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How does Time Pressure Affect Individual Attitudes towards Uncertainty?

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Abstract

Measurements of uncertainty attitudes have been studied extensively. The majority of research concentrate on the source of uncertainty concerned risk with known probability, while the other source of uncertainty concerned ambiguity with unknown probabilities is gradually but surely becoming more widely acknowledged. Unlike most previous work, which only focus on one type of uncertainty, I analyze the impact of time pressure on individual risk and ambiguity attitudes jointly in a pre-registered survey experiment with 264 participants. I test the effect of time pressure on risk aversion, ambiguity aversion, their perceived level of ambiguity (a-insensitivity) and noise. By separating noise in the decision-making process from the true preferences, I find no statistically significant effect of time pressure on risk and ambiguity aversion at either the individual or the aggregate levels. In line with previous literature, there is suggestive evidence that time pressure decreases the perceived level of ambiguity (increases a-insensitivity). Moreover, I find suggestive evidence that time pressure increases noisy decision making in the ambiguity aversion elicitation task. In addition, I also find evidence that noise biases the baseline measure of risk aversion and perceived level of ambiguity(a-insensitivity) at the aggregate level. These findings can help explain many realistic economic and financial issues such as policy-making rationality and financial bias under time constraints.

Keywords: risk aversion; ambiguity aversion; a-insensitivity; noisy decision making; time pressure

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1 Introduction and Literature Review

In our daily life, we frequently make our decision under uncertainty. In some of these decisions, we are either aware of the objective probabilities of the underlying alternatives (decisions under risk) or are at least able to evaluate subjective probabilities (decisions under ambiguity) (Knight, 1921). Most empirical studies have focused on the unique scenario of risk, where objective probabilities are known in uncertainty events. However, there are some occasions when we must make decisions in the face of uncertainty without knowing the likelihood of the results, which is called that we decide under ambiguity. People are typically ambiguity averse, meaning they strive to avoid making decisions when they are confronted with ambiguous events with unknown probabilities compared with risk events with known probabilities. The research on ambiguity attitudes began with the seminal paper of Ellsberg (1961), which contains both theoretical and experimental contributions. Then, a lot of research continued on studying participants' behavior under ambiguity events (e.g., Camerer and Weber, 1992; Trautmann and van de Kuilen, 2016; Wakker, 2010). Dicks and Fulghieri (2019), Bergen et al. (2018), and Gao and Driouchi (2018) are recent theoretical applications of the decision-theoretic models under ambiguity. The corona epidemic also provides numerous examples of how to make decisions in ambiguous situations (Durodié, 2020; Gassman et al., 2021; Kishishita et al., 2021). Decisions about pandemic management are influenced by a number of external factors that are difficult to evaluate. Examples include the decision-makers' time constraints or their ambiguity regarding their own vaccination decisions (Courbage and Peter, 2021; Lipscy, 2020). Inspired by those studies, this thesis focuses on how time pressure affects uncertainty attitudes (including risk attitudes and ambiguity attitudes) and noisy decision making jointly to study how individuals react to different types of uncertainty events under time pressure[1].

Time pressure is common to many economic decisions. Traders need to make decisions in financial markets within seconds after new information becomes available (Busse and Green, 2002). Negotiators must often reach agreements before a deadline (Roth et al., 1988; Sutter et al., 2003). In addition to its practical importance, time pressure has drawn special attention in the psychological literature (Ariely and Zakay, 2001; Essi and Jaussi, 2017). This is because time pressure offers a good framework for changing cognitive limitations. De Paola and Gioia (2015) and Spiliopoulos and Ortmann (2018) argued for the use of time pressure or response time as a tool in experimental economics. A growing number of studies gradually focus on how time pressure influences decision-making process through different ways. For instance, many researchers detected the effects of time constraints on risky decisions (Kocher et al., 2013; Young et al., 2012 and Maule et al., 2000). Baillon et al. (2018) introduced a simple method to elicit individuals' ambiguity attitudes under time pressure for natural events. However, except for the research studying on risk or ambiguity aversion under time pressure, time constraints have been proven to influence individual uncertainty perception level as well. Young et al. (2012) found that people become less sensitive to risk under time constraints. Baillon et al. (2018) found that time pressure affects ambiguity attitudes by increasing ambiguity insensitivity but has no effect on ambiguity aversion. Therefore, it is reasonable to say that cognitive limitations and irrationality induced by time constraints may truly have an impact on the degree of insensitivity or the degree of perceived uncertainty rather than specific uncertainty preferences. This has led to numerous research that divide uncertainty attitudes, especially ambiguity attitudes, into uncertainty

[1] In general, ambiguity attitudes are equivalent to uncertainty attitudes. In this thesis, risk attitudes and ambiguity attitudes are both collectively referred to as uncertainty attitudes, because decision under risk is a special case of decision under uncertainty.

aversion and perceived level of uncertainty. For ambiguity attitudes, the cognitive process of individual decision making would be that they firstly perceive the certain level of ambiguity, and then make their decisions according to their preferences.

The Ellsberg paradox suggests a special aversion to unknown probabilities relative to known probabilities, and names it such as ambiguity aversion, or pessimism which has been used in the literature to designate this phenomenon. This general result has been widely repeated and has significant ramifications for the economics of optimum contracting, financial decisions, and mechanism design. Examples of current empirical research on ambiguity aversion are Ryall and Sampson (2017) and Anderson (2019). However, to properly measure ambiguity aversion, we must take likelihood beliefs into account in the relevant events to calibrate the standard for ambiguity neutrality, since the preference we estimate does not necessarily reflects participants' ambiguity aversion level, especially when exogenous factors, such as historical learning (Baillon et al., 2013), stake level (Bouchouicha et al., 2017) or even time pressure (Baillon et al., 2018), come to influence their ambiguity attitudes. Consider a person who would rather receive $100 under the ambiguous event B of a rise in copper prices of at least 0.01% next week than receive $100 under the risky event K of a coin toss ending in heads (p = 0.5) next week. Plenty of literature focused on studying this heterogeneity of preferences under ambiguity – in the lab and the field (Baillon et al., 2012; Epstein, 2010; Klibanof et al., 2012; Machina, 2009). And some researchers split ambiguity attitudes into two parts—the preference towards ambiguity and perceived ambiguity level (Ahn et al., 2014; Cubitt et al., 2018; Dimmock et al., 2015; Baillon et al., 2013; Baillon et al., 2018). Optimism and pessimism are important features of a person's attitude towards ambiguity. For instance, business cycles and stock market fluctuations have been attributed to 'irrational' optimism and pessimism. Thus, the level of pessimism[2] is always regarded as the main attitude towards ambiguity. However, there are still other behavioral regularities that influence individuals' decision choice. People may distinguish categorically between situations which they consider as certain, just possible, or strictly impossible, which could be modeled by a transition from zero probability of an event to a positive probability. For instance, a typical lottery with a high prize on a very unlikely event can turn the certainty of low wealth for a poor person into the possibility of great riches, providing a reason for accepting an unfair gamble. This certainty and impossibility effects could be regarded as the perceived ambiguity level or the notion of belief towards ambiguity. Previous studies reveal that most people are ambiguity seeking for low likelihood ambiguous events, while ambiguity aversion is common for high likelihood events. Bell (1985) interpreted these psychological biases as disappointment aversion or elation-seeking behavior. Abdellaoui et al. (2011) interpreted such preferences as ambiguity-generated likelihood insensitivity, which describes a tendency to regard all ambiguous events as if they are 50–50% or showing too little sensitivity to the reference likelihood of events. Therefore, I choose to include this probabilistic insensitivity into our ambiguity attitudes estimation based on those research methods and name this index as ambiguity-generated likelihood insensitivity in my thesis. The higher this level, the less the decision-maker differentiates between the various likelihood levels and the more these levels are regarded similarly, blurring together. Hereinafter, a-insensitivity is referred as it in the following content.

In terms of how to test ambiguity attitudes, different studies used different methods. Most studies elicited certainty equivalents to measure ambiguity attitudes (Gneezy et al., 2015; Bouchouicha et al., 2017; Cubitt et al., 2018), which is the most commonly used method and easy to conduct. However, this method always entangles participants' risk attitudes and ambiguity attitudes together which is problematic in purifying

[2] In the pre-analysis plan, I called it as pessimism, which is also named as ambiguity aversion in this thesis.

ambiguity attitudes we want to detect. In addition, some studies tried to measure ambiguity attitudes using the method through matching probabilities (Baillon et al., 2018; Dimmock et al., 2016; Kahn and Sarin, 1988; Viscusi and Magat, 1992). The matching probability of an ambiguous event is the subjective probability participants refer to the ambiguity event at which they are indifferent between betting on this ambiguous event and betting on the objective probability for a given prize. Compared with other methods, using matching probabilities can capture ambiguity attitudes completely without measuring their risk preference. Dimmock et al. (2016) introduced a tractable method using the matching probability to estimate individuals' ambiguity attitudes in the lab, requiring only three indifferences and an average of five minutes per participants, and successfully applied it in a large representative sample. In their experiment, they asked participants three sets of questions that involved choices between an ambiguous and a risk prospect. Baillon et al. (2018) used the matching probability method for natural events. In their study, the ambiguity concerns the performance of the AEX (Amsterdam stock exchange). This method is close to and can be easily adapted into the multiple price list which is frequently used as risk preferences elicitation method.

Binswanger (1981), who elicited risk preferences of farmers in rural India, describes an early incentive-based use of the multiple price list (MPL) method. Then, the MPL technique was popularized by Holt and Laury (2002) in a significant work that employed it to calculate risk parameters of the utility function. In their measure, a participant is typically presented with a list of 10 decisions between paired gambles. The two gambles for each decision are stacked in rows, with gambles in the left and right columns labeled Option A and Option B, respectively. The participant then chooses which gamble she prefers to play from each pair by picking either Option A or B, making this choice for every decision row. The payoffs of gambles in Option A and Option B remain constant; the only thing that changes between decision rows is the probability associated with each payoff, which varies from 1/10 to 10/10 respectively across rows. After this work, researchers have been able to compare risk attitudes in a range of contexts and settings thanks to the widely used Holt and Laury (2002) measure or an adapted version of it where pairs consist of a safe amount and a gamble with fixed probability and varying stake levels (e.g., Andersson et al., 2016). By reducing methodological variance and seeking to define a more pervasive phenomenon, this has made it easier to conduct more unified research on risk preferences.

However, in the MPL used by Holt and Laury (2002) or other researchers, participants are typically free to switch between Options A and B as they move down the decision rows using the standard MPL method. This may result in some problematic issues, such as participants making inconsistent decisions by switching more than once or making "backwards" choices—starting with Option A and switching to B. (Dave et al., 2010; Holt and Laury, 2002). Some researchers (e.g., Andersen et al., 2006; Tanaka et al., 2010; Gneezy et al., 2015) use a unique switching point to address this issue, however this method may greatly skew the outcomes. If inconsistent choice data is treated as noise and removed, it is reasonable to say with some confidence that the persons who are left understood the instructions and are revealing their true preferences. Nevertheless, enforcing a single switch point includes confused persons in the sample who, given the chance to switch freely, would have made inconsistent choices. Besides, the enforced switch point also needs extra preferences assumptions that may not hold. Even if my assumption is that people make their decisions based on their true preferences, the disturbing noise may still contaminate observed decisions. In order to take this into consideration, participants in my experiments have to make their choice for each decision so that I can detect the noise they make due to any type of reason.

Some previous studies have found that there is potential for different types of errors within an MPL. The most common type of error is the Fechner error or "white noise" error, which was first developed by Becker, DeGroot and Marschak (1963), and popularized by Hey and Orme (1994) and Carbone and Hey (1994) in estimating a wide range of alternative models of choice under risk. This type of error always happens when individuals evaluate their decision, and Fechner error approach proposes that the individual maximizes some form of utility function which includes a stochastic disturbance term. This specification models that people make mistakes around their actual point of indifference for different reasons. For instance, people may calculate the wrong expected utility of the lotteries or have "thick indifference curves". The other type of error that attracts much concern is trembling-hand error or constant error, which was first introduced by Luce (1959) and developed by Harless and Camerer (1994). A tremble is said to occur when an agent makes a decision entirely at random at the action stage, disregarding the values of the explanatory variables, and this type of error was introduced by using different models. Luce (1959) added constant errors by introducing a noise exponent to the expected payoff based on the strict probabilistic choice rule, which was also used by Holt and Laury (2002). Moffat and Perters (2001) found evidence of nonzero tremble probabilities which could be used in a wider range of applications. According to Loomes et al. (2001), the reason for these trembles is that the individual momentarily loses focus while attempting to solve the decision problem. Charness et al. (2013) and Holzmeister and Stefan (2021) found that decision errors may bias baseline measurement of risk attitudes. In my experimental design, time pressure could complicate participants' decision-making processes. One of the reasons could be the stressful element of time pressure. A large number of studies found that stress can have a detrimental effect on various cognitive processes (e.g., Qin et al., 2009; McEwen and Sapolsky, 1995; Shields et al., 2016). Further, the tendency to exhibit noise in decisions under risk has been demonstrated to be inversely associated to cognitive ability (e.g., Andersson et al., 2016, 2020; Amador-Hidalgo et al., 2021). Thus, time pressure could potentially set cognitive limitations on individual decision-making processes, which may not only affect the perceived level of uncertainty, but also increase rate of noisy decision making especially in MPL experiments. However, there is little work on the topic of noise in the ambiguity measurements under time pressure.

In my setting, the noisy decision making is defined as the deviation of the assumption of monotonicity. Participants have to make a series of choices in four Multiple Price Lists (MPL) design based on Gneezy et al. (2015) and Andersen et al. (2006). Within a given MPL, the decision maker needs to make her choice between two lotteries, Option A and Option B. For risk elicitation task, I use the MPL design based on Andersen et al. (2006). The only value that changes across decisions within the price list is thus outcome of Option B. This outcome is increasing in value across decisions, making lottery Option B subsequently more attractive. Additionally, just as varying prices are helpful for characterizing risk attitudes, matching probability are essential for studying ambiguity attitudes (Dimmock et al., 2016). For three ambiguity elicitation tasks, I create MPLs based on the experiments of Gneezy et al. (2015) and Dimmock et al. (2016) to vary the probabilities of Option A or Option B and keep the price fixed to roughly estimate individual matching probability for ambiguity events. To elicit ambiguity aversion, I choose to vary the probabilities or reference likelihood of both lotteries, Option A and Option B, for each decision. As for eliciting a-insensitivity, I choose to just vary the objective probabilities of the lottery Option A. Bouchouicha et al. (2017) found that individual ambiguity aversion increases by not only a larger stake size, but also a higher reference probability. Similarly, I assume that the outcome is increasing in probability across decisions, making lottery Option A subsequently more attractive. As a result, a person who makes a decision satisfying monotone preference for both risk and ambiguity should start by selecting the safe lottery, which is Option

A for risk and Option B for ambiguity, and should only switch to the other side once. They should also avoid switching back to the less desirable option. Without making any further constrictive assumptions about the utility function's structure, a return to the less desirable choice could be seen as noise and based solely on the monotonicity argument. I thus count reverse switches as noise in my descriptive analyses.

To specify different types of errors, which could be seen as violations of assumptions, I use the structural estimation including the specific error terms in the functional form to detect the different types of errors which may bias the true preferences, and that is one of the major advantages of this complex elicitation method even though it requires some strict functional form assumptions. This approach can additionally account for not only how frequently errors occur, but also in which particular decision within a choice list they happen. Identifying the particular point within a MPL where the error happens is important since I distinguish the two most common types of errors, the trembling-hand errors analyzed by Moffatt and Peters (2001), which assign the probability that a given choice is random, and Fechner errors, which happen around the true switching point in a given MPL.

Previous studies that found that heterogeneity in noise across decision makers can induce a bias in the measurement of preferences mainly focus on the domain of risk preferences (e.g., Starcke and Brand, 2016; Andersson et al., 2016; Kirchler et al., 2017; Parslow and Rose, 2022). Except for the most common Fechner error model, they frequently detected constant error based on method of Luce (1959). Although Luce's constant error model is useful in many research circumstances, it requires a strict assumption for the probabilistic choice model in structural estimation, which may not be applicable for all cases. The exception is Baillon et al. (2013), who detected noise when measuring ambiguity attitudes under historical learning circumstances by introducing Fechner error model with fixed trembling probability, instead of just solely using Luce's constant error model to detect trembles. Based on that, I try to use the MPL along with this type of noise estimation method to find out whether ambiguity preferences would be contaminated by people's noisy decision making and how time pressure influences noisy decision making in risk and ambiguity elicitation tasks at both the individual and the aggregate level. At the individual level, I count the number of reverse switches as the general noise index for each participant. At the aggregate level, I first apply the trembling-hand errors model by just adding trembling probability as Moffatt and Peters (2001) did, and then use Fechner model with trembles to figure out which type of errors fits best in my observed decisions. In my data sets, the trembling-hand errors are found to be the main type of error participants made in their decision-making process.

