

# Generating ambiguity with a virtual bingo blower\*

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We propose the Virtual Bingo Blower (VBB) as a way to create ambiguity in computerized experiments. The VBB mimics a physical bingo blower using a physics engine. The number of balls, their colour and their speed, among other things, can be easily modified. We use the VBB to measure ambiguity attitudes in an online experiment. We find that it elicits similar ambiguity preferences compared to natural events. Further, we find that the VBB can be used to manipulate the level of ambiguity.

**Keywords:** ambiguity, risk, bingo blower, online experiment

**JEL Codes:** C91, D81

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# 1 Introduction

In recent years, experimental research has significantly shifted towards online environments, facilitated by platforms such as Amazon Mechanical Turk and Prolific, alongside adaptable software like oTree and Qualtrics. This shift presents opportunities but also creates new challenges. One such challenge involves credibly generating, communicating, and representing risk and ambiguity to subjects. To address this issue, we have developed the Virtual Bingo Blower (VBB), a novel tool designed for online and computerized experiments. The VBB is inspired by Hey et al. (2010) who used a physical bingo blower containing colored balls to study ambiguity. The constant motion of the balls makes it difficult to assess the proportions of balls of different colors, thus introducing ambiguity in a controlled way. Leveraging a real-time physics engine, the VBB mimics the physical bingo blower, inducing a natural movement of balls. It can be used to represent ambiguity and risk, or to provide a credible and simple way to implement randomness. The VBB allows customization of ball quantities, color distribution, and movement dynamics. To validate the VBB, we use it to measure ambiguity attitudes and compare it to the natural-events method of Baillon et al. (2018) in a pre-registered online experiment.<sup>1</sup>

Ellsberg famously used urns with unknown or known mixtures of colored balls to induce and measure ambiguity attitudes (Ellsberg, 1961). Subsequently, this method has been extensively used and developed in the literature (Halevy, 2007), but as noted by Hey et al. (2010) the method has several downsides. Firstly, the participants are not fully informed about the procedures for establishing compositions in unknown urns. This may lead to speculations on the design and create distrust in experimenters that may be harmful to the design and purpose of the experiment. Partly to mitigate these issues, researchers have turned to second-order probability methods when determining compositions of urns (see for example Moore and Eckel, 2006 and Halevy, 2007). In those designs, the outcome of one lottery influences the probabilities of another lottery which, if subjects follow the reduction of compound lotteries axiom, essentially reduces the task to one involving risk as opposed to ambiguity. Indeed, both Halevy (2007) and Abdellaoui et al. (2011) find pronounced differences in attitudes to second-order probabilities

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<sup>1</sup><https://osf.io/dm3kq>

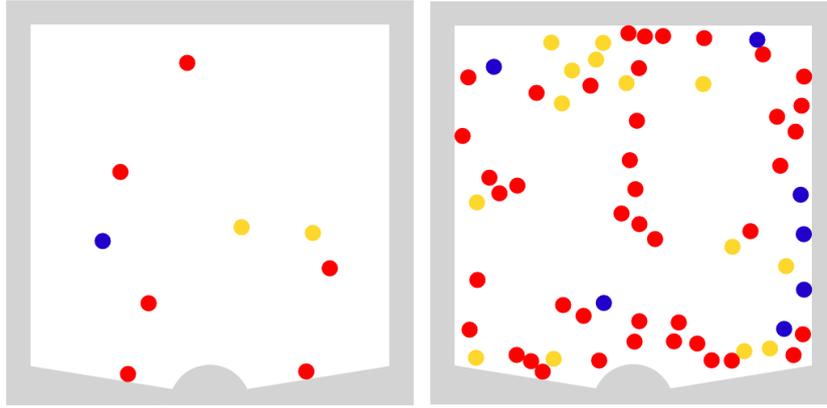
and ambiguity, suggesting that they measure different things.

To circumvent these issues Hey et al. (2010) used a physical bingo blower to generate ambiguity. In the bingo blower, balls are openly circulating so that probabilities exist but are simply unknown to subjects. This eliminates any suspicion regarding the experimenter’s intentions and potential rigging. Thus, the bingo blower effectively represents ambiguous situations while maintaining transparency and ensuring that probabilities exist but remain unknown to subjects. Our virtual version of the bingo blower shares these appealing features, and in addition to these upsides, it adds ease of online or computerized implementation.

Recently, Baillon et al. (2018) introduced a method to elicit ambiguity attitudes toward natural events, such as stock market outcomes. Using this method, they construct two indices that capture distinct aspects of ambiguity preferences: the traditional aversion to ambiguous events, and in addition, the extent to which a decision-maker discriminates between different likelihoods, i.e., measuring the intensity of ambiguity. A central feature is that these can be elicited without knowledge of beliefs about the likelihoods, typically required in e.g., Ellsberg-type elicitations. We apply this methodology, replacing the natural events with our VBB to create ambiguity and run two treatments using either 10 or 60 balls of three different colors to create two intensities of ambiguity. Indeed, increasing the number of balls arguably makes it harder to guess the actual distribution of colored balls, increasing the intensity of ambiguity. In contrast, the index measuring attitude towards ambiguity should arguably be invariant to such manipulations as both treatments represent ambiguous situations.

We elicit the two indices and see how these vary with the number of balls, and contrast the results to those under the natural event method of Baillon et al. (2018), which arguably entails the maximal intensity of ambiguity. In line with our preregistered hypotheses, we find that the average attitude towards ambiguity is invariant to our treatments. On average we find evidence for ambiguity neutrality, both with the VBB and with Natural events. The literature generally finds that artificial events generate ambiguity aversion while natural events generate ambiguity neutrality or even ambiguity seeking (Li et al., 2018). The fact that we obtain ambiguity neutrality with the VBB suggests that subjects perceived it as a natural source of ambiguity.

Further, we find that both the VBB treatments generates a significantly lower



**Figure 1:** VBB for low and high ambiguity.

intensity of ambiguity compared to the natural events treatment. Moreover, increasing the number of balls in the VBB significantly increases the intensity of ambiguity. The increase is, however, small. Previous research has also found that ambiguity intensity varies between different ambiguity sources, but that it is hard to manipulate the intensity within a given source (Garcia et al., 2020).

Finally, when exploring the data, we find that the dispersion of the two indices is statistically different across our VBB treatments, with less dispersion in the treatment with fewer balls. We also find that the two measures are largely unrelated and thus capture distinct features of ambiguity.

The paper is organized as follows: Section 2 describes the VBB in detail; Section 3 details the experiment conducted to validate the VBB; Section 4 discusses recruitment and other procedures in relation to the data collection; Section 5 presents experimental results and analysis; Section 6 concludes the paper.

## 2 The Virtual Bingo Blower

The VBB is built on JavaScript, one of the most popular programming languages and a cornerstone of the modern internet. Using JavaScript ensures that the VBB runs on all modern web browsers, *including on mobile*. As such, it can be used in any web-based experimental software, such as Qualtrics, oTree (Chen et al., 2016), or LIONESS (Giamattei et al., 2020).

