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Does it matter how we produce ambiguity in experiments?★

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Abstract

The Ellsberg urn is conventionally used in experiments to measure ambiguity attitudes, yet there is no uniformity in the method for producing Ellsberg urns, which complicates the comparability of results across studies. By surveying 69 experimental studies, we distill four different methods of ambiguity production—Ellsberg urns that are produced by (i) the experimenter, (ii) another random participant, (iii) compound risk lotteries, and (iv) compound risk derived from random numbers in nature. In an experiment we then assess participants' ambiguity attitudes concerning each production method and detect no statistically significant differences among them. However, a notable proportion of preference inconsistency is observed when utilizing compound risk lotteries for ambiguity generation. Generally, our findings suggest interchangeability among the four production methods in future laboratory experiments. Nevertheless, we suggest employing method (i) as it is the most uncomplicated and straightforward production method.

Keywords: Ambiguity, ambiguity aversion, likelihood insensitivity, uncertainty, Ellsberg, experiment

JEL-Classification: C90, D80

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1. Introduction

Over the past few decades, ambiguity has gained increasing attention in the realm of experimental economics. The conventional method for introducing ambiguity in experiments stems from Ellsberg's seminal work in 1961, where participants were tasked with betting on drawing a ball from either (i) a *risky urn* containing 50 black and 50 red balls or (ii) an *ambiguous urn* with 100 balls of an unknown composition of black and red[1]. In such experiments, individuals typically exhibit a preference for the risky urn over the ambiguous urn, a behavioral trait labeled ambiguity aversion (Trautmann & Van De Kuilen, 2015). This empirically observed behavioral phenomenon has been instrumental in understanding decision-making in real-world scenarios with uncertain properties, such as stock market participation in financial economics (Dimmock et al., 2016), the adoption of new crops in developmental economics (Barham et al., 2014; Warnick et al., 2011), the treatment choices of patients (Berger et al., 2013) and the uptake of genetic tests in health economics (Hoy et al., 2014).

In recent studies, as research on ambiguity has progressed, urns containing multiple colors have been employed. These urns are designed to evoke diverse likelihoods and potential loss outcomes, enabling a comprehensive investigation into ambiguity attitudes. Such investigations extend beyond ambiguity aversion as a singular behavioral characterization and encompass a broader spectrum of attitudes towards ambiguity (Kocher et al., 2018; Li et al., 2018). Henceforth in this paper, we will refer to these as ambiguity attitudes.

Table 1 presents a survey of 69 experimental studies[2] conducted in the past decade (i.e., from 2013 to now) employing the Ellsberg setup. Interestingly, despite the widespread use of Ellsberg urns, there is no unified method for composing the ambiguous urns, i.e., the method of producing ambiguity with urns.

Table 1: A survey of ambiguity operation methods in experimental studies in the past 10 years

Study	Method used to compose the ambiguous urn
Abdellaoui et al. (2015)	Unknown, Human
Ahn et al. (2014)	Unknown

[1] The classical Ellsberg urn has both a 2-color design and a 3-color design. For the sake of brevity, we only used the Ellsberg 2-color design.

[2] In this survey, we mainly focus on studies published in main economics and management journals, such as *American Economic Review*, *American Economic Journal: Microeconomics*, *Econometrica*, *Economic Journal*, *European Economic Review*, *Experimental Economics*, *International Economic Review*, *Journal of Economic Behavior & Organization*, *Journal of the European Economic Association*, *Journal of Economic Psychology*, *Journal of Economic Theory*, *Journal of Risk and Uncertainty*, *Management Science*, *Operations Research*, *Theory and Decision*, etc.

Anantanasuwong et al. (2024)	Nature
Attanasi et al. (2014)	Unknown, Compound risk
Baillon & Bleichrodt (2015)	Nature
Baillon & Emirmahmutoglu, (2018)	Unknown
Baillon et al. (2015)	Unknown
Baillon et al. (2016)	Unknown
Baillon et al. (2018a)	Nature
Baillon, et al. (2018b)	Nature
Baillon et al. (2022)	Unknown
Baillon & Placido (2019)	Unknown
Bajtelsmit et al. (2015)	Unknown
Balafoutas & Sutter (2019)	Unknown
Barham et al. (2014)	Unknown
Belissa et al. (2020)	Unknown
Berger & Bosetti (2020)	Unknown, Compound risk, Nature
Bianchi & Tallon, (2019)	Unknown
Bouchouicha et al. (2017)	Unknown
Brunette et al. (2015)	Unknown
Butler et al. (2014)	Unknown
Cavatorta & Schröder (2019)	Unknown
Calford, (2020)	Unknown
Calford & DeAngelo (2023)	Unknown
Charness et al. (2013)	Unknown
Chew et al. (2012)	Unknown
Chew et al. (2017)	Unknown
Chew et al. (2018)	Unknown
Conte & Hey (2013)	Compound risk
Cubitt et al. (2020)	Unknown
Dimmock et al. (2015)	Unknown
Dimmock et al. (2016)	Unknown
Duersch et al. (2017)	Unknown
Elabed & Carter (2015)	Compound risk
Eliaz & Ortoleva (2016)	Unknown
Ert & Trautmann (2014)	Unknown
Füllbrunn et al. (2014)	Human
Georgalos (2019)	Unknown
Georgalos (2021)	Unknown
Hao et al. (2016)	Unknown
Keck et al. (2014)	Unknown
Kocher et al. (2018)	Human
König-Kersting & Trautmann (2016)	Unknown
Kothiyal et al. (2014)	Unknown
Koudstaal et al. (2016)	Unknown
Kovářík et al. (2016)	Unknown
Li (2017)	Nature
Li et al. (2018)	Human, Nature
Li et al. (2020)	Unknown
Mengel et al. (2016)	Unknown
Moreno & Rosokha (2016)	Unknown
Ngangoué (2021)	Unknown
Oechssler & Roomets (2015)	Mechanical randomization device
Oechssler et al. (2019)	Unknown
Peysakhovich & Karmarkar (2016)	Unknown, Nature
Peysakhovich & Naecker (2017)	Unknown
Prokosheva (2016)	Human
Qiu & Weitzel, 2016)	Human
Rieger et al. (2014)	Unknown
Robinson et al. (2021)	Unknown
Salmon & Shniderman (2019)	Unknown

Shishkin & Ortoleva (2023)	Unknown
Sutter et al. (2013)	Unknown
Trautmann & Zeckhauser (2013)	Human
Trautmann & Van De Kuilen (2016)	Unknown
Tymula et al. (2013)	Unknown
Vieider et al. (2015)	Unknown
Voorhoeve et al. (2016)	Unknown
Watanabe & Fujimi (2024)	Unknown, Nature

Based on the survey in Table 1, four different methods of ambiguity production can be distinguished. The most prevalent technique involves the experimenter arbitrarily determining the composition of balls in two colors, which remains unknown to the participants. This approach, known as the *unknown* method, renders the urn ambiguous as any combination of colored balls is conceivable. Undoubtedly, the unknown method emerges as the simplest and most direct approach to craft an ambiguous urn. However, individuals might exhibit heightened aversion to uncertainty when others, most prominently the experimenter who produced the urn, possess knowledge regarding the underlying uncertainty of the urn (Chua Chow & Sarin, 2002). This asymmetry of information between experimenters and participants may foster suspicion among participants regarding the intentions of the experimenters. For example, there is a concern that participants might perceive the experimenter as orchestrating the ambiguous urn in a manner that minimizes experimental costs (Hey et al., 2010; Oechssler & Roomets, 2015). Consequently, participants may exhibit heightened aversion to ambiguity as a strategy to shield themselves from potential manipulation or exploitation.

One method to mitigate this suspicion is to allow participants to select the winning color themselves before drawing a ball from the ambiguous urn (Trautmann & Van De Kuilen, 2015). However, this approach may not fully eliminate strategic uncertainty concerning the experimenter's intentions. For instance, participants might assume that the experimenter is aware of the distribution of color preferences (e.g., more red than black) and could manipulate the urn accordingly to reduce experimental payouts. Consequently, suspicions regarding fundamental strategic uncertainty persist despite this procedure.

In contrast, some experimental studies employ a different approach, termed the *human* method, wherein other individuals—uninvolved in the experiment and uninformed about its setup—are tasked with composing the ambiguous urn. These individuals, sometimes selected randomly from among the participants or from a separate pool, are designated as urn composers and are excused from the experiment immediately afterward (Füllbrunn et al., 2014). Presumably, these individuals have no incentive to minimize experimental payoffs, thereby potentially eliminating strategic uncertainty. Occasionally, additional measures are taken to address strategic uncertainty. For instance, in Trautmann & Zeckhauser (2013), participants composed the risky and ambiguous urns while blindfolded for the latter. In other studies, multiple participants collaborated in determining the contents of the ambiguous urn to reduce suspicion (Chen & Schonger, 2022). Qiu & Weitzel (2016) even involved a 4-year-old child (the son of one of the authors) composing the ambiguous urn under the assumption that young children are less strategic than adults. Besides involving unrelated individuals in urn composition, another option is to use mechanical randomization devices, such as a bingo blower (Kothiyal et al., 2014) or a Galton box (Oechssler & Roomets, 2015), to physically draw the ball.

While the unknown and human methods concern **who** composes the ambiguous urn, alternative studies delve into the mechanisms of **how** the composition of the ambiguous urn is determined. Segal (1987) proposed a conceptualization where ambiguity is portrayed as a two-stage lottery. In this framework, the first stage resolves the second-order probability distribution over states, while the subsequent stage determines the probability of each potential outcome within each state. When this second-order probability is objectively defined, ambiguity emerges as a compound risk lottery. This approach, termed the *compound risk* method, entails one lottery draw to establish the quantity of balls of each color (in the 2-color Ellsberg urn), followed by another draw to resolve ambiguity by determining the actual ball color from the Ellsberg urn[3]. Notably, in the compound risk method, the second-order probability distribution over states is objectively discernible, as it emanates from a well-defined lottery.

Alternatively, the second-order probability may be rooted in naturally occurring events about which participants possess limited knowledge. For instance, the number of balls of a certain color could be contingent upon the decimals of specific temperature measurements at a given time and place (Abdellaoui et al., 2011, 2015), upon the true interpretation of a phrase in a foreign language (Li, 2017), or the fluctuations in a stock index across foreign markets (Baillon, Bleichrodt, et al., 2018; Baillon, Huang, et al., 2018). In such instances, ambiguity arises due to the challenge participants face in

[3] For instance, in the experiment conducted by Haisley and Weber (2010), participants were briefed on the presence of 20 chips, colored either red or blue, in both the risky bag and the ambiguous bag. The risky bag contained a predetermined 10 red and 10 blue chips, whereas the composition of the ambiguous bag was determined by a random draw from 0 to 20 for each color, following a uniform distribution. Subjects were asked to choose to randomly draw a chip from either the risky bag or the ambiguous bag.

formulating accurate subjective probabilities concerning these naturalistic events. Consequently, the second-order probability distribution is inherently imprecise. This approach is thus termed the *nature* method.