In sum, the method I use, which is based on the MPL, can not only measure risk attitudes and ambiguity attitudes jointly, but also, most importantly, can detect errors made in each choice list (Parslow and Rose, 2022; Kirchler et al., 2017), so that we could even find the degree of noisy decision making when participants are faced with both risk and ambiguity events. My experimental design is thus based on the task developed by Gneezy et al. (2015), which jointly elicits risk and ambiguity attitudes within MPLs where participants are asked to make decisions over gambles. But different from the method used by Gneezy et al. (2015), I add two additional ambiguity elicitation tasks to detect participants' ambiguity-generated likelihood insensitivity (a-insensitivity), and choose to vary probabilities rather than price across decisions in ambiguity elicitation tasks, so that I could roughly detect individual ambiguity aversion and a-insensitivity in descriptive analyses without any contamination from their risk attitudes. Although there already have been a large number of studies that detected ambiguity aversion and a-insensitivity respectively, most general ambiguity aversion index still incorporates both pessimism and a-insensitivity, and only a limited number of studies separated pure pessimism parameter, which means the ambiguity aversion per perceived level of ambiguity, from the general ambiguity aversion index to study it solely. I therefore create a new method to directly detect the ambiguity aversion per perceived level of ambiguity by just letting participants make their choices in a simple 9-decision list where I count the number of safe choices for each subject, to see how this ambiguity aversion varies across different treatments (Time Pressure (TP) and Control).

Finally, I do the analyses separately for women and other genders (almost men) to study whether there is any gender difference in risk and ambiguity attitudes under time pressure. There is plenty of literature studying on gender differences in risk aversion, and there is also some work focusing on the relation between gender and ambiguity. Borghans et al. (2009) studied whether there are gender differences in risk and ambiguity aversion, while a large range of studies, such as Friedl et al. (2020) and Charness and Gneezy (2012), did research on gender differences in risk attitudes. Parslow and Rose (2022) explored further whether there is a gender difference in noisy decision making when they elicit risk attitudes. To date, no studies have examined gender differences in ambiguity attitudes under time pressure. In addition, a-insensitivity, as a less known index than risk and ambiguity aversion, has not been studied in terms of potential gender differences. The explanatory analyses in this thesis extend the findings of gender differences in uncertainty attitudes, including risk aversion, ambiguity aversion, a-insensitivity, and noisy decision making as a new contribution to the current literature.

My results suggest that time pressure has no effect on individual risk and ambiguity aversion level but does have an impact on their perceived level of ambiguity, which means that participants' a-insensitivity level increases because of time pressure. Furthermore, participants' noisy decision making is largely influenced by time pressure when they are finishing ambiguity aversion elicitation task, and most of the noises are trembling-hand errors. People would make more random choices under time pressure when they are faced with ambiguity events mostly because they cannot perceive the same ambiguity level as well as they could under no time constraints. Additionally, I also find that noise biases risk aversion and a-insensitivity rather than ambiguity aversion at the aggregate level. In the gender differences analyses, I find that women have the tendency to be more risk averse than men and others in general, and are prone to make more noisy decisions under time pressure when they are confronted with ambiguity aversion elicitation task than men and others do.

2 Model Specification

To detect ambiguity attitudes, there are a number of theoretical models in the literature. Most of them are connected to the Ellsberg (1961) paradox. In the evolution of theoretical research on ambiguity, the Ellsberg experiment is not the beginning but rather what appears to be the turning point. Ellsberg revealed such a special case where one source of uncertainty (the known urn) concerned risk with known probabilities, and the other source (the unknown urn) concerned ambiguity with unknown probabilities. In his setting, which is named the Ellsberg Paradox, the known urn contains 50 red balls and 50 black balls, while the unknown urn contains 100 red and black balls in an unknow proportion. From each urn one ball will be drawn at random, and its color will be inspected. Gambling on an event, that a red ball is drawn from the known urn, means receiving \$100 if the event occurs, and nil otherwise. People typically prefer gambling on a color from the known urn to gambling on a color from the unknown urn. When people are given the option to choose their own color after the composition of the urn has been established, these preferences can also be observed. The literature up to this point has focused on this particular case. This technique is also used in my experiment, but it has been modified to take the multiple price lists, that frequently are used in the research on risk preferences, into account. I explain this further in the experimental design section.

Regarding theoretical models, many papers have applied the binary rank dependence utility models to their research, which includes theories such as Choquet expected utility, prospect theory (Tversky and Kahneman, 1992), multiple priors, and the α-MaxMin expected utility (Ghirardato and Marinacci, 2002; Wakker, 2010).

My approach works for every theory mentioned above that employs the evaluation

$$x_E y \rightarrow W(E)U(x) + W(E^C)U(y)$$

The prospect $x_E y$ yields outcome x under an uncertain event E and outcome y under the complementary event E^C. U is the utility function with $U(0) = 0$ and W is a probability weighting function[3]. I additionally consider Chateauneuf and Faro's (2009) confidence representation if the worst outcome is 0, so the representation becomes:

$$x_E 0 \rightarrow W(E)U(x)$$

for scenarios with a single nonzero result.

However, most theories, such as Choquet expected utility and prospect theory, are viewed as being excessively generic since there are too many probability-weighting functions for large state spaces. The source method proposed by Abdellaoui et al. (2011) and used by Dimmock et al. (2016) is a specification that is easier to follow. Then the prospect is evaluated as:

$$w_{S_0}(P(E))U(x)$$

Where $W(E) = w_{S_0}(P(E))$, and P denotes a reference likelihood measure under ambiguity events, justified by Chew and Sagi's (2008) conditions, implying ambiguity-neutral (a-neutral) probabilities[4], or objective probability measure under risk events. The source function w_{S_0} weights a-neutral probabilities or objective probabilities and is strictly increasing between 0 and 1. Low value of w_{S_0} gives low weights to the best outcome. The subscript S_0 indicates that the weighting function w depends on the source of uncertainty. Different sources have different weighting functions w_{S_0}. Groups of events produced by the same uncertainty mechanism are referred to as the source of uncertainty (Heath and Tversky, 1991; Tversky and Fox, 1995). In my case, S_0 could be divided into A and B separately, for we have two options with two sources of uncertainty in each choice list. When the source concerns objective probabilities from the risk events, the weighting function is w_A for risk; and when the source concerns unknown probabilities

[3] W is 0 at an empty event, 1 at the universal event.

[4] An ambiguity neutral decision maker would indeed treat these reference likelihoods as objective probabilities, irrespective of the underlying events. In my case, for instance, if the number of Success Chosen Colors is 4 out of potentially 10 colors in total, the reference likelihood will be 40%, which is also the a-neutral probability.

from the unknown urn, the weighting function is w_B for ambiguity. Wakker (2010) suggested that matching probabilities can be convenient for analyzing ambiguity. Machina and Schmeidler (1994) argued that when faced with ambiguity events, a probabilistically sophisticated individual still assigns subjective probabilities to events and judges each act solely on the basis of its implied probability distribution over outcomes, but not necessarily rank these probability distributions according to the expected utility principle. Dean and Ortoleva (2017) provided the axiom that a decision maker satisfies preference for objective risk if there is a way to reduce subjective uncertainty to objective risk that would make her (weakly) better off, which is also related to the intuition of the Ellsberg paradox. Based on these assumptions, in my case, the decision maker will directly generate an objective lottery rather than keeping the ambiguous Ellsberg bets. I thus choose to elicit the individual matching probability by using multiple price lists, which could be the probability in the interval of the switching point.

The matching probability is defined as

$$m(E) = \tau + \sigma P(E)$$

Where $P(E)$ denotes again the Chew and Sagi's (2008) a-neutral probabilities or reference likelihood in ambiguity events as I illustrated above. τ represents other factors other than reference likelihood itself that influence individual matching probability evaluation and σ denotes individual sensitivity to the reference likelihood. This formula captures the difference in weighting between unknown and known probabilities. So that, in my experiment:

$$w_A(m(E)) = w_B(P(E))$$

Where $w_B(P(E))$ is the weighting function of the reference likelihood or a-neutral probability $P(E)$ of the ambiguity events in Option B in my ambiguity tasks. And $w_A(m(E))$ is the weighting function of the objective matching probability $m(E)$ of the risk events in Option A in my ambiguity elicitation tasks.

Next, I begin with the ε-contamination model to detect ambiguity aversion and ambiguity-generated likelihood insensitivity, respectively. Previous literature on ambiguity often adopts a specification for ε-contamination (Epstein and Wang, 1994). Insurance theory (Carlier et al., 2003) and finance (Epstein and Schneider, 2010) have both used a tractable subcase of it. ε-contamination assumes that the decision-maker has a reference measure, π, which can be regarded as the reference likelihood of the ambiguity events in my setting. The decision maker considers their subjective possibility as $Q = (1-\varepsilon)\pi + \varepsilon D$, with $\varepsilon \in [0,1]$ and D is an alternative to π being relevant, which is the ambiguity aversion index in my case. Hence π is contaminated with the factor D, with the parameter ε determining the weight given to the alternative to π being relevant. The larger ε, the more weight on the factor D and less weight on the reference measure π. In previous subcases, D is often considered as the measure that makes the utility of the specific outcome inferior (Baillon et al., 2015; Dimmock et al., 2015; Gajdos et al., 2008; Chateauneuf et al., 2007; Walley, 1991), but they all assumed the expected utility for risk preference which is problematic. In my case, since participants are only confronted with the best outcome of the ambiguity events in Option B[5] and I assume

[5] The inferior outcome of each ambiguity event in my case is 0 SEK, and the best outcome is 200 SEK.

that participants are non-expected utility probabilistically sophisticated[6], I directly insert ε-contamination into my matching probability formula:

$$m(E) = \beta(1-\alpha) + (1-\beta)P(E)$$

Where $P(E)$ is defined as the a-neutral probability, α indicates the pessimism level or ambiguity aversion as the alternative to π being relevant, and β represents the reference likelihood insensitivity (a-insensitivity) or perceived level of ambiguity. Dimmock et al. (2015) derived the same specification through α-MaxMin expected utility model, which is different from how I define the cognitive process of the decision making. I will explain how the pessimism (ambiguity aversion) level and perceived level of ambiguity (a-insensitivity) could be detected through the multiple price lists below.

3 Experimental Design

The experiment was conducted in a Web survey which was designed in Qualtrics. The whole pre-analysis plan can be found at *https://osf.io/bhd7g* and Appendix C. A total of N = 518 participants participated, but after I exclude incomplete answers (as pre-registered in my pre-analysis plan) I have a sample size of 264 participants (105 female, 159 male and other genders). My participants are all students from the Stockholm School of Economics, the Royal Institute of Technology, the Karolinska Institute and Stockholm University. Participants are presented with four blocks in Qualtrics. The first block is for the risk elicitation MPL and the last three for the ambiguity elicitation MPLs. The decision order inside each block is randomized, but the block order is fixed. Instead of giving participants a choice list in one page and have them choose the switching point, like Gneezy et al. (2015) did, each decision, which includes a choice between a gamble Option A and a gamble Option B, is displayed separately on the screen in a random order inside one list of decisions. Through this way, I can detect errors by calculating the amount of switch reverses and estimating them in the structural estimation. Each participant makes their choice before moving onto the next randomly displayed decision. In the experiment, I have two treatments: a Control treatment and a Time Pressure treatment (Control and TP respectively). Participants were randomly assigned to one of two treatments. The tasks for two treatments are the same but in the time pressure treatment (TP), participants need to make each choice within 10 seconds[7].

The instructions emphasize the importance of choosing within the time allowed and the importance of avoiding being prompted to decide (could be found in Appendix B). A reminder sentence "Remember that you have a maximum of 10 seconds to make each decision" shows in the instructions before each part. The timer on the screen indicates how much time they had left to respond. If participants fail to answer the question under time limits, they still need to answer the question after the deadline. I do this setting in order

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[6] The agents, who are non-expected utility probabilistically sophisticated, would reduce subjective to objective risk in a coherent manner, using a probability measure over the states of the world, although she may violate expected utility in evaluating the lottery obtained.

[7] The level of time constraints placed on experiments varies across the literature. For example, Kirchler et al. (2017) and Parslow and Rose (2022) set 7 seconds time constraints for their participants to make each choice. Kocher et al. (2013) create a rather severe time pressure regime by giving individuals only 4 seconds of time to reply. I follow Rand et al. (2012) to apply less pressure to let respondents make each decision within 10 seconds because less pressure would lead to a lower rate of failing responses, especially in the ambiguity elicitation task, which is very important as it minimizes a potential selection bias.

to avoid the selection bias caused by failed responses. The survey is not completed until all the questions were answered.

Table 1: Design of the experiment

Between Participants	Within Participants			
	Risk Task	Ambiguity Task		
Control Treatment	MPL1	MPL2	MPL3	MPL4
Time Pressure Treatment	MPL1 with time pressure	MPL2 with time pressure	MPL3 with time pressure	MPL4 with time pressure

3.1 Risk Aversion Elicitation Task

To elicit risk attitudes, I use a MPL derived from the task developed by Andersson et al. (2016), which is one of the most widely used elicitation techniques for individual and aggregate risk preferences popularized by Holt and Laury (2002). This method not only allows participants to vary the switching point from the safer option to the riskier option to detect the risk aversion level, but also can capture the possible mistakes, which are manifested as reverse switches made by participants[8].

Unlike the choice list used by Holt and Laury (2002), which varied probabilities and fixed payoffs, I choose to keep the probabilities fixed at 50% and vary payoffs. It has the benefit of not requiring consideration for potential subjective probability weighting, and 50-50 gambles are easier for participants to understand. Further, Dave et al. (2010) discovered that individuals with low numeracy levels frequently struggle to comprehend MPL formats with different probabilities. Therefore, I use the MPL with varied payoffs and fixed probability in order to minimize the rate of observing noise.

Different from the two MPLs used by Andersson et al. (2016), I choose to use a single MPL rather than double MPLs to detect individual and aggregate risk attitudes. Andersson et al. (2016) argued that apparent changes in risk attitudes can be masked by increasing trembling errors made by participants in the process of making their choice. Parslow and Rose (2022) use the same double MPLs to tackle the risk attitude bias caused by stress, since stress may lead to higher rate of noisy decision making. However, this cognitive bias caused by errors was based on the assumption of risk neutrality, which does not easily hold before we actually know how participants react to risk events. For instance, a risk seeking subject would appear more risk averse, which is masked by increasing rate of noise caused by time pressure; but a risk averse participants would appear more risk seeking due to the same type of noise under time constraints[9]. This tendency to the specific attitude neutrality induced by trembling errors could be found in all types of choice list experiments. Nevertheless, we can still detect this type of errors by directly introduce the trembling error index in the structural estimation part followed by Wilcox (2011) to see whether it could influence the risk preference or not. Additionally, the drawback of using two lists is that the focus point serves as both the midpoint and

8 The assumption of preference monotonicity serves as the foundation for this. The reverse switches are not consistent with this assumption. This assumption is not very limiting and allows for descriptive studies without making numerous assumptions about the shape of a specific utility function. And the same assumption still applies to the subsequent ambiguity attitudes elicitation tasks (Chateauneuf et al. 2007).

9 The conclusion is calculated over the constant error model, or the tremble model (Harless and Camerer 1994). The argument is robust to a broad range of error structures. Theoretically, for ambiguity elicitation lists I will show below, this finding still applies.

the focal point, thus choices may not always accurately reflect preferences. Therefore, I narrow down the double MPLs to a single MPL to save participants' participation time.

In this risk elicitation task, participants are asked to make 10 decisions between pairs of gambles with objective probabilities over outcomes as showed in the table below.

Table 2: Risk aversion elicitation task

	MPL1	
No.	Option A	Option B
1	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 450 SEK
2	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 500 SEK
3	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 550 SEK
4	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 600 SEK
5	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 650 SEK
6	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 700 SEK
7	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 800 SEK
8	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 950 SEK
9	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 1350 SEK
10	1/2 chance of 250 SEK 1/2 chance of 450 SEK	1/2 chance of 50 SEK 1/2 chance of 2150 SEK

3.2 Ambiguity Aversion Elicitation Task

In order to elicit ambiguity attitudes, I use a method based on Ellsberg urns (Ellsberg, 1961) by using three separate MPLs that presented individuals with a series of decisions between gambles with known and unknown probabilities. Different from the method used by Gneezy et al. (2015), I fix the stake level in option B, because, on the one hand, I plan to detect a-insensitivity that needs to vary the reference likelihood; on the other hand, some studies found that stake level has effect on the individual ambiguity aversion and a-insensitivity level (e.g., Bouchouicha et al., 2017) in general, which may distort the a-insensitivity level I detect combining with varying probabilities.