In Figure 1 we show screenshots of the VBB, for a small and a large number

of balls. The VBB is better seen in action; see <https://geoffreycastillo.com/bingo-blower-js-demo> for a demo.

The movement of the balls in the VBB is not pre-recorded but follows a physics simulation (provided by `matter.js`). The simulation runs in real-time in the participant's browsers. Therefore, we have no way of predicting the ball drawn by the bingo blower. To convince participants, an option allows them to interact with the bingo blower, for example to move a ball with their mouse and see that the other balls react to their movements. We typically allow participants to do so in the instructions.

Researchers can easily customize several elements of the VBB. They can of course add different numbers of balls of different colours. They can also change the size of the bingo blower and its color. If needed, one can also adjust the parameters of the physics simulation, such as the air resistance or the bounciness of the balls.

Our VBB is open-source and available on GitHub at <https://github.com/geoffreycastillo/bingo-blower-js>. This ensures that anyone can use it and even create their own version—for example to maintain it in the years to come if we stop doing so.

### **3 Generating ambiguity with the VBB: An experiment**

The main aim of the experiment is to validate the VBB as a source of ambiguity. The experiment contains three treatments that are implemented in a between-subjects design. Two treatments use the VBB as the source of ambiguity, while the other uses natural events as the source of ambiguity. The natural events treatment follows Baillon et al. (2018) and is included as a benchmark of maximal ambiguity. In this section, we describe the experimental setup in detail, starting by describing the method we employ to elicit ambiguity attitudes.

#### **3.1 Ambiguity measures**

We follow Baillon et al. (2018) and measure ambiguity attitudes using matching probabilities. In that paper, the future daily percentage change in a stock market

index (the Amsterdam Exchange index) is used as a (Natural) source of ambiguity. A three-fold partition of the range between zero and one hundred percent is made to create events: elementary, composite and complementary. These events create a set of ambiguous options and let subjects choose between each ambiguous option, betting on an event happening or not, and a risky prospect with known probabilities. For each ambiguous option, the probabilities of the risky option are varied to find the matching probability that makes the decision maker indifferent between taking the ambiguous or risky bet. Matching probabilities capture ambiguity attitudes, free from any complications regarding risk attitudes and subjective probability judgments because those drop from the equations and thus do not need to be measured (Baillon et al., 2021). In the VBB treatments, we adhere to the same procedure. However, the ambiguous options are generated by using balls of three different colors to represent corresponding events. Subjects are then asked to place bets on the color of the ball drawn from the VBB, rather than the daily fluctuations of the stock market.

Using matching probabilities, Baillon et al. (2018) define two indexes to capture two orthogonal aspects of ambiguity attitudes. The first measure, the  $b$ -index, captures aversion to ambiguity, whereas the second measure, the  $a$ -index, captures the intensity of ambiguity.<sup>2</sup> The first measure is well established. Under neutrality toward ambiguity, the sum of the matching probabilities towards an event  $m_1$ , and its complement  $m_{23}$  should add up to one, whereas under aversion to ambiguity, it falls below. In particular, let  $\bar{m}_s = \frac{m_1+m_2+m_3}{3}$  denote the average matching probability for the three single events and  $\bar{m}_c = \frac{m_{12}+m_{13}+m_{23}}{3}$  denote the average composite-event matching probability. The ambiguity aversion index is then defined as

$$b = 1 - \bar{m}_c - \bar{m}_s.$$

It is normalized so that ambiguity neutrality is  $b = 0$ , maximal ambiguity aversion  $b = 1$ , and minimal ambiguity aversion  $b = -1$ . In essence, if  $b = 0$ , then the decision maker's likelihood judgments fulfill the assumptions of a probability measure.

The second measure, the  $a$ -index, describes the decision maker's discrimination between the likelihoods of different events. An increase in the tendency not to

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<sup>2</sup>See Baillon et al. (2021) for a theoretical motivation.

**Table 1:** Example Choice task (VBB)

Option 1		Option 2	
Blue ball is drawn	Other ball is drawn	X%	(1-X)%
Win £5	Win £0	Win £5	Win £0

discriminate between the likelihood of different events leads to an increase in this measure. Maximal insensitivity occurs when the subjective likelihoods are equal. The ambiguity insensitivity index is defined as

$$a = 3 \times \left( \frac{1}{3} - (\bar{m}_c - \bar{m}_s) \right)$$

Insensitivity is here captured at  $a > 0$ , and ambiguity neutrality at  $a = 0$ .  $a < 0$  implies attaching, on average, higher likelihoods to elementary events than to composite ones. For all purposes, this is irrational but could behaviorally arise.

## 3.2 Treatments

The treatments use the matching probability procedures of Baillon et al. (2018), with the source of ambiguity varying across treatments. The VBB treatment uses our bingo blower, whereas the natural events treatment follows Baillon et al. (2018) and uses changes in the stock market as the source ambiguity.

### 3.2.1 The VBB treatments

In the VBB treatments, each subject faces a set of decision tasks in which they are asked to choose between two options, one involving risk and one involving ambiguity. See Table 1 for an example question. Here, the ambiguous Option 1 is implemented using the VBB, whereas Option 2 is a risky option.

The VBB contains balls of three different colors (red, blue, and yellow), whose proportions are not revealed to the subjects (ambiguity). The relevant events for this study are the three basic events and the three composite events (excluding the entire partition). Hence the six relevant events are:

$$\left\{ \begin{array}{l} Red, Blue, Yellow, Red \cup Blue, \\ Red \cup Yellow, Blue \cup Yellow \end{array} \right\}.$$

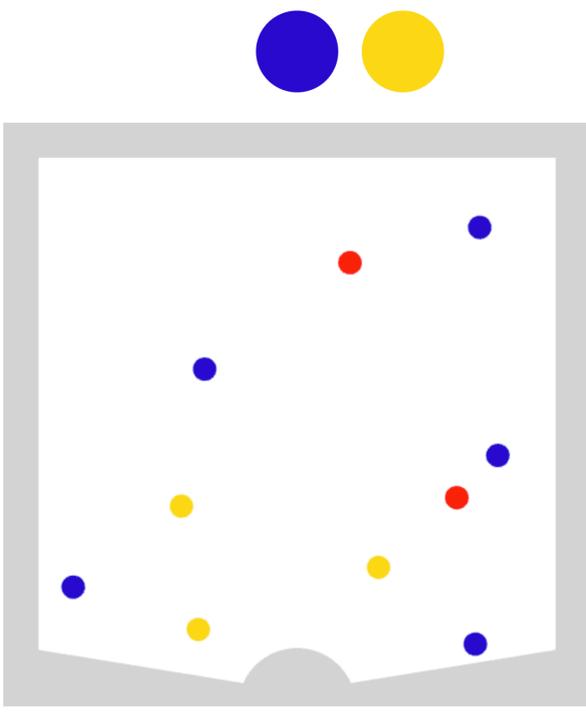
Option A You win £3 if one of the following balls is drawn:	Your choice	Option B You win £3 with the following chance:
	A B	0 %
	A B	20 %
	A B	35 %
	A B	40 %
	A B	45 %
	A B	50 %
	A B	55 %
	A B	60 %
	A B	65 %
	A B	70 %
	A B	75 %
	A B	80 %
	A B	85 %
	A B	90 %
	A B	93 %
	A B	95 %
	A B	97 %
	A B	98 %
	A B	99 %
	A B	100 %

Figure 2: Example of a task (A10 treatment).

