**Learning your own risk preferences**

**Literature review:**

**1. Elicitation methods**

Economists have developed a variety of experimental methodologies to elicit individuals' risk preferences. The methods are usually a single-shot decision, and the most commonly used ones are Eckel and Grossman (2002), Holt and Laoury (2002), and Gneezy and Potters (1997).

**2.1 Eckel and Grossman 2002 (EG)**

The Eckel and Grossman 2002/2008 (EG) risk elicitation method asks subjects to make one choice decision over a list of 5/6 lotteries, depending on which version they use (2002/2008). For example, in Eckel and Grossman (2002), participants were asked to decide over five gambles, as listed in Table 1.

**Table 1. Eckel and Grossman 2002 risk elicitation is broken down by Gamble and expected payoff.**

Each Gamble has a 50% chance of receiving the High Payoff (Event A) and a 50% chance of the Low Payoff ( Event B). Gamble 1 gives a certain payoff of $16 in the No-Loss framing. The main idea is that the expected gains from gambles 1-5 increase linearly with risk, and gambles with a higher expected payoff will also have a higher standard deviation. In this example, risk-averse subjects will choose Gambles 1-4, while risk-neutral subjects and risk-seeking ones will choose Gamble 5, which gives the highest expected payoff.

This method's main advantage is its simplicity. Players make only one decision, and all the gambles share the same probabilities, making it easy for the participants to understand the task. Simplicity has an essential effect on the accuracy of the risk elicitation method. To elicit players' risk attitude without noise, we want to make sure that they understand the task and decide without any error that could arise from failing to understand the task and the gambles.

The main disadvantage is that this method gives a broad parameter for risk attitudes for each decision, especially in the last group of players who choose gambles 5/6, representing a variety of risk-taking preferences from risk neutrality up to extreme risk-seeking.

We will offer a modified version of EG to deal with this disadvantage in our experimental design, which involves two more gamble options that distinguish between risk neutrality agents and risk-seeking ones.

**2.2 Holt and Laury 2002 (HL)**

Holt and Laury (2002) invent a multiply price list (MPL) elicitation method, one of the most common uses to elicit risk preferences in lab experiments. Players must make ten decisions over lotteries A and B (see Table 2). The pairs of the lotteries have the same payoffs in all the different rows, but the probability of event A increases from row to row. In the last row/decision, the likelihood is 100%, which means event A occurs and makes event B irrelevant.

**Table 2. Holt and Laury 2002(HL) risk elicitation is broken down by potions A and B pairs and the expected payoff difference.**

Given the structure of these gambles, the theory predicts that an agent with a constant risk attitude will have only one switching point in which they switch from Option A to Option B. For example, a risk-neutral agent will prefer Option A over B in rows 1-4, and after, they will pick Option B.  For each switching point, by using the assumption of CRRA, we can calculate the estimated risk coefficient for each player. However, if players are inconsistent in their decision and have more than one switching point, we cannot evaluate their risk attitude in this task. At Holt and Laury (2002), only 28 of 212 subjects ever switched back from B to A. This problem can be even worse depending on the subject pool, as Charness et al. (2013) discussed.

The main advantage of this method is the variety of risk attitudes that we can elicit from players' decisions. Compared to EG, we can elicit ten different risk attitudes, which is 4/5 more than EG.

One main disadvantage is that the complexity of the task involves making ten decisions instead of one, and the probability structure of the lotteries is more complex, which increases the probability of players making an error and therefore eliciting biased risk parameters. Additionally, this method requires participants to be more consistent in their choices. Participants who make inconsistent decisions cause difficulties in calculating their risk attitude, resulting in omitting them from the experiment/sample.

**2.3 Gneezy and Potters 1997 (GP)**

The Gneezy and Potters (GP) risk elicitation method asks players to decide in a financial context, and therefore it is also known as the investment game. Players have an endowment of $X, and they need to determine how much money k from their endowment they are willing to invest in a risky asset. The rest of the money that is not invested (X-k) is kept for the player (riskless payment). The risky asset can give a dividend d\*k with probability p and nothing in probability (1-p). In this game, when using parameters that follow this rule p\*d>1, all risk-neutral agents and risk-seeking ones will choose to invest all their money. We can calculate the risk election parameter based on the player's decision.

The main advantages of this method are the variety of risk attitudes that we can elicit from players' decisions. Given that the players' decision of the amount of money they are willing to invest is continuous, we can have a more extensive set of options of risk attitudes. Additionally, as discussed above, if we compare this task to HL, given that players need to take only one decision and the probabilities they face are 50%/50%, it is easier to understand the task structure.

The main disadvantage is that we cannot differentiate risk-seeking agents from risk-neutral ones, given the structure of the method.

**2.4 BRET:**

I can edit this task later if needed.

