Preferences for the Resolution of Risk and Ambiguity*

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Abstract

By definition, uncertainty includes both risk and ambiguity. Yet, all previous experimental studies investigating uncertainty resolution have only elicited preferences over uncertainty resolution in the objective domain of risk. We provide the first experimental examination of uncertainty resolution with respect to subjective uncertainty, i.e., ambiguity, in addition to risk. We find that most subjects exhibit a preference for early resolution of both risk and ambiguity and these preferences are positively correlated. Ambiguity-averse subjects who prefer early resolution of risk are also likely to prefer early resolution of ambiguity. Also, being ambiguity-loving decreases the probability of preferring early resolution of ambiguity. The paper reviews six representative recursive utility models used in the macroeconomic and finance literature and only the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) can plausibly explain these experimental findings. More generally, our results imply that examining uncertainty resolution only in the domain of risk produces a biased picture of an individual's overall preferences on uncertainty resolution.

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1 Introduction

Models of generalized recursive utility relax the assumption—often found in discounted expected utility model—of a direct linkage between preferences of uncertainty and intertemporal substitutability (Kreps and Porteus, 1978; Epstein and Zin, 1989; Weil, 1990). These models when applied to the macroeconomy explain a wide variety of anomalies regarding asset prices, trade, and inflation (see Section 1.1 for a review of related literature). An added implication of these models is that they necessarily 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 (see Brown and Kim, 2013, for a discussion). Experimental work is generally divided and elicitation of these preferences may be complicated by other factors (see next section and Nielsen, 2020).

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. This paper provides the first experimental elicitation of preferences of uncertainty resolution in the subjective domain as well as in the objective domain. We elicit the preference of ambiguity resolution and the preference of risk resolution, and examine their relation with ambiguity attitude.

The examination this paper provides is important for two separate reasons. The first concerns measurement and identification. Until this study, there has been no experimental elicitation of individuals' preferences over the resolution of ambiguity. All previous 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.

A second issue 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. At a basic level, certain models of generalized recursive utility can only account for uncertainty resolution in the form of risk resolution, some can only account for uncertainty resolution in the form of ambiguity resolution, and some implicitly imply that the preferences for risk resolution and ambiguous resolution are identical. Trivially, conclusions drawn about the validity of such models must necessarily include an investigation of both risk resolution and ambiguity resolution. More complex relations exist as well. After eliciting the preferences for risk resolution and ambiguity resolution through our laboratory experiments and studying their relation, we discover that first, the preference for early resolution of ambiguity exists. Second, there is a tight association between the preference for risk resolution and ambiguity resolution. Lastly, the attitude toward ambiguity affects the relationship. In the paper, we review six representative recursive utility models that have been axiomatized by decision theorists and adopted in the macroeconomics and finance literature. A deductive examination reveals that only the generalized recursive smooth ambiguity model of Hayashi and Miao (2011), which allows for a three-way separation between risk aversion, ambiguity aversion, and intertemporal substitution, is consistent with our results. This observation highlights the importance of separating the three parameters in applied works.

By using a non-linear time aggregator, Kreps and Porteus (1978) and Epstein and Zin (1989) provide the theoretical backgrounds for a preference on the timing of uncertainty resolution in the objective uncertainty domain. Adopting this model, Epstein et al. (2014) give a quantitative assessment of time premium, i.e., how much an agent is willing to pay to resolve long-run risk. While this model can explain a preference for risk resolution—and we show that their model can accommodate strict preferences for ambiguity resolution if proper use of subjective belief is allowed—it cannot capture the observed ambiguity aversion. Strzalecki (2013) has the first theoretical study on uncertainty resolution where ambiguity is considered; he identifies a large group of models with strict preferences for uncertainty resolution. In addition, Li (2020) characterizes preferences that display aversion to partial uncertainty resolution. However, since Strzalecki (2013) and Li (2020) focus on the subjective domain of uncertainty, the models examined by them can explain strict preferences for ambiguity resolution, but not risk. In this paper, we explicitly model both the objective and subjective domains of uncertainty resolution and elicit the preferences in experiments. 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 used in the macro and finance literature: all have the constant relative risk aversion forms and can be described by the parameter of risk aversion, the parameter of ambiguity aversion, and intertemporal rate of substitution. Among these models, we find that only the generalized recursive smooth ambiguity model of Hayashi and Miao (2011) can accommodate both the preferences for early resolution of risk and ambiguity, as well as non-neutral ambiguity attitude, and is consistent with the entirety of our experimental findings.

Finally, we note several key features about our experimental design. Following the pioneering approach of Nielsen (2020), all information in our study is non-instrumental. Our experimental environment does not allow participants to strategically use the information they have. Thus, we could elicit pure preference over the temporal resolution and these are not confounded by other concerns. 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. Hence, participants express preferences over larger choice sets.

