal{Q}^G](Q)$

	s_2^1	s_2^2		s_2^1	s_2^2		s_2^1	s_2^2		s_2^1	s_2^2
s_1^1	0.025	0.225	s_1^1	0.1	0.15	s_1^1	0.15	0.1	s_1^1	0.225	0.025
s_1^2	0.025	0.225	s_1^2	0.1	0.15	s_1^2	0.15	0.1	s_1^2	0.225	0.025
s_1^3	0.025	0.225	s_1^3	0.1	0.15	s_1^3	0.15	0.1	s_1^3	0.225	0.025
s_1^4	0.025	0.225	s_1^4	0.1	0.15	s_1^4	0.15	0.1	s_1^4	0.225	0.025

(c) $P[\mathcal{Q}^L](Q)$

Table 3: Three sets of joint distributions with different timings of ambiguity resolution

all other five models are either special cases of the HM model or can be approximated by the HM model, we assume there is a second-order belief μ over Q. Given μ, let $\tilde{\mu}$ be a second-order belief over $P[\mathcal{Q}^L](Q)$ whose marginal distribution over Q is consistent with μ, i.e., $\tilde{\mu}(q^k) = \mu(q^k)$ for $k \in \{1,2,3,4\}$. Due to the one-to-one correspondence between $P[\mathcal{Q}](Q)$ and Q, the only consistent $\tilde{\mu}$ must satisfy $\tilde{\mu}(p^k) = \mu(q^k)$ for $k \in \{1,2,3,4\}$. Now, we verify that knowing period-1 state s_1 does not provide any information on period-2 distribution. Given $s_1 \in S_1$, the posterior belief for $q^k \in Q$ to be the true period-2 distribution is equal to

$$\frac{\sum_{p \in P[\mathcal{Q}^L](Q)\, s.t.\, p(\cdot|s_1)=q^k} \tilde{\mu}(p) \cdot p(s_1)}{\sum_{p \in P[\mathcal{Q}^L](Q)} \tilde{\mu}(p) \cdot p(s_1)} = \frac{\tilde{\mu}(p^k) \cdot p^k(s_1)}{\sum_{p \in P[\mathcal{Q}^L](Q)} \tilde{\mu}(p) \cdot p(s_1)} = \frac{\mu(q^k) \cdot 0.25}{0.25} = \mu(q^k),$$

which is independent of $s_1 \in S_1$ and coincides with the prior. Hence, we say $P[\mathcal{Q}^L](Q)$ resolves ambiguity late (i.e., does not resolve ambiguity in period 1).

In Table 3(b), for any $\mu \in \Delta(Q)$, the only $\tilde{\mu} \in \Delta(P[\mathcal{Q}^G](Q))$ whose marginal distribution over Q is consistent with μ must satisfy that $\tilde{\mu}(p^k) = \mu(q^k)$ for $k \in \{1,2,3,4\}$. Upon receiving any $s_1 \in \{s_1^1, s_1^2\}$, one can immediately see that the true period-2 distribution q must be in $\{q^1, q^2\}$. Moreover, one can derive from $\tilde{\mu}$ that the posterior belief that q^1 or q^2 is the correct period-2 distribution is equal to $\mu(q^1|\{q^1, q^2\})$ or $\mu(q^2|\{q^1, q^2\})$ respectively, which is independent of $s_1 \in \{s_1^1, s_1^2\}$. We can hence claim that elements of $\{s_1^1, s_1^2\}$ are equivalent – the information of both states is that the set of possible period-2 distributions is $\{q^1, q^2\}$. If $s_1 \in \{s_1^3, s_1^4\}$ is received, the information is that the set of possible period-2 distributions is $\{q^3, q^4\}$. The set of joint distributions $P[\mathcal{Q}^G](Q)$ hence gradually resolves ambiguity (i.e., partially resolves ambiguity in period 1).

We remark on two features of $P[\mathcal{Q}](Q)$. First, its elements have a one-to-one correspondence with elements of Q in the following sense: (1) each joint distribution in $P[\mathcal{Q}](Q)$ can only lead to one posterior belief in Q, regardless of the period-1 state observed, and (2) different joint distributions in $P[\mathcal{Q}](Q)$ have different posterior beliefs in Q. Second, for a general partition $\mathcal{Q}$, there may be multiple period-1 states leading to the same set of possible period-2 distributions: these states are equivalent informationally. The number of these equivalent classes is equal to the cardinality of $\mathcal{Q}$. Different equivalent classes of states in S_1 inform the subject of different elements of $\mathcal{Q}$.

We define the preferences towards the timing of ambiguity resolution as follows.

Definition 2.

1. A subject is indifferent towards the timing of ambiguity resolution if $I_1\big[P[\mathcal{Q}](Q)\big](h) = I_1\big[P[\mathcal{Q}'](Q)\big](h)$ for any finite set $Q \subseteq \Delta(S_2)$, $h \in H$, partitions $\mathcal{Q}$ and $\mathcal{Q}'$ of Q, and $\mu \in \Delta(Q)$.

2. A subject prefers early resolution of ambiguity if she is not indifferent towards the timing of ambiguity resolution, and $I_1\big[P[\mathcal{Q}^E](Q)\big](h) \geq I_1\big[P[\mathcal{Q}](Q)\big](h)$ for any finite set $Q \subseteq \Delta(S_2)$, $h \in H$, partition $\mathcal{Q}$, and $\mu \in \Delta(Q)$.

3. A subject prefers late resolution of ambiguity if she is not indifferent towards the timing of ambiguity resolution, and $I_1\big[P[\mathcal{Q}^L](Q)\big](h) \geq I_1\big[P[\mathcal{Q}](Q)\big](h)$ for any finite set $Q \subseteq \Delta(S_2)$, $h \in H$, partition $\mathcal{Q}$, and $\mu \in \Delta(Q)$.

Below we characterize preferences for ambiguity resolution in the six representative recursive utility models. We begin with the HM model first. The proof of the following proposition is relegated to Appendix A.2.

Proposition 1. In the HM model, a subject prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity or is indifferent towards the timing of ambiguity resolution) if $\eta < \rho$ (resp. $\eta > \rho$ or $\eta = \rho$).