In MPL2, participants were presented with two options. Option A is the similar risk elicitation task with maximum outcome changed to 200 SEK and the minimum outcome changed to 0 SEK and varying objective probabilities from 10% to 90%; Option B is an opaque urn containing potentially 10 different colors of balls, but the distribution of colors is not known, and experimenter choose the certain number of colors which would act as the Success Chosen Colors[10]. Then they make a series of 9 decisions between gambles with known probabilities in Option A or pick up a ball from the opaque urn in Option B to see whether the color of the ball they picked matches one of the Success Chosen Colors. For Option B, if the color of the ball drawn from the opaque urn matched one of the chosen colors, then they would win the hypothetical prize 200 SEK corresponding to that decision. If the drawn color did not, then they would win nothing. The payoffs for Option B are the same as the payoffs for Option A and remain constant in each decision. The ratio of the number of Success Chosen Colors to the total number of colors in Option B is the same as the objective probability in Option A, which means the reference likelihood or a-neutral probability in each ambiguity event is equal to the objective probability in risk event for each decision. The choice list is designed such that unless the individual is very ambiguity averse, participants would start out with choosing Option B in the first decision and switch over to drawing from Option A by the last decision. This switch point characterized the individual's pessimism level regard to ambiguity event, which is also called ambiguity aversion level.

In this ambiguity elicitation task, participants will be asked to make 9 decisions between pairs of gambles between known probabilities and unknown probabilities over outcomes as showed in the table below.

Table 3: Ambiguity aversion elcitation task

	MPL2	
No.	Option A	Option B
	Risk task with objective probability	Potentially 10 different colors of balls with unknown probability
1	1/10 chance of 200 SEK 9/10 chance of 0 SEK	200 SEK if chosen color (one color) 0 SEK if not
2	2/10 chance of 200 SEK 8/10 chance of 0 SEK	200 SEK if chosen color (two colors) 0 SEK if not
3	3/10 chance of 200 SEK 7/10 chance of 0 SEK	200 SEK if chosen color (three colors) 0 SEK if not
4	4/10 chance of 200 SEK 6/10 chance of 0 SEK	200 SEK if chosen color (four colors) 0 SEK if not
5	5/10 chance of 200 SEK 5/10 chance of 0 SEK	200 SEK if chosen color (five colors) 0 SEK if not
6	6/10 chance of 200 SEK 4/10 chance of 0 SEK	200 SEK if chosen color (six colors) 0 SEK if not
7	7/10 chance of 200 SEK 3/10 chance of 0 SEK	200 SEK if chosen color (seven colors) 0 SEK if not
8	8/10 chance of 200 SEK 2/10 chance of 0 SEK	200 SEK if chosen color (eight colors) 0 SEK if not
9	9/10 chance of 200 SEK 1/10 chance of 0 SEK	200 SEK if chosen color (nine colors) 0 SEK if not

[10] In general case, I should let participants to choose the Success Chosen Color by themselves, so that there is no reason to suspect an unfavorable composition of the unknown urn. However, since I use the hypothetical choice, I change this setting to let experimenter choose the Success Chosen Color in order to lessen their burden of understanding the instructions.

Recall the matching probability function:

$$m(E) = \beta(1 - \alpha) + (1 - \beta)P(E)$$

In this choice list, participants will choose to switch from Option B to Option A in some point, so that we could deduce the matching probability is around the switching point.

Suppose that a participant switch between two certain rows, I can deduce that there exists a matching probability p^*, which places in the interval between two rows:

$$p^* = \beta(1 - \alpha) + (1 - \beta)p^*$$

Since in each row, the reference likelihood is equal to the objective probability, no matter what the weighting functions are for risk and ambiguity events.

Then we could directly get the matching probability:

$$p^* = 1 - \alpha$$

Which means that this matching probability can exactly capture the pure pessimism or ambiguity aversion level of that participant, so that we could use the number of Option A as the level of individual ambiguity aversion. More Option A participants choose, more ambiguity averse they are; more Option B participants choose, more ambiguity seeking they are.

3.3 A-insensitivity Elicitation Task

(Elicit ambiguity attitudes for low reference likelihood and high reference likelihood):

In order to detect the strength of ambiguity-generated likelihood insensitivity (a-insensitivity), which shows participants' subjectively perceived ambiguity level, and how that strength is distributed across the sampled population, I use two additional MPLs with another urn containing balls of potentially 4 different colors. The Success Chosen Color is unique in these two MPLs, which is also chosen by experimenter before they make their decisions in the choice lists. But reference probabilities in Option B are 25% in MPL3 and 75% in MPL4 respectively, for I set the reverse stake level in MPL4 compared to MPL3, the fix the number of chosen color and stake level for each list. For Option A, the same risk elicitation task would be used as that in ambiguity elicitation task 1 (ambiguity aversion elicitation task). Although exact probabilities for ambiguous events (Option B) are unknown, it is often still possible to assess whether an event is unlikely or highly likely. Previous studies reveal that most people are ambiguity seeking for low likelihood ambiguous events, while ambiguity aversion is common for high likelihood events (e.g., Cubitt et al., 2018).

In these two MPLs, participants are asked to make a series of 10 decisions for each MPL between gambles with known probabilities in Option A or pick up a ball from the opaque urn in Option B to see whether the color of the ball they picked matches the unique Success Chosen Color. In MPL3, for option B, if the color of the ball drawn from the opaque urn matched the chosen color, then they would win the hypothetical prize 200 SEK corresponding to that decision. If the drawn color did not, then they would win nothing. But In MPL4, participants would earn nothing if the color of the ball drawn from the urn matched the chosen color, otherwise they will earn the hypothetical prize 200 SEK if it does not match. The matching probability would lie in the probability interval between two rows where the switching point locates.

In these two ambiguity elicitation tasks, participants are asked to make 20 decisions in total between pairs of gambles between known probabilities and unknown probabilities over outcomes as showed in the table below.

Table 4: A-insensitivity elicitation task

	MPL3		**MPL4**	
	Option A	Option B	Option A	Option B
No.	Earn 200 SEK with known probability	4 different colors of balls with unknown probability	Earn 200 SEK with known probability	4 different colors of balls with unknown probability
1	10%	200 SEK if chosen color, 0 SEK if not	10%	0 SEK if chosen color, 200 SEK if not
2	20%	200 SEK if chosen color, 0 SEK if not	20%	0 SEK if chosen color, 200 SEK if not
3	30%	200 SEK if chosen color, 0 SEK if not	30%	0 SEK if chosen color, 200 SEK if not
4	40%	200 SEK if chosen color, 0 SEK if not	40%	0 SEK if chosen color, 200 SEK if not
5	50%	200 SEK if chosen color, 0 SEK if not	50%	0 SEK if chosen color, 200 SEK if not
6	60%	200 SEK if chosen color, 0 SEK if not	60%	0 SEK if chosen color, 200 SEK if not
7	70%	200 SEK if chosen color, 0 SEK if not	70%	0 SEK if chosen color, 200 SEK if not
8	80%	200 SEK if chosen color, 0 SEK if not	80%	0 SEK if chosen color, 200 SEK if not
9	90%	200 SEK if chosen color, 0 SEK if not	90%	0 SEK if chosen color, 200 SEK if not
10	100%	200 SEK if chosen color, 0 SEK if not	100%	0 SEK if chosen color, 200 SEK if not

Similarly, recall the matching probability function again:

$$m(E) = \beta(1-\alpha) + (1-\beta)P(E)$$

supposing that participants switch between two certain rows, there exist two matching probabilities $p^*_{25\%}$ and $p^*_{75\%}$ for MPL3 and MPL4 respectively no matter what the weighting functions are for risk and ambiguity events, then

$$p_{25\%} = \beta(1-\alpha) + (1-\beta) * 25\%$$
$$p_{75\%} = \beta(1-\alpha) + (1-\beta) * 75\%$$
$$p_{75\%} - p_{25\%} = (1-\beta) * 50\%$$

Which means that the difference of the number of option B choices in MPL4 and the number of option B choices in MPL3 can fully capture the individual a-insensitivity level. Larger the difference, more sensitive to the reference likelihood participants are.

4 Hypotheses and Analyses

In this section, I illustrate 4 main questions and 8 hypotheses to be studied:

The first question is: How does time pressure influence individual level risk aversion and ambiguity aversion?

Although there are mixed findings about how individual's risk preferences change under time constraints, some found that time pressure has no effect on individual risk aversion in gain domains (Kocher et al., 2000); more research argued that individual risk aversion level would be stronger under stress (e.g. Young et al., 2012; Kirchler et al., 2017; Parslow and Rose, 2022). In terms of most previous research, Hypothesis 1 with regard to risk aversion would be:

Hypothesis 1: Time pressure leads to more risk aversion than no time constraints.

For ambiguity aversion under time pressure, Baillon et al. (2018) did not find that time pressure would have influence on individual ambiguity aversion. Even though the ambiguity aversion they detected is slightly different from the ambiguity aversion level I elicit, for I detect the ambiguity aversion per perceived level of ambiguity rather than the general ambiguity aversion most studies did research on, I still set Hypothesis 2 for ambiguity aversion in the following:

Hypothesis 2: Time pressure has no effect on ambiguity aversion.

For descriptive analysis, in order to test the effect of time pressure on the individual level of risk and ambiguity aversion, I will firstly count the number of Option A choices for MPL 1 (N_1) and the number of Option B choices for MPL2 (N_2) for each individual and compare the mean value of them between two treatments by using two-sided sample t-test. More Option A participants chose, more risk or ambiguity averse they are.

As a robustness check, I run pooled OLS regression, with the number of Option A choices in MPL1 and the number of Option B choices in MPL2 (N_1 and N_2) as the dependent variables and consider dummy variables—TP and some control variables (Field of study, Gender and Age[11]) as independent variables to estimate the coefficient of the independent variable TP, then use the interactive terms of TP and control variables to detect the control variables' impact on the treatment effect.

For structural estimation, I introduce the risk aversion index r and ambiguity aversion index α. Index r represents individual level of risk averse, which could be analyzed by using the data collected from risk elicitation task. $r = 1$ represents risk neutrality; $r < 1$ for risk averse and $r > 1$ for risk seeking. Index α represents aggregate level of ambiguity aversion, which could be analyzed together with a-insensitivity index by using the data collected from the last three ambiguity elicitation tasks. $\alpha \in [0,1]$, larger α indicates participants are more pessimistic when faced with ambiguity events. $\alpha = 0.5$ represents ambiguity aversion neutrality. When $\alpha < 0.5$, participants are considered as ambiguity seeking; if $\alpha > 0.5$, participants are recognized as ambiguity averse. These two indices help illustrate the change of aggregate level of ambiguity aversion across different treatments.

The second question is: How does time pressure influence individual level ambiguity-generated likelihood insensitivity?

Since Baillon et al. (2018) found time pressure would decrease individual perceived level of ambiguity, which means that people would be less sensitive to ambiguity events under time pressure, and their a-insensitivity index is what I literally detect in my experiment, the Hypothesis 3 is that:

Hypothesis 3: Time pressure leads to more ambiguity insensitivity than no time pressure.

For that purpose, I select the difference of the number of Option B choices between MPL3 and MPL4 ($N_4 - N_3$) as what the a-insensitivity represents. The larger value of ($N_4 - N_3$), the more sensitive they are to the ambiguity events in my experiment. I firstly compare the mean value of it between two treatments by using two-sided sample t-test, and then use it as the dependent variable and use the same independent and control variables mentioned before to estimate the coefficient of TP to detect the effect of time pressure on a-insensitivity as robustness check in descriptive analyses.

In structural estimation part, I introduce ambiguity-generated likelihood insensitivity (a-insensitivity) index β of both treatments, which represents individual perceived level of ambiguity, by analyzing the data collected from the last three ambiguity elicitation tasks. With $\beta \in [0,1]$, the larger $(1 - \beta)$ indicates that participants are more confident in the reference likelihood. I will show how β changes between two treatments, which could represent the aggregate a-insensitivity level difference between two treatments.

The third question is: Does time pressure induce people to make more noisy decisions when making their choice?

As most research showed, even if there is no stress put on participants, they will also make errors when making their decisions in MPLs (e.g., Wilcox, 2011; Moffatt and Peters, 2002; Holt and Laury, 2002). And

[11] The options of field of study for participants to answer in the Qualtrics survey: Economics & Business; Science; Engineering; Arts; Others. But in the analyses, the field of study is coded as Economics & Business or not. For the control variable gender, the options available to choose: Male; Female; Other genders; Prefer not to say. And I also code gender as female or not in the analyses. As for age, participants could select the exact age number in the question.

stress would lead to larger degree of noise under risk elicitation tasks (e.g., Kirchler et al., 2017; Andersson et al. 2016; Parslow and Rose, 2022). Therefore, I speculate that time pressure causes more noise for both types of tasks:

Hypothesis 4: Time pressure leads to more noisy decisions.

For descriptive analyses, I count the number of reverse switches as the degree of noise for all MPLs and compare the mean value of them between two treatments by using two-sided sample t-test. As for robustness check, the effect of time pressure on the level of noise will also be detected through running pooled OLS regression with the number of reverse switches as the dependent variable.

For structural parameter estimation, I introduce two types of error indices, Fechner error μ and trembling-hand error ω, which will be explained in detail in the structural estimation section.

The fourth question is: What is the gender difference regarding to the ambiguity (risk) aversion and ambiguity insensitivity? And what is the difference of the effect of time pressure on them?

Although I have included the control variable Gender in the descriptive analyses as most previous studies did (e.g., Baillon et al., 2018; Parslow and Rose, 2022). There are a considerable number of studies mainly focusing on finding out gender differences in risk and ambiguity preferences (e.g., Borghans et al., 2009; Friedl et al., 2020). Most of them found women are more risk averse, more ambiguity averse and more sensitive to the ambiguity events than men do. Based on those studies, the hypotheses for gender difference under uncertainty events are as follows:

Hypothesis 5: Women are more risk averse than men other genders.
Hypothesis 6: Women are more ambiguity averse than men other genders.
Hypothesis 7: Women are less a-insensitive than men and other genders.

However, few studies found significant differences among different genders regarding to the time pressure effect on uncertainty preferences. In case of that, I assume:

Hypothesis 8: Time pressure has no effect on gender differences (in risk aversion, ambiguity aversion and a-insensitivity).

In this part of analysis, gender is coded as a binary variable (female or not) in my research. I estimate all parameters mentioned above for female and other genders (including male, other genders and prefer not to say) participants separately and compare them to see whether there are differences between two sub-samples, and compare the cumulative density functions of all dependent variables mentioned above between two treatments for female and other genders (including male, other genders and prefer not to say) participants respectively, by using Mann-Whitney U test in descriptive analyses[12].

[12] Mann-Whitney U test is the non-parametric equivalent of the parametric two-sided sample (unpaired) t-test. The reason why I use Mann-Whitney U test rather than two-sided sample t-test for gender differences is that two-sided sample t-test assumes the data is normally distributed, but Mann-Whitney U test is more general in that it can be applied to both normally and non-normally distributed data under more relaxed conditions. Because the sample size for different gender groups is rather small under two treatments, I cannot affirm the data for the analyses on gender differences is normally distributed, so that I choose Mann-Whitney U test here.

I cluster standard errors at the individual level because I obtain values of each variable per participant and have robust standard errors by default for all descriptive regressions.

5 Results

In this section, I present the results of the pre-registered analyses of the experiment, including the results of the risky elicitation task, the ambiguity elicitation tasks and other analyses which were not pre-registered[13]. I use two-sided independent sample t-test for all of the descriptive analyses, except that I use the Mann-Whitney U test for the gender differences analyses. I define a statistically significant effect as $p < 0.005$ and suggestive evidence of an effect as $p < 0.05$ (Benjamin et al., 2018). In a previous study, Baillon et al. (2018) detected the effects of time pressure on the individual level of ambiguity attitudes. Using their effect sizes and standard deviations, I calculate their standardized effect size is Cohen's d = 0.43. However, since Baillon et al. (2018) have a sample size that is quite small (around 50 for each group), I also calculate the sample size needed to achieve 90% statistical power for a standard two-tailed t-test with a point biserial model based on Cohen's d = 0.3 and p = 0.05. This sample size is 109 per treatment. If I instead choose to compare the two means between the different groups based on Cohen's d = 0.43 and p = 0.05, the sample size would have to be at least of 133 per treatment to have 90% power in a two-tailed t-test. Considering a potentially low response rate in the survey, I also calculated a smaller sample size of 60 per treatment as the minimum sample size I would need to find a large effect size with Cohen's d = 0.6.

I sent my survey link to nearly 3000 email addresses and received 518 responses in total (implying a response rate of 17.3%). Excluding the uncomplete responses, I have 264 responses available for analyses. So that the total rate of responses available for analyses is 8.8%. In my sample size of 264 participants with complete data, I have 90% power to find a Cohen's d effect size of 0.40 (which represents a small/medium effect) with p = 0.05, and 90% power to find a Cohen's d of 0.51 with p = 0.005.