This paper proceeds as follows. The next section surveys the related literature, covering experimental elicitations of uncertainty resolution, the various theories of recursive preferences, and the applications of these theories to explain existing macroeconomic and financial anomalies. 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, specifically, the elicitation of risk-resolution, ambiguity-resolution, and ambiguity aversion preferences. Section 4 provides hypotheses to test the six theoretical models. Section 5 provides results and Section 6 concludes.

1.1 Related Literature

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 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). That is, learning the information early may pose an additional benefit to an individual outside of these preferences. In both categories, the literature often, but not always, finds a preference for the early resolution of uncertainty.

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

Our experiment follows the general structure of Nielsen's, eliciting subjects' preference over uncertainty with non-instrumental information in multi-stage lottery 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.

Preference over uncertainty resolution is an implication of theoretical models that do not assume a direct link between the parameter of risk aversion, the parameter of ambiguity aversion, and the intertemporal elasticity of substitution. Agents with the discounted expected utility do not separate these parameters and do not have an intrinsic preference for the timing of uncertainty resolution. By allowing a separation between the parameter of risk aversion and the intertemporal elasticity of substitution, generalized recursive models of Kreps and Porteus (1978), Epstein and Zin (1989), and Weil (1990), all accommodating non-linear time aggregators, have been shown to capture strict preferences towards the timing of risk resolution.

By focusing on the subjective uncertainty exclusively, Strzalecki (2013) examines the preferences towards the timing of uncertainty resolution for a wide group of models under ambiguity, all with linear time aggregators. He shows that the recursive maxmin expected utility model of Gilboa and Schmeidler (1989) and Epstein and Schneider (2003) is the only model exhibiting indifference towards the timing of uncertainty resolution over the subjective domain; the smooth ambiguity aversion model of Klibanoff et al. (2005) and Klibanoff et al. (2009), among with many other models, can accommodate non-indifference towards uncertainty resolution over the subjective domain.

More generally, there have been other axiomatized models incorporating both non-linear time aggregators and non-neutral ambiguity attitudes: the model of Hayashi (2005) separates between the parameter of risk aversion and the intertemporal elasticity of substitution, assuming an infinite degree of ambiguity aversion; Hayashi and Miao (2011) allow a three-way separation between the parameter of risk aversion, the parameter of ambiguity aversion, and the intertemporal elasticity of substitution. These models are described in Section 2. The current paper tests the implications of them and finds that only the model of Hayashi and Miao (2011) is consistent with our experimental results.

Beginning with the pioneering work of Bansal and Yaron (2004), scholars have utilized models of generalized recursive utility to better explain previous anomalies found in the macroeconomic and finance literature quantitatively. One important application of these models is to explain the equity premium puzzle posed by Mehra and Prescott (1985) under the discounted utility model. For example, Bansal and Yaron (2004), Kim et al. (2009), and Epstein et al. (2014) adopt representative agent models with Epstein and Zin (1989) preferences; Collard et al. (2018) adopt the recursive smooth ambiguity aversion model introduced by Klibanoff et al. (2009); Trojani and Vanini (2002, 2004) adopt a continuous time version of the recursive maxmin expected utility model of Epstein and Schneider (2003);

Drechsler (2013) and Jeong et al. (2015) adopt a recursive maxmin expected utility model with separate parameters for risk aversion and intertemporal substitution, which is essentially the model axiomatized by Hayashi (2005); Ju and Miao (2012) adopt the generalized recursive smooth ambiguity model axiomatized by Hayashi and Miao (2011). In spite of many differences in modeling details, these calibrated models are able to explain the equity premium, the risk-free rate, and/or the volatility puzzles among others, to different degrees. Relatedly, Eraker et al. (2016) study a two-good economy where the representative agent has Epstein and Zin preferences; their model can explain the differential effects of inflation on durable-good-producing and non-durable-good-producing firms' asset prices as well as the volatilities and correlations within bond and equity returns.

In applications within international economics, Colacito and Croce (2013) develop a two-country two-good general equilibrium model where agents have Epstein and Zin preferences. They are able to explain two well-known anomalies involving currency exchange rates, the forward premium anomaly and the Backus and Smith (1993) anomaly. Additionally, Lee (2019) develops a model with Epstein and Zin preferences which can explain the uncovered interest rate parity (UIP) puzzle, provided agents have a preference for the early resolution of uncertainty.