The EG task is a discrete version of GP to elicit risk-seeking attitudes. Eckel and Grossman (2008) implemented an option with this possibility using the same approach as Binswanger (1980), who includes options with higher risk and lower expected values. HL has been criticized for using extreme probabilities since prospect theory can explain its results. In this respect, GP and EG can use lotteries with a 0.5 chance of each outcome. However, Holt (2019) mentions that this might create a problem since more mathematical-oriented subjects might easily calculate the expected value and bias their decisions. This effect might explain why we observe less risk aversion among educated people and people with higher cognitive ability (Harrison et al., 2007, Dohmen et al., 2011). Also, some extensions of HL include random presentation of decisions instead of lists (Brown and Healy, 2018) and dynamic elicitation (Li, 2017). The first extension generates inconsistent behavior (around 30% of subjects), and the second generates more consistent behavior with other gambling decisions in the laboratory.

Given the wide use of these methods and the risk elicitation puzzle resulting from inconsistent individual decisions across those tasks, we decided to explore how learning and experience with the task could influence players' risk preferences. It is essential to mention that although it is inconsistent at the individual level when we compare the risk parameter at the aggregate level, there is no significant difference across the methods.

See attached below a table that summarizes those methods together and provides the risk aversion parameters of each one of them.

**Table 3. risk elicitation comparison.**

**3.** **The risk elicitation puzzle**

The risk elicitation puzzle stems from numerous investigations showing significant inconsistencies in risk preferences when elicited using different or similar methods (Pedroni et al., 2017). This inconsistency makes the correlation of individuals' risk parameters between measures very low. This puzzle raises many crucial questions in economics. The main one is the origin of this inconsistency, and solving it would allow economists to better understand people's risk preferences and find better ways to elicit them.

All the methodologies in the literature were designed with different purposes to address different problems. However, all methodologies are assumed to measure the same constant risk attitudes. Results would need to be consistent across time and contexts to be useful in economic applications. Furthermore, the measures should be predictive of decisions in different settings to be relevant.

However, the literature highlights a weak relation between the risk attitudes elicited and significant changes depending on the characteristics of the method. For example, with the MPL, it is found by Holt and Laury (2002) that there are payoff magnitude effects for real payoffs and order effects. They found in their seminal paper that the payoff magnitude has a positive effect on the risk elicited parameter r from a CRRA utility function. Harrison et al. (2005) also discovered that there was higher risk aversion if measured after a list of lower payoffs, Holt and Laury (2005) then found that the effect of high payoffs was only present with real payoffs. Given these effects in a single task, it seems unsurprising that the correlation between measures is low.

Friedman et al. (2014) found a correlation of 0.27 between the original Holt-Laury and Eckel-Grossman, and no correlation with the balloon and deal-or-no-deal tasks. According to Friedman (2019), a lower than expected correlation is still present even when controlling for measuring error using the ORIV method, developed by Gillen, Snowberg, and Yariv (2019), since the highest correlation (0.55) between the closely related tasks Lottery and Project was still low, even after correcting for measurement error and considering uncensored data. Also, Charness et al. (2020) compared five risk measure tasks: Willingness to Take Risks task (WTR), GP, EG, HL, and multiple lists of paired lotteries (TCN), and found that only HL and GP were not statistically different. They found a correlation between task and laboratory financial decisions with a higher predictive power of simpler tasks—and no explanatory power of the measures of risk attitudes over field behavior. In another study, Holzmeister and Matthias (2019) found small correlations between four risk measures; however, subjects are aware of the variation in their risk attitudes. People might have task-dependent or reference-dependent preferences among the authors' potential explanations.

Under this evidence, Holt (2019) states that “numerical risk aversion should not be taken too seriously,” highlighting the importance of using the same measure for a particular question since risk preferences could be multidimensional and different characteristics of the context might affect the decision process and preferences. With this question in mind, we think that experience/learning will shed some light if the inconsistency of players' decisions among various tasks is due to failure to understand the task structure and their own preference by exploring them both—they could converge on a more consistent choice.

**4. Consistency:**

Our main contribution is to explore the effect of experience and learn about one’s risk choices. One crucial question that should be ask if risk preferences are stable (constant), and in that case, they should not change over time. In the past, most economics treated these preferences as stable across time and states (Stigler and Becker, 1977). “Neoclassical microeconomic choice theory is grounded in the assumption that people make choices according to a stable ranking that represents their true preferences.” From Delaney, Jacobson, and Moenig (2018)

However, many researchers explore the stability of risk preferences over time, and there is strong evidence that they could change over time due to many different factors. There is strong evidence that people become more risk-averse when they get older (Dohmen et al., 2017, Mata et al., 2016; Harrison. 2007). Anderson et al.,2008  ran an extensive study on the Danish population; they found some variation in risk attitudes over time but with no significant magnitude in one direction. Their results suggest that risk preferences are changing due to financial circumstances. Sahm, 2012 found similar effects on the American population. Many papers explain how different kinds of life events such as parenthood (Browne et al., 2016; Görlitz and Tamm, 2015), changes in health conditions(Decker and Schmidtz, 2016 ), exposure to conflict and violence (Kibris & Neslihan 2021, Kim &Lee 2014, Brown et al. 2017, Voors et al.,2012) and natural disasters ( Cameron and Shah, 2015; Cassar et al., 2017; Eckel et al., 2009; Hanaoka et al., 2018; Page et al., 2014; Said et al., 2015 ) influences people risks attitude over time. Nathan 2019 also suggests that emotional stability has a vital role in risk preferences.