**Table 2:** Example Choice task (natural events)

Option 1		Option 2	
DOW > 0.11%	DOW < 0.11%	X%	(1-X)%
Win £5	Win £0	Win £5	Win £0

For each event we generate 10 choice tasks as in Table 1, letting  $X$  vary between 0 and 100. In total, this produces 60 questions organized in 6 tables.

Across the two VBB treatments the proportions of balls are as follows: 20 percent Red, 50 percent Blue, 30 percent Yellow. In treatment A10, there are 10 balls in total and in treatment A60 there are 60 balls in total.

### 3.2.2 The natural events treatment

In this treatment, natural events are used to implement ambiguity. The event is the daily percentage change in the Dow Jones Industrial Average Index (DOW) for a specific day in the future after the experiment. In Table 2 we give an example choice task for the natural events treatment.

We use historical data on daily movements of the DOW index to calibrate the basic natural events to be approximately equal in terms of probability to the basic VBB events. The basic natural events that result from this calibration are DOW percentage changes in the intervals  $(-100, -0.51]$ ,  $(-0.51, 0.11]$  and  $(0.11, \infty)$ . The relevant events for this study are these three basic events and the three composite events (excluding the entire partition). The six relevant events are thus:

$$\left\{ \begin{array}{l} (-100, -0.51], (-0.51, 0.11], (0.11, \infty) \\ (-100, -0.51] \cup (-0.51, 0.11], (-100, -0.51] \cup (0.11, \infty) \\ (-0.51, 0.11] \cup (0.11, \infty) \end{array} \right\}.$$

For each event we generate 10 choice tasks as in Table 2, letting  $X$  vary between 0 and 100. In total, this produces 60 questions organized in 6 tables. As in Baillon et al. (2018) we keep the lists in all treatments centered on 1/3 and 2/3 for simple and composite events respectively.

**Table 3:** Treatments

Treatment	Source	Events
Natural	DOW	% change $\in \{(-100, -51), (-51, 0.11), (0.11, \infty)\}$
A10	VBB 10 balls	Ball drawn $\in \{\text{Blue, Red, Yellow}\}$
A60	VBB 60 balls	Ball drawn $\in \{\text{Blue, Red, Yellow}\}$

### 3.3 Hypotheses

Before stating our hypotheses we summarize the treatments in Table 3.

Let  $a(i)$  and  $b(i)$  denote the  $a$ - and  $b$ -index for treatment  $i$ . We test the following two preregistered hypotheses:

**Hypothesis 1** ( $b$ -index).  $b(\text{A10}) = b(\text{A60}) = b(\text{Natural})$ .

The first hypothesis is based on the idea that the general degree of ambiguity aversion should remain consistent across different sources of ambiguity. As such, the  $b$ -index should not be significantly impacted by the type or source of ambiguity in our treatments.

**Hypothesis 2** ( $a$ -index).  $a(\text{A10}) < a(\text{A60}) < a(\text{Natural})$ .

The rationale for the second hypothesis is that as the number of balls increases from A10 to A60, it will become more challenging for subjects to discern the colors, resulting in a higher level of perceived ambiguity. We anticipate that the natural events treatment will introduce even greater ambiguity, as the source of uncertainty is less tangible compared to the VBB treatments.

We estimated that we need about 150 subjects per treatment to be able to detect an effect of equivalent size as in Baillon et al. (2018), using significance level  $\alpha = 0.05$  and power  $1 - \beta = 0.8$ . Therefore, in total, we aimed to recruit 450 subjects.

### 3.4 Recruitment and experimental procedures

We recruited participants on the online labor market Prolific. Participants were paid a fixed fee of £1 for participating in the experiment. In addition, participants were able to earn a bonus of £0 to £3 depending on the decisions they made during

the experiment. Participants were restricted to living in the UK, speak English fluently and have a Prolific approval rating of at least 95 percent. Recruitment was ongoing until we had reached the number of desired participants. The experiment was programmed using oTree.<sup>3</sup>

481 subjects finished the experiment. We excluded one subject that did not do the experiment on a laptop or desktop as instructed, as well as 14 subjects whose screen had a refresh rate lower than 50 FPS—both exclusion criteria were pre-registered. That leaves us with 466 remaining subjects, whereof 166, 155 and 149 participated in A10, A60 and Natural, respectively.

## 4 Results

Figure 3 provides an overview of the data, displaying histograms and box plots for the  $a$ - and  $b$ -indices. Consistent with our first hypothesis, there are no visually discernible differences in the location of the distribution of the  $b$ -index values across treatments. On the contrary, the  $a$ -index seems to be affected by our treatment conditions. More precisely, in line with our second hypothesis, increasing the number of balls in the VBB or using the Natural condition seems to generate higher values of the  $a$ -index, indicating a higher degree of insensitivity.