We see our paper as complementary to this literature. The reason scholars began using generalized recursive utility models in representative agent models was that the best-fitting discounted expected utility models required unrealistic parameter values. For instance, to explain the equity premium puzzle, the risk-aversion parameter would need to be very large. While this 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 introspection or anecdotal observation. The aforementioned generalized recursive models have different implications on an individual's preference on uncertainty resolution. Recent experimental data shows this is a reasonable implication of a model, but only in the domain of risk. Since the implications of these generalized recursive utility models include preferences over both risk and ambiguity resolution, this paper investigates the full reasonableness of these theoretical implications.[1]

[1] In econometric terms, it is now apparent that early attempts to calibrate models of asset returns using

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 predominating in applied works, the generalized recursive 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 intertemporal rate of substitution, which make them particularly tractable in the macroeconomics and finance literature.[2]

These models differ from each other along two dimensions. First, they take two different 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

discounted expected utility were misspecified. The unrealistically high levels of risk aversion were actually capturing other preferences not considered by the model (e.g., separation of parameters of uncertainty aversion and/or intertemporal rate of substitution), once models began to account for these elements, the risk parameter was reduced to more reasonable levels. Since we have less intuitive understanding of preferences for uncertainty resolution, experiments like these are important to determine a general range of preferences to ensure these newer estimates using recursive models are not misspecified.

[2]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 preference for risk resolution. We hence only review the smooth ambiguity model as a representative one among this class.

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.

		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

For simplicity, we focus on two-period problems. Let 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 compact set of such joint distributions representing ambiguity. 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.

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

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

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

In the KMM model, a subject has a subjective probability measure (second-order belief) over potential probability measures (first-order beliefs) and does not reduce compound lotteries.[3] The continuation utility conditional on s_1 being observed in period 1 is given by

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

When $\eta > \alpha$, i.e., when v is strictly less concave than u, the subject is ambiguity loving. 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.

[3] See Halevy (2007) for an experimental study on the relationship between ambiguity attitude and the axiom of reduction of compound lotteries.

In the EZ model,

$$I_2(h|s_1) = u^{-1}(\int_{s_2\in S_2} u(h_2(s_2))dp(s_2|s_1)) = [\int_{s_2\in S_2} h_2^{\alpha}(s_2)dp(s_2|s_1)]^{\frac{1}{\alpha}}. \quad (1)$$

In the H model,

$$I_2(h|s_1) = \min_{p\in P} u^{-1}(\int_{s_2\in S_2} u(h_2(s_2))dp(s_2|s_1)) = \min_{p\in P}[\int_{s_2\in S_2} h_2^{\alpha}(s_2)dp(s_2|s_1)]^{\frac{1}{\alpha}}.$$

In the HM model,

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

We remark that the HM model is a general model. 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 incorporates the DEU model and can approximate the MEU model. Hence, in later sections, we mostly rely on the certainty equivalent expression $I_1(h|s_1)$ adopted by the HM model rather than the continuation utility expression $V_2(h|s_1)$.

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 $I_1[p](h)$ and $I_1[P](h)$ denote the ex-ante certainty equivalent of consumption process h before period-1 state is realized. In the remaining sections, we assume for simplicity that S_1 and S_2 are both finite sets.

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. Consider a distribution over S_2, $q = (0.5, 0.5)$. In Table 2, under each of the three joint distributions, the marginal distribution over S_2 is given by q.

	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 timing of risk resolution

Thus, from an ex-ante perspective, all three joint distributions are equally risky about the period-2 state. 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 signal s_1 is neither fully uninformative nor fully informative about which s_2 will be realized, and thus partially resolves period-2 risk.

Definition 1.

1. A subject prefers early resolution of risk if $\arg max_{p \in P(q)} I_1[p](h) \supseteq P^E(q)$ for all $h \in H$ and $q \in \Delta(S_2)$, and $\arg max_{p \in P(q)} I_1[p](h) = P^E(q)$ for some $h \in H$ and $q \in \Delta(S_2)$.

2. A subject prefers late resolution of risk if $\arg max_{p \in P(q)} I_1[p](h) \supseteq P^L(q)$ for all $h \in H$ and $q \in \Delta(S_2)$, and $\arg max_{p \in P(q)} I_1[p](h) = P^L(q)$ for some $h \in H$ and $q \in \Delta(S_2)$.

3. 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 joint distributions $p, p' \in P(q)$.

According to the first part of the definition, a subject exhibits a preference for early resolution of risk, if (1) for any consumption process h, among all joint distributions over

$S_1 \times S_2$ with marginal distribution over S_2 equal to q, the ones that resolve risk early can attain the highest certainty equivalent level, and (2) there exists a consumption process for which *only* those resolve risk early attain the highest level. The second part of the definition can be interpreted similarly. According to the third part, a subject is indifferent towards the timing of risk resolution, if the ex-ante certainty equivalent levels of a consumption process are identical across all joint distributions with the same marginal distribution over S_2.

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 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 to the timing of risk resolution in the MEU/KMM/DEU model.

2.2 Ambiguity Resolution

Let Q be a finite set of distributions over S_2 with $|S_1| \geq |Q|$ representing the set of all possible period-2 distributions. Since all other five models are either special cases of the HM model or can be approximated by the HM model, we assume that ex-ante, there is a subjective second-order belief over Q, denoted by μ.