5.1 Descriptive Statistics

In total, 264 participants completed my study, 145 in the TP treatment and 119 in the Control treatment. The share of Male and Others in TP treatment (about 58.49%) is larger than that of Female group (about 49.52%). In Male and Others sub-sample, the number of participants who chose other two options, "other genders" and "prefer not to say", is one each, thus male participants dominate this Male and Others sub-sample. Most participants come from the field of business & economics (244 participants, 92.4%). A detailed overview of the composition of my sample can be found in Table 5. The mean age of participants is 24.15 years.

[13] The analyses code in Stata could be found in the pre-registration site (*https://osf.io/bhd7g*) online.

Table 5: Descriptive statistics: The table gives an overview of the main demographic characteristics of the subject sample. Standard deviations for the participants' age are in parentheses.

	Treatment		
	Control	TP	Total
Age	24.25	24.07	24.15
	(5.98)	(7.82)	(7.04)
Gender			
Female	53	52	105
Male and Others	66	93	159
Major			
Business & Economics	92.44%	92.41%	92.42%
Engineering	3.36%	0.69%	1.89%
Science	3.36%	1.38%	2.27%
Others	0.84%	5.52%	3.41%
Total	119	145	264

I define failed responses as responses that are not made within the time period of 10 seconds in the TP treatment. The fraction of failed responses among all choices is low and varies between 2% and 6.6% across blocks for the TP treatment. The failed response rate in risk elicitation task (MPL1) is the lowest, which is only 2%, while the failed response rate in the ambiguity elicitation tasks is slightly larger. In the ambiguity aversion elicitation task (MPL2), around 6.6% of the total number of answers are shown to be failed under time pressure, which is the largest rate among all blocks. In the a-insensitivity elicitation task (MPL3 & MPL4), the failed response rate is about 2.4%. Besides, the mean of response time for each type of elicitation task in time pressure treatment (risk aversion, ambiguity aversion and a-insensitivity) is 3.8, 4.9 and 2.9 seconds respectively, which are all far below the time limits (10 seconds) I set. In this sense, my time pressure experiment worked well[14].

Table 6: Failed response rate in TP treatment

	Task			
	MPL1	MPL2	MPL3 & MPL4	Total
Failed Response Rate	2.00%	6.59%	2.38%	3.25%

In total 518 responses, 242 responses are allocated into TP treatment, while 242 responses are allocated into Control treatment (others did not enter the task page, so that there is no treatment allocation for them). However, according to the complete data, I have more participants in TP treatment compared to Control treatment, which means that there is non-random attrition to these two treatments. The attrition rate of Control treatment (50.8%) is larger than that of TP treatment (40.1%). There is suggestive evidence that participants are more likely to drop out when they were randomized into the Control treatment (p = 0.018).

[14] I did the same analyses as robustness checks where I exclude respondents who did not answer questions under the given time constraints. I find that effect sizes and p-values are quite similar.

Table 7: Two-sample test of attrition rates: Number of observations for each treatment = 242. And diff = prop (TP) - prop (Control) with z = -2.3735.

Treatment	Mean	Std. Err.	z	P>z	[95% Conf. Interval]	
TP	0.401	0.032			0.339	0.463
Control	0.508	0.032			0.445	0.571
diff	-0.107	0.045			-0.196	-0.019
	Under H0: (diff = 0)	0.045	-2.370	0.018		

5.2 Descriptive Analyses Results

I first analyze the number of safe choices made by an individual in the risk aversion and ambiguity aversion elicitation tasks, and the number of safe choices differences between MPL3 and MPL4 in the a-insensitivity elicitation tasks[15]. For my first measure of noise, I count the number of times that an individual switch their choices after their first switching point (reverse switches). This noise index can vary between 0 and 5 in MPL1, MPL3 and MPL4, while it can vary between 0 and 4 in MPL2. Table 8 represents the overview of the main variables of interest, which are the mean number of safe choices (or differences), as well as the number of reverse switches overall and across treatments.

I observe that participants in my experiment are risk averse on the aggregate, since the average number of safe choices is round 6 and a risk-neutral subject would choose the safer option five times. But the difference for risk aversion is not statistically significant between time pressure and control treatments with $p = 0.762$. In the ambiguity aversion task, participants in general showed a tendency to be ambiguity averse, because the mean numbers of Option B choices for both treatments are all below 5[16]. I find no conclusive evidence that time pressure affects choices for ambiguity aversion with $p = 0.516$, at least at the individual level. However, there is suggestive evidence in the difference of perceived level of ambiguity or a-insensitivity between two treatments with $p = 0.007$, indicating that time pressure may have an effect on the individual's perceived level of ambiguity and that participants become less sensitive to the reference likelihood in ambiguity events under time pressure.

[15] The number of safe choices is referred to the number of Option A choices for MPL1, and the number of Option B choices for MPL2 respectively. In a-insensitivity elicitation tasks (MPL3 and MPL4), it is referred to the number of Option B choices differences between MPL3 and MPL4. As for ambiguity elicitation tasks, I cannot say that the Option B is the "real safe" choice for participants, since fewer Option B (more Option A) choices represents more ambiguity aversion. According to my assumption, a(mbiguity)-neutral participants would choose Option B in the first row of the ambiguity elicitation choice lists, and risk-neutral participants would choose Option A in the first row of the risk elicitation choice list. Based on this assumption, I choose different safe choice definitions for risk and ambiguity tasks.

[16] In MPL2, according to the definition of ambiguity-neutrality, the fifth row is defined as the switching point for a-neutral participants.

Table 8: Descriptive results – means. Standard deviations are in parentheses. *p*-values are obtained using two-sided sample t-test. The total number of possible safe choices were 10 or 9 (for all of the decisions in the multiple price lists); the maximum number of reverse switches is therefore 5 or 4 for each part, but 19 for all parts.

Variable	Total	Control	TP	*p*-value
Number of safe choices				
(differences for a-insensitivity)				
risk aversion	6.08	6.042	6.111	0.762
	(1.82)	(1.85)	(1.80)	
ambiguity aversion	4.345	4.471	4.242	0.516
	(2.85)	(3.00)	(2.73)	
a-insensitivity	1.852	2.294	1.49	0.007
	(2.42)	(2.51)	(2.29)	
Number of reverse switches (total)	1.71	1.39	1.97	0.006
	(1.72)	(1.61)	(1.77)	
risk aversion	0.254	0.185	0.31	0.066
	(0.55)	(0.45)	(0.62)	
ambiguity aversion	0.83	0.655	0.973	0.005
	(0.92)	(0.85)	(0.95)	
a-insensitivity	0.625	0.546	0.69	0.242
(MPL3 & MPL4)	(0.99)	(1.00)	(0.98)	

Figure 1 graphically presents differences for three indices across treatments including 95% confidence intervals (left panel) and gives an overview of the actual distributions plotting the cumulative distribution functions for the perceived level of ambiguity or a-insensitivity level (right panel). The latter adds more detailed information about the actual distributions of the number of safe choices differences across treatments, rather than only informing about (differences in) means. The figures of cumulative distribution functions of the number of safe choices for risk and ambiguity aversion indices can be seen in Appendix A.

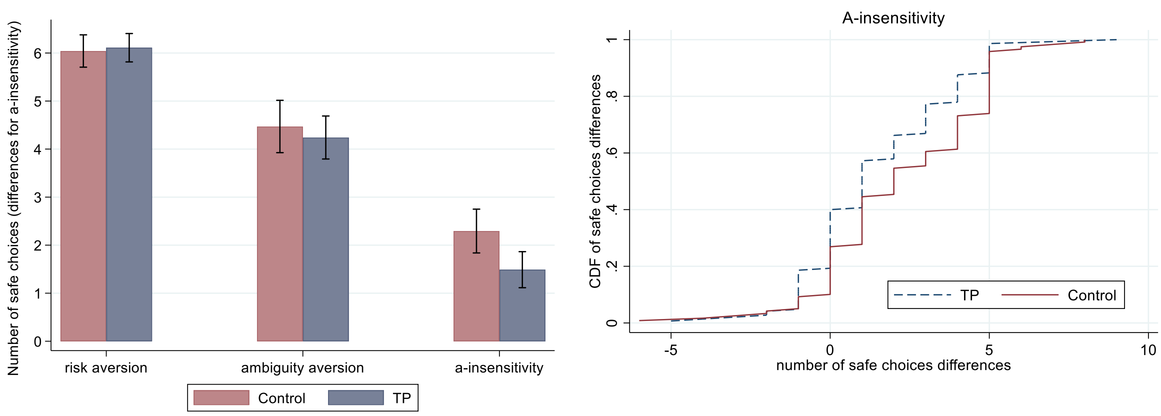

Figure 1: Mean number of safe choices (or differences) across treatments. The left panel of this figure depicts the mean number of safe choices (or differences) in the Control treatment compared to the TP treatment. The mean number of safe choices (or differences) is calculated using the relevant choice lists.

The error bars represent the 95% confidence intervals. The right panel of this figure presents the cumulative distribution functions of the number of safe choices differences between MPL3 and MPL4 across treatments. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

I also present the results of pooled OLS regression analyses by including three control variables. I get the similar results as the two-sided t-test above[17]. The results reveal suggestive evidence that time pressure affects the a-insensitivity level ($p < 0.05$) and has no effect on risk aversion and ambiguity aversion, which thus provides substantial evidence for Hypothesis 2 and Hypothesis 3. For Hypothesis 1, this strengthens my findings where I do not find a statistically significant difference in the mean number of safer choices in the risk elicitation task. In addition, gender is found to be a factor that influences risk preferences ($p < 0.05$) with suggestive evidence.

Table 9: OLS regression results – uncertainty attitudes. This table shows the coefficients for the regression of treatment (TP or Control) on the number of safe choices across all choice lists in risk and ambiguity aversion elicitation tasks (the number of safe choices differences between a-insensitivity elicitation tasks). Robust standard errors are in parentheses. Stars indicate significance levels, * $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$.

VARIABLES	(1) risk aversion	(2) ambiguity aversion	(3) a-insensitivity
Treatment	0.112	-0.203	-0.828*
	(0.226)	(0.358)	(0.299)
Gender	0.529*	0.341	-0.196
(1 = female)	(0.235)	(0.361)	(0.301)
Age	-0.014	-0.018	-0.035
	(0.015)	(0.019)	(0.019)
Business &	0.021	-0.255	0.431
Economics	(0.462)	(0.613)	(0.574)
Constant	6.133***	4.996***	2.835***
	(0.590)	(0.762)	(0.804)
Observations	264	264	264
R-squared	0.023	0.007	0.043

Result 1 *Counting the number of safe choices, there is no statistically significant difference in risk aversion between the TP and Control treatments. In particular, I find no evidence for increased risk aversion under time pressure.*

Overall, I do not find evidence for Hypothesis 1, where I expected that risk aversion increases under time pressure.

Result 2 *Counting the number of safe choices, there is no statistically significant difference in ambiguity aversion between the TP and Control treatments. In particular, I find no evidence for increased ambiguity aversion under time pressure.*

[17] I also included the interaction terms of the variable Treatment and 3 control variables respectively but achieved no significant results. Therefore, I did not include those interaction terms here. The same goes for the following OLS regression for number of reverse switches.

I thus find evidence in line with Hypothesis 2, where I expected that the ambiguity aversion would not change under time pressure.

Result 3 *Counting the number of safe choices differences between MPL3 and MPL4, I find suggestive evidence of a difference in a-insensitivity between TP and Control treatments. In particular, I find increased a-insensitivity under time pressure.*
I do find the evidence for our Hypothesis 3, where I expected that the a-insensitivity level increases under time pressure, or perceived level of ambiguity decreases under time pressure.

Except for underlying uncertainty attitudes, decision-making noise may also influence people to choose the safe choice. To capture noise, I count how often participants switch back to the safe option after the switching point. If participants make their choice based on their true preferences for every decision, they only ever switch once in each choice list. To this sense, I consider any participant switching back to be the noise. Therefore, if a participant only switches once, our noise measure is equal to 0. Our noise measure has a value of 2 (the person switched back twice to the safe option) if a person switches 5 times from the beginning in each choice list. This is named as the number of reverse switches in this thesis.

In total, the mean number of reverse switches under time pressure is significantly larger than that under no time pressure. This is mainly caused by the difference of that in ambiguity aversion elicitation task between two treatments with $p = 0.005$. I also find no evidence that time pressure has effect on the noisy decision making in the risk elicitation task and the a-insensitivity elicitation task, with the significance level $p = 0.066$ and $p = 0.242$ respectively.

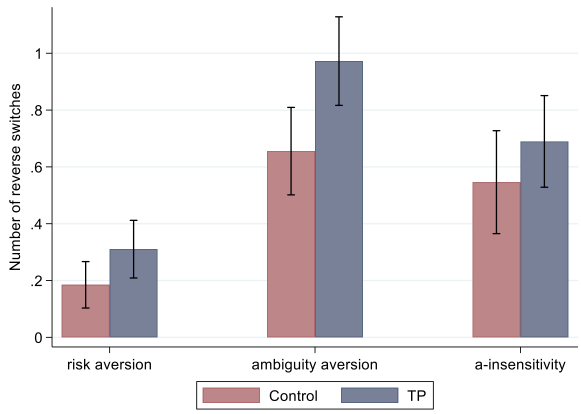

Figure 2: Mean number of reverse switches across treatments for different types of uncertainty attitudes. This figure depicts the mean number of reverse switches for different types of uncertainty attitudes in the Control treatment compared to the TP treatment. The mean number of reverse switches is calculated using the relevant choice lists. The error bars represent the 95% confidence intervals.

Figure 3 shows noise across treatments in total. I do find evidence that time pressure increases noise, but mainly in the ambiguity aversion elicitation task. Out of a maximum of 19, participants in the Control treatment switch back 1.39 times, against 1.97 reverse switches in the TP treatment. Thus, if anything, it seems that behavior becomes noisier under time pressure. Furthermore, the evidence is suggestive given the two-sided sample t-test ($p = 0.006$). Other figures of the cumulative density functions of the number of reverse switches for all uncertainty attitudes across treatments could be seen in Appendix A.

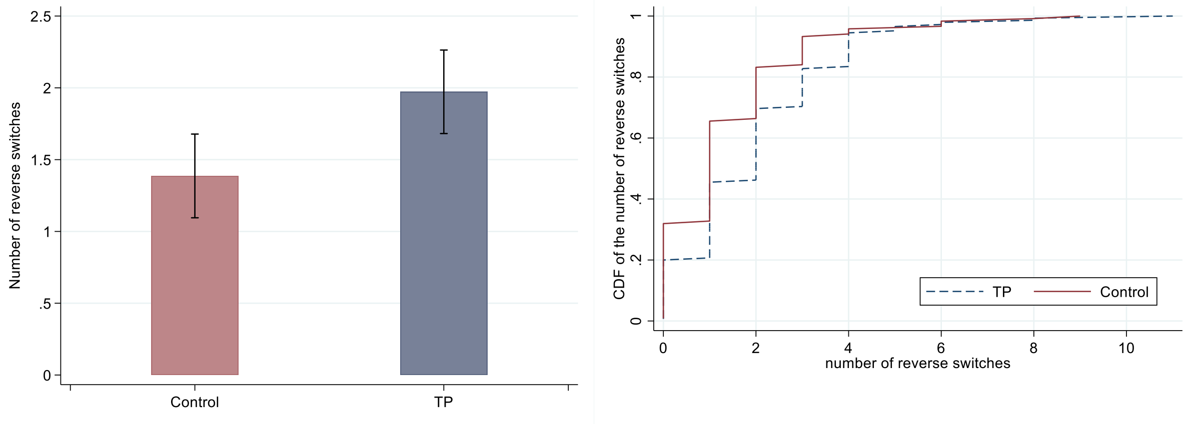

Figure 3: Mean number of reverse switches across treatments in total. The left panel of this figure depicts the mean number of reverse switches in the Control treatment compared to the TP treatment. The mean number of reverse switches is calculated using all choice lists. The error bars represent the 95% confidence intervals. The right panel of this figure presents the cumulative distribution functions of the number of reverse switches in total across treatments. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

As a robustness check, I also estimate the OLS regression by controlling for the same three variables previously as shown in Table 10, and I achieve the same main conclusion as the results in the two-sided sample t-tests. Rather than the suggestive evidence, I find the statistically significant evidence ($p < 0.005$) in the pooled OLS regression.

Table 10: OLS regression results – number of reverse switches. This table shows the coefficients for the regression of treatments (TP or Control) on the number of reverse switches across choice lists. Robust standard errors are in parentheses. Stars indicate significance levels, * $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$.