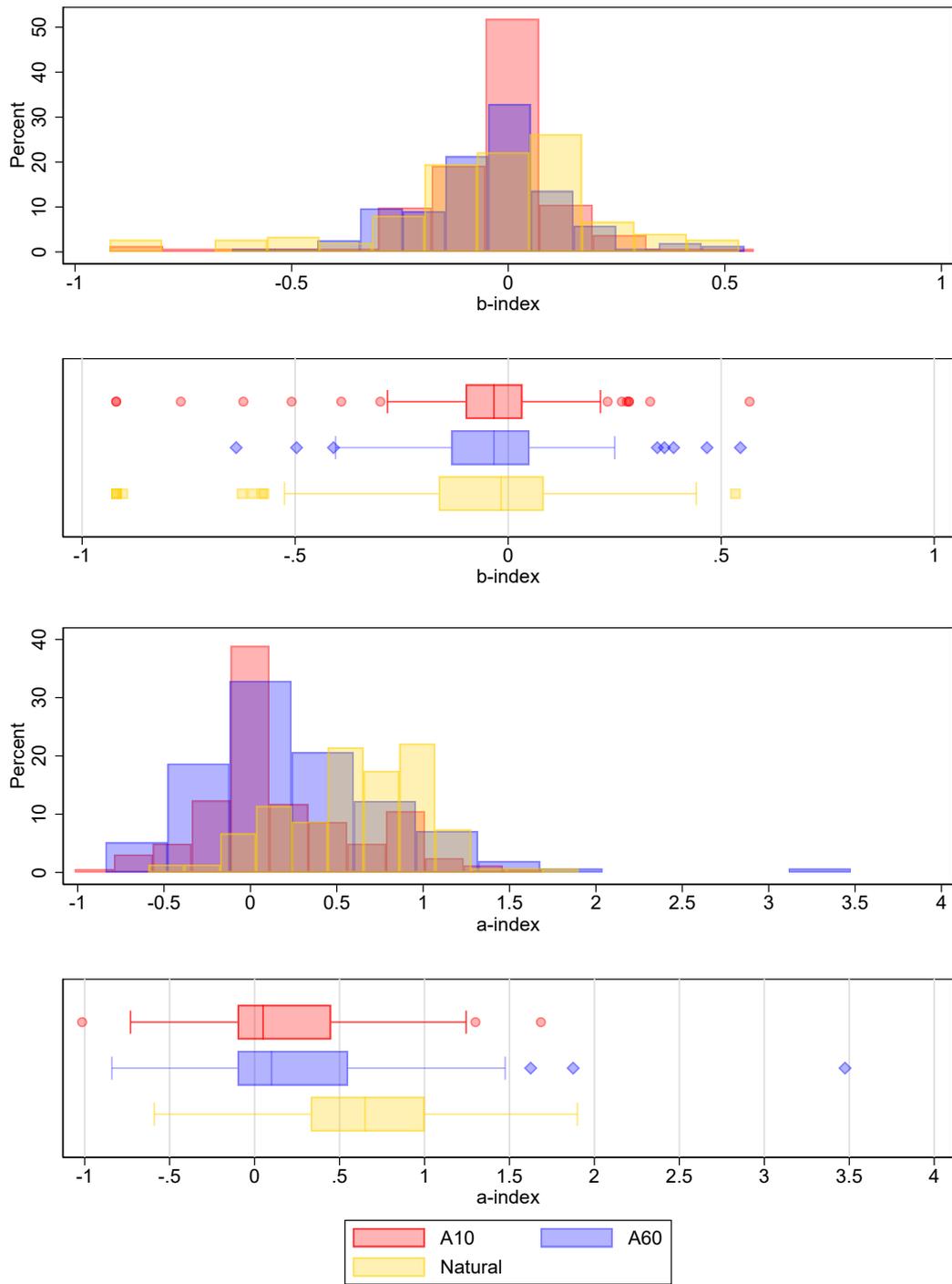
We follow Baillon et al. (2018) and start the analysis with seemingly unrelated regressions (SUR).<sup>4</sup> We report the full regression table, with and without controls, in Appendix B. In Figure 4 we show the  $a$ - and  $b$ -indices estimated from the SUR with controls. As we can see in the Figure, the  $b$ -index is slightly negative in all treatments so we consistently estimate that subjects are slightly ambiguity-seeking in our experiment. There are no significant differences across treatments, in line with our first hypothesis.

For the  $a$ -index, we find it to be positive in all treatments, indicating ambiguity

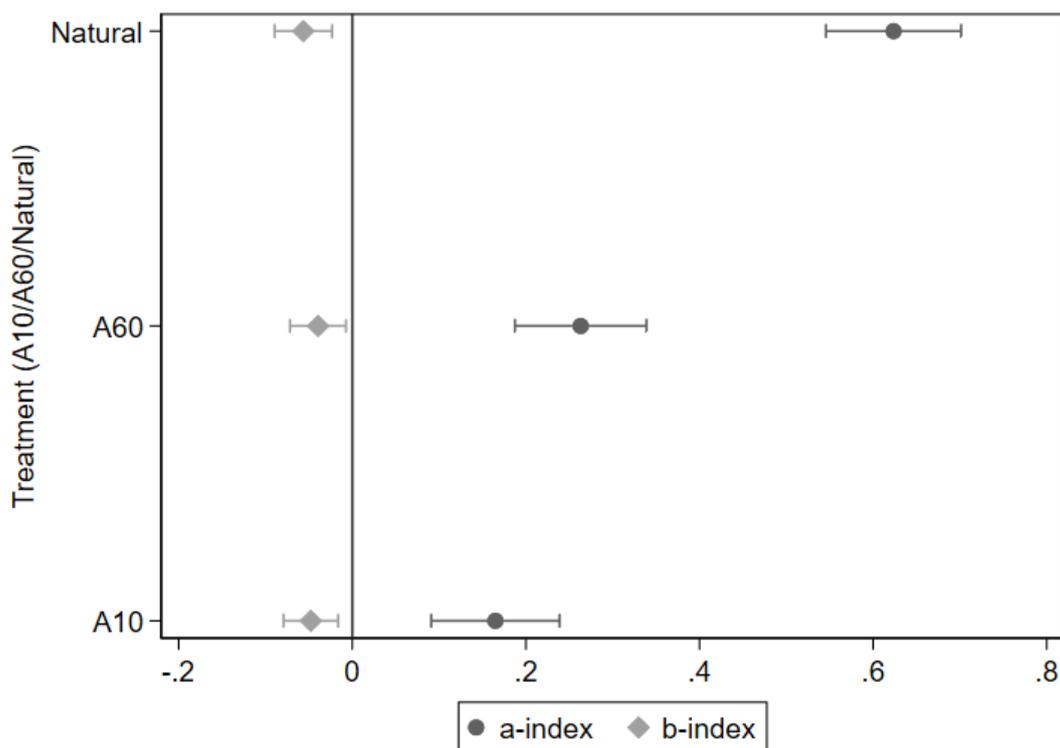
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<sup>3</sup>Our code is available at <https://github.com/geoffreycastillo/otree-virtual-bingo-blower>.

<sup>4</sup>We pre-registered separate OLS regressions for each index. However, the Breuch-Pagan test (also reported at the bottom of Table B1) shows that the residuals from these OLS regressions are correlated, in which case the separate OLS regressions are invalidated and the SUR is preferred. Baillon et al. (2018) made the same observation, which also led them to use SUR. We report the results of the separate OLS regressions in Appendix B. Compared to the SUR in Table B1, with the OLS we find a one-sided treatment effect of A60 on the  $a$ -index only when controls are included.



**Figure 3:** Histograms and box plots for the *b*- and *a*-index.



**Figure 4:**  $a$ -index and  $b$ -index estimates across treatments based on the most general SUR estimation in Table B1.

insensitivity. In line with the pre-registered Hypothesis 2 we use one-sided tests. Here, we find a significant effect at the 10% level without controls, and at the 5% level with controls. Consequently, we also confirm our pre-registered second hypothesis: both the Natural treatment and the A60 treatment display higher  $a$ -index values compared to the A10 treatment.

Comparing our results to Baillon et al. (2018), for the  $b$ -index they also found slight ambiguity seeking in their experiment. For the  $a$ -index, our Natural treatment generates a somewhat higher mean  $a$ -index, indicating higher insensitivity.