We denote by $P(Q)$ a finite set of joint distributions over $S_1 \times S_2$ such that the set of all posterior beliefs over S_2, $\{p(\cdot|s_1) \in \Delta(S_2)\}_{s_1 \in S_1}$, is equal to Q. The collection of all such sets $P(Q)$ is denoted by $\mathcal{P}(Q)$. Furthermore, we let $\tilde{\mu}[P(Q), \mu]$ be a full-support distribution over $P(Q)$ such that for all $q \in Q$,

$$\mu(q) = \sum_{s_1 \in S_1} \sum_{p \in P(Q)\, s.t.\, p(\cdot|s_1)=q} \tilde{\mu}[P(Q), \mu](p) \cdot p(s_1). \tag{2}$$

Namely, the second-order belief over $P(Q)$, when projected to Q, is consistent with μ. For convenience, we call such a second-order belief over $P(Q)$ a *consistent* second-order belief and denote a generic consistent second-order belief by $\tilde{\mu}[P(Q), \mu]$. The posterior belief that $q \in Q$ is the true period-2 distribution, upon receiving $s_1 \in S_1$, is denoted by

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

We say $P^E(Q) \in \mathcal{P}(Q)$ resolves ambiguity early, if $\tilde{\mu}[P^E(Q), \mu](q|s_1) \in \{0, 1\}$ for each $\mu \in \Delta(Q)$, consistent second-order belief $\tilde{\mu}[P^E(Q), \mu]$, $q \in Q$, and $s_1 \in S_1$. Namely, early resolution of ambiguity requires that observing s_1 specifies a unique $q \in Q$ that can be the true distribution in period 2. We say $P^L(Q) \in \mathcal{P}(Q)$ resolves ambiguity late, if $\tilde{\mu}[P^L(Q), \mu](q|s_1) = \mu(q)$ for each $\mu \in \Delta(Q)$, consistent second-order belief $\tilde{\mu}[P^L(Q), \mu]$, $q \in Q$, and $s_1 \in S_1$. Namely, late resolution of ambiguity requires that observing s_1 does not provide any additional information on the likelihood of $q \in Q$ being the true distribution in period 2. Any other element $P^G(Q) \in \mathcal{P}(Q)$ is said to resolve ambiguity gradually. Let $\mathcal{P}^E(Q)$, $\mathcal{P}^G(Q)$, and $\mathcal{P}^L(Q)$ be the collection of all $P^E(Q)$, $P^G(Q)$, and $P^L(Q)$ respectively.

As an illustration, we look at an example.

Example 2. Let $Q = \{q^1 = (0.1, 0.9), q^2 = (0.4, 0.6), q^3 = (0.6, 0.4), q^4 = (0.9, 0.1)\}$. Table 3 shows three sets of joint distributions over $S_1 \times S_2$.

For any subjective second-order distribution $\mu \in \Delta(Q)$, the only consistent second-order belief over $P^E(Q)$ must satisfies $\tilde{\mu}[P^E(Q), \mu](p^k) = \mu(q^k)$ for $k \in \{1, 2, 3, 4\}$ where p^k refers to the k-th joint distribution in the set $P^E(Q)$ in Table 3. Similar claims can be made for $P^G(Q)$ and $P^L(Q)$.

In Table 3(a), when s_1 is realized, there is only one joint distribution in $P^E(Q)$ generating s_1 with positive probability, and thus the subject knows the true distribution over S_2 immediately, i.e., ambiguity is resolved early. In Table 3(c), knowing period-1 state s_1 does not give any additional information on which joint distribution or period-2 distribution is true, because for each $q^k \in Q$, the posterior belief for q^k to be the correct period-2 distribution

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

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

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

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

(a) $P^E(Q)$

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

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

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

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

(b) $P^G(Q)$

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

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

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

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

(c) $P^L(Q)$

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

given s_1 is equal to

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

which is independent of s_1. In Table 3(b), upon receiving any $s_1 \in \{s_1^1, s_1^2\}$, the true period-2 distribution q must be in $\{q^1, q^2\}$. Moreover, the posterior belief that q^1 is the correct period-2 distribution given s_1 is equal to

$$\frac{\sum_{p \in P^G(Q)\, s.t.\, p(\cdot|s_1)=q} \tilde{\mu}[P^G(Q),\mu](p)\cdot p(s_1)}{\sum_{p\in P^G(Q)} \tilde{\mu}[P^G(Q),\mu](p)\cdot p(s_1)} = \frac{\mu(q^1)\cdot 0.5}{(\mu(q^1)+\mu(q^2))\cdot 0.5} = \mu(q^1|q^1 \text{ or } q^2),$$

which is not equal to 0, 1, or $\mu(q^1)$ (when μ has full support).