VARIABLES	(1) total	(2) risk aversion	(3) ambiguity aversion	(4) a-insensitivity
Treatment	0.615**	0.130	0.324**	0.161
	(0.208)	(0.066)	(0.110)	(0.124)
Gender	0.340	0.047	0.085	0.208
(1 = female)	(0.225)	(0.071)	(0.116)	(0.133)
Age	-0.000	0.004	-0.003	-0.001
	(0.014)	(0.005)	(0.010)	(0.007)
Business &	-0.567	-0.091	-0.350	-0.125
Economics	(0.527)	(0.179)	(0.216)	(0.263)
Constant	1.763*	0.162	1.013**	0.587
	(0.646)	(0.224)	(0.352)	(0.316)
Observations	264	264	264	264
R-squared	0.046	0.019	0.042	0.017

Result 4 *Counting the number of reverse switches, I find a significant difference between TP and Control treatments. In particular, I find increased noisy decision making in ambiguity aversion elicitation task under time pressure.*
I do find the evidence for our Hypothesis 4, where I expected that the noise increases under time pressure. I address different specific types of noise later in the structural estimation section, where I estimate noise and uncertainty attitudes jointly.

Finally, I conduct an additional analysis, which is not pre-registered in my pre-analysis plan, to explore how noise biases the baseline measure of individual uncertainty attitudes I estimate. In this regression, the number of safe choices (or differences) is the dependent variables, while the number of reverse switches is an in independent variable (along with other controls).

Table 11: OLS regression results – the effect of noise on uncertainty attitudes. This table shows the coefficients for the regression of the number of reverse switches on the number of safe choices (or differences) across choice lists. Robust standard errors are in parentheses. Stars indicate significance levels, * $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$.

VARIABLES	(1) risk aversion	(2) ambiguity aversion	(3) a-insensitivity
Reverse Switches	-0.545**	0.219	-0.357*
	(0.179)	(0.174)	(0.153)
Treatment	0.182	-0.274	-0.770*
	(0.226)	(0.364)	(0.301)
Gender	0.554*	0.322	-0.122
(1 = female)	(0.235)	(0.362)	(0.297)
Age	-0.012	-0.018	-0.035*
	(0.014)	(0.020)	(0.018)
Business &	-0.029	-0.179	0.386
Economics	(0.441)	(0.617)	(0.573)
Constant	6.221***	4.774***	3.045***
	(0.569)	(0.783)	(0.805)
Observations	264	264	264
R-squared	0.050	0.012	0.064

The results show that noise, or the number of reverse switches, affects the estimated individual uncertainty attitudes. To be specific, the results suggest that risk reversion and the perceived level of ambiguity are negatively correlated with noisy decision making. This finding coincides with the results revealed by Andersson et al. (2016), who found that people with high cognitive ability are less prone to noisy behavior, while noisy decision making is demonstrated to be negatively correlated with risk aversion in a similar choice list as I use, which produces the positive correlation between cognitive ability and risk aversion[18]. Their

[18] Andersson et al. (2016) argued that people with low cognitive ability tend to make more errors when they make their decisions. In their argument, there are two types of individuals, A and B, who are heterogeneous in their likelihood to make errors. A-types are perfectly error-free, but B-types make a mistake with probability e, and choose the lottery that maximizes expected utility with 1-e. When both types are risk averse, for instance it is optimal for everyone to switch at decision 6, meaning A-types make 6 safe

arguments, that there is a negative correlation between noisy decision making and risk aversion, are consistent with my findings. I cannot disentangle whether there less risk averse (more a-insensitive) participants make more errors or whether participants who are make more noisy decisions appear to be less risk averse (more a-insensitive) in my experiment. But I do find that the noise biases individual risk aversion and the a-insensitivity level and has no impact on the individual ambiguity aversion level. Even if time pressure increases participants' noisy decision making in the ambiguity aversion elicitation task, noise would not have any effect on the observed ambiguity aversion level I estimate here. I illustrate it more in the following structural estimation part.

Result 5 *Through the OLS regression, I find a statistically significantly negative relationship between risk aversion and noisy decision making, and suggestive evidence of a positive relationship between a-insensitivity and noisy decision making.*

6 Structural Estimation

In this section, I provide structural estimates of the risk aversion, ambiguity aversion, a-insensitivity and noise parameters. This allows me to do a more thorough test of how time pressure affects underlying risk attitudes and ambiguity attitudes as opposed to merely counting the number of safe options and reverse switches. The cost of doing so is that more assumptions about the utility function and the types of errors that participants commit must be made.

I follow the approach used by Loomes et al. (2002) and Parslow and Rose (2022) and divide the decision process into three steps. Preference selection is the initial stage, where participants choose which preferences they currently have. The second stage is the evaluation of prospects, which in my situation corresponds to the calculation of lottery outcomes. The Fechner error, is the type of error that occurs in this step. The third stage is where participants actually take actions and make their choices. In my situation, this entails clicking one of two options. The type of error in this step is the trembling-hand error.

In our estimates, I first provide the outcomes of a model that does not account for errors. Then I take into account heterogeneity within participants by incorporating trembling-hand error first and then the Fechner type error with trembles. By doing so, I can compare treatment variations in a meaningful way and quantify the observed inconsistencies. The following analyses are based on Gneezy et al. (2015).

In order to structurally estimate the ambiguity and risk attitudes index, I assume expected utility for risk for simplicity, because adding probability weighting functions would insert too many indices which are not this study's interest. I also assume constant relative risk aversion (CRRA) and constant relative ambiguity aversion (CRAA), so that the utility function form is:

$$u(x) = x^r$$

choices in this list while B-types choose the safe gambles with probability (1-e)*1+e*0.5=1-0.5e at the first 6 rows, and remain on the safe gambles when he trembles with probability 0.5e at the last 4 rows. Taken together, B-types make (6-e) safe choices in this list. Hence, B-types, who have more noisy in decision making, on average appear to be less risk averse despite having the same risk preferences with A-types.

, where x is the stake level of the gamble, and r represents risk aversion index. $r = 1$ represents risk neutrality; $r < 1$ for risk averse and $r > 1$ for risk seeking[19].

In order to detect risk aversion parameter in risk elicitation task (MPL1), I derive the likelihood function for the choices made by the participants. Firstly, I specify the contribution to the likelihood of the choices made on the risk attitude MPL1.

Given that there are two possible outcomes for each gamble, let the utility from a gamble take the following form:

$$V_i(y; r) = \sum_{j=1,2} p(x_j)\, u_i(x_j; r)$$

, where x_j is one of the two outcomes, $p(x_j)$ is the probability of that outcome, which is $\frac{1}{2}$ in this task, and y is a gamble from the set Y, for $Y = \{y_A, y_B\}$, where y_A is Option A and y_B is Option B for that decision.

Assuming individuals maximize the following random utility model:

$$U_i(y; r) = V_i(y; r) + \varepsilon_{iy}$$

, while ε_{iy} is independently, identically distributed extreme value (Gumbel and type I extreme value). For individuals, they choose y^* such that $U_i(y^*; .) \geq U_i(y; .)$ for all $y \in Y$. The distribution of ε_{iy} leads to logistic choice probabilities of choosing a particular gamble y that can be expressed in the following form[20]:

$$Pr^{Risk}(y) = \frac{e^{V_i(y;r)}}{\sum_{k=A,B} e^{V_i(y_k;r)}}$$

I get the structural estimate for r by specifying this using a maximum likelihood method. Then I next use conventional post-estimation Wald-tests to look for differences between TP and Control treatments. Additionally, by clustering standard errors at the individual level, I control for multiple responses from a single participant (each participant is required to make a total of 10 decisions).

Next, in order to detect ambiguity attitudes in ambiguity elicitation tasks, I specify individual utility of choosing Option A in those tasks:

$$V_i(z^A; r) = \sum_{j=1,2} p(x_j)\, u_i(x_j; r)$$

---

[19] The utility function here is different from that in pre-analysis plan since structural estimation programming in my case requires the parameter to be non-negative, which means that participants need to be risk averse (r > 0) rather than risk seeking (r < 0) and this is a very strict assumption. But the utility function here doesn't need this strict assumption, and r will always be non-negative.
[20] The derivation of this formula could be found in Chapter 3 of "Discrete choice methods with simulation" written by Train (2009).

, where x_j is one of the two outcomes, $p(x_j)$ is the probability of that outcome. z^A corresponds to Option A. In my setting, $\{x_1, x_2\} = \{200,0\}$, and p varies from 0.1 to 1.0 in ambiguity elicitation tasks.

Then, I specify the utility of drawing a ball from the urn in Option B as:

$$V_i(z^B; \alpha, \beta, r) = ((1-\beta)p + (1-\alpha)\beta)u_i(x_1; r)$$

, where parameters are defined as the model specification part. I also assume individuals maximize a random utility model as shown before. Hence, defining $Z = \{z^A, z^B\}$, the probability of choosing to draw from the urn in Option B can be expressed as:

$$Pr^{Amb}(z) = \frac{e^{V_i(z;r,\alpha,\beta)}}{\sum_{k=A,B} e^{V_i(z_k;r,\alpha,\beta)}}$$

So that I could get the structural estimate for α and β by specifying this using a maximum likelihood method. Similarly, I next use conventional post-estimation Wald-tests to look for differences between TP and Control treatments.

In the second step, I augment this model by adding errors. In other words, this approach allows participants to make some errors in all tasks.

The first specification I use is the trembling-hand model analyzed by Moffatt and Peters (2001). By this I mean that the individual implements the choice indicated by above with probability $(1-\omega)$ and chooses at random between the two lotteries with probability ω. The parameter ω is called the "tremble probability", while $\omega \in [0,1]$ and $\omega = 1$ represents fully randomization. Introducing this parameter, the likelihood contributions become:

$$Pr^*(z) = (1-\omega)\frac{e^{V_i(z;\cdot)}}{\sum_{k=A,B} e^{V_i(z_k;\cdot)}} + \frac{\omega}{2}$$

Then, I introduce a framework established originally by Fechner, popularized by Hey and Orme (1994). Due to this specification, errors happen at the stage of making the decision.

Then, the random utility function of each lottery changes into this form:

$$U_i(y;r) = V_i(y;r) + \mu\varepsilon_{iy}$$

, where μ is a noise parameter used to allow errors from the perspective of the deterministic EU model.

The original likelihood contributions for risk and ambiguity become to this form[21]:

[21] The derivation of inserting the scale parameter in this formula could also be found Chapter 3 of "Discrete choice methods with simulation" written by Train (2009).

$$Pr^*(z) = \frac{e^{\frac{V_i(z;\cdot)}{\mu}}}{\sum_{k=A,B} e^{\frac{V_i(z_k;\cdot)}{\mu}}}$$

Then adding the trembles illustrated above:

$$Pr^*(z) = (1-\omega)\frac{e^{\frac{V_i(z;\cdot)}{\mu}}}{\sum_{k=A,B} e^{\frac{V_i(z_k;\cdot)}{\mu}}} + \frac{\omega}{2}$$

Noise parameters would be estimated jointly with the risk and ambiguity attitudes parameters.

All parameters mentioned above are obtained via maximum likelihood estimations using the Broyden-Fletcher-Goldfarb-Shannon (BFGS) optimization algorithm with post-estimation Wald tests by default for all analyses.

7 Estimation Results

The results for the structural estimations of the three model specifications for risk and ambiguity attitudes are provided in Table 12. In each uncertainty attitudes estimation, the first three columns present the results for the model without any error specification, the middle three columns show results obtained by the trembling-hand model, and the last three columns reveal the results obtained by the Fechner error model with trembles. All *p*-values are obtained via post-estimation Wald tests unless mentioned otherwise.

Table 12: Parameter estimates for utility function curvature and error parameters. This table shows the parameter estimates for the utility function curvature as well as the parameter estimate for choice errors. All parameters are obtained via maximum likelihood estimations using the Broyden-Fletcher-Goldfarb-Shannon (BFGS) optimization algorithm. In each uncertainty attitudes estimation, the left three columns include estimations without an error specification, the middle three columns include estimations obtained the trembling-hand model, and the right three columns include estimations obtained via the Fechner error model with trembles. Standard errors are clustered on the individual level. Stars indicate significance levels, * $p < 0.05$; ** $p < 0.005$; *** $p < 0.001$. All p-values are obtained via post-estimation Wald tests.

	Risk attitudes									Ambiguity attitudes								
	Without errors			Trembling-hand model			The Fechner model with trembles			Without errors			Trembling-hand model			The Fechner model with trembles		
	Control	TP	*p*-val.	Control	TP	*p*-val.	Control	TP	*p*-val.	Control	TP	*p*-val.	Control	TP	*p*-val.	Control	TP	*p*-val.
Utility Parameter *r*	0.439***	0.433***	0.6793	0.523***	0.567***	0.3256	0.663***	0.662***	0.9847									
	(0.010)	(0.010)		(0.037)	(0.024)		(0.038)	(0.030)										
Utility Parameter *α*										0.576***	0.556***	0.6206	0.541***	0.590***	0.4289	0.591***	0.565***	0.5662
										(0.032)	(0.024)		(0.052)	(0.031)		(0.038)	(0.026)	
Utility Parameter *β*										0.186***	0.241***	0.0942	0.116***	0.426***	0.0002	0.365***	0.476***	0.0601
										(0.023)	(0.024)		(0.022)	(0.081)		(0.046)	(0.037)	
Error Parameter *μ*							3.018***	2.688***	0.7053							4.498***	5.126***	0.2704
							(0.701)	(0.522)								(0.434)	(0.370)	
Error Parameter *ω*				0.150***	0.193***	0.4383	0.104***	0.131***	0.4271				0.302***	0.395***	0.0112	0.055*	0.013	0.2709
				(0.046)	(0.031)		(0.023)	(0.024)					(0.029)	(0.022)		(0.029)	(0.024)	
Log likelihood	-510.109	-631.292		-498.766	-604.158		-469.221	-576.558		- 3438.890	- 4355.445		- 1797.402	- 2260.548		-1708.150	-2084.127	
Observations	2,640	2,640	2,640	2,640	2,640	2,640	2,640	2,640	2,640	7,656	7,656	7,656	7,656	7,656	7,656	7,656	7,656	7,656

Across all specifications in the estimation of risk attitudes, the estimated parameters for utility function curvature indicate risk aversion with $r < 1$, confirming the descriptive results, together with a slightly higher degree of risk aversion under time pressure. The risk aversion parameters between the Control and TP treatments are not statistically significantly different for either of the columns (p = 0.3256, Wald Chi-Squared test). With respect to the estimated noise parameters under Control and TP, I find that trembling-hand errors are not significantly different across specifications (p = 0.4384, Wald Chi-Squared test), which is similar for the Fechner errors specifications (p = 0.7053, Wald Chi-Squared test). After controlling for the noise parameters, the difference of the risk aversion parameter between two treatments is even smaller. However, I do find evidence of noise biasing the baseline preferences. The parameters of risk aversion in the error models (above 0.5) are larger than those in the model without errors (below 0.5). Comparing the three different models, I find that the main effect of ignoring errors is a downward bias in the estimate of the risk aversion parameter r, and participants are prone to be less risk averse at the aggregate level after controlling those errors, which confirms the additional descriptive results.

For the estimation of ambiguity attitudes, the estimated parameters for utility function curvature indicate ambiguity aversion with $\alpha > 0.5$, and I find that there is a statistically significant difference of a-insensitivity parameter between two treatments (p = 0.0002, Wald Chi-Squared test) by just controlling for trembling-hand error. I also find suggestive evidence of time pressure increasing trembling-hand errors (p = 0.0112, Wald Chi-Squared test). These results thus confirm the descriptive results. Furthermore, noise biases the a-insensitivity level in general since ignoring errors would lead to a downward bias in the estimate of the a-insensitivity parameter β, which also demonstrates the additional descriptive results above.

Additionally, there is a decreased risk aversion level and an increased a-insensitivity level after controlling for all types of errors. This reveals that errors, especially trembling-hand errors, have effects on uncertainty attitudes. Particularly, my findings coincide with the results of Andersson et al. (2016), which showed that in a similar risk elicitation experiment, participants appear to be more risk seeking if they have more noisy decision making. In my structural estimation results, participants appear to be more risk averse in the model without errors, but less risk averse in the models with errors, suggesting that more noisy decision making maps into more risk aversion in the model without errors, while the models with errors allow more participants with less risk aversion, who are more prone to make noise in their decisions, to show up in the estimation.

As the new discovery, this same conclusion applies to explaining the relationship between noisy decision making and a-insensitivity. As my descriptive analyses show above, participants with more noisy decisions are more prone to be insensitive to the reference likelihood in ambiguity events. Therefore, in the structural estimation model without errors, noisy decisions map into less a-insensitivity. Conversely, participants with more noisy decisions, who appear to be more a-insensitive, could be observed in the model with errors, so that the a-insensitivity parameter in the models with errors are generally larger than that in the model without errors.