We also preregistered testing for treatment differences using Mann-Whitney  $U$  (MWU) tests (see Appendix C for the full details). The test results for the  $b$ -index fully corroborate our regression results, showing no difference between treatments. The MWU-test results of the  $a$ -index show that the distribution, in both the A10 treatment (p-value < 0.000) and the A60 treatment (p-value < 0.000), significantly

differs from that of the Natural treatment, but not from each other. One reason for the difference in significance between the SUR and MWU test may be that the latter is ordinal and thus less sensitive to the dispersion of the index values. As noted earlier in Figure 3, the A60 treatment clearly displays a higher degree of dispersion compared to A10.<sup>5</sup>

It is also interesting to note that the indices appear to capture distinct facets of ambiguity preferences as postulated in Baillon et al. (2018). Figure 5 presents the estimates for the  $a$ -index and  $b$ -index for each participant. We find no discernible correlation between individual  $a$ - and  $b$ -indices. If anything there is a tendency for a weakly negative correlation, which is borderline significant using Pearson’s correlation test ( $\rho = 0.090$ ,  $p$ -value = 0.051). Regarding differences across treatments, Figure 5 again illustrates that the index values for the A10 treatment show greater centralization compared to the A60 treatment and in particular compared to the Natural treatment.

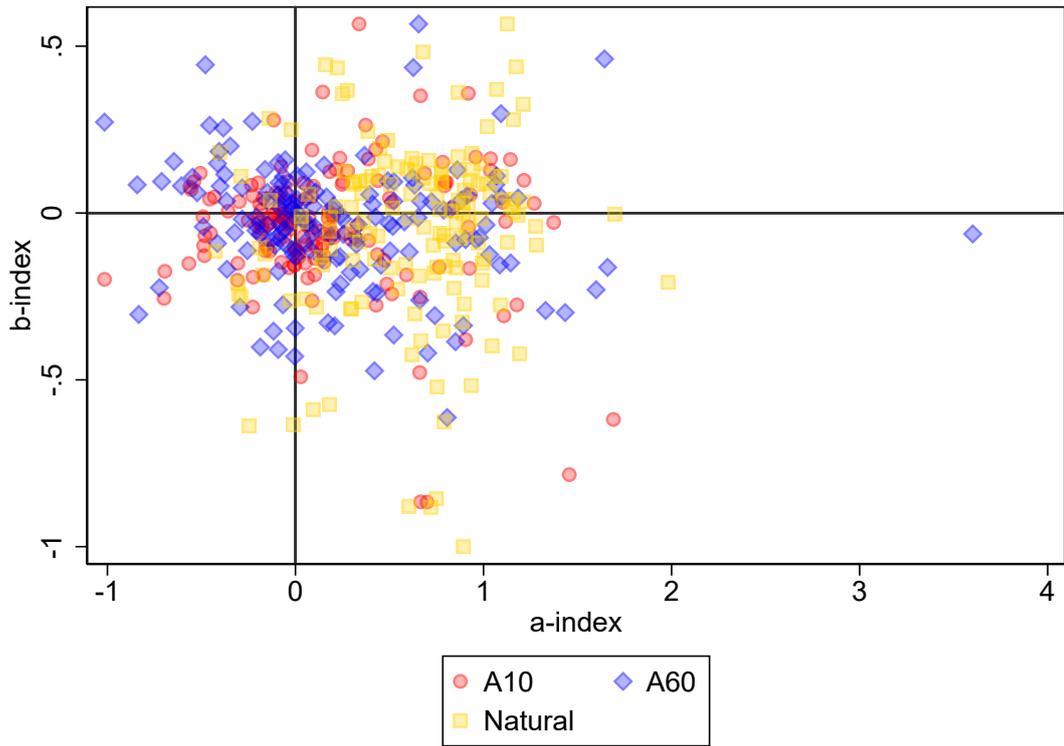
Finally, to investigate the perception of the VBB and the natural events, in Appendix D we classify the comments written by subjects at the end of the experiment. Most of the comments are classified as engagement, understanding, or technical issues, and we do not observe a difference between the treatments.

## 5 Conclusion

In this paper, we introduce and test the VBB, designed to address the challenges of credibly inducing varying levels of ambiguity and conducting random draws in computerized and online experiments. Despite its digital nature, the VBB preserves a crucial element of tangibility, thereby retaining the intuitive nature associated with physical lottery devices. Its flexibility is a key feature, allowing researchers to vary the degree of ambiguity effectively and simulate different situations of uncertainty.

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<sup>5</sup>We further study the dispersion of the indices by, following the procedure in Baillon et al. (2018), taking the absolute value of each index normalized around its treatment mean, and running a regression to see how the dispersion around the mean varies across treatments. To make it consistent with the previous regression analysis we apply the same specifications. In Table B3 in the Appendix we see a significant difference in dispersion between the two VBB treatments for the  $a$ - but not  $b$ -index. Clearly, the A10 treatment causes less dispersion than the A60 treatment.



**Figure 5:** *a*-index and *b*-index estimates by treatment.

In our experiment, we used the VBB tool to induce varying degrees of ambiguity by changing the number of balls. We also compared the ambiguity induced by the VBB to the Natural events approach by Baillon et al. (2018). Our experiment confirmed that the level of ambiguity aversion reflected by the  $b$ -index was consistent across different sources of ambiguity, supporting one of our pre-registered hypotheses. We also find support for the second pre-registered hypothesis. The Natural treatment yielded higher  $a$ -index values compared to the other treatments, reflecting greater insensitivity. While the difference is smaller, we observe an increase in the  $a$ -index when comparing the A60 with A10 treatments, indicating that increasing the number of balls results in more insensitivity.

In conclusion, we believe the VBB is a useful tool when conducting experiments with risk and ambiguity in digital contexts. Its ability to enable controlled manipulation of ambiguity and random draws offers a versatile, scalable, and user-friendly alternative to traditional real-world experimental procedures and other less credible online implementations. The VBB offers flexibility, and the degree of ambiguity could further be modified by for example setting a time limit, using closely related colors, or amplifying the circulation speed of the balls. Hopefully the VBB can serve as a valuable tool for studies in behavioral economics and decision science, contributing to our understanding of human behavior under uncertainty.

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# Appendices

## Appendix A Summary statistics on the sample

Table A1 describes the sample in terms of gender and age. As we can see there are subjects of varying ages present and slightly more females in the sample.

## Appendix B Regression results

We preregistered to run OLS regressions with and without controls. As mentioned in the main text, residuals from the estimation of the two indices reveal that these are correlated, thus warranting a SUR approach. For completeness, we report the results from the regressions here. Results are reported in Table B2 and corroborate the previous results. The only notable difference is that the  $a$ -index in A10 is not significantly different from A60.