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

Definition 2.
1. A subject prefers early resolution of ambiguity if $I_1[P(Q)](h) \geq I_1[P'(Q)](h)$ for all finite set $Q \subseteq \Delta(S_2)$, $h \in H$, $P(Q) \in \mathcal{P}^E(Q)$, $P'(Q) \in \mathcal{P}(Q) \setminus \mathcal{P}^E(Q)$, $\mu \in \Delta(Q)$, $\tilde{\mu}[P(Q), \mu]$ and $\tilde{\mu}[P'(Q), \mu]$, and the strict inequality holds for some Q, h, $P(Q)$, $P'(Q)$, μ, $\tilde{\mu}[P(Q), \mu]$, and $\tilde{\mu}[P'(Q), \mu]$.

2. A subject prefers late resolution of ambiguity if $I_1[P(Q)](h) \geq I_1[P'(Q)](h)$ for all finite set $Q \subseteq \Delta(S_2)$, $h \in H$, $P(Q) \in \mathcal{P}^L(Q)$, $P'(Q) \in \mathcal{P}(Q) \setminus \mathcal{P}^L(Q)$, $\mu \in \Delta(Q)$, $\tilde{\mu}[P(Q), \mu]$, and $\tilde{\mu}[P'(Q), \mu]$, and the strict inequality holds for some Q, h, $P(Q)$, $P'(Q)$, μ, $\tilde{\mu}[P(Q), \mu]$, and $\tilde{\mu}[P'(Q), \mu]$.

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

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 the Appendix.

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-loving 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 the Appendix.

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 $\eta < \rho$ (resp. $\eta > \rho$, or $\eta = \rho$).

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 EZ (with subjective beliefs), KMM, 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 attitude. 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 attitude. 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.

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

Table 4: Theoretical predictions from six models

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 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 message 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.

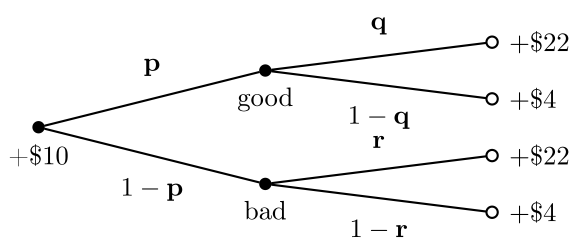


Figure 1: A general consumption process in risk resolution experiment

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.

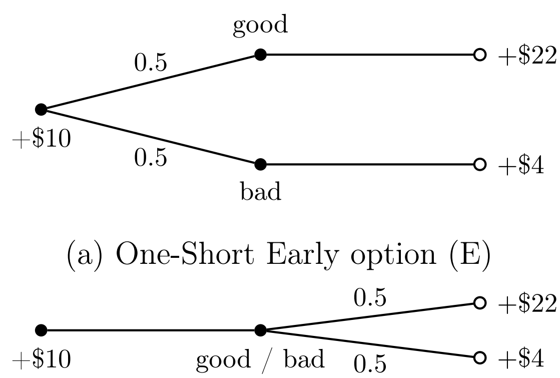
Options	**Information Structure**
One-Shot Early	$\mathbf{p}$=0.5, $\mathbf{q}$=1, $\mathbf{r}$=0
Gradual (non-skewed)	$\mathbf{p}$=0.5, $\mathbf{q}$=0.75, $\mathbf{r}$=0.25
Gradual (positively skewed)	$\mathbf{p}$=0.2, $\mathbf{q}$=0.9, $\mathbf{r}$=0.4
Gradual (negatively skewed)	$\mathbf{p}$=0.8,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



(a) One-Short Early option (E)

(b) One-Short Late option (L)

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

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-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 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 belief 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 $t = 1$, subjective 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 **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.

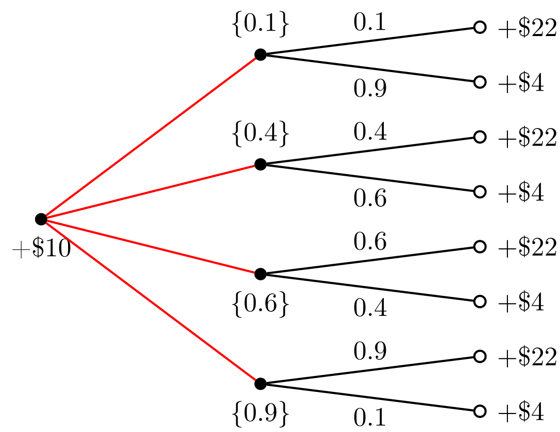
An information structure is a partition of the set $\{0.1, 0.4, 0.6, 0.9\}$. In three questions, subjects are asked to choose their most preferred option from a subset of the five alternatives listed in Table 6.

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	$\{0.1, 0.4, 0.6, 0.9\}$

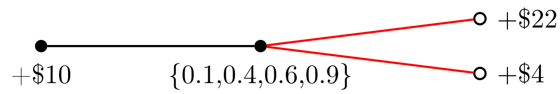
Table 6: Options in ambiguity resolution experiment

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 $\mathbf{p}$ 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. On conditional of a piece of news that has been realized, the black edges starting from the $t = 2$ nodes are realized with known probability.