For the types of error models used here, it seems like the trembling-hand error model fits my sample better. This is mostly because in the trembling-hand model, the main estimated parameters are shown to be as statistically significant as I find in the descriptive analyses results above. In the Fechner model with trembles, I cannot expect the Fechner errors to have an impact only when the subject is close to being indifferent between the two lotteries because the parameters of Fechner errors are very large (all greater than 1). The parameter of the Fechner error, to some degree, can be regarded as the standard deviation with respect to the normalization of the utility (Conte et al., 2011), which captures lottery-specific heteroskedasticity in the error term. The larger Fechner error parameter is, the "thicker" the participants' indifference curves of the utility functions are. In my estimation results, the Fechner error parameters are too large so that it is more possible the errors are mostly caused by trembles rather than "thick" indifference curve. Furthermore, the parameters of the Fechner error as shown in the Fechner model with trembles in ambiguity elicitation tasks are significantly larger than that in risk elicitation tasks, which could explain that participants are more uncertain with their true preferences about their ambiguity attitudes than risk attitudes. Although I cannot definitively identify the types of errors based solely on these models, my data suggests that participants make more inconsistent choices in ambiguity tasks for a variety of reasons, such as randomness or the lack of comprehension to instructions, compared to their behavior in risk tasks.

Result 6 *In the estimation, risk aversion and ambiguity aversion are stable across TP and Control treatments. But the a-insensitivity level increases statistically significantly under time pressure in the trembling-hand error model.*
Those results are consistent with the descriptive analyses above.

Result 7 *Controlling for noise, participants' risk aversion level decreases and a-insensitivity level increases in general.*
Overall, I find that errors do not increase under time pressure in the risk elicitation task, but trembling-hand errors do increase under time pressure in the ambiguity elicitation task as also confirmed by the estimation results. Moreover, I find that participants appear to be more risk averse and less insensitive to ambiguity in general when I do not control for the errors.

8 Exploratory Analyses: Gender Effects on Attitudes towards Uncertainty

In addition to my main analyses presented above, I include exploratory analyses about the gender difference on ambiguity and risk attitudes under no time constraints and the gender difference of the time pressure effect on those variables and indices. This is based on the findings of the previous literature on gender differences in risk and ambiguity attitudes in general (e.g., Charness and Gneezy, 2012; Borghans et al., 2009; Friedl et al., 2020). In this part, I firstly detect uncertainty attitudes differences only in the Control treatment across female and male & others sub-samples and find suggestive evidence of a gender difference in risk aversion. Then I analyze the treatment effects within these two sub-samples. The descriptive results and structural estimation show that uncertainty attitudes are affected almost equally by time pressure for all genders, but women are prone to make more errors when they participate in the ambiguity aversion elicitation task.

When it comes to gender differences on uncertainty attitudes, I only find suggestive evidence of women being less risk averse ($p = 0.0244$, Mann-Whitney U test). For ambiguity attitudes and noisy decision making, there is no evidence of gender differences.

Figure 4 shows the cumulative density functions of the number of safe choices for risk aversion under Control treatment between two sub-samples. Women are shown to be more risk averse in general.

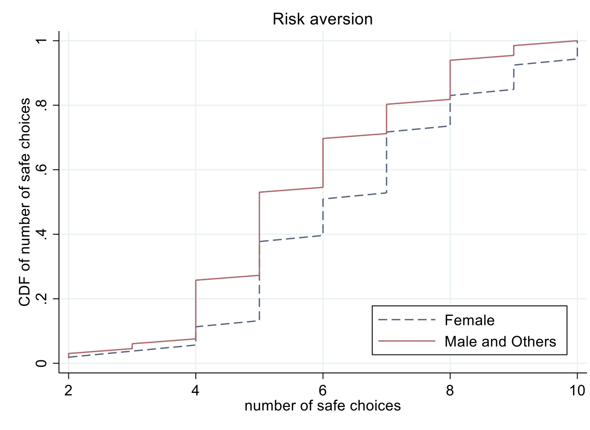

Figure 4: Mean number of safe choices in risk elicitation task across gender sub-samples. This figure presents the cumulative density functions of the number of safe choices in risk elicitation task across gender sub-samples in Control treatment. The dashed blue line represents female participants, the red line represents male and other participants.

Result 8 *Counting the number of safe choices, there is suggestive evidence of a gender difference in risk aversion. In particular, I find female are more risk averse than male and others.*

I thus find suggestive evidence in line with my Hypothesis 5, where I expected that women would be more risk averse than others.

Result 9 *Counting the number of safe choices, there is no statistically significant difference in ambiguity aversion between Female and Male and Others sub-samples.*

I find no evidence for my Hypothesis 6, where I expected that women are more ambiguity averse than others. I conduct a Mann-Whitney U test and find $p = 0.4558$.

Result 10 *Counting the number of safe choices, there is no significant difference in a-insensitivity level between Female and Male and Others sub-samples.*

I find no evidence for my Hypothesis 7, where I expected that women are less a-insensitive than others. The difference between these two sub-samples is not significant ($p = 0.6146$, Mann-Whitney U test).

For the gender difference of the time pressure effect on uncertainty attitudes, the treatment effect of a-insensitivity certainly exists in both two sub-samples. Figure 5 shows the cumulative density functions of the number of safe choices differences between MPL 3 and MPL4, which represents a-insensitivity index, between the treatments for female (left panel) and male & others (right panel) participants. For female participants, there is suggestive evidence of a difference in distributions ($p = 0.0314$, Mann-Whitney U test), as is the case for male and other participants ($p = 0.0267$, Mann-Whitney U test). But for other uncertainty attitudes, the differences are not statistically significant across treatments. Other figures showing the cumulative density functions of the number of safe choices for risk and ambiguity aversion for both sub-samples can be seen in Appendix A.

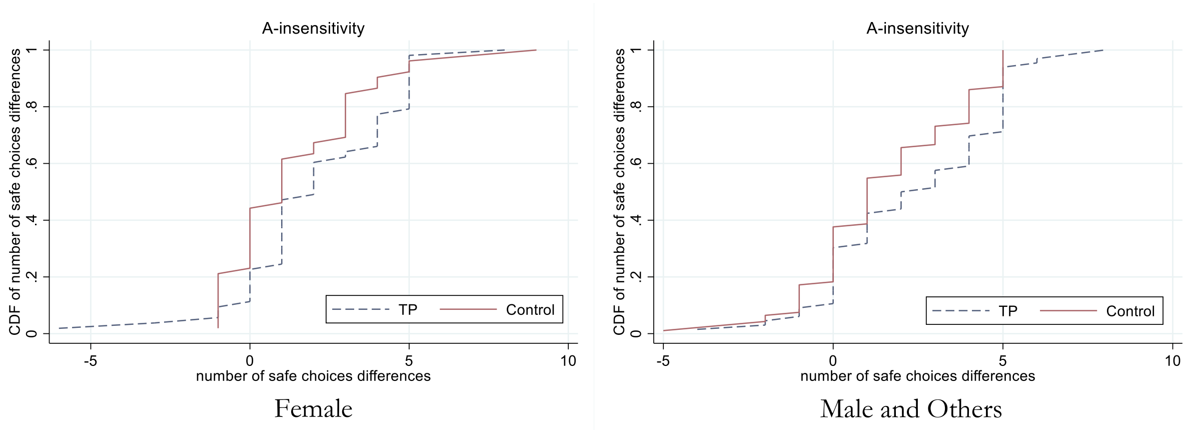

Figure 5: Mean number of safe choices differences between MPL3 and MPL4 across treatments—gender differences. The left panel of this figure presents the cumulative density functions of the number of safe choices differences between MPL3 and MPL4 across treatments for female participants, the right panel for male and other participants. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

In addition, I find suggestive evidence that women exhibit more noisy decision making in the ambiguity aversion elicitation task (MPL2) under time pressure with p = 0.0124 by using Mann-Whitney U test, but men and others do not (p = 0.1129, Mann-Whitney U test). Figure 6 exhibits the cumulative density function of the number of reverse switches for female and male & others.

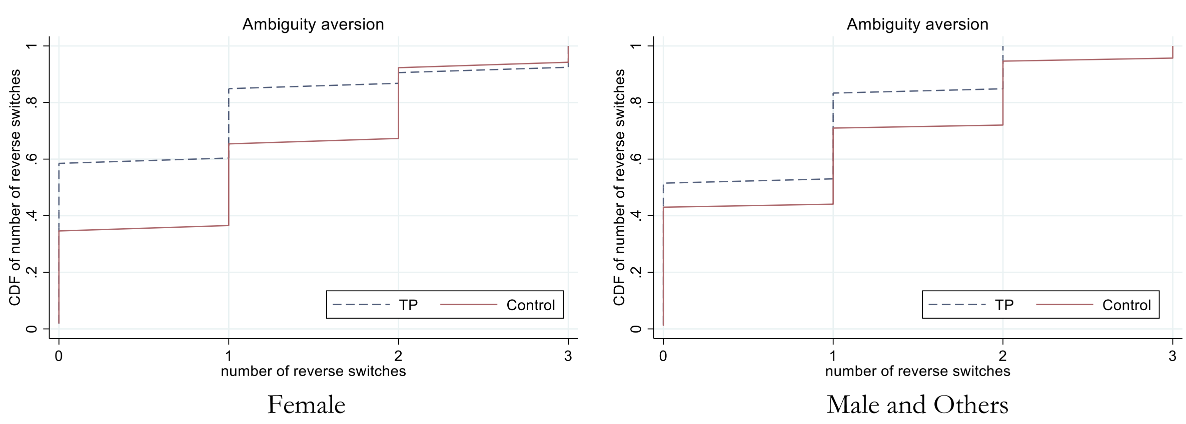

Figure 6: Mean number of reverse switches in ambiguity aversion elicitation task across treatments—gender differences. The left panel of this figure presents the cumulative density functions of the number of reverse switches in ambiguity aversion elicitation task across treatments for female participants, the right panel for male and other participants. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

Result 11 *For female participants, the a-insensitivity level and noise in ambiguity aversion elicitation task is different across treatments with suggestive evidence. For male and others, there is no clear evidence for noise difference, but the a-insensitivity level does differ across treatments.*

Finally, I do the same parameter estimation as shown for the whole sample but now on the female and male & others sub-groups separately. The results are presented in Table 13.

For each of the models, I estimate all parameters for female and male & others separately. The results show that the estimations without including a specific model for errors do not support a significantly higher degree of a-insensitivity level difference for neither male nor female participants across treatments. After controlling for the trembling-hand errors, I thus reach the same conclusion as mentioned above. Both female and male (and other) participants show significantly different a-insensitivity level across treatments ($p = 0.0000$ and $p = 0.0346$ respectively, Wald Chi-Square test). In addition, there is suggestive evidence of female participants making more trembling noise in ambiguity elicitation tasks under time pressure ($p = 0.0076$, Wald Chi-Square test) while men and others do not ($p = 0.1826$, Wald Chi-Square test), which means that the errors in ambiguity elicitation tasks are made by female participants. However, I additionally find that male and others are less risk averse under time pressure after controlling the trembling-hand errors with statistical significance ($p = 0.0000$, Wald Chi-Square test).

Table 13: Parameter estimates for utility function curvature and error parameters – gender differences. This table shows the parameter estimates for the utility function curvature as well as the parameter estimate for choice errors for different gender sub-samples. All parameters are obtained via maximum likelihood estimations using the Broyden-Fletcher-Goldfarb-Shannon (BFGS) optimization algorithm. In each uncertainty attitudes estimation, the left three columns include estimations without an error specification, the middle three columns include estimations obtained the trembling-hand model, and the right three columns include estimations obtained via the Fechner error model with trembles. Standard errors are clustered on the individual level. Stars indicate significance levels, * $p < 0.05$; ** $p < 0.01$; *** $p < 0.005$. All p-values are obtained via post-estimation Wald tests.

	Risk attitudes									Ambiguity attitudes								
	Without errors			Trembling-hand model			The Fechner model with trembles			Without errors			Trembling-hand model			The Fechner model with trembles		
	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.
Parameter r																		
Female	0.425***	0.408***	0.4079	0.529***	0.553***	0.6124	0.589***	0.632***	0.5950									
	(0.015)	(0.015)		(0.030)	(0.036)		(0.054)	(0.061)										
Male and Others	0.455***	0.452***	0.8936	0.484***	0.657***	0.0000	0.720***	0.675***	0.4739									
	(0.012)	(0.013)		(0.037)	(0.020)		(0.054)	(0.033)										
Parameter a																		
Female										0.495***	0.505***	0.8519	0.541***	0.510***	0.5907	0.510***	0.513***	0.9608
										(0.040)	(0.039)		(0.052)	(0.027)		(0.044)	(0.041)	
Male and Others										0.644***	0.584***	0.2678	0.607***	0.616***	0.9191	0.676***	0.590***	0.2278
										(0.045)	(0.030)		(0.078)	(0.035)		(0.063)	(0.032)	
Parameter β																		
Female										0.197***	0.229***	0.4837	0.116***	0.649***	0.0000	0.377***	0.459***	0.3087
										(0.030)	(0.036)		(0.022)	(0.082)		(0.057)	(0.057)	
Male and Others										0.185***	0.252***	0.1819	0.104***	0.369***	0.0346	0.369***	0.486***	0.1449
										(0.038)	(0.033)		(0.029)	(0.122)		(0.064)	(0.047)	

	Risk attitudes									Ambiguity attitudes								
	Without errors			Trembling-hand model			The Fechner model with trembles			Without errors			Trembling-hand model			The Fechner model with trembles		
	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.	Control	TP	p-val.
Parameter μ																		
Female							1.700***	2.154***	0.6549							4.037***	4.991***	0.1809
							(0.618)	(0.805)								(0.422)	(0.575)	
Male and Others							4.616***	3.002***	0.2877							5.423***	5.145***	0.7281
							(1.360)	(0.676)								(0.666)	(0.444)	
Parameter ω																		
Female				0.169***	0.246***	0.2495	0.146***	0.206***	0.3287				0.302***	0.427***	0.0076	0.076	0.047	0.6195
				(0.040)	(0.054)		(0.037)	(0.049)					(0.030)	(0.037)		(0.041)	(0.041)	
Male and Others				0.073	0.211***	0.1124	0.064**	0.085***	0.5610				0.304***	0.370***	0.1826	-0.006	-0.003	0.9302
				(0.083)	(0.027)		(0.029)	(0.024)					(0.039)	(0.031)		(0.028)	(0.027)	
Observations																		
Female	530	520		530	520		530	520		1,537	1,508		1,537	1,508		1,537	1,508	
Male and Others	660	930		660	930		660	930		1,914	2,697		1,914	2,697		1,914	2,697	
Log likelihood																		
Female	-229.137	-246.854		-220.813	-238.980		-218.046	-234.214		-1494.499	-1657.431		-793.360	-825.955		-752.163	-768.711	
Male and Others	-278.783	-378.428		-277.414	-361.647		-242.974	-336.877		-1918.974	-2684.949		-999.695	-1422.123		-944.379	-1309.470	

9 Discussion

In this thesis, I analyze the impact of time pressure on individual attitudes towards uncertainty in a pre-registered study with 264 participants for whom I have complete data. I find no statistically significant differences in risk and ambiguity aversion across treatments, but suggestive evidence of a difference in the ambiguity-generated likelihood insensitivity across treatments. In particular, my contribution to the literature is that I create a new method to elicit ambiguity aversion per perceived level of ambiguity and a-insensitivity by using multiple price lists method, which just need around 5 minutes for participants to join. Besides, since no previous study accounts for the noise in ambiguity events under time constraints, I account for the noise in decision-making process for both risk and ambiguity tasks jointly under time pressure, and therefore can distinguish between a genuine change in preferences across treatments versus an increase in noise.

I successfully conduct the time pressure in the treatment group by letting participants make each decision in 10 seconds without auto-skipping to the next one in Qualtrics, based on the low rate of failed responses in my experiment.

My findings first show that participants were more energetic under time pressure, since there is suggestive evidence that the involvement rate of time pressure treatment are larger than that of control treatment. My main results in descriptive analyses are all supported by both structural estimation and pooled OLS regression analyses as well. In particular, the descriptive analyses show that there is suggestive evidence of a positive impact of time pressure on a-insensitivity level, which is also strengthened by the statistically significant structural estimation result after controlling for trembling-hand errors and suggestively significant OLS regression result. Furthermore, I have evidence that all the robust null results are not driven by increased noise in decision-making process under time pressure, even though time pressure does increase participants' noisy decision making in ambiguity aversion elicitation task. The robust treatment effect on the a-insensitivity level can even be confirmed by controlling the trembling-hand errors in the structural estimation. The structural estimation results also show that noise certainly bias the risk aversion level upwards and a-insensitivity downwards on the aggregate level but has no effect on ambiguity aversion level.

In my exploratory analysis of gender effects on attitudes towards uncertainty, I investigate whether there might be gender differences in risk and ambiguity attitudes in general. I find suggestive evidence that women are more risk averse than men, but there is no significant difference of ambiguity attitudes between female and male & others sub-samples. I also study whether there might be gender differences of the time pressure effect on uncertainty attitudes and not only find some evidence that the a-insensitivity level of both sub-groups are certainly influenced by time pressure, but also that women are prone to make more noise in ambiguity elicitation tasks under time pressure while men and others are not. The structural estimation results additionally show that men and others are inclined to be less risk averse under time pressure after I control the trembling-hand errors.