Given the diversity of ambiguity studies using different methods to operationalize ambiguity in Ellsberg urns, an important methodological question arises: are participants' ambiguity attitudes influenced by different methods of producing ambiguity? The answer to this question might largely depend on the way one views ambiguity. The three perspectives delineated by Chew et al. (2017) regarding individuals' perceptions of ambiguity provide elucidation to the aforementioned inquiry.

The first perspective regards ambiguity as a spectrum of potential priors representing various compositions of colored balls within the ambiguous urn, known as the *multiple-prior* perspective. This perspective is mirrored in models such as the Choquet expected utility model (Schmeidler, 1989) and the maxmin expected utility model (Gilboa & Schmeidler, 1989). Within this framework, the reduction of compound lottery axiom (RCLA) holds true in both models, which implies that individuals would perceive ambiguity differently depending on whether it is composed via the compound risk method or the other three methods. Because the satisfaction of the RCLA enables individuals to disentangle and resolve the two layers of uncertainty inherent in the compound risk lottery, thus simplifying it into a more understandable and simple form of risk.

In the second perspective, ambiguity is viewed as a two-stage lottery, where a subjective probability distribution is assigned in the initial stage across various compositions of balls in the subsequent stage, referred to as the *two-stage* perspective. This approach finds representation in models such as the recursive expected utility model (Klibanoff et al., 2005) and the recursive rank-dependent utility model (Segal, 1987), both of which relax the RCLA. Relaxing the RCLA suggests that individuals may not be indifferent between a compound risk lottery and its simplified counterpart (i.e., the simple even-chance lottery). Consequently, when considering ambiguity within a two-stage framework and relaxing the RCLA, it is uncertain whether discernible differences in attitudes towards ambiguity would emerge between the four production methods, despite a strong association of preference for compound risk and ambiguity found in previous study, such as Halevy (2007) and Chew et al. (2017).

Furthermore, ambiguity can be perceived differently based on the mechanism from which it originates, namely, the *source of uncertainty* (Abdellaoui et al., 2011; Chew & Sagi, 2008; Fox & Tversky, 1995; Li et al., 2018). This perspective, referred to as the *source* perspective, suggests that ambiguity generated by the four various production methods in this paper can be attributed to different sources of uncertainty. Specifically, ambiguity may arise from (i) variations in ball composition and experimenter intention, (ii) variations in ball composition and the intentions of the urn composer, (iii) uncertainties in the distribution of possible urn compositions and the actual probabilities of drawing certain colored balls, and (iv) uncertainties in the distribution of naturalistic events and the actual probabilities of drawing certain colored balls. Consequently, individuals perceiving ambiguity from a source perspective may interpret it differently depending on the method involved, leading to varying attitudes toward ambiguity.

From the aforementioned, it becomes evident that regardless of the perspective employed to perceive and understand ambiguity, it is challenging to make consistent predictions regarding whether the four ambiguity production methods measure identical ambiguity preferences. Therefore, in this paper, we refrain from formulating specific hypotheses regarding ambiguity attitudes and preference consistency. Instead, we opt to pursue an exploratory investigation across the four distinct production methods.

To this end, we compared the four ambiguity production methods (surveyed in Table 1) in one experiment using a between-subject design, with the method of ambiguity production serving as the main treatment effect. After carefully explaining the method of ambiguity production, we elicited participants' ambiguity attitudes for three different likelihoods (0.1, 0.5, and 0.9) with matching probabilities in a multiple-choice list format (Jaffray, 1991; Kahn & Sarin, 1988; Wakker, 2010). Participants' matched probabilities for these three likelihoods were econometrically used as input to establish individual ambiguity aversion and the ambiguity-generated likelihood insensitivity (henceforth a-insensitivity) (Abdellaoui et al., 2011, 2015; Dimmock et al., 2015, 2016). Furthermore, for each likelihood, participants also made a direct choice between a risky and ambiguous urn. The responses to this binary choice were compared to the matched probability from the multiple-choice list to establish participants' choice consistency.

For the experiment, we enrolled 233 university students representing various disciplines, resulting in an average of 58 participants per treatment group. Analysis of the experimental data revealed no statistically significant differences in the levels of ambiguity aversion and a-insensitivity across the four ambiguity production methods. Furthermore, we assessed the consistency of participants' choices and observed notable inconsistency when employing the compound risk method to construct the ambiguous urn. To ensure the robustness of our findings, we conducted a thorough check by excluding all participants with inconsistent choices and reanalyzing the data. Remarkably, the results remained consistent: none of the four ambiguity production methods exhibited variance in terms of ambiguity aversion and a-insensitivity. Based on these findings, we recommend utilizing the simplest and most straightforward production method, namely the unknown method, where the experimenter constructs the ambiguous urn and delegates the selection of the winning color to the participants, promising a streamlined and effective approach for future laboratory experiments.

Our paper offers two significant contributions to the literature. Firstly, it presents a comprehensive and systematic comparison of various ambiguity production methods commonly used in previous studies. Traditionally, ambiguity studies primarily relied on controlled laboratory settings, where ambiguity attitudes were assessed within artificially constructed scenarios, such as the ball-drawn task. However, as research needs evolve, there is an increasing demand to explore ambiguity and ambiguity attitudes within specific real-world contexts (Abdellaoui et al., 2005, 2011, 2021; Baillon, Huang, et al., 2018; Berger & Bosetti, 2020; Chew et al., 2012; Fox & Weber, 2002; Heath & Tversky, 1991; Li, 2017; Li et al., 2018). Recognizing this necessity, Baillon, Huang, et al. (2018) developed a novel method in which ambiguity can be induced by all types of events, encompassing both artificial ball-drawn events and specific real-life events. Li et al. (2019) further extended this method to game theory, where ambiguity is also generated from other individuals' choices and behavior. Additionally, in a recent study by Watanabe & Fujimi (2024), ambiguity was composed using both artificial Ellsberg-type events and local precipitation as a natural source of ambiguity to investigate the association between individual ambiguity attitudes and real-life behaviors, such as flood preparedness. Our study compares and incorporates the four commonly used methods of producing ambiguity, providing a reference and validation for future studies that may require the use of a particular method other than the prevailing one. Thus, our comparative analysis of different ambiguity composition methods serves as a valuable resource for advancing research in this area.

Secondly, our study deepens the comprehension of individuals' perceptions regarding various forms of uncertainty. In early investigations exploring the correlation between compound risk and ambiguity, Halevy (2007) discovered individuals' preference for compound risk scenarios over ambiguous ones, despite a notable correlation between attitudes toward compound risk and ambiguity. In a subsequent study, Chew et al. (2017) conducted a more expansive study, discerning individual attitudes toward three distinct types of partial ambiguity—interval ambiguity, disjoint ambiguity, and two-point ambiguity—and their correlation with compound risk. Echoing findings from Halevy (2007), theirs revealed unique attitudes toward these partial ambiguity types, alongside a robust correlation between partial ambiguity and compound risk. Similarly, Li et al. (2018) delved into ambiguity across diverse uncertain events (lab-based versus real-life scenarios) and outcomes (e.g., monetary, temporal, and health-related), illuminating the reliance of individual ambiguity attitudes on the source of uncertainty. In a more policy-oriented inquiry, Berger & Bosetti (2020) explored policymakers' preferences regarding different types of uncertainty and their policy inclination's relationship with their uncertainty attitudes. Furthermore, recent investigations by Aydogan et al. (2023) identified three distinct layers of uncertainty and their influence on preferences. These studies underscore the significance of ambiguity composition, suggesting that varying types, sources, or layers of uncertainty may elicit divergent attitudes, thereby substantially impacting research outcomes. Through an examination of ambiguity composition across four commonly employed production methods, our study enhances this understanding.

In the next section, we explain the design of our experiment. Section 3 presents the results and Section 4 concludes.

2. Experimental design

2.1 General setting

Drawing upon recent advancements in ambiguity research, which have expanded the measurement of ambiguity to encompass both high and low likelihood events (Abdellaoui et al., 2011; Dimmock et al., 2015, 2016), this paper's experiment similarly broadens its focus. Specifically, we investigate ambiguity attitudes across low, moderate, and high likelihood events, resulting in three locally measured ambiguity attitudes. Subsequently, two global ambiguity attitude indices—the ambiguity aversion index and the a-insensitivity index—are derived to comprehensively capture ambiguity attitudes across the entire likelihood spectrum.

Each participant in our experiment undertook three tasks[4], wherein ambiguity attitudes were assessed for low, moderate, and high likelihood events respectively. By mentioning low, moderate, and high likelihood events, we mean events with ambiguity-neutral subjective probability of 0.1, 0.5, and 0.9. Within each task, participants encountered a choice list table consisting of 20 rows. In each row, they were instructed to draw a chip from one of two urns: urn U or urn K. Both urns contained 100 chips each, with the composition of chips known for participants in urn K but unknown in urn U. Specifically, in Task 1 (refer to a screenshot in Figure 1), focused on measuring ambiguity attitudes for moderate likelihood events, each urn contained chips with a maximum of two colors (green or yellow), denoted as urn K2 for known composition and urn U2 for unknown. Similarly, in Task 2 and Task 3, aimed at assessing ambiguity attitudes for low and high likelihood events respectively, the urns contained chips with a maximum of ten colors, labeled as urn K10 and urn U10, with K10 having a known composition and U10 an unknown one.

Figure 1: Screenshot of the multiple-choice list table participants faced in Task 1

To minimize suspicion, participants were instructed to select a color for which they would receive payment, referred to as the winning color throughout the paper, before any tasks. In each task, while

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[4] In the experiment, subjects experienced four tasks in total. The first three tasks were those explained in the main body of this paper. As for the fourth task, it was a choice list task used to elicit subjects' risk preference for a companion study by Fairley & Weitzel (2017). Since the fourth task was conducted after the other three tasks were completed, the subjects' choices in our experiment were not influenced. Considering the irrelevance of the fourth task to our study, we only presented the details of the first three tasks in this paper.

the composition in urn U remained unknown and consistent across all 20 rows, the composition of colored chips in urn K varied across rows in a way of gradually increasing its attractiveness as participants scrolled down the list[5]. As the attractiveness of urn K heightened with each row, participants reached a point where they transitioned from choosing urn U to selecting urn K, known as the switching row. We computed a participant's matching probability as the midpoint between the objective probability of the respective urn K in the switching row and that in the row directly above it. At the end of the experiment, one of the 20 rows from one of the three tasks was randomly chosen to determine the payoff. In the selected row, one chip was drawn at random from the chosen urn. If the color of the drawn chip matched the participant's winning color, they earned €15 on top of their show-up fee (€4); otherwise, they received no additional payoff beyond the show-up fee.

All instructions for each task were verbally communicated. Prior to the tasks, participants were required to complete a brief questionnaire[6] regarding the task setup. Any incorrect responses were clarified to ensure a thorough understanding. Before commencing the experiment, urns U2 and U10 were physically constructed using poker chips based on the experimental treatment's production method[7], placed at the front of the lab room, and covered with a cloth to maintain the unknown composition[8]. Participants were permitted to inspect all urns after the end of the experiment.

2.2 Methods of ambiguity production

In the unknown method, the ambiguous urns were prepared by one of the experimenters before the start of the experiment. Participants received no additional information regarding the composition of colored chips in the ambiguous urns, except that there were 100 chips, either green or yellow.