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 stage 1 under 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) One-Shot Early option (E)



(b) One-Shot Late option (L)

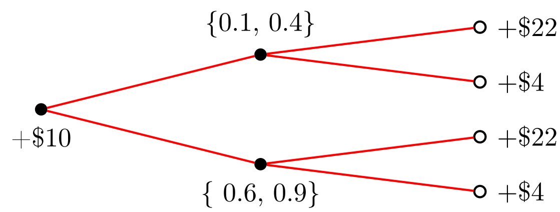
Figure 3: Information structures for early and late ambiguity resolution options

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

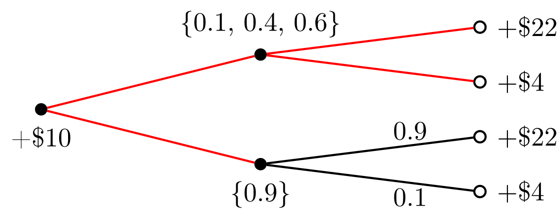
Similarly, under **Gradual (negatively skewed)**, one of the two messages will be realized in $t = 1$: $\{0.1\}$ and $\{0.4, 0.6, 0.9\}$. It tells the individual whether the winning chance is 0.1 or not. We illustrate the process in Figure 4(c).

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).

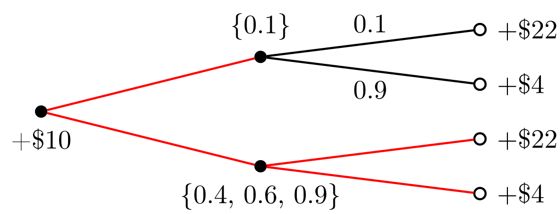
The remaining steps are the same as in risk-resolution-preference elicitation experiment. Subjects encounter another set of questions from the Raven test during the 30-minute delay.



(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

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.

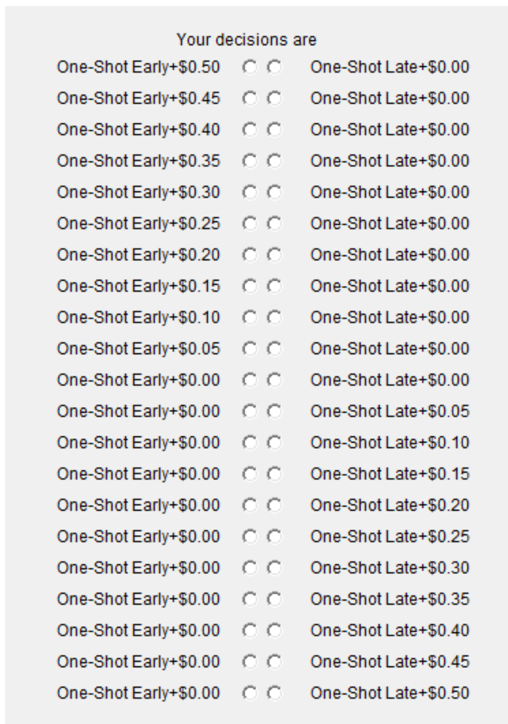


Figure 5: Multiple price list questions

After finishing all four sections on risk resolution/ambiguity resolution, subjects receive news/messages based on their choices of information structures, conduct Raven's Progressive Matrices test for the next 30 minutes, and then the outcome is revealed. The ordering of the questions in the two elicitation tasks was partially randomized 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

	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

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

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

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 subjects' 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.

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 for 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 loving. 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.

			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 Loving		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 depend on ambiguity attitudes

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

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-loving 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 loving 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%
	Loving	5	6	1	12	41.7%
	Total	86	42	7	135	63.7%

Table 11: Preferences for resolution of ambiguity depend 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 lovers: only 41.7% prefer early resolution of ambiguity.

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

$$P(y = 1) = F(b_1x_1 + b_2x_2), \tag{3}$$

where y is the binary dependent variable that equals 1 when a subject chooses the early option in the ambiguity resolution task, x_1 is a binary variable that equals 1 when a subject chooses the early option in the risk resolution task, and x_2 is an binary variable that equals 1 when a subject exhibits ambiguity loving 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 Loving	−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.[4] Preferring early resolution of risk increases the likelihood of preferring early resolution of ambiguity by 43.6 percentage points (p-value < 0.001). Being ambiguity loving 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 loving 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

[4] The result of the regression is in the appendix.

provides the average switching points of each group.[5]

	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 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 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

[5]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.

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 loving, 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 the 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).

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A Appendix: Omitted Proofs

Proof of Proposition 1. For convenience, we 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).