Proposition 1 shows that the preference for timing of ambiguity resolution is determined by two key factors: ρ and η. Recall the conclusion on risk resolution: α and ρ determine the preference for timing of risk resolution in the HM model.

In view of the two results, we can find the following connections between preferences towards the timing of risk resolution and ambiguity resolution.

Corollary 1. In the HM model,

1. if an ambiguity-averse subject prefers early resolution of risk, then she also prefers early resolution of ambiguity;

2. an ambiguity-neutral subject prefers early resolution of risk (resp. prefers late resolution of risk, or is indifferent towards the timing of risk resolution) if and only if she prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity, or is indifferent towards the timing of ambiguity resolution);

3. if an ambiguity-seeking subject prefers late resolution of risk, then she also prefers late resolution of ambiguity.

Although the H model can be viewed as a limiting case of the HM model with $\eta \to -\infty$, the following result shows that the H model does not accommodate strict preferences towards the timing of ambiguity resolution. The proof is relegated to Appendix A.2.

Proposition 2. In the H model, a subject is indifferent towards the timing of ambiguity resolution.

As the DEU model is equivalent to the HM model with $\alpha = \rho = \eta$, the KMM model is equivalent to the HM model with $\alpha = \rho$, the EZ model is equivalent to the HM model with $\alpha = \eta$, and the MEU model is equivalent to the H model with $\alpha = \rho$, we have the following four corollaries.

Corollary 2. In the DEU model, a subject is indifferent towards the timing of ambiguity resolution.

Corollary 3. In the KMM model, a subject prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity, or is indifferent towards the timing of ambiguity resolution) if $\eta < \alpha$ (resp. $\eta > \alpha$, or $\eta = \alpha$).

Corollary 4. In the EZ model, a subject prefers early resolution of ambiguity (resp. prefers late resolution of ambiguity, or is indifferent towards the timing of ambiguity resolution) if $\alpha < \rho$ (resp. $\alpha > \rho$, or $\alpha = \rho$).

Corollary 5. In the MEU model, a subject is indifferent towards the timing of ambiguity resolution.

2.3 Summary of Predictions

Table 4 shows the summary of theoretical implications from each model. The first column means that the EZ, H, and HM models accommodate non-indifference in the timing of risk resolution under some parameter values. The second column implies the KMM, EZ (with subjective beliefs), and HM models support non-indifference in the timing of ambiguity resolution under some parameter values. The last column shows that the MEU, KMM, H, and HM models can be used to explain non-neutral ambiguity attitudes. Hence, among these models, only the HM model can simultaneously accommodate strict preferences towards the timing of risk resolution and ambiguity resolution, as well as non-neutral ambiguity attitudes. Moreover, among the six models, the HM model is the only one that allows differential strict preferences in the timing of risk resolution and in the timing of ambiguity resolution.

3 Experimental Design and Procedures

The experiment consists of two parts: the risk-resolution-preference elicitation part and the ambiguity-resolution-preference elicitation part. Each part utilizes 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

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

Table 4: Theoretical predictions from six models

in four ways comprising four separate, within-subjects treatments. Full details of the random ordering are explained in Section 3.3.

3.1 Risk-Resolution-Preference Elicitation

In the risk-resolution-preference elicitation experiment, subjects participate in a two-period consumption process. In $t = 1$, subjects receive \$10 advance payment. In $t = 2$, a lottery is drawn and the additional payoff is realized. The lottery has 50% chance leading to a "high prize (\$22)" and 50% chance leading to a "low prize (\$4)" ex-ante, and thus subjects have the same prior belief at the beginning of $t = 1$: the overall probability of winning the high prize is 0.5.

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

An information structure is a vector $(\mathbf{p}, \mathbf{q}, \mathbf{r})$ satisfying the constraint that $\mathbf{pq}+(1-\mathbf{p})\mathbf{r} = 0.5$, where the value $\mathbf{p}$ is the probability to receive good news, $\mathbf{q}$ is the probability to win the high prize conditional on receiving good news, and $\mathbf{r}$ is the probability to win the high prize conditional on receiving bad news. Following Nielsen (2020), we impose the restriction that $\mathbf{pq} + (1 - \mathbf{p})\mathbf{r} = 0.5$ to ensure that the prior belief of winning a high prize is equal to 0.5. A general consumption process is shown in Figure 1.

In three separate questions, subjects are asked to select their most preferred information structure from a subset of options listed in Table 5. The options are described as follows.

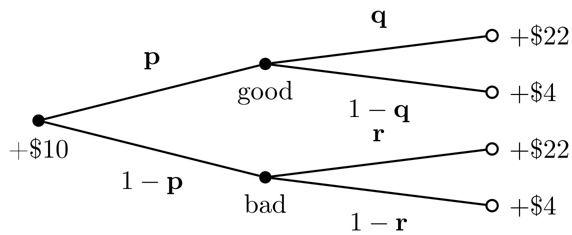


Figure 1: A general consumption process in risk resolution experiment

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

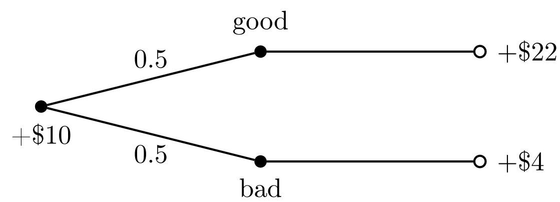
Table 5: Options in risk resolution experiment

Under **One-Shot Early** option, all the risk is resolved in the first stage solely. To see this, if a subject receives good news, she will receive the high prize ($22) for sure ($\mathbf{q} = 1$). Otherwise, she will receive the low prize ($4) for sure ($\mathbf{r} = 0$). Hence, under One-Shot Early option, the consumption process shown in Figure 1 can be simplified into Figure 2(a).