In the human method, two randomly selected participants composed the ambiguous urns instead of the experimenter. At the beginning of the experiment, two participants were chosen randomly. The first participant was assigned to construct urn U2, while the second participant was tasked with urn U10. Instructions given to these two selected participants were openly explained to all participants present

[5] This was achieved by incrementally increasing the number of chips matching the winning color (one out of the two colors) in urn K2 from 23 to 80, with an increase of three chips per row in Task 1. In Task 2, the number of chips matching the winning color (one out of ten colors) in urn K10 increased from 2 to 40, with an increment of two chips. Task 3 saw a rise in the number of chips matching the winning colors (nine out of ten colors) in urn K10, from 60 to 98, with an increment of two chips.

[6] The comprehensive instructions for the entirety of the experiment and the detailed queries in this control questionnaire are outlined in Appendix D.

[7] The details for each production method can be seen in Appendix C.

[8] Please refer to the photo materials in Appendix A.

in the session. The selected participants then privately composed the ambiguous urns within the same laboratory room. Subsequently, they received a show-up fee and were dismissed. The remaining instructions were distributed to the other participants who were not involved in the initial composition process. This ensured that the selected participants had no prior knowledge of the experimental tasks, preventing both the experimenters and other participants from knowing the exact composition of the colored chips in the ambiguous urns. Additionally, participants were informed that they could check the composition of colored chips in each urn after the experiment ended if they had any suspicions.

In the compound risk method, one participant was randomly chosen to construct both urn U2 and urn U10. For urn U2, the selected participant randomly drew one number from an envelope containing numbers between 0 and 100, determining the number of green chips (and therefore also implicitly the number of yellow chips). For urn U10, the participant randomly drew ten numbers from ten separate envelopes filled with numbers between 0 and 9. Each of these numbers was then divided by the sum of the ten numbers and rounded to a percentage. These rounded percentages determined the distribution of colored chips in urn U10.[9]

The nature method closely resembles the compound risk method. Again, one participant was randomly selected to compose both urn U2 and urn U10. However, instead of using randomly drawn numbers, the number of green chips in urn U2 was determined by the first decimal of temperatures in Sydney and Warsaw at the time of composing the ambiguous urns[10]. For urn U10, the number of colored chips was determined by the first decimal of temperatures in ten cities[11]. Similarly, each of these ten generated numbers was divided by their sum and rounded to a percentage, determining the distribution of colored chips for each of the ten colors. After the experiment, participants were allowed to verify the temperatures used in the composition process.

2.3 Measuring ambiguity attitudes

As explained in Section 2.1, we first calculated three locally measured ambiguity attitudes indices

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[9] For example, if the ten numbers drawn from the ten envelopes were 0, 1, 2, ... ,9, the ten rounded percentages after each of the ten numbers being divided by the sum were 0%, 2%, 4%, ..., 20%. Then, the number of chips for the ten colors was 0, 2, 4, ..., 20.

[10] The temperature information was obtained from www.weatherbug.com, which updated the temperature information every 5 minutes.

[11] Next to Sydney and Warsaw, the other eight cities were Los Angeles, Mexico City, Madrid, St Petersburg, New York, Cape Town, Delhi, Buenos Aires, Tokyo and London.

using the elicited matching probabilities as follows:

$$AA_p = p - m(p), \ \ p = 0.1, 0.5, 0.9. \tag{1}$$

Each positive AA_p index indicates a matching probability $m(p)$ smaller than the ambiguity-neutral subjective probability p (henceforth a-neutral probability), suggesting an aversion to ambiguity[12]. Moreover, negative $AA_{0.9}$ and positive $AA_{0.1}$ imply a tendency toward insensitivity to likelihoods, resulting in a transformation of subjective probabilities toward 0.5.

We then calculated two global ambiguity attitude indices—index-a, which measures the degree of a-insensitivity, and index-b, which gauges the degree of ambiguity aversion. Specifically, for each participant, we estimated a best-fitting line between the matching probability and the a-neutral probability through ordinary least squares (OLS) regression. Denoting c as the intercept and s as the slope of the best-fitting line (i.e., $m(p) = c + sp$), we calculated d as the distance of the best-fitting line at $p = 1$ from 1 (i.e., $d = 1 - c - s$). Subsequently, following (Abdellaoui et al., 2011), the two global ambiguity attitude indices were derived as follows:

$$a = 1 - s, \tag{2}$$

$$b = 1 - s - 2c = d - c. \tag{3}$$

2.4 Consistency

To assess the consistency of participants' preferences, each participant encountered three consistency check questions before engaging in the three tasks. In each consistency check question, participants were presented with a choice between an ambiguous situation—identical to the ambiguity presented in each of the subsequent three tasks—and a risky situation with a winning probability matching the corresponding a-neutral probability. Preference-consistent participants were expected to maintain the same preferences between the consistency check and the subsequent choice list table of the corresponding task. That is, those who opted for the risky urn in the binary choices during the consistency check also exhibited a matching probability equal to or smaller than the corresponding a-neutral probability in the ambiguous contexts. For example, a participant who preferred the risky urn

[12] For example, in a low likelihood event with an ambiguity-neutral subjective probability of 0.1, an elicited matching probability that is smaller than 0.1 would result in a positive AA0.1, which therefore implies an aversion to ambiguity.

over the ambiguous urn in a two-color urn event and switched before row 10 in Task 1 would be considered preference consistent.

2.5 Procedures

The experiments were conducted at the Individual Decision Lab at Radboud University and the Experimental Laboratory for Sociology and Economics (ELSE) lab at Utrecht University. A total of 233 students[13], of which 55.79% were female[14], were recruited from all disciplines at the two universities. The experiments were computerized with z-Tree (Fischbacher, 2007). The average payment per participant was €11.50. We conducted 17 experimental sessions in total, with each session lasting around 90 minutes. We administered all treatments between-subject, i.e., in each session we only administered one of the four methods of ambiguity production.

3. Experimental results

3.1 Ambiguity attitudes

In this section, we first elucidate participants' behavior when facing ambiguity composed by each of the four production methods. Subsequently, we examine whether variations in the degree of ambiguity aversion and a-insensitivity exist among specific methods of ambiguity production.

Table 2 presents the mean of the three local and two global ambiguity attitude indices measured in each of the four ambiguity production methods. In Panel A of Table 2, consistent with previous studies, participants in our experiment generally displayed matching probabilities below the a-neutral probabilities of 0.9 and 0.5 in high and moderate likelihood events (indicated by the significantly positive $AA_{0.5}$ and $AA_{0.9}$ indices), yet demonstrated matching probabilities above the a-neutral probability of 0.1 in the low likelihood event (reflected by the significantly negative $AA_{0.1}$ index). Moreover, Panel A also illustrates the proportion of participants whose local ambiguity attitudes are consistent with the majority in previous studies. That is, the proportion of participants who have a

[13] We conducted a power analysis using G*Power software (Faul et al., 2009) to determine the minimum required sample size necessary to detect a statistically significant and practically meaningful difference in index-b and index-a among the four production methods. Setting the effect size at 0.03, which aligns with a relatively small magnitude based on our review of ambiguity studies in the literature, employing a significance level of 0.05 and a power level of 0.8, we calculated a sample size requirement of 232. Importantly, the number of subjects in our study meets this requirement, ensuring sufficient statistical power for meaningful analysis.
[14] See the gender distribution in Appendix B Table B.2.

negative $AA_{0.1}$ index and positive $AA_{0.5}$ and $AA_{0.9}$ indices. We observe no significant difference in the consistency between locally measured ambiguity attitudes and those measured in previous studies across the four methods.

Table 2: Local and global ambiguity attitude indices measured from each production method.

Panel A: *Local ambiguity attitude index*				
a-neutral probability	Mean of local ambiguity attitude index $AA_{j/10}$ (percentage of participants with the majority ambiguity attitude)			
(*j/10*, j=1, 2, 9)	Unknown	Human	Compound risk	Nature
0.1	-0.158***	-0.129***	-0.135***	-0.156***
	(77.78%)	(50.91%)	(75.00%)	(73.33%)
0.5	0.038***	0.023**	0.029***	0.008
	(81.48%)	(65.45%)	(76.56%)	(60.00%)
0.9	0.172***	0.176***	0.145***	0.148***
	(96.30%)	(98.19%)	(90.63%)	(95.00%)
Panel B: *Global ambiguity attitude index*				
Ambiguity aversion Index-b	0.102***	0.114***	0.092***	0.066***
A-insensitivity Index-a	0.288***	0.257***	0.225***	0.255***
Correlations between index-b and index-a	0.502***	0.366***	0.599***	0.415***

Notes: Statistical tests performed in this table are Wilcoxon signed-rank tests that examine the difference of each global and local ambiguity attitude index between zero for each production method. $^{*}p\leq0.10$; $^{**}p\leq0.05$; $^{***}p\leq0.01$.

Regarding the two global ambiguity attitude indices, Figure 2 presents two graphs illustrating the degrees of ambiguity aversion and a-insensitivity across the four methods of ambiguity production. While there is a clear overall tendency towards ambiguity aversion and insensitivity to likelihoods, visual inspection of these figures indicates no significant differences in the degree of ambiguity aversion or a-insensitivity among the four ambiguity production methods.

Panel B in Table 2 provides a closer look at the two global indices. We observed that the ambiguity aversion index (index-b) generally and significantly surpassed zero across all four production methods, indicative of a prevalent tendency towards ambiguity aversion. Furthermore, the index of a-insensitivity (index-a) significantly exceeded zero on average as well, underscoring a widespread inclination towards insensitivity to likelihoods under ambiguity. To further check whether there exists a difference in the two global ambiguity attitude indices, a multivariate analysis of variance (MANOVA) was performed to formally test for potential differences in the levels of ambiguity aversion and a-insensitivity across the four production methods. The two global ambiguity attitude indices were utilized as dependent variables, a decision supported by a significant positive correlation between the two variables (coefficient=0.339, p=0.000 via Spearman correlation test). The results of our analysis indicate that there were no significant differences observed in either the degree of ambiguity aversion or a-insensitivity among the four ambiguity production methods (p>0.1016).

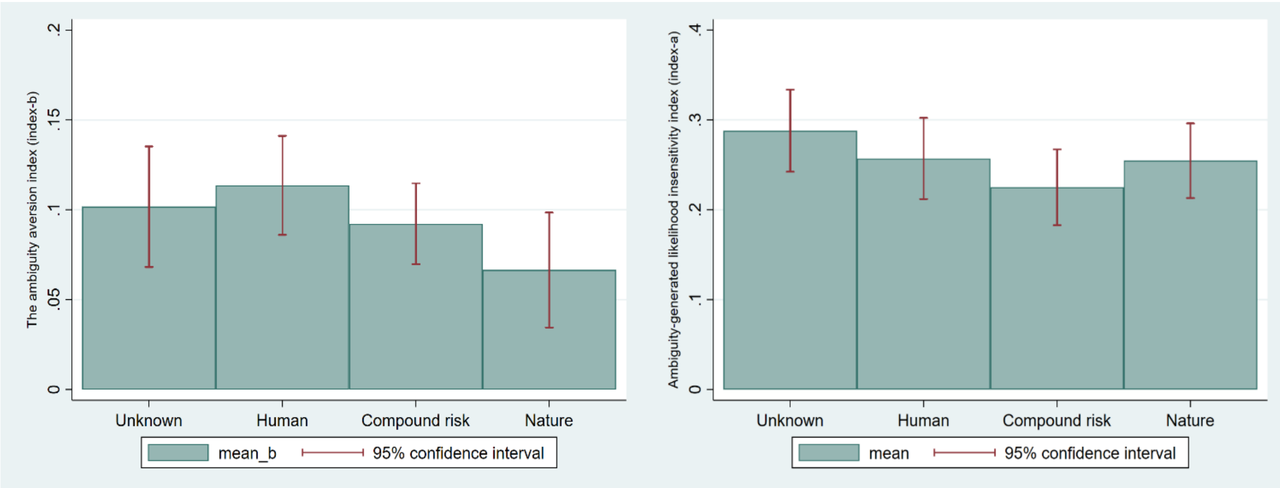

Figure 2: Mean and 95% confidence interval of the ambiguity aversion index and the a-insensitivity index.