**4. Learning**

So far, not many researchers have focused on the effect of experience and learning on risk attitude.

The most related papers to our work, Ert and Haruvy,2017 explore the impact of experience and repetitions of HL risk elicitation tasks on players' risk preferences. They found that over time players become more risk-neutral. Bradbury et al. 2015, find similar results with investment decisions with risk. In their paper, simulated experience with investment decisions improves participants’ understanding of the underlying risk-return profile. It prompts them to reconsider their investment decisions and choose riskier financial products without regretting their higher risk-taking behavior.

We are continuing in this direction, and our main goal is to shed some light on the role of the experience (repetition) with the same task on players' risk preferences. We find similar results as Ert and Haruvy,2017 with a different risk elicitation task, which makes it more robust that experience with the task makes players more risk-neutral, suggesting that this experience effect is not task-specific. We offer, supported by our data, that the experience also helps the subject learn more about the task structure (expected payoffs)  and be familiar with making decisions under risk, which allows them to take more risks and become more risk-neutral.

We have two explanations for the learning/experience effect. First, experience and learning could make participants understand the risk-elicitation task better and thus reduce some errors that players may make in a one-shot task without fully understanding the full information given to them. Both Ert and Haruvy,2017 and Bradbury et al. 2015 results adopt this direction as the primary cause, which is a similar approach to overcoming inexperience was used in Engelmann and Hollard (2010) in considering the endowment effect. Their idea was that people who did not have experience with trading might be reluctant to trade their endowed goods for another of equal value. In their treatment condition, people were endowed with a good that would have no value

if not traded (for a good that would have value). Making this trade gave them experience. While there was a significant endowment effect present in the control treatment, there was no significant endowment effect for the group with trading experience (from inro).

However, there is an extensive discussion in the economic literature led by Plott 1996 that people learn their own preferences through experience/consumption. Besides learning something about the task strucetre, it could be the case that agents are not fully awere of their own risk perfrences and by exploring decisions under risk, they become more aware of their preferences. Delaney, Jacobson, and Moenig (2018) provide experimental evidence on preference discovery, suggesting that preference discovery processes can explain choice instabilities observed in observational and laboratory studies of behavior, especially in cases of items that are unlikely to have been “consumed” often by the agent. In that case, we can consider deciding over lottries as a “good.” Some agents are unfamiliar with making these kinds of decisions, making this preference discovery effect larger.

**5. Extra:**

1. Erev & Mark 2022 paper:

It could explain what is going on in our paper, I think  "The RUB assumption and the impact of experience" is super relevant for us. The main idea is that participants violate this assumption, and the experience makes them learn, trust, and explore the task structure (expected payoff and variance) and trust the experiment's mechanism. People's decision-making process is similar to machine learning classification algorithms, and they use the repetitions to learn the task structure and trust it. Even though it is useless, they already have all the information to figure out what is going on.

**Abstract**

Mainstream decision research rests on two implicit working assumptions, inspired by subjective expected utility theory. The first assumes that the underlying processes can be separated into judgment and decision-making stages without affecting their outcomes. The second assumes that in properly run experiments, the presentation of a complete description of the incentive structure replaces the judgment stage (and eliminates the impact of past experiences that can only affect judgment). While these working assumptions seem reasonable and harmless, the current paper suggests that they impair progress. The negative effect of the separation assumption is clarified by the predicted impact of rare events. Studies that separate judgment from decision making document oversensitivity to rare events, but without the separation people exhibit the opposite bias. The negative effects of the assumed impact of description include masking of the large and predictable effect of past experiences on decisions from description. Analyses that relax these working assumptions suggest that the cognitive processes that underlie decision making resemble machine learning classification algorithms. Instead of judging probabilities, or trusting descriptions, the results suggest feature-based sampling of past experiences. Recent studies are reviewed that highlight the predictive advantage of simple abstractions of this hypothesis.

2)

I found this paper maybe also relevant:

Robin P. Cubitt , Chris Starmer & Robert Sugden (2001) Discovered

preferences and the experimental evidence of violations of expected utility theory, Journal of

Economic Methodology, 8:3, 385-414, DOI: 10.1080/13501780110103748

Abstract:

The discovered preference hypothesis appears to insulate expected utility theory (EU) from disconfirming experimental evidence. It asserts that individuals have coherent underlying preferences, which experiments may not reveal unless subjects have adequate opportunities and incentives to discover which actions best satisfy their preferences. We identify the confounding effects to be expected in experiments, were that hypothesis true, and consider how they might be controlled for. We argue for a design in which each subject faces just one distinct choice task for real. We review the results of some tests of EU which have used this design. These tests reveal the same violations of the independence axiom as other studies have found. We conclude that the discovered preference hypothesis does not justify scepticism about the reality of these effects.

The paper is a little bit old school and hard for me to understand. Still, I think the main take ways of the paper is that discovered preference theory does not explain the inconsistency observed in the lab (violations of the independence axiom). The last sentence of the paper is more relevant for us: “Whether violations of EU become less frequent as subjects gain experience remains an open question”.