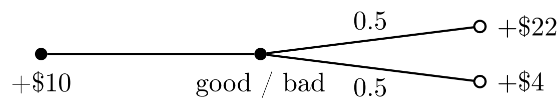
Under the three Gradual options, risk is resolved gradually throughout two periods. Under the **Gradual (non-skewed)** information structure, good news and bad news are equally likely to arrive. Under the **Gradual (positively skewed)** information structure, the subject is more likely to receive bad news ($\mathbf{p} = 0.2$). However, the good news is informative in the sense that the conditional probability of winning the high prize is very high upon receiving good news ($\mathbf{q} = 0.9$). **Gradual (negatively skewed)** implies the opposite: the probability of receiving good news is high ($\mathbf{p} = 0.8$), but the good news is not that informative ($\mathbf{q} = 0.6$) compared to the good news under **Gradual (positively skewed)**. However, if a subject receives bad news, she has 90% chance to get the low prize.

The **One-Shot Late** option means risk is resolved all at once in the second stage. In this case, the news is useless, because regardless of the news she receives, her conditional winning probability remains the same ($\mathbf{q} = \mathbf{r} = 0.5$). Hence, one can simplify the consumption process as is illustrated in Figure 2(b).

It is important to note that the choice of information structure does not affect the ex-



(a) One-Short Early option (E)



(b) One-Short Late option (L)

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

ante probability of winning the high prize, which is equal to 0.5. Also, the choice of the information structure does not change the timing of the payment of the lottery, which takes place in $t = 2$.

There is a 30-minute lag after subjects receive a piece of news at the end of $t = 1$ and before they observe the realization of the lottery in $t = 2$. An inappropriate choice of time lag might cause an instrumental information issue. That means, subjects may *use* this information to adjust their future consumption, which implies that subjects' preference for early resolution might not be intrinsic. To prevent this potential issue, we implement a 30-minute lag between two stages where subjects will be occupied with another activity. To identify preferences for non-instrumental information, 30-minute is considered as a minimum, but substantial, time delay in existing studies (Masatlioglu et al., 2017; Nielsen, 2020).

During the 30-minute lag, subjects participate in Raven's Progressive Matrices. The Raven test is one of the most widely used methods to measure abstract reasoning and analytic intelligence, by non-verbal multiple choice questions. Each question consists of a visual pattern with a missing piece, and the subjects are asked to pick the right element to fill in. Previous studies have found that people with high Raven test scores more accurately predict others' behavior (Burks et al., 2009), and update their beliefs with fewer errors (Charness et al., 2011). In our study, the main purpose of this test is to make subjects stay focused during the time delay. Our experiment consists of two parts and each part has the same 30-minute lag.

3.2 Ambiguity-Resolution-Preference Elicitation

The ambiguity-resolution-preference elicitation experiment is similar to the aforementioned risk-resolution experiment. Subjects are involved in a two-period consumption process. In $t = 1$, subjects receive the advance payment of \$10. In $t = 2$, a lottery is drawn and the payoff is realized. Subjects could earn a "high prize (\$22)" or a "low prize (\$4)" from this lottery. However, subjects do not know the winning probability of the lottery at the beginning of $t = 1$. Instead, subjects are given the following description:

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

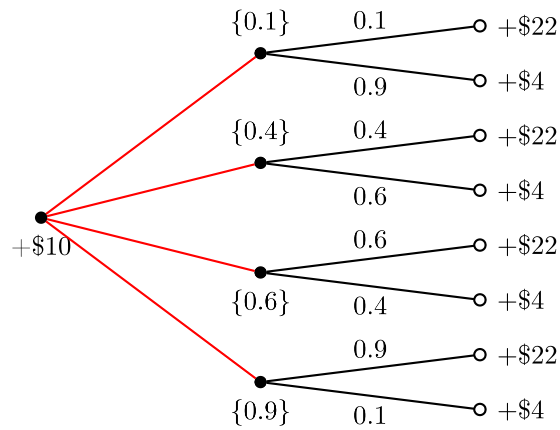
As the proportion of each ball is unknown, at the beginning of $t = 1$, the probability of drawing each ball is unknown. Notice that it is not necessary that the case that 0.1, 0.4, 0.6, and 0.9 are drawn uniformly at random. At the end of $t = 1$, subjects receive a piece of news about the value of $\mathbf{p}$ from the ball they draw. Depending on the information structure, this news provides no information, partial information, or complete information about the winning probability.

An information structure is a partition of the set $\{0.1, 0.4, 0.6, 0.9\}$. In three questions, subjects are asked to choose their most preferred option from a subset of the five alternatives listed in Table 6.

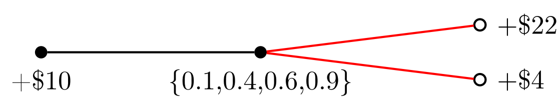
Options	**Information Structure**
One-Shot Early	$\{0.1\}$ $\{0.4\}$ $\{0.6\}$ $\{0.9\}$
Gradual (non-skewed)	$\{0.1, 0.4\}$ $\{0.6, 0.9\}$
Gradual (positively skewed)	$\{0.1, 0.4, 0.6\}$ $\{0.9\}$
Gradual (negatively skewed)	$\{0.1\}$ $\{0.4, 0.6, 0.9\}$
One-Shot Late	$\{0.1, 0.4, 0.6, 0.9\}$

Table 6: Options in ambiguity resolution experiment

One-Shot Early is the fully revealing information structure. If a subject chooses **One-Shot Early**, she will be informed of the exact winning chance **p** at the end of $t = 1$. Hence, ambiguity is resolved in $t = 1$. The consumption process has been summarized in Figure 3(a). The red edges starting from the $t = 1$ node are realized with unknown probability. Conditional on a message that has been received, the black edges starting from the corresponding $t = 2$ node is realized with known probability.