While ambiguity aversion and a-insensitivity are conceptually distinct, stemming from different cognitive processes, they frequently demonstrate empirical correlation. This correlation emerges as both phenomena entail deviations from Bayesianism and rationality. In the last row of Panel B in Table 2, we conducted tests to examine the correlation between the two global indices within each production method and identified a significantly positive correlation in all four production methods.

3.2 Individual consistency

Preference consistency is an additional criterion of significance for researchers when assessing methods for ambiguity production. Consequently, our investigation delved into whether the four production methods exhibited variations in consistency rates. Table 3 delineates the consistency rates for each check question across the four ambiguity production methods. Additionally, the consistency rate across all three check questions, denoted as the *consistent sample*[15], is presented in the last column

[15] As a robustness check for the analysis in section 3.1, we ran MANOVA again only with participants in the "consistent sample". Again, we observed no significant differences in the two ambiguity attitude indices (i.e., ambiguity aversion and a-insensitivity) for the four ambiguity production methods (p>0.1583).

of Table 3. Notably, we observed a relatively high consistency rate within each check question. Furthermore, our analysis revealed no significant discrepancies in consistency rates across the four ambiguity production methods, except for a distinct consistency rate noted for the compound risk method.

Table 3: The proportion of preference-consistent participants in each production method

Method of ambiguity production	**Consistency check question for events with a-neutral probability of**			**Overall**
	0.1	**0.5**	**0.9**	
Unknown	77.78%	85.19%	98.15%	66.67%
Human	85.45%	85.45%	94.55%	69.09%
Compound risk	68.75%	78.13%	92.19%	48.44%
Nature	75.00%	80.00%	93.33%	56.67%

To rigorously evaluate whether the four methods of ambiguity production displayed variations in consistency rates, logistic regressions were performed for models (1) to (4) as delineated in Table 4. Concerning the dependent variables, in model (1), a binary dependent variable named "*Consistency*" was established to indicate participants' consistent preferences across the three check questions. It assumes a value of 1 if a participant's preferences remained consistent across the three questions, and 0 otherwise. Similarly, in models (2), (3), and (4), the dependent variables were designated as "*Consistency01*", "*Consistency05*", and "*Consistency09*" to stand for the consistency rate in events with a-neutral probability of 0.1, 0.5, and 0.9. Here, a value of 1 indicated consistent behavior in each corresponding check question, while the alternative was denoted by a value of 0. Regarding the independent variables, considering the distinction of consistency rate in the compound risk method as shown in Table 3, in all four models, we used the compound risk method as a reference category and introduced three dummy variables—namely, *Unknown*, *Human*, and *Nature*—to signify the method of ambiguity production. Here, a value of 1 represented the specific production method, and 0 denoted otherwise.

Table 4: The regression analysis of production method on consistency rates

Variables	(1) *Consistency*	(2) *Consistency01*	(3) *Consistency05*	(4) *Consistency09*
Unknown	0.7557**	0.4643	0.4762	1.5022
	(0.3828)	(0.4250)	(0.4891)	(1.1141)
Human	0.8669**	0.9822**	0.4978	0.3845
	(0.3851)	(0.4690)	(0.4886)	(0.7563)
Nature	0.3308	0.3102	0.1133	0.1710
	(0.3619)	(0.4029)	(0.4432)	(0.6978)

Constant	-0.0625	0.7885***	1.2730***	2.4681***
	(0.2507)	(0.2073)	(0.3030)	(0.4668)
No. of observations	233	233	233	233
Wald Chi2	6.58	4.54	1.61	1.89
Prob>Chi2	0.0811	0.2090	0.6582	0.5953
Pseudo R-square	0.0214	0.0191	0.0074	0.0256

Notes: Standard errors in the parentheses. $^{*}p\leq0.10$; $^{**}p\leq0.05$; $^{***}p\leq0.01$.

Consistent with the findings in Table 3, the predominantly positive coefficients in Table 4 suggest a comparatively lower consistency rate associated with the compound risk method when compared to the other three methods of ambiguity production. Notably, this lower consistency rate in the compound risk method was found to be statistically significant across the three check questions when compared with the human and unknown methods. However, when focusing solely on consistency within each check question, we generally observed no significant difference in the consistency rates between the compound risk method and the other three methods, except for a discrepancy noted when comparing with the human method in low likelihood events.

4. Conclusion

Building upon the classical Ellsberg setup, our investigation aimed to scrutinize whether diverse operationalizations of the Ellsberg urn yielded comparable ambiguity attitudes. Aligning with an extensive survey covering 69 experimental studies conducted over the past decade, we delineated four distinct methods of ambiguity production: ambiguity generated (i) by the experimenter, (ii) by another participant, (iii) through compound risk lotteries, and (iv) derived from compound risk using random nature numbers. Our analysis unveiled no statistically significant disparity in ambiguity attitudes, encompassing both ambiguity aversion and a-insensitivity, across the four methods of ambiguity production. However, a noteworthy observation emerged regarding preference inconsistency during the construction of the ambiguous urn utilizing the compound risk method.

As the application of ambiguity expands across various fields, the demand for composing ambiguity varies according to specific research questions. For instance, in studies with limited tasks and experiment duration, such as Bianchi & Tallon (2019), simplicity and straightforwardness of the ambiguity production method take precedence. Conversely, in field studies where the specific decision-making scenario holds importance, composing ambiguity that closely mirrors the actual scenario faced by participants becomes paramount. Hence, the aim of our study is to furnish a reference for future ambiguity-related studies, indicating that ambiguity can be generated by any of the four methods investigated in our paper depending on the specific research need.

Despite our focus on comparing the four different methods of producing ambiguity, our attention remains centered on individual decision-making. From a broader perspective, ambiguity can also stem from uncertainty surrounding others' choices and decisions, such as the social ambiguity studied by Li et al. (2020). Exploring whether differences in generating ambiguity in social contexts influence one's attitude towards ambiguity might serve as a potential direction for future studies.

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Appendix

A. Photo materials and screenshots

A.1 Photo materials

Figure A.1: Physical chips and the two urns used in the experiment.

Figure **A.2:** One session of the experiment

A.2 Screenshots

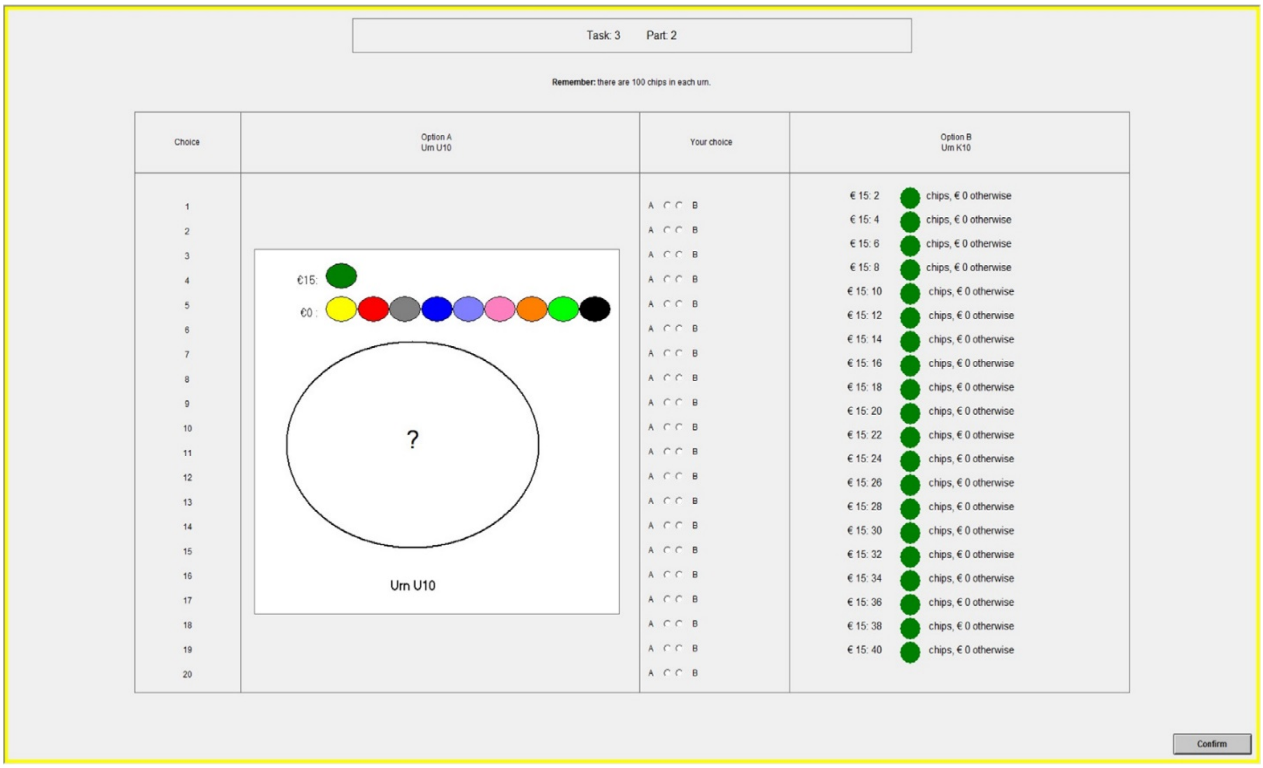


Figure A.3: Screenshot for the elicitation of m(0.1)