We further study the dispersion of the indices by, following the procedure in Baillon et al. (2018), taking the absolute value of each index normalized around its treatment mean, and running a regression to see how the dispersion around the mean varies across treatments. To make it consistent with the previous regression analysis we apply the same specifications. In Table B3 we see a significant difference in dispersion between the two VBB treatments for the  $a$ - but not  $b$ -index. Clearly, the A10 treatment causes less dispersion than the A60 treatment.<sup>6</sup>

To study difference in variation we also run OLS-regressions on the absolute value of our indices. Results are reported in Table B4.

## Appendix C Non-parametric tests

Following the pre-analysis plan, we apply the Mann-Whitney-U (MWU) test to compare the distributions. None of the pairwise comparisons of treatments are significant, i.e., when considering any pair of random observations from different treatments, the probability that one observation has a higher  $b$ -index value than the other is not different from 0.5. See Tables C1 and C2.

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<sup>6</sup>Corresponding OLS-regression results can be found in Table B4 in the Appendix.

**Table A1:** Proportion of the different demographic categories by treatment

	A10	A60	Natural
Sex:			
Male	0.41	0.45	0.38
Female	0.59	0.55	0.62
Prefer not to say	0.00	0.00	0.01
Age:			
18–29	0.26	0.30	0.26
30–39	0.30	0.30	0.29
40–49	0.15	0.20	0.20
50–59	0.20	0.15	0.14
60–69	0.07	0.04	0.07
70+	0.02	0.01	0.04

**Table B1:** Effect of treatments on  $a$ - and  $b$ -indices, SUR regression.

	(1)		(2)	
	$a$ -index <sup>1</sup>	$b$ -index	$a$ -index <sup>1</sup>	$b$ -index
A60	0.073 (0.055)	0.009 (0.023)	0.098 <sup>•</sup> (0.054)	0.008 (0.023)
Natural	0.449 <sup>***</sup> (0.055)	-0.011 (0.023)	0.459 <sup>***</sup> (0.055)	-0.009 (0.023)
Age category (ref.: 18-29)				
28-37			0.162 <sup>**</sup> (0.063)	0.008 (0.027)
38-47			0.039 (0.069)	-0.025 (0.030)
48-57			0.170 <sup>*</sup> (0.071)	0.013 (0.030)
58+			0.240 <sup>**</sup> (0.084)	-0.045 (0.036)
Female			0.041 (0.046)	0.016 (0.020)
Time taken			-0.000 (0.000)	0.000 (0.000)
Prolific score			0.038 (0.052)	-0.001 (0.022)
FPS			0.001 (0.001)	0.000 (0.000)
Constant	0.176 <sup>***</sup> (0.038)	-0.047 <sup>**</sup> (0.016)	-3.805 (5.150)	0.043 (2.191)
Observations	463		463	
$R^2$	0.138	0.002	0.167	0.013
Wald $\chi^2$	74.133	0.733	92.672	5.947
Prob > $\chi^2$	0.000	0.693	0.000	0.820
Breuch-Pagan $\chi^2$	3.298		3.675	
Prob > Breuch-Pagan $\chi^2$	0.069		0.055	

*Notes.* Standard errors in parentheses.

<sup>•</sup>  $p < 0.1$ , <sup>\*</sup>  $p < 0.05$ , <sup>\*\*</sup>  $p < 0.01$ , <sup>\*\*\*</sup>  $p < 0.001$ .

<sup>1</sup>As our preregistered hypotheses are one-sided for the  $a$ -index, one should halve the  $p$ -values for those tests.

**Table B2:** Effect of treatments on  $a$ - and  $b$ -indices, OLS regressions.

	$a$ -index	$b$ -index	$a$ -index	$b$ -index
A60	0.073 (0.058)	0.009 (0.020)	0.098 <sup>•</sup> (0.058)	0.008 (0.020)
Natural	0.449 <sup>***</sup> (0.050)	-0.011 (0.025)	0.459 <sup>***</sup> (0.049)	-0.009 (0.025)
Age category (ref.: 18-27)				
28-37			0.162 <sup>*</sup> (0.066)	0.008 (0.026)
38-47			0.039 (0.062)	-0.025 (0.030)
48-57			0.170 <sup>*</sup> (0.075)	0.013 (0.029)
58+			0.240 <sup>**</sup> (0.086)	-0.045 (0.047)
Female			0.041 (0.045)	0.016 (0.019)
Time taken			-0.000 <sup>**</sup> (0.000)	0.000 <sup>•</sup> (0.000)
Prolific score			0.038 (0.062)	-0.001 (0.026)
FPS			0.001 (0.001)	0.000 (0.000)
Constant	0.176 <sup>***</sup> (0.036)	-0.047 <sup>***</sup> (0.014)	-3.805 (6.177)	0.043 (2.549)
Observations	463	463	463	463
$R^2$	0.138	0.002	0.167	0.013

*Notes.* Robust standard errors in parentheses.

<sup>•</sup>  $p < 0.1$ , <sup>\*</sup>  $p < 0.05$ , <sup>\*\*</sup>  $p < 0.01$ , <sup>\*\*\*</sup>  $p < 0.001$ .

**Table B3:** Effect of treatments on absolute value of  $a$ - and  $b$ -indices, SUR regression.

	(1)		(2)	
	$ a $ -index	$ b $ -index	$ a $ -index	$ b $ -index
A60	0.076 <sup>*</sup> (0.034)	0.019 (0.017)	0.079 <sup>*</sup> (0.034)	0.024 (0.016)
Natural	-0.019 (0.035)	0.074 <sup>***</sup> (0.017)	-0.021 (0.035)	0.071 <sup>***</sup> (0.017)
Age category (ref.: 18-27)				
28-37			0.005 (0.040)	-0.024 (0.019)
38-47			-0.027 (0.044)	-0.009 (0.021)
48-57			0.040 (0.045)	-0.019 (0.021)
58+			0.031 (0.053)	0.068 <sup>**</sup> (0.026)
Female			0.026 (0.029)	0.023 (0.014)
Time taken			-0.000 (0.000)	-0.000 (0.000)
Prolific score			-0.081 <sup>*</sup> (0.033)	-0.008 (0.016)
FPS			-0.000 (0.001)	0.000 (0.000)
Constant	0.357 <sup>***</sup> (0.024)	0.108 <sup>***</sup> (0.012)	8.435 <sup>**</sup> (3.249)	0.934 (1.562)
Observations	463		463	
$R^2$	0.018	0.042	0.041	0.081
Wald $\chi^2$	8.356	20.315	19.858	41.044
Prob > $\chi^2$	0.015	0.000	0.031	0.000
Breuch-Pagan $\chi^2$	7.931		7.006	
Prob > Breuch-Pagan $\chi^2$	0.005		0.008	

Notes. Standard errors in parentheses.

<sup>\*</sup>  $p < 0.1$ , <sup>\*</sup>  $p < 0.05$ , <sup>\*\*</sup>  $p < 0.01$ , <sup>\*\*\*</sup>  $p < 0.001$ .