(a) One-Shot Early option (E)

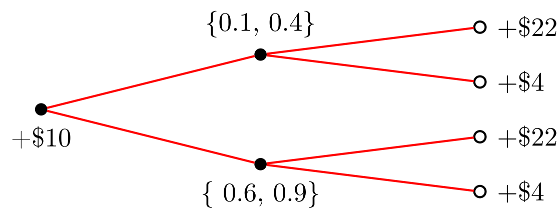


(b) One-Shot Late option (L)

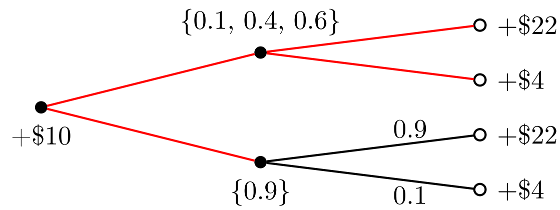
Figure 3: Information structures for early and late ambiguity resolution options

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

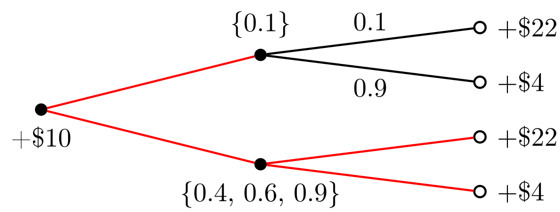
A subject choosing **Gradual (positively skewed)** option will either receive the message $\{0.9\}$ or $\{0.1, 0.4, 0.6\}$ at the end of $t = 1$. Hence, a subject will know if the true winning probability is 0.9 or not. Upon receiving $\{0.1, 0.4, 0.6\}$, the subject knows the winning



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



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



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

Figure 4: Information structures for three gradual ambiguity resolution options

probability in $t = 2$ is 0.1, 0.4, or 0.6, but she is not informed of the likelihood of each realization, and thus ambiguity still exists in $t = 2$. If $\{0.9\}$ is received, then ambiguity is dissolved immediately and only risk exists in $t = 2$. The consumption process is summarized in Figure 4(b).

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

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

The remaining steps are the same as in risk-resolution-preference elicitation experiment. Subjects encounter another set of questions from the Raven test during the 30-minute delay.

After 30 minutes have elapsed, all risk and ambiguity are resolved.

3.3 Choice Set

The risk-resolution-preference/ambiguity-resolution-preference elicitation experiment utilizes four questions to determine subjects' preferences. The first three involve subjects picking their most preferred option from subsets of the five-option sets shown in Table 5/Table 6. The first question, denoted by RR1/AR1, is an unrestricted choice from the risk-resolution-preference/ambiguity-resolution choice set. The second question, denoted by RR2/AR2 removes the option "One-Shot Early" to eliminate the possibility that the subject's choice in the first question was due to a preference for simply one-shot resolution. The third question, denoted by RR3/AR3 removes the option "One-Shot Late." The last question, denoted by RRMPL/ARMPL, aims to measure the strength of preference for early resolution or late resolution by using the multiple price list. Each row presents a mini question that asks the subject to choose from two options "One-Shot Early + \$$x$" and "One-Shot Late + \$$y$." The values of x and y vary among different rows (see Figure 5). For example, if a subject is indifferent to the timing of resolution, she will always choose the option with additional payment. However, if she strictly prefers early resolution, then she might give up some additional payment to choose one-shot early. This multiple price list questions rule out the potential problem that subjects are indifferent between One-Shot Early and One-Shot Late. Table 7 provides a summary of these procedures.

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

Table 7: Choice sets used in the experiment

After finishing all four sections on risk resolution/ambiguity resolution, subjects receive

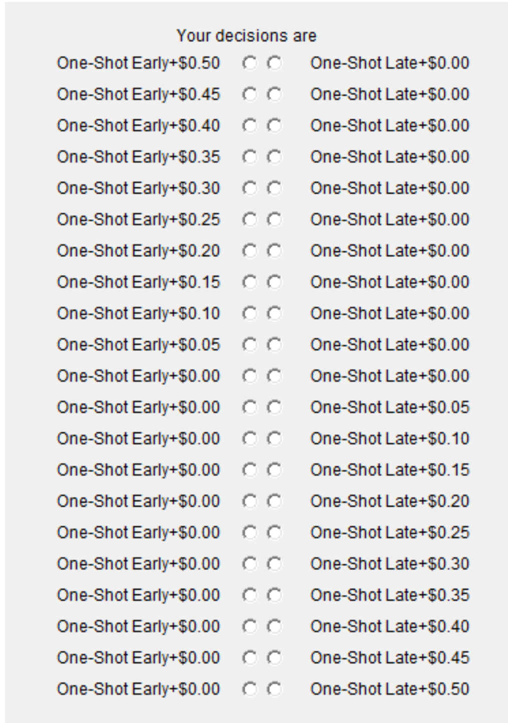


Figure 5: Multiple price list questions

news/messages based on their choices of information structures, conduct Raven's Progressive Matrices test for the next 30 minutes, and then the outcome is revealed. The ordering of the questions in the two elicitation tasks was partially randomized to reduce ordering effects. We randomize the order of decisions in four different ways.

Order 1. RR1, RR2, RR3, RRMPL; AR1, AR2, AR3, ARMPL

Order 2. RR1, RR3, RR2, RRMPL; AR1, AR3, AR2, ARMPL

Order 3. AR1, AR2, AR3, ARMPL; RR1, RR2, RR3, RRMPL

Order 4. AR1, AR3, AR2, ARMPL; RR1, RR3, RR2, RRMPL

3.4 Ellsberg Questions

Subjects also answered two Ellsberg (1961) questions in the ambiguity-resolution-preference elicitation task section. Each subject has a small chance to receive an additional $10, depending on their answers to the questions. There are two reasons why these questions are necessary.

First, we need to elicit each subject's attitude toward ambiguity. Theoretically, ambiguity aversion may or may not affect the preference for early resolution depending on the theoretical model (see Section 2). Hence, to know which model best explains the experimental results, it is essential to elicit the ambiguity attitude.

Another reason is to confirm that subjects are not using subjective expected utility (i.e., Savage, 1954) in the ambiguity-resolution-preference elicitation task. If they use subjective belief in this task, the preference for resolution of ambiguity is no longer different from the preference for risk resolution. To make sure that ambiguity resolution questions and Ellsberg questions do not affect each other, Ellsberg questions are given to subjects after they have completed all ambiguity resolution questions, but before the revelation of the winning probability.

Subjects are given the following statement.

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

Subjects are asked to choose their preferred options between A & B and between C & D. The four options are listed in Table 8.

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

Table 8: Subjective belief formation questions

A subject that prefers A to B and D to C demonstrates a traditional representation of ambiguity aversion. That is, there is no formulation of subjective probabilities that can rationalize this decision. We would thus infer the subject does not use subjective probabilities to make decisions under ambiguity.