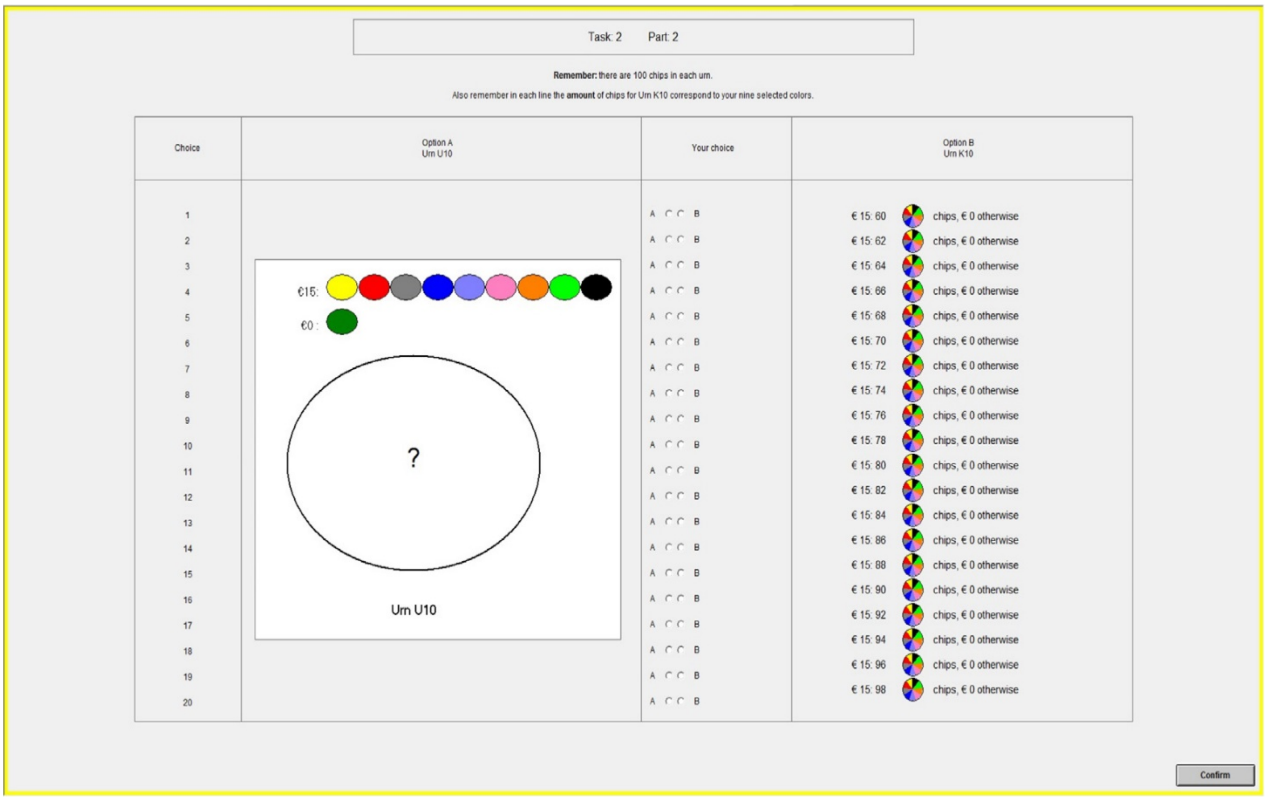


Figure A.4: Screenshot for the elicitation of m(0.9)

B. Additional tables

Table B.1: Descriptive statistics of matching probabilities, ambiguity aversion index and a-insensitivity index

	Mean	Median	Standard deviation	Minimum	Maximum
Unknown method					
m(0.1)	0.1580	0.1500	0.0756	0.02	0.41
m(0.5)	0.4619	0.4850	0.0888	0.23	0.8
m(0.9)	0.7279	0.7100	0.1098	0.6	0.98
index-b	0.1017	0.1167	0.1229	-0.4667	0.3233
index-a	0.2880	0.3125	0.1673	0	0.7625
Human method					
m(0.1)	0.1291	0.1100	0.0624	0.02	0.33
m(0.5)	0.4771	0.4850	0.0717	0.23	0.635
m(0.9)	0.7235	0.6900	0.1115	0.6	0.91
index-b	0.1136	0.1100	0.1019	-0.0633	0.4333
index-a	0.2570	0.2500	0.1671	-0.025	0.6625
Compound risk method					
m(0.1)	0.1352	0.1300	0.0492	0.02	0.31
m(0.5)	0.4714	0.4850	0.0742	0.23	0.755
m(0.9)	0.7552	0.7500	0.1110	0.3	0.98
index-b	0.0922	0.0700	0.0902	-0.13	0.2633
index-a	0.2250	0.2375	0.1688	-0.2125	0.5375
Nature method					
m(0.1)	0.1560	0.1500	0.0680	0.07	0.41
m(0.5)	0.4920	0.4850	0.0901	0.245	0.8
m(0.9)	0.7523	0.7800	0.1066	0.6	0.93
index-b	0.0664	0.0533	0.1237	-0.3467	0.37
index-a	0.2546	0.2500	0.1607	0	0.6125

Table B.2: Gender and age distribution under each ambiguity production method

Method	Gender (% of female)	Age (mean)
Unknown	46.30%	21.02
Human	60.00%	20.80
Compound risk	53.13%	23.13
Nature	63.33%	21.55
Total	55.79%	21.68

C. Instructions for the production of ambiguous urns

Unknown

Urn U2 is already produced and has an unknown composition of green and yellow chips. Please see urn U2 here. Urn U10 is also already produced and has an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips. Please see urn U10 here.

Human

We will first explain how urn U2 will be produced. Before you came into the lab, we have randomly drawn two persons from the pool of participants. Both are waiting outside the lab now and know nothing about the experiment. Shortly, the first of these randomly drawn persons will be called into the lab. This person may create Urn U2 without any of us knowing its composition. We will ask him/her to go behind the curtain where you can see two holders each filled with 100 green and 100 yellow chips. Shortly, the randomly selected person may step behind the curtain and create an urn with 100 chips in any combination of green and yellow chips as he/she pleases. This urn is urn U2, which will be visibly placed for all to see in the lab once it is produced. As we all cannot look into the urn, nobody in the lab except the randomly drawn person knows the exact composition of green and yellow chips. After having produced urn U2, the person will be dismissed without learning anything else about the experiment. Now we call in the first randomly selected person and instruct him/her to create urn U2 as described above.

The instructions for the first randomly chosen subject can be seen as below:

> *You may create an urn which we call urn U2. Behind the curtain you find two bowls each filled with 100 green and 100 yellow chips. In a moment you may step behind the curtain and create an urn with 100 chips in any combination of green and yellow chips as you please. Please step behind the curtain, create the urn, and put the urn on the table here.*
>
> [The experimenter waited for the person to be finished.]
>
> *We will now pay you a fixed amount for your participation and you may leave the room now. To keep your payment private, we give it to you in an envelope. Please sign this receipt after you have looked into the envelope and checked its content. Your payment does not depend in any way on the choices yet to be made in this experiment. Thank you for your cooperation.*
>
> [The first randomly chosen participant leaves the laboratory.]

We will now explain how urn U10 will be produced. Behind the curtain you can see 10 holders each filled with 100 red, 100 yellow, 100 grey, 100 green, 100 blue, 100 purple, 100 pink, 100 orange, 100 light green and 100 black chips. Shortly, the second randomly selected person may step behind the curtain and create an urn with 100 chips in any combination of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips as he/she pleases. This urn is U10, which will be visibly placed for all to see in the lab once it is produced. As we all cannot look into the urn, nobody in the lab except the randomly drawn person knows the exact composition of urn U10. After having produced U10, the person will be dismissed without learning anything else about the experiment. Now we call in the second randomly selected person and instruct him/her to create urn U10 as described above.

The instructions for the second randomly chosen subject can be seen as below:

> *You may create an urn which we call urn U10. Behind the curtain you find ten holders each filled with 100 red, 100 yellow, 100 grey, 100 green, 100 blue, 100 purple, 100 pink, 100 orange, 100 light green and 100 black chips. You (the selected person) can create an urn with 100 chips in any combination of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips as you please. Please step behind the curtain, create the urn, put the urn on the table here and leave the experiment.*
>
> [The experimenter waits for the person to be finished.]
>
> *We will now pay you a fixed amount for your participation and you may leave the room now. To keep your payment private, we give it to you in an envelope. Please sign this receipt after you have looked into the envelope and checked its content. Your earnings will not depend in any way on the choices yet to be made in this experiment. Thank you for your cooperation.*
>
> [The second randomly chosen participant leaves the laboratory.]

Compound risk

We will first explain how urn U2 will be produced.

Before you came into the lab, we have randomly drawn one person from the pool of participants. This person is waiting outside the lab now and knows nothing about the experiment. Shortly, this randomly drawn person will be called into the lab. This person may create urn U2 without any of us knowing its composition. Let us explain to you how he/she will be instructed to produce Urn U2.

Here we have 101 pieces of paper. Each is labeled with a number between 0 and 100 (including 0 and 100). We place these numbered pieces of papers in one envelope. In a short moment the randomly selected person will be called into the lab and select one piece of paper from the envelope. The number of GREEN chips in urn U2 will then be equal to the number written down on the paper he/she will draw from the envelope. The number of YELLOW chips in urn U will then be equal to 100 minus the number of green chips. For example: suppose he/she will draw the number 45 from the envelope, then urn U2 will contain 45 green chips and 55 yellow chips. He/she will produce urn U2 behind the curtain by means of the number he draws from the envelope. Urn U2 will be visibly placed for all to see in the lab once it is produced. As we all cannot look into the urn, nobody in the lab except the randomly drawn person knows the exact composition of urn U2.

The randomly drawn person will also create urn U10 without any of us knowing its composition. We will now explain how urn U10 will be produced. Here we have 10 piles each consisting of 10 pieces of paper. In each pile, every number between 0 and 9 (including 0 and 9) is written down on these pieces of paper exactly once. We now place each pile in a separate envelope. Thus, we have 10 envelopes, one for each color, with numbers running from 0 to 9.

In a short moment the randomly selected person will be called into the lab and select one number from each envelope. Each number drawn will be linked to a color.

Please see Table C.3 for the sequence of drawn numbers that will be linked to each color.

Table C.3: The sequence of the drawn numbers that are linked to each color.

Color	Number selected
Red	Number drawn from the first envelope
Yellow	Number drawn from the second envelope
Grey	Number drawn from the third envelope
Green	Number drawn from the fourth envelope
Blue	Number drawn from the fifth envelope
Purple	Number drawn from the sixth envelope
Pink	Number drawn from the seventh envelope
Orange	Number drawn from the eighth envelope
Light green	Number drawn from the ninth envelope
Black	Number drawn from the tenth envelope

We will now scale up the number of chips to 100 in total as follows: Behind the curtain, an empty table can be found, similar like Table C.4. After the randomly selected participant draws a number from one envelope, he/she goes behind the curtain and writes that number behind the correct color (red). Then he/she draws a number from the second envelope, walks behind the curtain and again puts the number behind the correct color (yellow). He/she will repeat this process ten times so that every color has a number written behind it.

Table C.4: The empty table the randomly selected subject needs to fill in.

Color	Number selected	Chips of this color in urn U10
Red	5	5/sum*100=X, X chips
Yellow		
Grey		
Green		
Blue		
Purple		
Pink		
Orange		
Light green		
Black		
Sum	Sum	100 chips

For example: suppose that he/she draws the number 5 linked to the color red (column 2 in Table C.4). In this case, he/she enters the number 5 in the second column in the row for red. The randomly selected person will then produce Urn U10 in the following way: he/she will fill in the ten numbers in an excel file which will automatically sum all numbers that are listed behind each color (Column 2). Then for each individual color the ratio of its number to the sum of all numbers is automatically calculated and rounded (see first cell column 3 in Table C.4). This ratio number will determine the amount of chips each color gets represented in the urn U10.