**Table B4:** Effect of treatments on absolute values of  $a$ - and  $b$ -indices, OLS regressions.

	$a$ -index	$b$ -index	$a$ -index	$b$ -index
A60	0.076* (0.037)	0.019 (0.015)	0.079* (0.037)	0.024• (0.015)
Natural	-0.019 (0.031)	0.074*** (0.019)	-0.021 (0.031)	0.071*** (0.018)
Age category (ref.: 18-27)				
28-37			0.005 (0.044)	-0.024 (0.019)
38-47			-0.027 (0.038)	-0.009 (0.022)
48-57			0.040 (0.046)	-0.019 (0.022)
58+			0.031 (0.056)	0.068* (0.031)
Female			0.026 (0.029)	0.023• (0.014)
Time taken			-0.000* (0.000)	-0.000*** (0.000)
Prolific score			-0.081* (0.040)	-0.008 (0.016)
FPS			-0.000 (0.000)	0.000 (0.000)
Constant	0.357*** (0.023)	0.108*** (0.011)	8.435* (3.964)	0.934 (1.577)
Observations	463	463	463	463
$R^2$	0.018	0.042	0.041	0.081

Notes. Robust standard errors in parentheses.

•  $p < 0.1$ , \*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ .

**Table C1:**  $b$ -index: means (on diagonal) and p-values from MWU-tests (off diagonal)

	A10	A60	Natural
A10	-0.047		
A60	0.774	-0.038	
Natural	0.438	0.657	-0.053

**Table C2:**  $\alpha$ -index:means (on diagonal) and p-values from MWU-tests (off diagonal)

	A10	A60	Natural
A10	0.176		
A60	0.454	0.249	
Natural	0.000	0.000	0.622

## Appendix D Comment Categories

### D.1 Methodology for Comment Categorization

The categorization of comments was initially carried out using a pattern-based classification approach, implemented with a machine learning model (ChatGPT) and Python.<sup>7</sup> This approach goes beyond simple keyword spotting and takes into account contextual clues and patterns in the text. The categories were initially suggested by the language model and were subsequently manually reviewed and adjusted by the authors for accuracy. Based on this analysis, comments were assigned to one of the following categories:

- **Understanding:** Comments that mentioned confusion, difficulty in understanding, or explicitly stated incomprehension.
- **Engagement:** Comments that discussed interest, enjoyment, boredom, or difficulty in focusing on the experiment.
- **Technical Issues:** Comments that reported glitches, technical issues, or slow loading times.
- **Neutral/No comments:** Comments that explicitly stated no opinion or feedback.

We restrict attention to the 466 subjects used in the main analysis. A total of 87 comments were received in the experiment, out of which 19 were either neutral or had no comment. Table D1 provides a summary of the categorized comments received from participants across different treatment groups. Each category is followed by the number of comments corresponding to it, broken down by treatment type (A10, A60, Natural). To offer a glimpse into the nature of the comments, representative examples for each category are also included in the table.

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<sup>7</sup>See <https://bit.ly/46gujYR> for the full set of ChatGPT prompts used for the classification.

**Table D1:** Categorization of comments

<b>Category</b>	<b>A10</b>	<b>A60</b>	<b>Natural</b>	<b>Total</b>	<b>Example Comments</b>
Engagement	10	13	6	29	“I found it interesting! really enjoy these types of surveys.”, “I found this explanation very confusing”, “I took a shot but was unlucky ”
Neutral/No Comment	9	8	2	19	“no”, “No further comments”, “None. ”
Technical Issues	2	3	3	8	“It was difficult to count the number of each coloured ball as they were jumping all the time. There was also slightly delay for the program to response to clicks”, “It was a bit slow to load each page so I was worried it would crash. Otherwise it was fine and pretty fun.”, “Very interesting study. The page seemed to load rather slowly at times (even on pages without the balls present) but everything worked with patience. ”
Understanding	10	8	13	31	“I had absolutely no idea what was going on despite reading the instructions several times. The description of Option B was completely baffling to me”, “Although I did my best I apologize for struggling to fully understand the instructions. Thank you for giving me the opportunity to participate.”, “confusing ”
<b>Total</b>	<b>31</b>	<b>32</b>	<b>24</b>	<b>87</b>	

## Appendix E Instructions

When entering the experiment, subjects first saw a consent form. Then, they saw the instruction page.

### E.1 Overall instructions

#### E.1.1 A10 and A60 treatments

Welcome! In this experiment you will be asked to make various decisions. Depending on your decisions you may earn a sizable amount of money that will be paid to you after the experiment. This will be composed of the £1 participation fee plus your 'earnings' from the outcome of your decisions.

These earnings will depend partly on the decisions you take during the experiment and partly on chance. So you will need to read these instructions carefully.

**Outline of the experiment** You will be asked 6 questions of the same type. In each question you will be presented with two options, Option A and Option B.

After you have answered all 6 questions, one of them will be selected at random, and the Option you chose in this question will be played for real.

Therefore, it is in your interest to answer each question as if that were the question to be played out.

**The Bingo Blower** You will notice a virtual Bingo Blower below. You can see there are balls of three different colours: red, blue and yellow. It is a real physics simulation and not a pre-recorded video, meaning that we have no control on how the balls move.

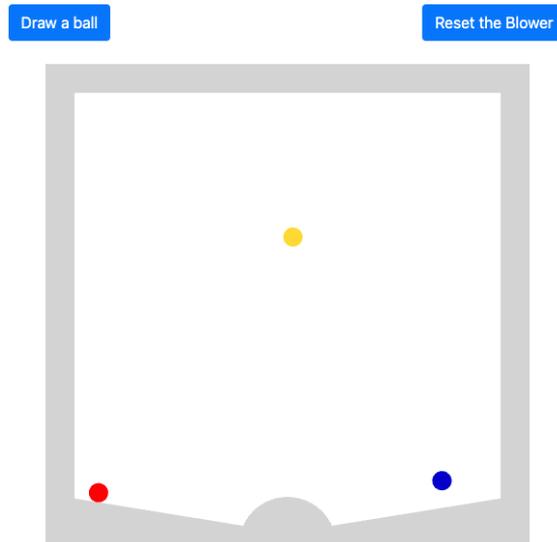
To convince yourself that this Bingo Blower is simulated in real-time, on this page only you can manipulate the balls by clicking on one, dragging it and seeing how the other balls react. Later on you will not be able to control the balls to prevent you from affecting the outcome.

At the end of the experiment, in order to determine a colour, the Bingo Blower will be stopped and the ball closest to the center selected. Since the Bingo Blower is a real physics simulation, we cannot control the colour of the ball drawn.

You can use the buttons below to see how drawing a ball will work. After you click on 'Draw a ball', the balls keep tumbling for 3 seconds. Thereafter the balls are frozen and the ball closest to the center is chosen. If you want to try drawing a ball multiple times, click on 'Reset the Blower'.