3.5 Experimental Procedures

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

Subjects were fully informed about the procedure and the total time of the session at the beginning of the experiment. After the experiment concluded subjects were paid based on one randomly selected decision out of the eight that they made (see Table 7). In addition, subjects have another chance to receive an additional $10 from the "bonus" question. The average payment for each participant was $23.33 including a $10 participation payment.

4 Hypotheses and Predictions

Table 4 provides theoretical predictions of the six models studied in this paper. Each makes a distinct set of predictions about our experiment highlighted by the following hypotheses.

Hypothesis 1. Subjects exhibit no preference for the resolution of risk. The answers provided in RR1–RR3 appear to be random. There is no preference for early or late resolution of risk demonstrated in RRMPL.

A falsification of Hypothesis 1 would falsify the DEU, MEU and KMM models and provide differential support for the EZ, H, and HM models. Previous literature suggests Hypothesis 1 would be falsified.

Hypothesis 2. Subjects will not exhibit ambiguity aversion in the Ellsberg task. Their responses will be in line with the use of subjective probabilities.

A falsification of Hypothesis 2 would falsify the DEU and EZ model and provide differential support for the MEU, H, KMM, and HM models. Previous literature suggests Hypothesis 2 would be falsified.

Hypothesis 3. Subjects will exhibit no preference for the resolution of ambiguity. The answers provided in AR1–AR3 will appear to be random. There is no preference for early or late resolution of ambiguity demonstrated in ARMPL.

A falsification of Hypothesis 3 would falsify the DEU, MEU and H models and provide differential support for the EZ, KMM, and HM models. There is no precedent in previous literature to evaluate Hypothesis 3.

A rejection of all three hypotheses is only consistent with the HM model. That model allows subjects to exhibit preferences for early resolution of risk, preferences for early resolution of ambiguity, and ambiguity aversion.

5 Results

5.1 Risk Resolution and Ambiguity Resolution

Table 9 shows the summary of the choices of risk resolution and ambiguity resolution. Consistent with previous literature, the modal response of subjects is the preference for early resolution of risk (64 of 135, 47.4%). A majority of subjects prefer the early resolution of ambiguity (86 of 135, 63.7%). The most commonly occurring combination of the two preferences is a preference for the early resolution of both risk and ambiguity (57 of 135, 42.2%).

		Ambiguity Resolution			
		Early	Gradual	Late	Total
Risk Resolution	Early	57	6	1	64
	Gradual	22	32	3	57
	Late	7	4	3	14
	Total	86	42	7	135
Chi-square test p-value ≈ 0.000					

Table 9: Choices of risk resolution and ambiguity resolution

The statistical analysis supports that the preferences for risk resolution and ambiguity resolution are not randomly distributed. Both the chi-square test and Fisher's exact test reject the null hypothesis that these classifications are randomly distributed (both p-values <

0.001). Further, the preference for early resolution of ambiguity and early resolution of risk are positively correlated ($\rho \approx 0.5$, p-value < 0.001). The combined result suggests both the existence of and a relationship between these two preferences.

Result 1. The preferences most expressed by subjects in our data are preferences for the early resolution of both risk and ambiguity.

Result 2. Preferences for risk resolution and ambiguity resolution are positively correlated.

The preceding results reject Hypothesis 1, that the preference for risk resolution does not exist. They also reject Hypothesis 3, that preference for ambiguity resolution does not exist.

5.2 Ambiguity Attitudes

Among 135 subjects, 63 (46.7%) were ambiguity averse, 60 (44.4%) were ambiguity neutral, and 12 (8.9%) were ambiguity seeking. A chi-square test rejects the null hypothesis of these results being randomly distributed at standard levels of significance ($p < 0.001$).

Result 3. The ambiguity attitudes most expressed by subjects in our data are ambiguity aversion and ambiguity neutral.

The existence of ambiguity aversion rejects Hypothesis 2. The combination of Results 1–3, falsifies all 3 hypotheses. Hence, among the six models, the HM model is the only model which is consistent with our experimental findings.

5.3 Relationship between Preference for Resolution and Ambiguity Attitude

In the remainder of this section, we further explore the observed relationship between the preference for risk resolution, the preference for ambiguity resolution, and ambiguity attitudes.

Table 10 illustrates the choices of risk resolution and ambiguity resolution conditional on different ambiguity attitudes. As an implication of the HM model, Corollary 1, is composed of three parts:

			Ambiguity Resolution			
			Early	Gradual	Late	Total
Ambiguity Averse	Risk Resolution	Early	28	2	0	30
		Gradual	12	11	1	24
		Late	4	2	3	9
		Total	44	15	4	63
Ambiguity Neutral		Early	24	4	0	28
		Gradual	10	16	2	28
		Late	3	1	0	4
		Total	37	21	2	60
Ambiguity Seeking		Early	5	0	1	6
		Gradual	0	5	0	5
		Late	0	1	0	1
		Total	5	6	1	12

Table 10: Preferences for resolution of risk and ambiguity conditional on ambiguity attitudes

1. If an ambiguity-averse subject prefers early resolution of risk, then she also prefers early resolution of ambiguity;
2. An ambiguity-neutral subject prefers early resolution of risk if and only if she prefers early resolution of ambiguity;
3. If an ambiguity-seeking subject prefers late resolution of risk, then she also prefers late resolution of ambiguity.

Concerning the first prediction, among 30 subjects who are ambiguity averse and prefer early resolution of risk, 28 (93.3%) also prefer early resolution of ambiguity vs. 58 out of 105 (55.2%) for the remaining subjects ($p < 0.001$, Fisher Exact Test). For the second prediction, among 28 subjects who are ambiguity neutral and prefer early resolution of risk, 24 (85.7%) also prefer early resolution of ambiguity vs. 62 of 107 (57.9%) for the remaining subjects ($p \approx 0.007$, Fisher Exact Test). Among 37 subjects who prefer early resolution of ambiguity and are ambiguity neutral, 24 (64.8%) also prefer early resolution of risk compared with 40 of 98 (40.1%) without that classification ($p \approx 0.02$, Fisher Exact Test). For the third prediction, only 1 subject is both ambiguity seeking and prefers the late resolution of risk – that subject prefers the gradual resolution of ambiguity. This last result is admittedly inconsistent with the model, but is based on a single subject decision. Taken together, we can conclude that our results are generally consistent with the HM model.