For the unlikely event that all randomly drawn numbers are 0 (effectively not a single color is drawn, and the sum of all colors is 0), then he/she will be instructed to fill the urn with 10 chips of each color. It is possible that only one color has a positive number, and all colors have a zero. In that case the urn only contains one color. It is also possible each color has the same positive number drawn. In that case, all colors are equally frequent. All other distributions in between these two extremes are also possible. He/she will produce urn U10 behind the curtain by means of the ten numbers he draws from the ten envelopes. Urn U10 will be visibly placed for all to see in the lab once it is produced. As we all cannot look into the urn, nobody in the lab except the randomly drawn person knows the exact composition of urn U10.

Now we call in the randomly selected person and instruct him/her to create urns U2 and U10 as described above. The instructions for the randomly selected subject can be seen as below:

You may create an urn which we call urn U2. Let us explain to you how Urn U2 will be produced now. In this envelope you can find 101 pieces of paper. Each is labeled with a number between 0 and 100 (including 0 and 100). In a short moment you may draw one piece of paper from the envelope. The number of GREEN chips in urn U2 will then be equal to the number written down on the paper you will draw from the envelope. The number of YELLOW chips in urn U2 will then be equal to 100 minus the number of green chips. For example: suppose you will draw the number 45 from the envelope, then urn U2 will contain 45green chips and 55 yellow chips. Please select one number from the envelope now.

[The randomly selected participant chooses number now].

Now please walk behind the curtain, create urn U2 accordingly and put the urn on the table here. Please put the selected piece of paper with the number in urn U2 so we can check the content after the experiment for anybody who wishes to see.

You may now also create a second urn called Urn U10. Let us explain to you how Urn U10 will be produced now. In a moment you may draw one number from each of these 10 envelopes. Each envelope is filled with pieces of papers numbered from 0-9. Please see Table C.3 for the sequence of the numbers you will draw, and you will link to each color.

[The experimenter show Table C.3]

Behind the curtain you will find an empty table, similar like Table C.4. After you have drawn a number from one envelope, please go behind the curtain and write that number behind the correct color (red), exactly as you can see in Table C.4 (second column). Then draw a number from the second envelope, walk behind the curtain and again put the number behind the correct color (yellow). You will repeat this process ten times so that every color has a number written behind it, as in Table C.4.

[Participants selects the 10 numbers].

Let us assume for illustration purposes that you draw the number 5 from the first envelope which then will be linked to the color red (column 2 in Table C.4). In this case, you enter a 5 in the second column in the row for red. The remaining nine numbers you will draw, you will enter in the same column for each color. You may produce Urn U10 in a moment in the following way: fill all these ten numbers in an excel file on the laptop behind the curtain. Automatically the sum of all numbers that are listed behind each color (Column 2) will be calculated. Then for each individual color the ratio of its number to the sum of all numbers is calculated and rounded (see column 3 in Table C.4). This ratio number will determine the amount of chips each color gets represented in the 10-color urn U10. For the unlikely event that all randomly drawn numbers are 0 (effectively not a single color is draw and the sum of all colors is 0), then please fill the urn with 10 chips of each color.

Now please walk behind the curtain, create urn U10 accordingly to the table you have made based on the ten numbers you have drawn which are automatically calculated via excel. Then put Urn U10 on the table here. Please save the table with all the information on the desktop of the laptop so we can check the content of urn U10 after the experiment for anybody who wishes to see.

We will now pay you a fixed amount for your participation and you may leave the room now. To keep your payment private, we give it to you in an envelope. Please sign this receipt after you have looked into the envelope and checked its content. Your earnings will not depend in any way on the choices yet to be made in this experiment. Thank you for your cooperation.

[Participant leaves the laboratory].

Nature

We will first explain how urn U2 will be produced. Before you came into the lab, we have randomly drawn one person from the pool of participants. This person is waiting outside the lab now and knows nothing about the experiment. Shortly, this randomly drawn person will be called into the lab. This person may create urn U2 without any of us knowing its composition.

Let us explain to you how he/she will be instructed to produce Urn U2. The randomly selected person will browse to the weather website WeatherBug on this laptop to check the current temperature in Sydney (Australia) and Warsaw (Poland). This website updates the exact temperature on a 5-minute interval. Then he/she will have to make a print screen of the current temperature and will have to save the information on the desktop. Based on the current temperatures in Sydney and Warsaw Urn U2 will then be produced in the following manner. The number of GREEN chips in urn U will be equal to the digit after the decimal point of Sydney and Warsaw. The number of YELLOW chips in urn U will be equal to 100 minus the number of green chips.

For example: suppose that it is 24.4 degrees Celsius in Sydney and 3.5 degrees in Warsaw. In this case, urn U2 will contain 45 green chips and 55 yellow chips. He/she will produce urn U2 behind the curtain by means of the actual temperatures in Sydney and Warsaw. Urn U2 will be visibly placed for all to see in the lab once it is produced. As we all cannot look into the urn, nobody in the lab except the randomly draw person knows the exact composition of urn U2. The randomly drawn person will also create urn U10 without any of us knowing its composition.

We will now explain how urn U10 will be produced. The randomly selected person will browse to the weather website WeatherBug on this laptop to check the current temperature in Los Angeles (USA), Mexico City (Mexico), Madrid (Spain), St Petersburg (Russia), New York (USA), Cape Town (South Africa), Delhi (India), Buenos Aires (Argentina), Tokyo (Japan) and London (UK). This website updates the exact temperature on a 5-minute interval. Then he/she will have to make a print screen of the current temperatures in these ten cities and will have to save the information on the desktop. Based on the current temperatures in these ten cities Urn U10 will then be produced in the following manner. The temperatures in each city will be linked to a color in the sequence of Table C.5.

Table C.5: The link between the temperatures in cities and the ten colors.

Color	**City**	**Temperature (first number behind comma)**
Red	Los Angeles	?
Yellow	Mexico City	?
Grey	Madrid	?
Green	St. Petersburg	?
Blue	New York	?
Purple	Cape Town	?
Pink	Delphi	?
Orange	Buenos Aires	?
Light green	Tokyo	?
Black	London	?
Sum		Sum of all numbers above (0 through 9)

The randomly selected person will list the first number behind the digit of the temperature in these ten cities. Please see column 3 in Table C.6. For example: suppose that it is 24,5 degrees Celsius in Los Angeles. In this case, he /she enters a 5 (1st digit after comma of 24,5) in the second column in the row for Los Angeles. He/she will fill all ten numbers (based on the 1st digit after the comma of the temperature of these 10 cities) in an excel file on the laptop behind the curtain. Automatically the sum of all numbers that are listed behind each color (Column 3) will be calculated. Then for each individual color the ratio of its number to the sum of all numbers is calculated and rounded (see column 4 in Table C.6). This ratio number will determine the amount of chips each color gets represented in the 10-color urn U10. For the unlikely event that all randomly drawn numbers are 0 (effectively not a single color is drawn and the sum of all colors is 0), then please fill the urn with 10 chips of each color.

Table C.6: The empty table concerning the temperature of cities subjects need to fill in.

Color	**City**	**First number behind comma**	**Chips of this color in urn U**

Red	Los Angeles	5	5/sum*100=X, X chips
Yellow	Mexico City		
Grey	Madrid		
Green	St. Petersburg		
Blue	New York		
Purple	Cape Town		
Pink	Delphi		
Orange	Buenos Aires		
Light green	Tokyo		
Black	London		
Sum		Sum	100 chips

It is possible that only one color has a positive number, and all colors have a zero. In that case the urn only contains one color. It is also possible each color has the same positive number drawn. In that case, all colors are equally frequent. All other distributions in between these two extremes are also possible.

He/she will produce urn U10 behind the curtain by means of the ten temperatures (first digit behind the comma) he/she looked up on WeatherBug. Urn U10 will be visibly placed for all to see in the lab once it is produced. As we all cannot look into the urn, nobody in the lab except the randomly drawn person knows the exact composition of urn U10.

Now we call in the randomly selected person and instruct him/her to create urns U2 and U10 as described above. The instructions for the randomly selected subject can be seen as below:

> *In a moment you may browse to the weather website WeatherBug on this laptop to check the current temperature in Sydney (Australia) and Warsaw (Poland). This website updates the exact temperature on a 5-minute interval. Then you will have to make a print screen of the current temperature and you will have to save the information on the desktop.*
>
> [The experimenter shows the laptop and how/where to save print screen.]
>
> *Based on the current temperatures in Sydney and Warsaw, Urn U2 will then be produced in the following manner. The number of GREEN chips in urn U2 will be equal to the digits after the decimal point in both cities. The number of YELLOW chips in urn U2 will be equal to 100 minus the number of green chips. For example: suppose that it is 24.4 degrees Celsius in Sydney and 3.5 degrees in Warsaw. In this case, urn U2 will contain 45 green chips and 55 yellow chips. Please go to the laptop and check the current temperature in Sydney and Warsaw and save the print screens.*
>
> [Participant walks to the laptop.]
>
> *Now please walk behind the curtain, create urn U2 accordingly and put the urn on the table here. You may now also create Urn U10. In a moment you will have to look up the temperature in Celsius in the 10 following cities: Los Angeles (USA), Mexico City (Mexico), Madrid (Spain), St Petersburg (Russia),*

New York (USA), Cape Town (South Africa), Delhi (India), Buenos Aires (Argentina), Tokyo (Japan) and London (UK). The temperatures in each city will be linked to a color in the sequence of Table C.5.

[The experimenter shows Table C.5].

Again, you can look up the temperature on the weather website WeatherBug on this laptop. Then you will have to make a print screen of the temperature in all 10 cities, and you will have to save the information.

[The experimenter shows the laptop and how/where to save print screen.]

Based on the current temperatures in the 10 cities Urn U10 will then be produced in the following manner. Behind the curtain you will find an empty table, similar like Table C.6.

[The experimenter shows Table C.6].

With your ten print screens of the actual temperature in the ten cities listed above, you will fill in Table C.6. We will explain to you how. First note for each temperature, the first number behind the digit (column 3 in Table C.6). For example: suppose that it is 24,5 degrees Celsius in Los Angeles. In this case, enter a 5 (1st digit after comma of 24,5) in the second column in the row for Los Angeles. Please fill the ten numbers (based on the 1st digit after the comma of the temperature of these 10 cities) in an excel file on the laptop behind the curtain. Automatically the sum of all numbers that are listed behind each color (Column 3) will be calculated. Then for each individual color the ratio of its number to the sum of all numbers is calculated and rounded (see column 4 in Table C.6). This ratio number will determine the amount of chips each color gets represented in the 10-color urn U10. For the unlikely event that all randomly drawn numbers are 0 (effectively not a single color is draw and the sum of all colors is 0), then please fill the urn with 10 chips of each color.

Now please walk behind the curtain, fill in the empty table by the temperatures on your ten print screens and create urn U10 accordingly. Please save the table with all the information on the desktop of the laptop so we can check the content of urn U10 after the experiment for anybody who wishes to see. Then put Urn U10 on the table here.

We will now pay you a fixed amount for your participation and you may leave the room now. To keep your payment private, we give it to you in an envelope. Please sign this receipt after you have looked into the envelope and checked its content. Your earnings will not depend in any way on the choices yet to be made in this experiment. Thank you for your cooperation.

[Participant leaves the laboratory.]