Given a finite set $Q \in \Delta(S_2)$, a set of joint beliefs resolving ambiguity early $P^E(Q)$, second-order belief $\mu \in \Delta(Q)$, and a consistent second-order belief $\tilde{\mu}[P^E(Q), \mu]$, the ex-ante certainty equivalent of h is given by

$$
\begin{aligned}
&I_1[P^E(Q)](h) \\
=&\Big(\sum_{s_1 \in S_1} \Big(h_1^\rho + \beta\big(\sum_{q \in Q} I_2^\eta[q](h)\tilde{\mu}[P^E(Q), \mu](q|s_1)\big)^{\frac{\rho}{\eta}}\Big)^{\frac{\eta}{\rho}}\big(\sum_{p \in P^E(Q)} \tilde{\mu}[P^E(Q), \mu](p)p(s_1)\big)\Big)^{\frac{1}{\eta}},
\end{aligned}
$$

where $I_2[q](h)$ is defined in expression (1). Since for each $s_1 \in S_1$, $\tilde{\mu}[P^E(Q), \mu](\cdot|s_1)$ is a distribution over Q, the definition of early resolution of ambiguity implies that there exists a unique $q^* \in Q$ such that $\tilde{\mu}[P^E(Q), \mu](q^*|s_1) = 1$ and $\tilde{\mu}[P^E(Q), \mu](q'|s_1) = 0$ for any other $q' \in Q \setminus \{q^*\}$. Hence,

$$
h_1^\rho + \beta\big(\sum_{q \in Q} I_2^\eta[q](h)\tilde{\mu}[P^E(Q), \mu](q|s_1)\big)^{\frac{\rho}{\eta}} = h_1^\rho + \beta\big(I_2^\eta[q^*](h)\big)^{\frac{\rho}{\eta}}.
$$

There may be multiple $p \in P^E(Q)$ and $s_1 \in S_1$ such that $p(\cdot|s_1) = q^*$. By expression (2), we further have

$$
I_1[P^E(Q)](h) = \Big(\sum_{q^* \in Q} \Big(h_1^\rho + \beta\big(I_2^\eta[q^*](h)\big)^{\frac{\rho}{\eta}}\Big)^{\frac{\eta}{\rho}} \mu(q^*)\Big)^{\frac{1}{\eta}} = \mathbb{E}_{q \in Q}^{\frac{1}{\eta}}[w(I_2^\eta[q](h))],
$$

where each $q \in Q$ happens with probability $\mu(q)$. We remark that this expression is independent of consistent belief $\tilde{\mu}[P^E(Q), \mu]$, when μ is fixed.

Given a finite set $Q \in \Delta(S_2)$, a set of joint beliefs $P^L(Q)$, second-order belief $\mu \in \Delta(Q)$, and a consistent second-order belief $\tilde{\mu}[P^L(Q), \mu]$, the ex-ante certainty equivalent of h is given by

$$
\begin{aligned}
&I_1[P^L(Q)](h)\\
=&\Big(\sum_{s_1\in S_1}\Big(h_1^\rho+\beta\big(\sum_{q\in Q}I_2^\eta[q](h)\tilde{\mu}[P^L(Q),\mu](q|s_1)\big)^{\frac{\rho}{\eta}}\Big)^{\frac{\eta}{\rho}}\big(\sum_{p\in P^L(Q)}\tilde{\mu}[P^L(Q),\mu](p)p(s_1)\big)\Big)^{\frac{1}{\eta}}\\
=&\Big(\Big(h_1^\rho+\beta\big(\int_{q\in Q}I_2^\eta[q](h)\mu(q)\big)^{\frac{\rho}{\eta}}\Big)^{\frac{\eta}{\rho}}\Big)^{\frac{1}{\eta}}\\
=&w^{\frac{1}{\eta}}(\mathbb{E}_{q\in Q}\big[I_2^\eta[q](h)\big]),
\end{aligned}
$$

where the second equality comes from the fact that $\tilde{\mu}[P^L(Q),\mu](q|s_1)=\mu(q)$ for all $q\in Q$ and $s_1\in S_1$. This certainty equivalent is also independent of the consistent belief $\tilde{\mu}[P^L(Q),\mu]$ once μ is fixed.

The ex-ante certainty equivalent of h under a finite set $Q\in\Delta(S_2)$, a set of joint distributions $P^G(Q)$, a second order belief μ, and a consistent second-order belief $\tilde{\mu}[P^G(Q),\mu]$ is given by

$$
\begin{aligned}
&I_1[P^G(Q)](h)\\
=&\Big(\sum_{s_1\in S_1}\Big(h_1^\rho+\beta\big(\sum_{q\in Q}I_2^\eta[q](h)\tilde{\mu}[P^G(Q),\mu](q|s_1)\big)^{\frac{\rho}{\eta}}\Big)^{\frac{\eta}{\rho}}\big(\sum_{p\in P^G(Q)}\tilde{\mu}[P^G(Q),\mu](p)p(s_1)\big)\Big)^{\frac{1}{\eta}}\\
=&\mathbb{E}_{s_1}^{\frac{1}{\eta}}[w\big(\mathbb{E}_{q|s_1}[I_2^\eta[q](h)|s_1]\big)],
\end{aligned}
$$

where s_1 occurs with probability $\sum_{p\in P^G(Q)}\tilde{\mu}[P^G(Q),\mu](p)p(s_1)$, and q occurs with probability $\tilde{\mu}[P^G(Q),\mu](q|s_1)$ conditional on s_1.