Result 4. Conditional on different ambiguity attitudes, preferences for risk resolution and ambiguity resolution are correlated in a way consistent with Corollary 1 overall.

We also investigate the marginal effect of ambiguity attitude on ambiguity resolution.

		Ambiguity Resolution				
		Early	Gradual	Late	Total	Early %
Ambiguity Attitude	Averse	44	15	4	63	69.8%
	Neutral	37	21	2	60	61.7%
	Seeking	5	6	1	12	41.7%
	Total	86	42	7	135	63.7%

Table 11: Preferences for resolution of ambiguity depending on ambiguity attitudes

Table 11 shows the preference for ambiguity resolution with different ambiguity attitudes. Among subjects with ambiguity averse and ambiguity neutral, 69.8% and 61.7% of them choose the early option in the ambiguity resolution task. This rate decreases among the group of ambiguity seekers: only 41.7% prefer early resolution of ambiguity.

To validate these observations, we utilize the logistic regression below:

$$P(y = 1) = F(b_1x_1 + b_2x_2), \tag{2}$$

where y is the binary dependent variable that equals 1 when a subject chooses the early option in the ambiguity resolution task, x_1 is a binary variable that equals 1 when a subject chooses the early option in the risk resolution task, and x_2 is a binary variable that equals 1 when a subject exhibits ambiguity seeking behavior on the Ellsberg task.

Marginal Effects on Choosing Early in AR			
	Marginal Effect	Standard Error	p-value
Early in RR	0.436	0.045	0.000
Ambiguity Seeking	−0.256	0.123	0.037

Table 12: The average marginal effects in percentage points

Table 12 shows marginal effects of the logistic regression model.[6] Preferring early res-

[6]The full results of the regression are available in Appendix B.

olution of risk increases the likelihood of preferring early resolution of ambiguity by 43.6 percentage points (p-value < 0.001). Being ambiguity seeking decreases the likelihood of preferring early resolution of ambiguity by 25.6 percentage points (p-value ≈ 0.037).

Result 5. A smaller proportion of ambiguity seeking subjects favor early resolution of ambiguity compared with those who are ambiguity neutral or ambiguity averse.

5.4 Willingness to Pay

If someone is indifferent between early and late resolution, the switching point of the multiple price list questions will be 10 or 11. That means she only chooses the option with the additional payment and she does not want to give up any amount of money for any option. If someone prefers the early (late) resolution and is willing to pay some amount of money for her preferred option, the switching point will be greater (smaller) than 11 (10). Table 13 provides the average switching points of each group.[7]

	Risk Resolution		Ambiguity Resolution	
Group	Number	Average Switching Point	Number	Average Switching Point
Early	54	11.7	81	12.6
Gradual	47	10.9	32	10.9
Late	13	8.3	5	9.4
Total	114	10.9	118	12.0

Table 13: The average switching points of the multiple price list questions

The values of the switching points are correlated to the preference for the resolution of ambiguity. In both risk resolution and ambiguity resolution tasks, the average switching point of subjects who chose the gradual option is 10.9. It implies that on average, they were indifferent between early or late resolution of ambiguity.

The average switching point of the subjects who prefer early resolution of risk and ambiguity are 11.7 and 12.6, respectively. That means a large portion of them gave up some amount of payment to resolve the ambiguity earlier. Similarly, subjects who chose late resolution gave up the additional payment for the late resolution, considering the average

[7] Among 135 subjects, 21 (15.6%) and 17 (12.6%) exhibited multiple switching behavior in risk-resolution-preference elicitation questions and ambiguity-resolution-preference elicitation questions. We only use subjects who has a single switching point (114 (84.4%) and 118 (87.4%)) for our analysis.

switching points 8.3 and 9.4. The Cuzick non-parametric trend test across ordered groups reveals these differences are significant for both risk-resolution-preference and ambiguity-resolution-preference categorizations. (p-values < 0.001 in both cases.)

Result 6. In both risk resolution and ambiguity resolution, subjects who prefer early or late resolution have a significantly greater willingness to pay for that respective resolution than subjects who choose gradual options.

6 Conclusion

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

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

We review six representative models of recursive utility that are widely used in the macroeconomics and finance literature. Most of these theoretical models of recursive utility, including the EZ model and the KMM model, are not consistent with these results. The totality of our findings is consistent with only one model, the generalized recursive smooth ambiguity models of Hayashi and Miao (2011).

References

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

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

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

Backus, D. K. and Smith, G. W. (1993). Consumption and real exchange rates in dynamic economies with non-traded goods. *Journal of International Economics*, 35(3-4):297–316.

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

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

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

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

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

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

Colacito, R. and Croce, M. M. (2013). International asset pricing with recursive preferences. *The Journal of Finance*, 68(6):2651–2686.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Kim, H., Lee, H. I., Park, J. Y., and Yeo, H. (2009). Macroeconomic uncertainty and asset prices: A stochastic volatility model. In *AFA 2010 Atlanta Meetings Paper*.

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

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

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

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

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

Lee, E. (2019). Asset prices with stochastic volatilities and a UIP puzzle. *International Review of Economics & Finance*, 64:41–61.

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

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

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

Masatlioglu, Y., Orhun, A. Y., and Raymond, C. (2017). Intrinsic information preferences and skewness. *Working Paper*.

Mehra, R. and Prescott, E. C. (1985). The equity premium: A puzzle. *Journal of monetary Economics*, 15(2):145–161.

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

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

Savage, L. J. (1954). The foundations of statistics. *New-York: Wiley*, page 294.

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

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

Trojani, F. and Vanini, P. (2002). A note on robustness in merton's model of intertemporal consumption and portfolio choice. *Journal of Economic Dynamics and Control*, 26(3):423–435.

Trojani, F. and Vanini, P. (2004). Robustness and ambiguity aversion in general equilibrium. *Review of Finance*, 8(2):279–324.