D. Instructions for the whole part of the experiment

Welcome to this experiment. In this experiment, you will make several decisions. You can earn money depending on the decisions that you will make. For this reason, it is very important that you read these instructions carefully. Additionally, to your earnings, you will ALWAYS receive € 4 for your participation in this experiment. You will be paid in cash at the end of the experiment. This payment will be done in private, and thus no other participant will learn how much you earned.

Please note that you are not allowed to communicate with other participants in this experiment. Also please turn off your cell phone to avoid any distractions and remain seated and quiet during the course of the experiment. If at any moment in time you have a question, please raise your hand and an experimenter will come to you.

This experiment consists of four independent tasks and a questionnaire at the final end. At the beginning of each new task, you will receive instructions. At the final end of this experiment, the computer will randomly select one choice from one of the four tasks. This selected choice will be played out for real in order to determine your earnings. Thus, you should take all tasks seriously as any of the four tasks can determine your payoff at the end.

The first three tasks in this experiment involve lotteries with urns filled with 100 chips of different colors. One urn is filled with 100 chips and is composed in any combination of 2 colors: green and yellow (called U2) and another urn has also 100 chips but can be composed in any combination of up to 10 colors: red, yellow, grey, green, blue, purple, pink, orange, light green and black chips (called U10). Thus the urn can either contain only one color or two colors, three, four, etc. or all ten colors with any possible number of chips per color. We will produce both these urns as follows.

Production of the urns

[Insert specific production treatment here]

These two urns will be used in the following three tasks. U2 will be used in the first task and U10 in task 2 and 3.

Let us now carefully explain the first task of this experiment to you.

TASK 1

In this task you will make several decisions between two different urns each filled with 100 chips. Let us first inform you about these urns.

Urns

In this task there are two urns, named ‘urn U2’ and ‘urn K2’. Urn U2 and urn K2 are each filled with 100 chips. Each chip is either green or yellow.

- Urn K2 has a fixed composition of green and yellow chips which will be described to you below.
- Urn U2 was produced at the beginning of this experiment and has an unknown composition of green and yellow chips.

Your decisions

Part 1

In part 1 of this task you have to chose between a draw from urn U2, which we produced at the beginning of the experiment, and urn K2. Remember, that both urns have 100 chips that can either have a green or yellow color. In urn U2 you do not know how many chips are of the one or the other color. In part 1 of this task urn K2 has exactly 50 green and 50 yellow chips. See the screen shot below for an illustration of this task. Remember that you have selected a color right at the start of the experiment. In the screenshot we assume, but only for illustration purposes, that you have selected the color green at the beginning of the experiment. In part 1 of this task you simply have to choose from which of the two urns you would like to draw a chip (without looking): from urn U2 (Option A) or from urn K2 (Option B).

If part 1 of this task is selected at the end of the experiment to determine your payoff, you can draw a chip from the urn you have chosen (without looking). If the drawn chip has the color you selected at the beginning of the experiment, you will win €15. If the drawn chip has the other color, you win nothing (€0).

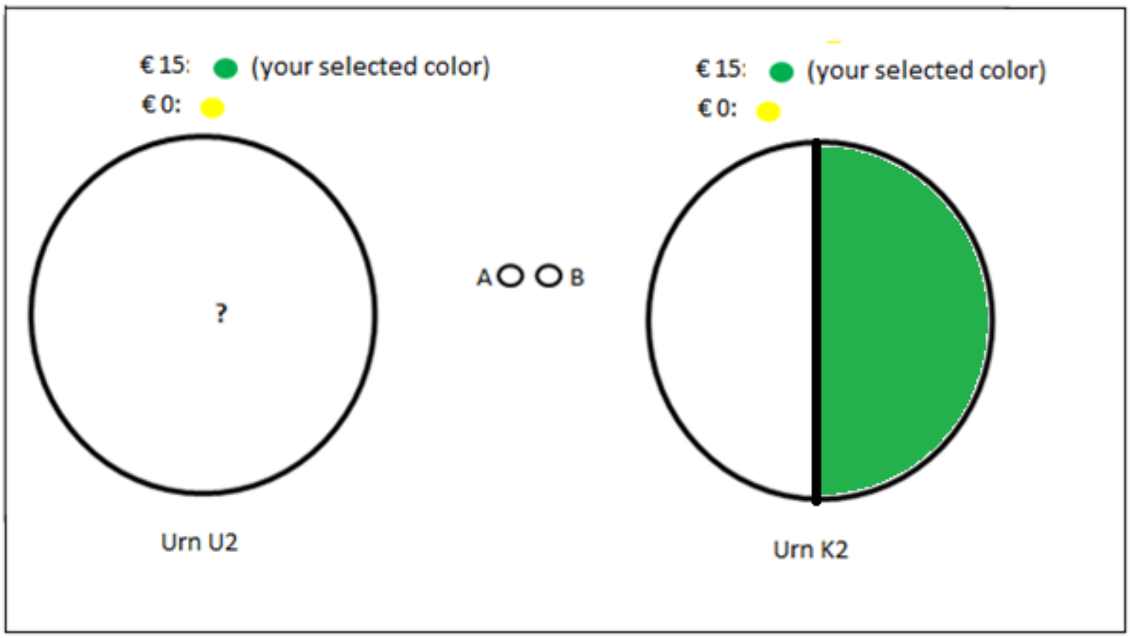
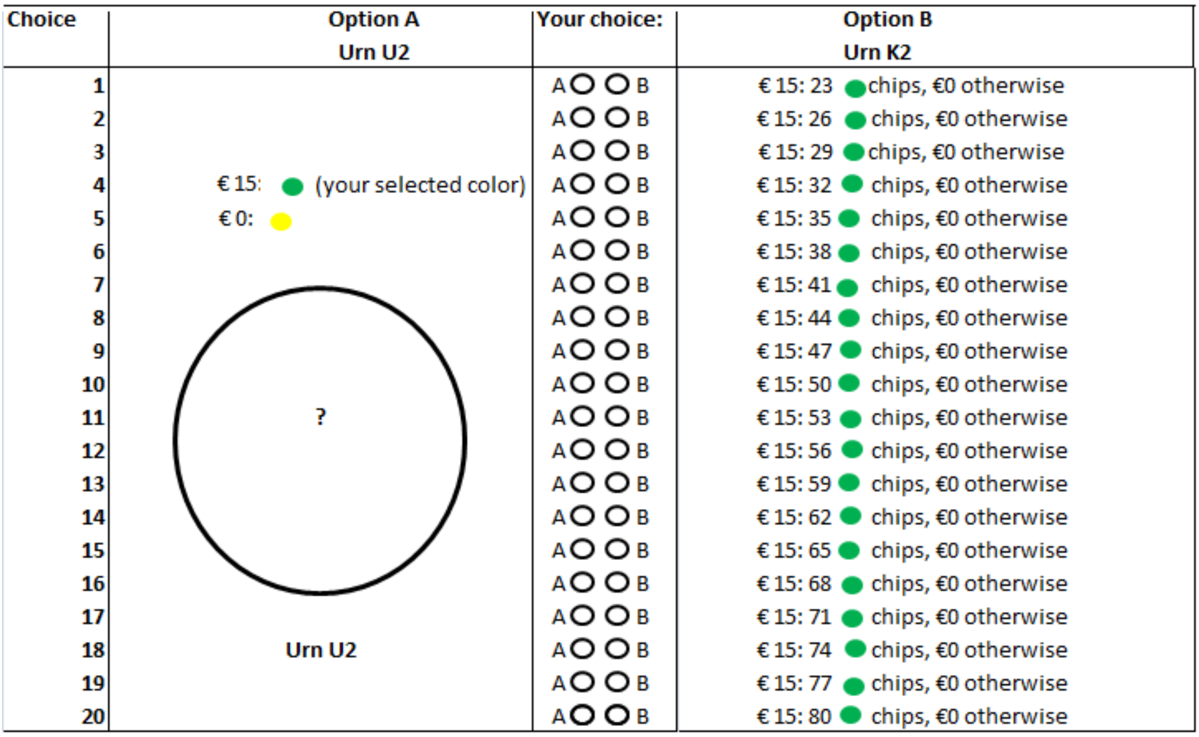


Figure D.1: *Choice screen Part 1 (with* ***green simply as illustration****)*

Part 2

After the choice in part 1, you will make several choices in part 2 of this task where you will again decide if you wish to draw a chip from Urn U2 or Urn K2. We again assume here for illustration purposes that you had selected green at the beginning of the experiment. Please see Fig. 2 for a screenshot of the choice screen on which you may indicate your choices.

As you can see in Fig 2 you will have to make 20 choices. These are all displayed on one screen. In every choice you will have to decide between Urn U2 and Urn K2. Urn U2 is the urn produced at the beginning of the experiment. Just as a reminder, Urn U2 has 100 chips in an unknown composition of green and yellow marbles. Urn K2 also has 100 chips, but in a composition you will know. For every choice you will be informed how many of the 100 chips in urn K2 have the color you selected at the beginning of the experiment (in the screen shot below it is green). The remaining marbles are then yellow.



Choice	Option A Urn U2	Your choice:	Option B Urn K2
1		A O O B	€ 15: 23 chips, €0 otherwise
2		A O O B	€ 15: 26 chips, €0 otherwise
3		A O O B	€ 15: 29 chips, €0 otherwise
4	€ 15: (your selected color)	A O O B	€ 15: 32 chips, €0 otherwise
5	€ 0:	A O O B	€ 15: 35 chips, €0 otherwise
6		A O O B	€ 15: 38 chips, €0 otherwise
7		A O O B	€ 15: 41 chips, €0 otherwise
8		A O O B	€ 15: 44 chips, €0 otherwise
9		A O O B	€ 15: 47 chips, €0 otherwise
10		A O O B	€ 15: 50 chips, €0 otherwise
11	?	A O O B	€ 15: 53 chips, €0 otherwise
12		A O O B	€ 15: 56 chips, €0 otherwise
13		A O O B	€ 15: 59 chips, €0 otherwise
14		A O O B	€ 15: 62 chips, €0 otherwise
15		A O O B	€ 15: 65 chips, €0 otherwise
16		A O O B	€ 15: 68 chips, €0 otherwise
17		A O O B	€ 15: 71 chips, €0 otherwise
18	Urn U2	A O O B	€ 15: 74 chips, €0 otherwise
19		A O O B	€ 15: 77 chips, €0 otherwise
20		A O O B	€ 15: 80 chips, €0 otherwise

Figure D.2: ***Choice screen Part 2 (with green simply as illustration)***

Let us describe choice number 6, see line 6 in Fig. 2, as an example. Let us first look at the left hand side (Option A): Option A is always Urn U2. Your selected color (in the example it is green) will be visually displayed behind the winning amount of €15. The other color, yellow, is visually displayed behind the amount of €0. Now let's look at the right hand side (Option B): Option B for choice (row) number 6 is Urn K2 and it states that 38 chips out of the total amount of 100 chips are of your selected color (in the example it is green). The remaining chips, 62, are thus yellow.