My findings warrant some discussion given the findings in the related literature. As outlined in the previous literature, there is no real consensus on in which direction the effects of time pressure on risk preferences go. My analyses support the results of a null effect of time pressure on risk aversion. Although many studies show that individual risk preferences would not be influenced by stress (e.g., Parslow and Rose, 2022; Kocher et al., 2013), there are also plenty of results suggesting that time pressure has an impact on risk preferences (e.g., Kirchler et al., 2017; Young et al., 2012). Based on my experimental results, I cannot exclude the possible explanation that the time pressure I put on participants in the experiment may not be large enough to induce a difference in risk aversion across treatments, since I set a 10 seconds limits which is longer compared with the 7 or 4 seconds limits used in the previous research.

For ambiguity attitudes, my results are similar to the result of Baillon et al. (2018). The null effect of time pressure on ambiguity aversion and the positive impact of time pressure on a-insensitivity come from my descriptive analyses as well as structural estimation. In addition, participants' noisy decision making is detected to be more significantly frequent under time pressure when they make their decision in the ambiguity aversion elicitation task, which has not earlier been shown and can be regarded as the contribution to the literature. At a minimum, I can conclude that the individual ambiguity aversion level is less stable under time pressure in the probability-varying ambiguity elicitation task due to the increased noise making.

The parameter estimation results suggest that the trembling-hand errors may be the most frequent errors made by participants because the trembling-hand model fits well in my data sets, especially in the ambiguity attitudes elicitation tasks. This fact may be due to various reasons. Firstly, although there is some evidence that individual ambiguity aversion level could increase with the reference likelihood of the ambiguity events, some studies show that the assessment of probability-varying preference elicitation task is cognitively more difficult than stake-varying preference elicitation task (Bleichrodt et al., 2001; Callen et al., 2001). Time pressure further interferes with participants' evaluation process of ambiguous events, which would lead participants to be more uncertain about their true preferences and more likely to make inconsistent decisions when they are faced with ambiguity. Secondly, because my experimental design is constrained by realistic conditions, for example, it is not appropriate to design a long-time experiment in order to maintain a sufficient sample size due to the form of survey experiment. Besides, I did not elicit participants' decisions twice to test for consistency as most previous research did and I also did not add control questions in the survey to test whether participants understood the instructions. All those factors could influence participants' decision quality, even though I can detect the relative noise in my analyses.

Another important factor that may influence the internal validity is the hypothetical incentives used in my experiment. The validity of hypothetical choices has been hotly debated in the literature, yet the results are conflicting. On the one hand, numerous research that compared hypothetical choices and real incentives revealed no discernible changes, indicating that hypothetical choices can be a reliable replacement. However, other research did discover differences, disproving the validity of the fictitious decision. There is no one-size-fits-all rule, and hypothetical choice applicability appears to depend on the specific circumstances. When it comes to risky choices, most studies find no differences between real incentives and hypothetical choices. As for ambiguity elicitations, Gneezy et al. (2015) also found no difference between real incentives and hypothetical choices. Usually, hypothetical choices work well for sophisticated participants with simple stimuli that take no effort from the participants, since Dimmock et al. (2016) found that the bias was driven almost entirely by participants with low education under hypothetical choice. All participants in my experiments are well-educated students or teachers in universities, I thus make the assumption that most participants will show their real preferences among those hypothetical choices. But future research could randomly allocate real and hypothetical monetary incentives in this context and investigate the results.

As for external validity, compared to the previous study by Baillon et al. (2018), who use a method for natural events by eliciting the performance of the AEX (Amsterdam stock exchange) which increased the external validity, I still use the artificial created ambiguity events which were commonly used as Ellsberg (1961) did. It seems that my experiment does not increase the external validity. However, based on our results, the survey experiments of this kind of artificial created ambiguity events are proved to work well even if I use hypothetical choice to elicit participants' preferences. Furthermore, I find that the trembling-hand model analyzed by Moffatt and Peters (2001) fits my data well. Compared to the Luce's (1959) constant error model used by most studies in risk preferences, the trembling-hand model with fixed probability of trembles can be better adapted to various scenarios. At least according to my data analyses results, tremble-hand error model is better at capturing noise in survey experiment. This application improves the external validity of the study. Additionally, compared with the small sample size in the previous study of Baillon et al. (2018), my sample size is twice theirs, which makes my results more conclusive and thus increases the external validity as well.

Other concerns about how to improve my experiment can also be considered. Firstly, since I use the MPL method to induce participants' preferences with just a limited number of questions (around 10 for each list), the matching probabilities I can elicit from the ambiguity elicitation tasks are located in the relatively wide interval of the two adjacent probabilities, which is 10%. This measure may thus not be as precise as the previous literature investigated individual ambiguity attitudes (e.g., Dimmock et al., 2015 and 2016), but I can still measure approximate individual preferences so it would not influence the main results. Additionally, the structural estimation still needs the assumption of expected utility for risk which could be problematic, notwithstanding that my model specification does not need the expected utility assumption for risk in the descriptive analyses. In future research, this part can be updated by using rank dependent utility functions or other forms for risk to make parameter estimation models more consistent with human-being cognitive processes (Wakker, 2010).

Naturally, there are a lot of points, that I do not account for in this study, are valuable for further research. The first point is the correlation between risk attitudes and ambiguity attitudes. This is investigated broadly in the literature. Camerer and Weber (1992) point out most early studies find ambiguity and risk attitudes to be largely independent; and some more recent studies, e.g., Abdellaoui et al. (2011), and Bossaerts et al. (2009) find a significant positive correlation. Others, like Cubitt et al. (2018) and Sutter et al. (2013), find a small but negative relation between risk and ambiguity premium. How time pressure influences this relation could be studied in future. Secondly, future research could also try to detect whether risk insensitivity is affected by external factors. Similar to the a-insensitivity, individuals have different level of risk aversion when they are confronted with different objective probability of the risk events (e.g., Fehr-Duda and Epper, 2012; Wakker, 2010). However, few previous research has focused on the effect of external factors on individual probability insensitivity to the risky events. Thirdly, most studies including my thesis just focus on gain domain, but how people react to ambiguity events in loss domain under time pressure is another valuable topic that has a high potential for future research.

Finally, this topic provides a platform for talking about some potential consequences in the real world. Given that ambiguity is more realistic and frequent than risk, my findings may be crucial for improving our knowledge of these processes. Since the global economic situation in 2020 and 2021 is characterized by great uncertainty concerning future market developments, especially due to the Covid 19 pandemic, new opportunities for studies of ambiguity emerge. For instance, my findings show that the perceived level of ambiguity would be significantly influenced by time pressure, which could explain some current realistic problems related to Covid 19 pandemic. People are inclined to regard the small-probability ambiguous events as equal to risk events with larger objective probability when they have to make their decisions under time pressure, and this tendency leads them to invest more money and effort unnecessarily in avoiding small-probability ambiguous negative events, such as the low mortality and severe disease rate of pandemic, because they see those events as higher probability risk events under time pressure, which definitely results in a waste of resources. Being conscious about that will help policy makers or business managers to make more rational decisions by eliminating the interference of time pressure when facing ambiguous issues.

Ambiguity attitudes have also been indicated as a possible cause of financial biases, such as the stock market participation puzzle (Cao et al., 2005; Easly and O'Hara, 2009). Dimmock et al. (2015) found that stock market participation, as well as the ownership of small businesses, is negatively correlated with ambiguity-induced insensitivity—the higher the a-insensitivity, the lower the participation rate. Agarwal et al. (2018) found that political uncertainty reduced households' stock market participation, especially in the pre-election stage, but has less effect on this reduction where uncertainty remains high after elections. This finding further confirms my results in this thesis. Limited time for people to make decisions under ambiguous events would make them more a-insensitive so that they would rather make more conservative decisions to shy away from such investments even facing the same uncertainty.

10 Conclusion

In conclusion, compared to previous study work on time pressure and risk and ambiguity aversion, I use the MPL method to elicit individual risk and ambiguity attitudes jointly and count for the noise making to study how people react to different types of uncertainty. This method is easy to conduct in the field and takes participants very little time. The indices for risk aversion and ambiguity attitudes that I get by counting the number of safe options (or differences) and reverse switches are valid for both risk and ambiguity attitudes elicitation without any assumptions about probability weighting functions.

I apply these indices in a study where I randomly vary time pressure. My findings are consistent with what we know about human cognitive decision-making process and psychologically plausible, since it demonstrates that time pressure affects cognitive components (perceived level of ambiguity) but not motivational components (risk aversion and ambiguity aversion). Noisy decision making is also captured in our analyses, and it happens frequently to in the ambiguity aversion elicitation task, so that ambiguity attitudes are prone to be less stable than risk attitudes. The descriptive analyses, OLS regression and structural estimation all reach the same conclusion.

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12 Appendix

12.1 Appendix A – Figures

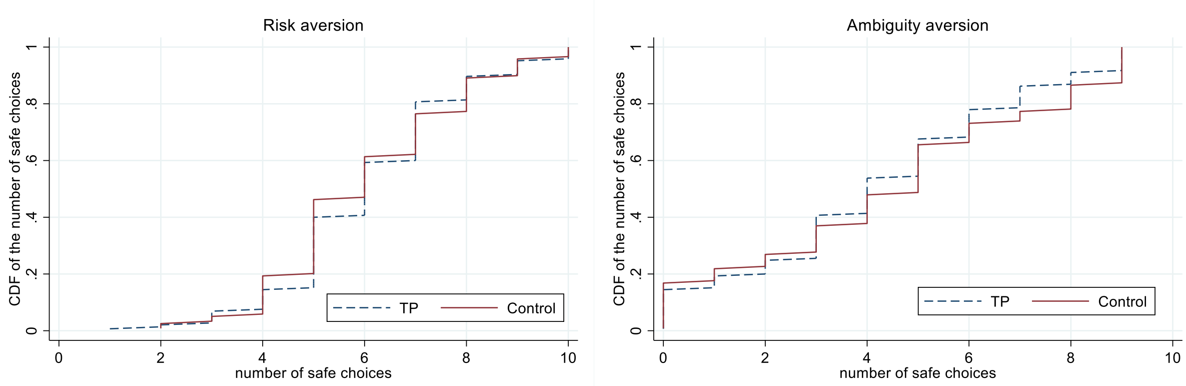


Figure 7: Mean number of safe choices across treatments. The left panel of this figure depicts the cumulative distribution functions of the number of safe choices in risk aversion elicitation task across treatments. The right panel of this figure presents the cumulative distribution functions of the number of safe choices in ambiguity aversion elicitation task across treatments. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

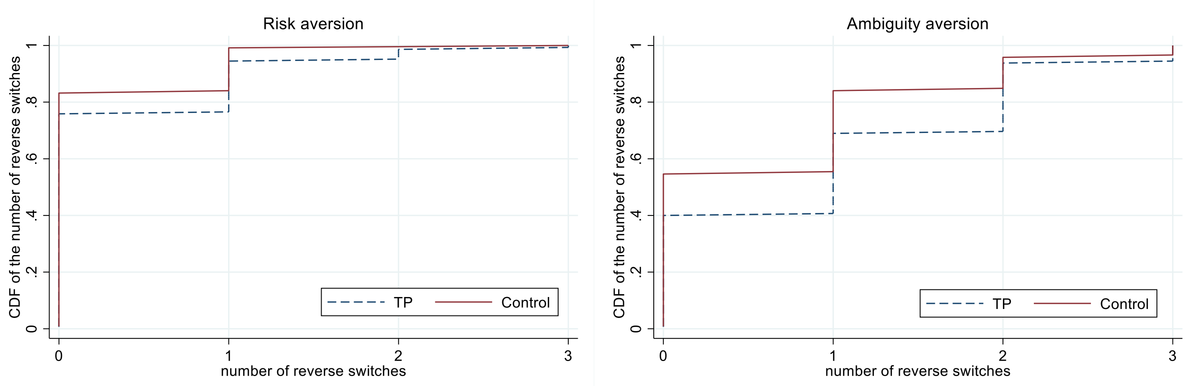


Figure 8: Mean number of reverse switches across treatments. The left panel of this figure depicts the cumulative distribution functions of the number of reverse switches in risk aversion elicitation task across treatments. The right panel of this figure presents the cumulative distribution functions of the number of reverse switches in ambiguity aversion elicitation task across treatments. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

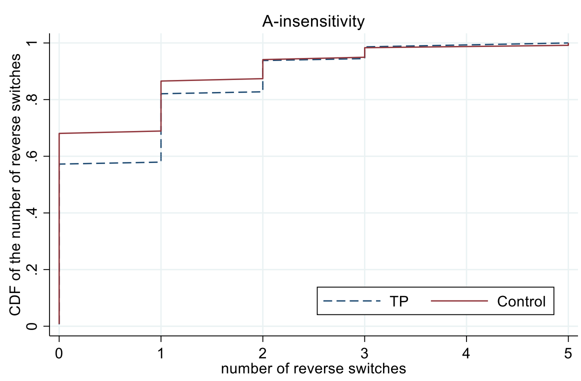


Figure 9: Mean number of reverse switches across treatments. This figure depicts the cumulative distribution functions of the number of reverse switches in a-insensitivity elicitation tasks across treatments. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

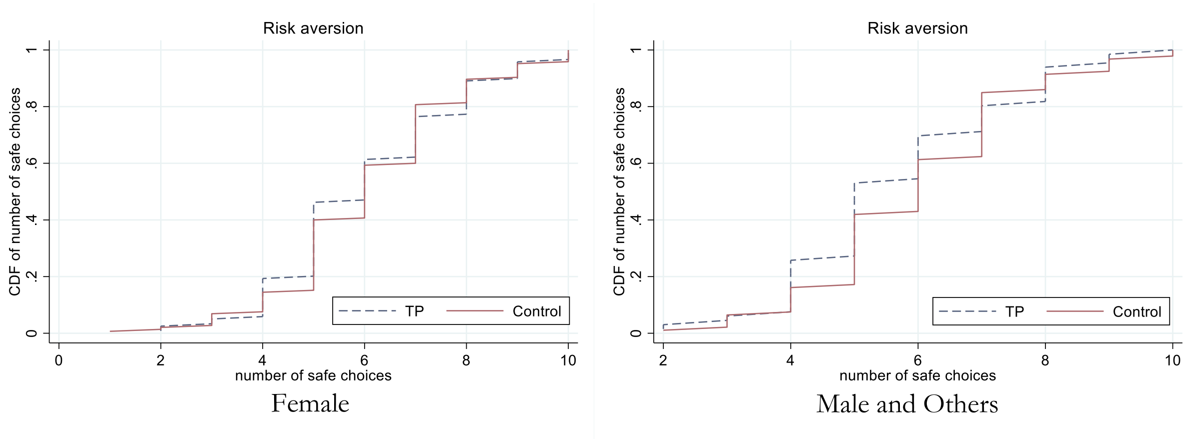


Figure 10: Mean number of safe choices in risk aversion elicitation task across treatments—gender differences. The left panel of this figure presents the cumulative density functions of the number of safe choices in risk aversion elicitation task across treatments for female participants, the right panel for male and other participants. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

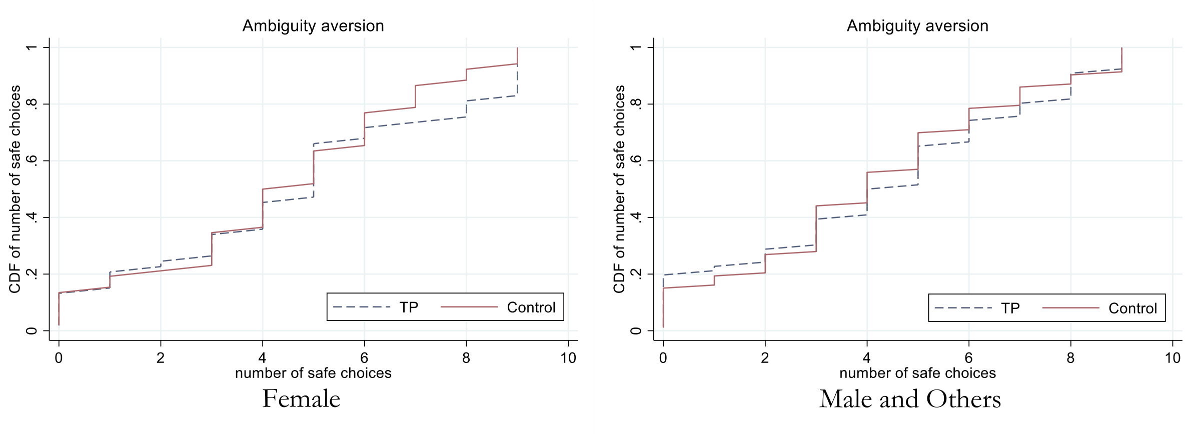


Figure 11: Mean number of safe choices in ambiguity aversion elicitation task across treatments - gender differences. The left panel of this figure presents the cumulative density functions of the number of safe choices in ambiguity aversion elicitation task across treatments for female participants, the right panel for male and other participants. The dashed blue line represents the TP treatment, the red line represents the Control treatment.