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

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

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

A Appendix

A.1 Construction of $P[\mathcal{Q}](Q)$

Fix any bijection $\xi : Q \to S_1$. Denote elements of $\mathcal{Q}$ by Q^1, Q^2,..., Q^K. The collection of sets $\{S_1^k \equiv \xi(Q^k)\}_{k=1,...,K}$ forms a partition of S_1. For each $k \in \{1, ..., K\}$ and $q \in Q^k$, define a joint distribution $p[\mathcal{Q}, q] \in \Delta(S_1 \times S_2)$ by

$$p[\mathcal{Q}, q](s_1, s_2) = \begin{cases} \dfrac{q(s_2)}{|S_1^k|} & \text{for } s_1 \in S_1^k \text{ and } s_2 \in S_2, \\ 0 & \text{for } s_1 \notin S_1^k \text{ and } s_2 \in S_2. \end{cases}$$

Notice that given any $s_1 \in S_1$ that occurs with positive probability under $p[\mathcal{Q}, q]$, the updated belief of $p[\mathcal{Q}, q]$ over S_2 is equal to q. Also, notice that all period-1 states that occur with positive probability under $p[\mathcal{Q}, q]$ occur with equal probability $\frac{1}{|S_1^k|}$, and the collection of all such period-1 states is equal to S_1^k.

It is easy to see that the set of joint distributions $P[\mathcal{Q}](Q) \equiv \{p[\mathcal{Q}, q] : q \in Q\}$ has a one-to-one relationship with the set Q.

Let μ denote any second-order belief over Q. Now consider a second-order belief $\tilde{\mu}$ over $P[\mathcal{Q}](Q)$. In order for the marginal distribution of $\tilde{\mu}$ over Q to be consistent with μ, i.e., $\tilde{\mu}(q) = \mu(q)$ for all $q \in Q$, we must have $\tilde{\mu}(p[\mathcal{Q}, q]) = \mu(q)$ for all $q \in Q$. This is due to the one-to-one correspondence between $P[\mathcal{Q}](Q)$ and $\mathcal{Q}$. For any S_1^k, upon receiving any element $s_1 \in S_1^k$, the posterior belief of each $q \notin Q^k$ is equal to zero, and the posterior belief of each $q \in Q^k$ is given by

$$\begin{aligned}\frac{\sum_{p\in P[\mathcal{Q}](Q)\, s.t.\, p(\cdot|s_1)=q} \tilde{\mu}(p)\cdot p(s_1)}{\sum_{p\in P[\mathcal{Q}](Q)} \tilde{\mu}(p)\cdot p(s_1)} =& \frac{\tilde{\mu}(p[\mathcal{Q},q])\cdot p[\mathcal{Q},q](s_1)}{\sum_{\tilde{q}\in Q^k} \tilde{\mu}(p[\mathcal{Q},\tilde{q}])\cdot p[\mathcal{Q},\tilde{q}](s_1)} \\ =& \frac{\mu(q)\cdot \frac{1}{|S_1^k|}}{\sum_{\tilde{q}\in Q^k} \mu(\tilde{q})\cdot \frac{1}{|S_1^k|}} = \mu(q|Q^k),\end{aligned}$$

which is independent across all $s_1 \in S_1^k$. Hence, elements in S_1^k can be viewed as in an equivalent class, informing the subject of the set of period-2 distributions Q^k.

A.2 Omitted Proofs

Proof of Proposition 1. Define $w(x) \equiv [h_1^\rho + \beta x^{\frac{\rho}{\eta}}]^{\frac{\eta}{\rho}}$. It is easy to verify that $w(x)$ is strictly convex in x (resp. linear, or strictly concave) if $\frac{\rho}{\eta} > 1$ (resp. $= 1$, or < 1).

Fix a finite set $Q \subseteq \Delta(S_2)$ with $|S_1| = |Q|$, $h \in H$, second-order belief $\mu \in \Delta(Q)$, and any partition $\mathcal{Q}$ of Q. List all elements of $\mathcal{Q}$ by Q^1, Q^2, ..., Q^K. Recall that the construction of $P[\mathcal{Q}](Q)$ is such that S_1 can be divided into K equivalent classes: upon receiving $s_1 \in S_1^k$, the subject knows that the set of possible period-2 distributions is Q^k. Then the period-2 certainty equivalent is given by $\big(\sum_{q\in Q^k} I_2^\eta[q](h)\mu(q|Q^k)\big)^{\frac{1}{\eta}}$, where $I_2[q](h)$ is defined in expression (1). The ex-ante certainty equivalent of h is

$$\begin{aligned}I_1\big[P[\mathcal{Q}](Q)\big](h) =& \Bigg(\sum_{Q^k\in\mathcal{Q}} \Big(h_1^\rho + \beta\big(\sum_{q\in Q^k} I_2^\eta[q](h)\mu(q|Q^k)\big)^{\frac{\rho}{\eta}}\Big)^{\frac{\eta}{\rho}} \mu(Q^k)\Bigg)^{\frac{1}{\eta}} \\ =& \mathbb{E}^{\frac{1}{\eta}}_{Q^k\in\mathcal{Q}}\Big[w\big(\mathbb{E}_{q\in Q^k}\big[I_2^\eta[q](h)|Q^k\big]\big)\Big].\end{aligned}$$

Under the set of joint distributions $P[\mathcal{Q}^E](Q)$ representing early resolution of ambiguity, each element of $\mathcal{Q}^E$ is a singleton. Hence, the ex-ante certainty equivalent of h is given by

$$I_1\big[P[\mathcal{Q}^E](Q)\big](h) = \mathbb{E}^{\frac{1}{\eta}}_{q\in Q}\big[w\big(I_2^\eta[q](h)\big)\big] = \mathbb{E}^{\frac{1}{\eta}}_{Q^k\in\mathcal{Q}}\Big[\mathbb{E}_{q\in Q^k}\big[w\big(I_2^\eta[q](h)\big)|Q^k\big]\Big],$$

where the second equality uses the law of iterated expectations.