If part 2 of task 1 is randomly chosen at the end of the experiment as the one that determines your payoff, your payment will be determined as follows. The computer will randomly select with equal chances one of the 20 choices. If the computer, for instance, selects choice (row) number 6 from this task to be played for real in order to determine your earnings at the end of this experiment, we will let you draw a chip from the urn that you indicated to prefer in that row:

- If you have chosen option A, you may draw one chip from urn U2. Remember this is the urn produced at the beginning of the experiment. If the color you draw corresponds to your selected color, you win €15. If you draw the other color, you win nothing.
- If you have chosen option B, we will create a see-through urn with as many chips in your selected color as indicated in that row. For example, in row 6 (choice 6) we would put 38 chips of your selected color (green) into the urn and 62 chips of the other color. You may then draw one chip from this urn without looking. If you draw a chip corresponding to your selected color, you win €15, and nothing if you draw a chip in the other color.

In this part 2 of task 1 you will have to make 20 decisions like the one described above. Each time you will be asked to indicate your preference for drawing a chip from urn U2 (option A) or urn K2 (option B).

Quiz

To make sure that everything is clear to you, you may answers the questions below. These answers are **not** related at all to the earnings you can win in this experiment. If you have completed all questions you can raise your hand and an experimenter will come to check your answers. If anything is unclear, you may also raise your hand.

Please take your time to fill in the questions. You may start making decisions in Task 1 once all participants are ready.

Please indicate whether the statements below are true or false:

1. I will be informed about the exact content of urn K2 throughout task 1

   True / False
2. In Part 2, Urn K2 is always composed of 50 green and 50 yellow chips

   True / False
3. I have selected a color at the start of the experiment

   True / False
4. What is the minimum amount of colors in urn U2?

   Minimum ____ different colors
5. How many chips do both urns contain?

   ___ balls
6. What is the probability that you will draw a chip in your selected color if urn K2 has a composition as shown in choice number 7 in Fig 2?

   ____% chance of winning
7. Do you know the probability that you will draw a chip in your selected color from urn U2?

   Yes / No
8. The content of urn U2 changes between the decisions I need to make

   True / False

TASK 2

In this task you will again make several decisions between two different urns each filled with 100 chips. Let us first inform you about the urns in task 2.

Urns

In this task there are two urns, named 'urn K10' and 'urn U10'. Urn K10 and urn U10 are each filled with 100 chips. There are 10 possible colors: black, green, grey, red, light green, blue, orange, purple, pink and yellow chips.

- Urn K10 has a fixed composition of 10 colors which will be described to you below.
- Urn U10 is the urn that was produced at the beginning of the experiment and it has an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips.

Your decisions

Part 1

In part 1 of this task you have to choose between a draw from urn U10, which we produced at the beginning of the experiment, and urn K10. Remember, that both urns have 100 chips that can either have a red, yellow, grey, green, blue, purple, pink, orange, light green or black color. In urn U10 you do not know how many chips are of each of the ten possible colors. In part 1 of this task urn K10 has exactly 10 red, 10 yellow, 10 grey, 10 green, 10 blue, 10 purple, 10 pink, 10 orange, 10 light green and 10 black chips, so 10 chips of each color. In the following we again assume, but only for illustration purposes, that you have selected the color green at the beginning of the experiment. In part 1 of this task you simply have to choose once from which of the two urns you would like to draw a chip: from urn U10 (Option A) or from urn K10 (Option B).

If part 1 of this task is selected at the end of the experiment to determine your payoff, you can draw a chip (without looking) from the urn you have chosen. If the drawn chip has the color you selected at the beginning of the experiment, you will win €15. If the drawn chip has the other color, you win nothing (€0).

Part 2

After your decision in part 1, you will make several choices in part 2 of this task where you will again decide if you wish to draw a chip from Urn U10 or Urn K10. We again assume here for illustration purposes that you had selected green at the beginning of the experiment. You will have to make 20 choices which are all displayed on one screen. In every choice you will have to decide between Option A: Urn U10 and Option B: Urn K10. Urn U10 is the urn produced at the beginning of the experiment. Just as a reminder, Urn U10 has 100 chips in an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green or black chips. Urn K10 also has 100 chips, but in a composition you will know. For every choice you will be informed how many of the 100 chips in urn K10 have the color you selected at the beginning of the experiment. The remaining marbles are then a combination of the remaining 9 colors.

If part 2 of task 2 is randomly chosen at the end of the experiment as the one that determines your payoff, your payment will be determined as follows. The computer will randomly select with equal chances one of the 20 choices. If the computer, for instance, selects the following choice (row) to be played for real in order to determine your earnings; a choice between Option A (urn U10) and Option B (urn K10) which gives you information that 15 chips in Urn K10 are of your selected color. We will let you draw a chip from the urn that you indicated to prefer in that row:

- If you have chosen option A, you may draw one chip from urn U10. Remember this is the urn produced at the beginning of the experiment. If the color you draw corresponds to your selected color, you win €15. If you draw the other color, you win nothing.
- If you have chosen option B, we will create a see-through urn with as many chips in your selected color as indicated in that row. In this example, we would put 15 chips of your selected color (green) into the urn and 85 chips of the other nine colors. You may then draw one chip from this urn without looking. If you draw a chip corresponding to your selected color, you win €15, and nothing if you draw a chip in the other color.

In this part 2 of task 2 you will have to make 20 decisions like the one described above. Each time you will be asked to indicate your preference for drawing a chip from urn U10 (option A) or urn K10 (option B).

Quiz

To make sure that everything is clear for you, you may answers the questions below. If you have completed all questions you can raise your hand and an experimenter will come to check your answers. If anything is unclear, you may also raise your hand.

Please take your time to fill in the questions. We will continue with Task 2 once all participants are ready.

Please indicate whether the statements below are true or false:

1. The content of <u>Urn K10</u> changes throughout part 2 of this task
   True / False
2. In part 1 of this task, <u>Urn K10</u> is composed of 50 green and 50 yellow chips
   True / False
3. Is green the selected color for all participants
   True / False
4. Is <u>urn U10</u> composed of all 10 colors
   True / False
5. What is the probability that you will draw a chip in your selected color from urn K10 in Part 1?
   ____% chance of winning
6. How many balls do both urns contain?
   Both urns contain ___ balls
7. What is the probability that you will draw a chip in your selected color if <u>urn K10 has a composition of 30 marbles in your selected color</u>?
   ____% chance of winning
8. Do you know the probability that you will draw a chip in your selected color from <u>urn U10</u>?
   Yes / No

TASK 3

In this task you will make again several decisions between two different urns each filled with 100 chips. Let us first inform you about the urns in task 3.

Urns

In this task there are two urns, named 'urn K10' and 'urn U10'. These urns are the exact same urns from the previous task! As a reminder, urn K10 and urn U10 are each filled with 100 chips. There are 10 possible colors: black, green, grey, red, light green, blue, orange, purple, pink and yellow.

- Urn K has a fixed composition of 10 colors which will be described to you below.
  - Urn U has an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green and black chips. It is the exact same urn from the last task! It was produced at the beginning of the experiment.

Selected colors

In the beginning of the experiment you selected one color; either green or yellow. Let us assume, only for illustration purposes, that you chose green. The other nine colors are then: black, grey, red, light green, blue, orange, purple, pink and yellow. In this task these are then your **nine selected colors.**

Part 1

In part 1 of this task you have to choose between a draw from urn U10, which we produced at the beginning of the experiment, and urn K10. Remember, that both urns have 100 chips that can either have red, yellow, grey, green, blue, purple, pink, orange, light green or black chips. In urn U10 you do not know how many chips are of each of the ten possible colors. In part 1 of this task urn K10 has exactly 10 red, 10 yellow, 10 grey, 10 green, 10 blue, 10 purple, 10 pink, 10 orange, 10 light green and 10 black chips, so 10 chips of each color. In the following we again assume, but only for illustration purposes, that you have selected the color green at the beginning of the experiment and thus that black, grey, red, light green, blue, orange, purple, pink and yellow are your nine selected chips. In part 1 of this task you simply have to choose from which urn you would like to draw a chip: from urn U10 (Option A) or from urn K10 (Option B).

If part 1 of this task is selected at the end of the experiment to determine your payoff, you can draw a chip (without looking) from the urn you have chosen. If the drawn chip has any of your **nine selected colors**, you will win €15. If the drawn chip has the other color, you win nothing (€0).

Part 2

After your decision in part 1, you will make several choices in part 2 of this task where you will again decide if you wish to draw a chip from Urn U10 or Urn K10. We again assume here for illustration purposes that you had selected green at the beginning of the experiment. **Also, for this part it means that the other nine colors are your selected colors for task 3, part 2: black, grey, red, light green, blue, orange, purple, pink and yellow.** You will have to make 20 choices which are all displayed on one screen. In every choice you will have to decide between Urn U10 and Urn K10. Urn U10 is the urn produced at the beginning of the experiment. Just as a reminder, Urn U10 has 100 chips in an unknown composition of red, yellow, grey, green, blue, purple, pink, orange, light green or black chips. Urn K10 also has 100 chips, but in a composition you will know. For every choice you will be informed how many of the 100 chips are of your nine selected colors. The remaining marbles are then green (or yellow depending on the color you selected at the beginning of the experiment).

If part 2 of task 2 is randomly chosen at the end of the experiment as the one that determines your payoff, your payment will be determined as follows. The computer will randomly select with equal chances one of the 20 choices. If the computer, for instance, selects the following choice (row) to be played for real in order to determine your earnings; a choice between Option A (urn U10) and Option B (urn K10) which gives you information that 75 chips in Urn K10 are of your nine selected colors. We will let you draw a chip from the urn that you indicated to prefer in that row:

- If you have chosen option A, you may draw one chip from urn U10. Remember this is the urn produced at the beginning of the experiment. If the color you draw corresponds to one of your nine selected colors, you win €15. If you draw the other color, you win nothing.
- If you have chosen option B, we will create a see-through urn with as many chips in your nine selected color as indicated in that row. In this example, we would put 75 chips of your nine selected color into the urn and 15 chips of the remaining color (in this example thus green). You may then draw one chip from this urn without looking. If you draw a chip corresponding to one of your nine selected colors, you win €15, and nothing if you draw a chip in the remaining color.

In this part 2 of task 3 you will have to make 20 decisions like the one described above. Each time you will be asked to indicate your preference for drawing a chip from urn U10 (option A) or urn K10 (option B).

Quiz

To make sure that everything is clear for you, you may answer the questions below. If you have completed all questions, you can raise your hand and an experimenter will come to check your answers. If anything is unclear, you may also raise your hand.
Please take your time to fill in the questions. We will continue with Task 3 once all participants are ready.

Please indicate whether the statements below are true or false:

1. The content of <u>Urn U10</u> is the same as from Task 2
True / False
2. In Task 3 there are nine selected colors
True / False
3. If <u>Urn K10</u> is composed as in part 1 of this task, I have 90% chance to draw a chip corresponding to one of my nine selected colors
True / False

4. I also have a 90% chance to draw a chip corresponding to one of my nine selected colors for <u>urn U10</u>

True / False

5. How many balls do both urns contain?

Both urns contain ___ balls

6. What is the probability that you will draw a chip in your selected color if <u>urn K10 has a composition of 70 marbles in your nine selected color</u>?

____% chance of winning

7. Do you know the probability that you will draw a chip in your selected color from <u>urn U10</u>?

Yes/No