Notice that for all $q\in Q$, it must be true that

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

where the first equality follows from expression (2), the second equality is easy to see, and the third equality comes from the definition of $\tilde{\mu}[P^G(Q),\mu](q|s_1)$. Hence, by the law of iterated expectation, one can also rewrite $I_1[P^E(Q)](h)$ and $I_1[P^L(Q)](h)$ into the following forms:

$$I_1[P^E(Q)](h) = \mathbb{E}_{q\in Q}^{\frac{1}{\eta}}[w(I_2^\eta[q](h))] = \mathbb{E}_{s_1}^{\frac{1}{\eta}}\left[\mathbb{E}_{q|s_1}[w(I_2^\eta[q](h))|s_1]\right],$$
$$I_1[P^L(Q)](h) = w^{\frac{1}{\eta}}(\mathbb{E}_{q\in Q}\left[I_2^\eta[q](h)\right]) = w^{\frac{1}{\eta}}\left[\mathbb{E}_{s_1}[\mathbb{E}_{q|s_1}(I_2^\eta[q](h))|s_1]\right],$$

where s_1 occurs with probability $\sum_{p\in P^G(Q)}\tilde{\mu}[P^G(Q),\mu](p)p(s_1)$, and q occurs with probability $\tilde{\mu}[P^G(Q),\mu](q|s_1)$ conditional on s_1.

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 $I_1[P^E(Q)](h)\geq I_1[P^G(Q)](h)\geq I_1[P^L(Q)](h)$ for all $h\in H$, finite $Q\in\Delta(S_2)$, $P^E(Q)$, $P^G(Q)$, $P^L(Q)$, $\mu\in\Delta(Q)$, consistent second-order beliefs $\tilde{\mu}[P^E(Q),\mu]$, $\tilde{\mu}[P^G(Q),\mu]$, and $\tilde{\mu}[P^L(Q),\mu]$. In fact, as we remark above, $I_1[P^E(Q)](h)$ and $I_1[P^L(Q)](h)$ are independent of the consistent second-order beliefs. Also, $I_1[P^E(Q)](h)>I_1[P^G(Q)](h)>I_1[P^L(Q)](h)$ some $h\in H$, $Q\in\Delta(S_2)$, $P^E(Q)$, $P^G(Q)$, $P^L(Q)$, $\mu\in\Delta(Q)$, $\tilde{\mu}[P^E(Q),\mu]$, $\tilde{\mu}[P^G(Q),\mu]$, and $\tilde{\mu}[P^L(Q),\mu]$ 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. For the purpose of illustration, we view the H model as the limit of the HM model with $\eta\to-\infty$ here. Given $Q\in\Delta(S_2)$ and second-order belief $\mu\in\Delta(Q)$, the ex-ante certainty equivalents of a consumption process $h\in H$ under the three sets of joint distributions $P^E(Q)$, $P^G(Q)$, and $P^L(Q)$ as well as consistent second-order beliefs $\tilde{\mu}[P^E(Q),\mu]$, $\tilde{\mu}[P^G(Q),\mu]$, and $\tilde{\mu}[P^L(Q),\mu]$ are as follows:

$$I_1[P^E(Q)](h) = \min_{q\in Q}\left(h_1^\rho+\beta I_2^\rho[q](h)\right)^{\frac{1}{\rho}} = \min_{q\in Q}W(h_1, I_2[q](h)),$$
$$I_1[P^G(Q)](h) = \min_{s_1\in S_1}\left(h_1^\rho+\min_{q|s_1}\beta I_2^\rho[q](h)\right)^{\frac{1}{\rho}} = \min_{s_1\in S_1}W(h_1,\min_{q|s_1}I_2[q](h)),$$
$$I_1[P^L(Q)](h) = \left(h_1^\rho+\beta\big(\min_{q\in Q}I_2[q](h)\big)^\rho\right)^{\frac{1}{\rho}} = W(h_1,\min_{q\in Q}I_2[q](h)),$$

where by $\min_{q|s_1} I_2[q](h)$ we mean the worst-case $I_2[q](h)$ across all $q \in Q$ such that $\tilde{\mu}[P^G(Q), \mu](q|s_1) > 0$.

Since $W(x, y)$ is increasing in each component, we know that $I_1[P^E(Q)](h) = I_1[P^G(Q)](h) = I_1[P^L(Q)](h)$ for all $h \in H$. Hence, a subject is indifferent towards the timing of ambiguity resolution. $\square$

B The Result of Logistic Regression

	Coefficients	Standard Error	p-value
Early in RR	2.59	0.49	0.000
Ambiguity Loving	−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 (3) (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 (3), 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 Loving	−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 Loving	−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 to 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.