Under the set of joint distributions $P[\mathcal{Q}^L](Q)$ representing late resolution of ambiguity, the only element of $\mathcal{Q}^L$ is Q. Hence, the ex-ante certainty equivalent of h is given by

$$I_1\big[P[\mathcal{Q}^L](Q)\big](h) = w^{\frac{1}{\eta}}\big(\mathbb{E}_{q\in Q}\big[I_2^\eta[q](h)\big]\big) = w^{\frac{1}{\eta}}\Big(\mathbb{E}_{Q^k\in\mathcal{Q}}\big[\mathbb{E}_{q\in Q^k}\big[I_2^\eta[q](h)\big|Q^k\big]\big]\Big).$$

When $\rho > \eta$ (i.e., $\eta > 0$ and $\frac{\rho}{\eta} > 1$, or $\eta < 0$ and $\frac{\rho}{\eta} < 1$), by applying Jensen's inequality, we know that $I_1\big[P[\mathcal{Q}^E](Q)\big](h) \geq I_1\big[P[\mathcal{Q}^G](Q)\big](h) \geq I_1\big[P[\mathcal{Q}^L](Q)\big](h)$ for all $h \in H$, finite $Q \subseteq \Delta(S_2)$ with $|S_1| = |Q|$, partition $\mathcal{Q}^G$ of Q that is neither the finest nor coarsest one, and $\mu \in \Delta(Q)$; also, the strict inequalities hold for some $h \in H$, $Q \subseteq \Delta(S_2)$, $\mathcal{Q}^G$, and $\mu \in \Delta(Q)$ due to the strict convexity of w when $\eta > 0$ or the strict concavity of w when $\eta < 0$. Hence, the subject prefers early resolution of ambiguity.

Similarly, when $\rho < \eta$ (i.e., $\eta > 0$ and $\frac{\rho}{\eta} < 1$, or $\eta < 0$ and $\frac{\rho}{\eta} > 1$), the subject prefers late resolution of ambiguity; when $\rho = \eta$ (i.e., $\frac{\rho}{\eta} = 1$), the subject is indifferent towards the timing of ambiguity resolution. □

Proof of Proposition 2. Fix a finite set $Q \subseteq \Delta(S_2)$ with $|S_1| = |Q|$, $h \in H$, and a set of joint distributions $P[\mathcal{Q}^G](Q)$ representing gradual ambiguity resolution. The ex-ante certainty equivalents of $h \in H$ under $P[\mathcal{Q}^E](Q)$, $P[\mathcal{Q}^G](Q)$, and $P[\mathcal{Q}^L](Q)$ are as follows:

$$\begin{aligned}
I_1\big[P[\mathcal{Q}^E](Q)\big](h) &= \min_{q\in Q}\big(h_1^\rho + \beta I_2^\rho[q](h)\big)^{\frac{1}{\rho}} = \min_{q\in Q} W(h_1, I_2[q](h)),\\
I_1\big[P[\mathcal{Q}^G](Q)\big](h) &= \min_{Q^k\in\mathcal{Q}^G}\big(h_1^\rho + \beta\min_{q\in Q^k} I_2^\rho[q](h)\big)^{\frac{1}{\rho}} = \min_{Q^k\in\mathcal{Q}^G} W\big(h_1, \min_{q\in Q^k} I_2[q](h)\big),\\
I_1\big[P[\mathcal{Q}^L](Q)\big](h) &= \Big(h_1^\rho + \beta\big(\min_{q\in Q} I_2[q](h)\big)^\rho\Big)^{\frac{1}{\rho}} = W\big(h_1, \min_{q\in Q} I_2[q](h)\big),
\end{aligned}$$

where $I_2[q](h)$ is defined in expression (1). Since $W(x,y)$ is increasing in y, the three expressions are equal. Hence, a subject is indifferent towards the timing of ambiguity resolution. □

B The Result of Logistic Regression

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

Table A.1: The result of logistic regression model

Tables A.1 shows the results of the logistic regression shown in equation (2) (pseudo $R^2 \approx 0.2310$).

C Consistency

To check if our results are robust, we divide the population into subjects who made consistent choices and subjects who did not.

If someone's choice violates the weak axiom of revealed preference (WARP) even once, such as choosing One-Shot Early in RR1 and One-Shot Late in RR2, we consider her choice is inconsistent. 77% of the subjects show consistency in both the risk-resolution-preference elicitation part and the ambiguity-resolution-preference elicitation part.

Choices	Number	Percentage
Consistent	104	77%
Inconsistent	31	23%
Total	105	100%

Table A.2: Consistency of choices

We ran the same logistic regression model in equation (2), but only with consistent subjects this time.

Tables A.3 and A.4 show that the results are basically the same when using the whole population or the subjects whose choices were consistent.

	Coefficients	Standard Error	p-value
Early in RR	2.67	0.59	0.000
Ambiguity Seeking	−1.53	0.80	0.057
LR chi-square test p-value = 0.000			

Table A.3: The result of logistic regression model with consistent subjects

Marginal Effects on Choosing Early in AR			
	Marginal Effect	Standard Error	p-value
Early in RR	0.471	0.060	0.000
Ambiguity Seeking	−0.269	0.134	0.045

Table A.4: The average marginal effects in percentage points with consistent subjects

D Investigation of Order Effects across Treatments

We used 4 different orders to see whether there exists an order effect. Table A.5 shows the results.

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

Table A.5: Key results with different orders

Percentages in Table A.5 represent proportions of subjects who revealed ambiguity aversion or preference for early resolution of risk and ambiguity. The p-value of F-test provides the evidence that there is no order effect on the timing of resolution.

E Further Detail on Skewness Preferences

Tables A.6 and A.7 show the preferences of subjects who chose gradual options.

63.2% and 71.4% of subjects who chose gradual options in risk and ambiguity resolution tasks prefer non-skewed gradual resolution. In both cases, positively skewed revelations are least preferred. This result contrasts with the findings of Masatlioglu et al. (2017), suggesting

Group	Number	Percentage
Non-Skewed	36	63.2%
Positively Skewed	6	10.5%
Negatively Skewed	15	26.3%
Total	57	100.0%

Table A.6: Subjects who chose gradual options in risk resolution task

Group	Number	Percentage
Non-Skewed	30	71.4%
Positively Skewed	4	9.5%
Negatively Skewed	8	19.1%
Total	42	100.0%

Table A.7: Subjects who chose gradual options in ambiguity resolution task

people prefer positively skewed information over negatively skewed information when they are equally informative. It leaves open questions for further research.