12.2 Appendix B – Instructions

This is the content of instructions participants would see before they enter into the tasks in Qualtrics.

Page 1

Hi, welcome to this experiment! I am Dong, a master's student at the Stockholm School of Economics (SSE) and I need your help for my thesis!

You will be asked to make a few decisions in this experiment. The responses will be used in an anonymous manner (I will not collect IP-addresses or identifying information). The time it takes to complete this survey is around 5 minutes.

Page 2

This is an experiment in the economics of decision making.

In this experiment you will **hypothetically** receive some money from us. How much you hypothetically receive will depend on the choices you make. The experiment consists of four parts, each part containing around 10 decisions. For each decision, you will be asked to make choices **between Option A and Option B.**

The questions are not designed to test you. What we want to know is what choices you would make in them. The only right answer is what you really would choose.

Participation in this experiment is entirely voluntary and you may quit this experiment whenever you want. **If you choose to finish it (which I hope!) you need to make all decisions to submit it.**

By proceeding with this survey, you are indicating your willingness to participate in this Msc thesis study.

Part 1

Please imagine the following **hypothetical scenario**:

You are presented with 10 separate decisions numbering 1 through 10. Each of these decisions is a choice between "Option A" and "Option B". You need to choose one option for each decision.

For example, one choice could be between the following:
Option A:
1/2 chance of 250 SEK
1/2 chance of 450 SEK
Option B:
1/2 chance of 50 SEK
1/2 chance of 700 SEK

If you choose Option A, then Option A would be used to determine your hypothetical payoff. You would have a 1/2 chance of earning 250 SEK, and a 1/2 chance of earning 450 SEK.
If you choose Option B, then Option B would be used to determine your hypothetical payoff. You would have a 1/2 chance of earning 50 SEK, and a 1/2 chance of earning 700 SEK.

(Time Pressure Condition)
You have a **maximum of <u>10 seconds</u>** to make each decision!

<u>Try your best to answer them as quickly as possible!</u>
A counter on the screen will indicate how much time you have left.
When you click the arrow the following question will appear! Please proceed to mark your choices when you are ready.

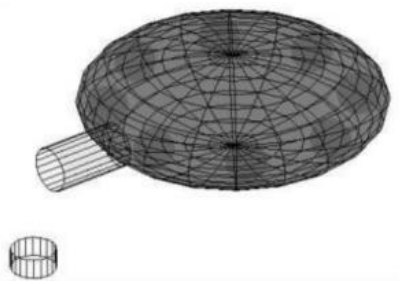
(Control Condition)
You have **no time limit** to make each decision. When you click the arrow the following question will appear! Please proceed to mark your choices when you are ready.

Part 2

Please imagine the following **hypothetical scenario**:

You are presented with 10 seperate decisions numbering 1 through 10. Each of these decisions is a choice between "Option A" and "Option B". You need to choose one option for each decision.

For Option A, you are provided with the gamble with **objective probability.**
For Option B, you are faced with **an opaque urn** containing **10** balls of potentially **10** different colors with **<u>unknown probability</u>** for each color, which means that, for instance, there may exist 0, 3, 8 or even 10 red balls in this urn, and you don't know what the exact probability of red balls is inside the opaque urn.



The experimenter will select some colors as the **Chosen Success Colors**. The number of colors being chosen varies among different decisions. If you **pick a ball of a color that matches one of the chosen colors, you will earn 200 SEK; if it does not match, you will earn 0 SEK.**

For example, one choice could be between the following:

Option A:
4/10 chance of 200 SEK
6/10 chance of 0 SEK

Option B:
200 SEK if the color of the ball matches one of the 4 Chosen Success Colors
(potentially **10** different colors in total)
0 SEK if it does not match.

(Time Pressure Condition)
You have a **maximum of <u>10 seconds</u>** to make each decision!

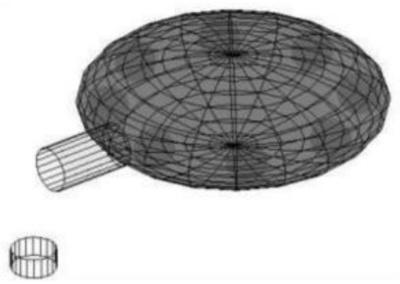
<u>Try your best to answer them as quickly as possible!</u>
A counter on the screen will indicate how much time you have left.
When you click the arrow the following question will appear! Please proceed to mark your choices when you are ready.

(Control Condition)
You have **no time limit** to make each decision. When you press 'next' the following question will appear. Please proceed to mark your choices.

Part 3

In this part, you will be faced with **a <u>similar</u> hypothetical scenario as the one you just did**, but with **the number of balls** in the opaque urn being **<u>4</u>** rather than 10.

For Option A, you are provided with the objective probability as shown before.
For Option B, you are faced with **an opaque urn** containing **4** balls of potentially **4** different colors with **<u>unknown probability</u>** for each color, which means that, for instance, there may exist 0, 1, 2, 3 or even 4 red balls in this urn, and you don't know what the exact probability of red balls is inside the opaque urn.



One of these 4 colors is selected as the unique Chosen Sucess Color for all B options in the choice list.

For example, one choice could be between the following:
Option A:
4/10 chance of 200 SEK
6/10 chance of 0 SEK
Option B:
200 SEK if the color of the ball matches the unique chosen color.
(potentially **4** different colors in total)
0 SEK if it does not match.

(Time Pressure Condition)
You have a **maximum of <u>10 seconds</u>** to make each decision!
<u>Try your best to answer them as quickly as possible!</u>
A counter on the screen will indicate how much time you have left.
When you click the arrow the following question will appear! Please proceed to mark your choices when you are ready.

(Control Condition)
You have **no time limit** to make each decision. When you press 'next' the following question will appear. Please proceed to mark your choices.

Part 4

In this part, you will be faced with **the <u>same</u> hypothetical scenario as the one you just did**, **but with <u>the stake levels</u> in Option B being the <u>reverse</u>.**

For example, one choice could be between the following:

Option A:
4/10 chance of 200 SEK
6/10 chance of 0 SEK

Option B:
You will pick up a ball from the opaque urn containing **4** balls of potentially **4** different colors with unknown probability, and will earn
0 SEK if the color of the ball matches the unique chosen color
200 SEK if it does not match.

(Time Pressure Condition)
You have a **maximum of <u>10 seconds</u>** to make each decision!
<u>Try your best to answer them as quickly as possible!</u>
A counter on the screen will indicate how much time you have left.
When you click the arrow the following question will appear! Please proceed to mark your choices when you are ready.

(Control Condition)
You have **no time limit** to make each decision. When you click the arrow the following question will appear. Please proceed to mark your choices.

The following test is the text from the email sent out to potential participants to invite them to participate in the experiment:

Hey,

My name is Dong, I am running an experiment for my master thesis project in economics here at Stockholm School of Economics, and I would really appreciate it if you would participate!

The experiment is short (around 5 minutes), and you only need to click your choice between two hypothetical options for each question. You can participate in the experiment on your phone or computer using the link below:
<u>https://qfreeaccountssjc1.az1.qualtrics.com/jfe/form/SV_3dFmPop7Bal0fxI</u>

Your participation is super helpful! A large sample is crucial for me to draw valid conclusions. The survey will be deactivated on the 5th of November. I may send you a reminder ten days from now.

Thank you so much for your time!
Best wishes,
Yuanqing Dong (42147@student.hhs.se)

Data protection: The survey is fully anonymous, and it will not be storing any contact information after completing this project. If you have any questions, send me an e-mail to 42147@student.hhs.se.

12.3 Appendix C – Pre-registration

This content could be found on the website https://osf.io/bhd7g.

1) Data collection.
Have any data been collected for this study already?

No, no data have been collected for this study yet.

2) Hypothesis
What's the main question being asked or hypothesis being tested in this study?

There are 4 main questions and 8 hypotheses that will be studied:

i. How does time pressure influence individual level risk aversion and ambiguity aversion?
Hypothesis 1: Time pressure leads to more risk aversion than no time constraints.
Hypothesis 2: Time pressure has no effect on ambiguity aversion.

ii. How does time pressure influence individual level ambiguity insensitivity?
Hypothesis 3: Time pressure leads to more ambiguity insensitivity than no time constraints.

iii. Does time pressure induce people to make more noisy decisions when making their choice?
Hypothesis 4: Time pressure leads to more noisy decisions.

iv. What is the gender difference regarding to the ambiguity (risk) aversion and ambiguity insensitivity? And what is difference of the effect of time pressure on them?
Hypothesis 5: Women are more risk averse than other genders.
Hypothesis 6: Women are more ambiguity averse than other genders.
Hypothesis 7: Women are more ambiguity insensitive than other genders.
Hypothesis 8: Time pressure has no effect on gender differences (in risk aversion, ambiguity aversion and ambiguity insensitivity).

3) Dependent variable

Describe the key dependent variable(s) specifying how they will be measured.

I analyze the effects of time pressure on the level of ambiguity aversion, risk aversion and the ambiguity insensitivity. And I also detect the effect of time pressure on noisy decision making when participants are making their choices in the experiment.

I set the utility function $u(x) = \frac{x^{1-r}}{1-r}$. For options in risk elicitation task and option A in ambiguity elicitation tasks, the individual utility could be represented by $V(y) = V(z_A) = P * \frac{x_{min}^{1-r}}{1-r} + (1-P) * \frac{x_{max}^{1-r}}{1-r}$; for option B in ambiguity elicitation tasks, the individual utility could be represented by $V(z_B) = \left((1-\beta)\pi + (1-\alpha)\beta\right) * \frac{x_{max}^{1-r}}{1-r}$, where x_{min} corresponds to the lower outcome in a binary gamble, and x_{max} corresponds to the greater outcome; P is the objective probability and π is the reference probability in the opaque urn.

The key dependent variables are the following:

i. Aggregate level: Risk aversion index r of both treatments, which represents individual level of risk averse, by analyzing the data collected from risk elicitation tasks. When $r = 0$, $u(x) = x$, which represents risk neutrality; $r > 0$ for risk averse and $r < 0$ for risk seeking.

Pessimism (ambiguity aversion) index α of both treatments, which represents individual level of ambiguity aversion, by analyzing the data collected from ambiguity elicitation tasks 3. $\alpha \in [0,1]$, larger α indicates subjects are more pessimistic when faced with uncertainty. $\alpha = 0.5$ represents ambiguity neutrality. When $\alpha < 0.5$, subjects are ambiguity seeking; if $\alpha > 0.5$, subjects are ambiguity averse.

Ambiguity-generated likelihood insensitivity (a-insensitivity) index β of both treatments, which represents individual perceived level of ambiguity, by analyzing the data collected from ambiguity elicitation tasks. $\beta \in [0,1]$, larger (1-β) indicates more confidence in the reference likelihood π.

Noise parameter μ (Fechner errors) of two treatments. $\mu \in [0,1]$, Larger μ, more noise made by subjects. If possible, trembling errors ω may be added (which depends on the data quality).

All of those parameters can be estimated by maximizing the likelihood function using the Broyden-Fletcher-Goldfarb-Shanno optimization algorithm.

ii.Individual level:

The number of Option A choices for Part 1 (N_1) and the number of Option B choices for Part 2 (N_2), which can represent individual risk and ambiguity aversion level respectively (N_i represents the number of safe choices for Part i).

The difference of the number of Option B choices between Part 3 and Part 4, which can represent individual ambiguity-generated likelihood insensitivity ($N_4 - N_3$). The larger ($N_4 - N_3$), the more reference likelihood sensitive subjects are.

The number of reverse switches for each part.
All of those variables can be directly calculated from the data I will collect.

4) Conditions
How many and which conditions will participants be assigned to?

Participants will finish the survey by volunteering and will be assigned randomly by the Qualtrics to one of two conditions – the Time Pressure or the Control condition.

In the Time Pressure (TP) condition, each participant will complete four tasks, one for risk preference elicitation, three for ambiguity preference elicitation. In each task, participants need to finish around 10 questions in total, and make their choice between two options for each question showed on the screen in 10 seconds. They should finish all the questions to submit the survey.

In Control condition, each participant will complete four tasks which are the same as those in the TP treatment. But in each task, participants do not need to finish the questions under time pressure – they can take the time they want for this. They should finish all the questions to submit the survey.

Therefore, this is a between-subject study with two conditions—a Time Pressure condition and a Control condition.

Between Subjects	Within Subjects			
	Risk	Ambiguity (different reference likelihoods)		
Control Condition	Part 1	Part 2	Part 3 (25%)	Part 4(75%)
Time Pressure Condition	Part 1 with time pressure	Part 2 with time pressure	Part 3 with time pressure	Part 4 with time pressure

5) Analyses
Specify exactly which analyses you will conduct to examine the main question/hypothesis.

We use two-sided independent samples t-tests for all of the analyses except for the gender effects.
In order to test the effect of time pressure on the individual level of risk and ambiguity aversion (H1 and H2), I will firstly compare the number of Option A choices for Part 1 and the number of Option B choices for Part 2 between two treatments.

As a robustness check, I will run pooled OLS regression, with the number of Option A choices in Part 1 and the number of Option B choices in Part 2 (N_1 and N_2) as the dependent variables and consider dummy variables- TP, some control variables (Field of study, Gender and Age) and interactive terms of TP and control variables as independent variables (H1 and H2). Then, I select the difference of the number of Option B choices between Part 3 and Part 4 ($N_4 - N_3$) as the dependent variable and use the same independent and control variables to detect the effect of time pressure on a-insensitivity (H3). Besides, the effect of time pressure on the level of noise will also be detected through running OLS regression with the number of reverse switches as the dependent variable (H4).

I will cluster standard errors at the individual level because I obtain values of each variable per subject and have robust standard errors by default for all regressions above.

For control variables, there are three of them, and I will set options for subjects to choose in the questionnaire as the following:
Field of study: Economics & Business; Science; Engineering; Arts; Others.
Gender: Male, Female, Other genders, Prefer not to say.
Age: Let them click the exact age number.

For aggregate level, I will compare pessimism, a-insensitivity and risk aversion indexes and the noise parameter (potentially two parameters), which are obtained via maximum likelihood estimations using the Broyden-Fletcher-Goldfarb-Shannon (BFGS) optimization algorithm, between two treatments using post-estimation Wald tests.

6) Outliers and Exclusions
Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.

Outliers: subjects who did not answer questions (at least one question) under the 10 seconds limit in time pressure treatment.

The instructions will emphasize the importance of choosing within the time allowed and the importance of avoiding being prompted to make a decision. A reminder sentence "Remember that you have a maximum of 10 seconds to answer each question" shows in the instructions. The timer on the screen indicates how much time they have left to respond. If subjects fail to answer the question under time limits, they still need to answer the question. The survey will not be completed until all the questions will be answered.

I will do the main analysis using data from all participants who were randomly assigned to the two conditions, no matter whether they exceed the time limit or not. In a robustness check I will exclude outliers.

7) Sample Size
How many observations will be collected or what will determine sample size?

I define a statistically significant effect as $p < 0.005$ and suggestive evidence of an effect as $p<0.05$ (following Benjamin et al. 2018). In a previous study, Baillon et al. (2018) detected the effects of time pressure on individual level of ambiguity attitudes. Using their effect sizes and standard deviations, I find that their standardized effect size is Cohen's d = 0.43. However, since Baillon et al. have a sample size that is quite small (around 50 for each group), I also calculate the sample size needed to achieve 90% statistical power for a standard two-tailed t-test with a point biserial model based on Cohen's d=0.3 and p=0.05. To have 90% power in a two-tailed t-test with a point biserial model and p=0.05, I would need a sample size of 109 per condition. But if I choose to compare two means between different groups based on Cohen's d=0.6 and p=0.05, the sample size should be at least of 60 per condition to have 90% power in a two-tailed t-test.

8) Other

Anything else you would like to pre-register?
(e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

I will study whether there are gender differences on ambiguity and risk attitudes under no time constraints and whether there is a gender difference of the time pressure effect on those variables and indexes. Gender will be coded as a binary variable (female or not) in my research, but I will set a few options for participants to choose in the survey (male, female, other genders, prefer not to say).

I will estimate all parameters mentioned above for female and other genders (including male, other genders and prefer not to say) participants separately and compare them (H5, H6, H7).

I will also compare the cumulative density functions of all dependent variables mentioned above between two treatments for female and other genders (including male, other genders and prefer not to say) participants respectively, by using Mann-Whitney U test (H8).

9) Name
Give a title for this AsPredicted pre-registration
Suggestion: use the name of the project, followed by study description.

Time pressure on risk and ambiguity attitudes

Finally. For record keeping purposes, please tell us the type of study you are pre-registering.
Experiment