The ball drawn is: *[colour of the ball drawn]*

**The questions** In each question you will choose between two options, Option A and Option B:



- Option A (Bingo Blower option): you win £3 if the ball drawn from the Bingo Blower is of a certain colour, and nothing otherwise.
- Option B (given chance to win option): you have some chance to win £3.

You will be asked to state which one of these two options you prefer for various chances to win in Option B, from 0% to 100%. For example:

- If the chance to win in Option B is 100%, you will most likely prefer Option B because you are then guaranteed to win £3.
- If the chance to win in Option B is 0%, you will most likely prefer Option A because you might win something, as opposed to Option B where there is no chance to win at all.

You can think of the chance to win as the range of winning numbers in a bag containing numbers between 1 and 100. If the chance to win is 50%, it means you would win if a number between 1 and 50 is drawn from the bag, and you would lose if a number between 51 and 100 is drawn.

**Example question** The questions will look like this:

In this example, Option A would lead to a gain of £3 if the ball drawn from the Bingo Blower is red or yellow. Option B is presented with ascending chances to win. For each line we ask you to choose between Option A and Option B.

If you prefer Option A when, for instance, Option B offers a 40% chance to win, then you should also prefer Option A when Option B offers an even lower chance to win, say 25%. Similarly, if you prefer Option B with a 60% chance to win, then you should also prefer Option B with an even better chance to win, say 70%. Accordingly, in the figure above Option A is selected for every chance to win between 0 to 45%, and Option B, for every chance to win between 50% and 100%.

To save you the trouble of clicking for each line, you can click on Option A or

Option A You win £3 if one of the following balls is drawn:	Your choice	Option B You win £3 with the following chance:
 	<input type="checkbox"/> A <input checked="" type="checkbox"/> B	0 %
	<input type="checkbox"/> A <input type="checkbox"/> B	1 %
	<input type="checkbox"/> A <input type="checkbox"/> B	2 %
	<input type="checkbox"/> A <input type="checkbox"/> B	5 %
	<input type="checkbox"/> A <input type="checkbox"/> B	10 %
	<input type="checkbox"/> A <input type="checkbox"/> B	15 %
	<input type="checkbox"/> A <input type="checkbox"/> B	20 %
	<input type="checkbox"/> A <input type="checkbox"/> B	25 %
	<input type="checkbox"/> A <input type="checkbox"/> B	30 %
	<input type="checkbox"/> A <input type="checkbox"/> B	35 %
	<input type="checkbox"/> A <input type="checkbox"/> B	40 %
	<input type="checkbox"/> A <input type="checkbox"/> B	45 %
	<input type="checkbox"/> A <input checked="" type="checkbox"/> B	50 %
	<input type="checkbox"/> A <input type="checkbox"/> B	55 %
	<input type="checkbox"/> A <input type="checkbox"/> B	60 %
	<input type="checkbox"/> A <input type="checkbox"/> B	65 %
	<input type="checkbox"/> A <input type="checkbox"/> B	70 %
	<input type="checkbox"/> A <input type="checkbox"/> B	75 %
	<input type="checkbox"/> A <input type="checkbox"/> B	85 %
	<input type="checkbox"/> A <input type="checkbox"/> B	100 %

Option B for one line and the computer will automatically fill your choices for the other lines. For example, in the figure above, button ‘B’ has been clicked only for the line corresponding to 50%.

You can change your choices as many times as you want. Once you are happy with your choices, click the ‘Next’ button at the bottom. You will not be allowed to go back to a question once you have clicked on the ‘Next’ button.

**Payment** After you have answered all 6 questions, one of them will be randomly selected by the computer. This question will be the question that counts for your payment. Then the computer will also select one of the lines:

- If, on this line, you had selected Option A, you will win £3 if the colour of the ball drawn from the Bingo Blower matches one of the colours displayed in Option A.
- If, instead, you had selected Option B, you will play that option. To do so the computer will randomly draw a number between 0 and 100. For example if Option B is ‘You win £3 with a 74% chance’ then you will win £3 if the number drawn by the computer is strictly smaller than 74, and you will win nothing if it is equal to or larger than 75.

### E.1.2 Natural treatment

*[Identical to the instructions for A10 and A60, except:]*

**The questions** In each question you will choose between two options, Option A and Option B:

- Option A (Dow option): you win £3 if the Dow (Dow Jones Industrial Average Index) increases or decreases by some percentages between the opening and closing price on *[date about a week after the experiment]*, and nothing otherwise.
- Option B (given chance to win option): you have some chance to win £3.  
*[Remaining of section 'The questions' identical]*

**Example question** The questions will look like this:

Option A You win £3 if the Dow evolves in one of the following ways:	Your choice	Option B You win £3 with the following chance:
<ul style="list-style-type: none"> <li>• The Dow decreases by more than 0.51%</li> <li>• The Dow increases by more than 0.11%</li> </ul>	A B	0 %
	A B	1 %
	A B	2 %
	A B	5 %
	A B	10 %
	A B	15 %
	A B	20 %
	A B	25 %
	A B	30 %
	A B	35 %
	A B	40 %
	A B	45 %
	A B	50 %
	A B	55 %
	A B	60 %
	A B	65 %
	A B	70 %
	A B	75 %
	A B	85 %
	A B	100 %

In this example, Option A would lead to a gain of £3 if the Dow decreases by more than 0.51% or increases by more than 0.11%. Option B is presented with ascending chances to win. For each line we ask you to choose between Option A and Option B.

*[Remaining of section 'Example question' identical]*

**Payment** After you have answered all 6 questions, one of them will be randomly selected by the computer. This question will be the question that counts for your payment. Then the computer will also select one of the lines:

- If, on this line, you had selected Option A, you will win £3 if the evolution of the Dow matches one of the descriptions displayed in Option A. We will use historical data from Yahoo Finance (available by clicking on this link: <https://finance.yahoo.com/quote/%5EDJI/history/>): the opening price is in the column 'Open', and the closing price in the column 'Close\*'.
- If, instead, you had selected Option B, you will play that option. To do so the computer will randomly draw a number between 0 and 100. For example

if Option B is ‘You win £3 with a 74% chance’ then you will win £3 if the number drawn by the computer is strictly smaller than 74, and you will win nothing if it is equal to or larger than 75.

## E.2 Control questions

### E.2.1 A10 and A60 treatments

To test your understanding we have designed the following control questions.

Imagine one of the questions is as follows:

Option A	Your choice	Option B
You win £3 if one of the following balls is drawn:		You win £3 with the following chance:
 	<input type="checkbox"/> A <input type="checkbox"/> B	0 %
	<input type="checkbox"/> A <input type="checkbox"/> B	1 %
	<input type="checkbox"/> A <input type="checkbox"/> B	2 %
	<input type="checkbox"/> A <input type="checkbox"/> B	5 %
	<input type="checkbox"/> A <input type="checkbox"/> B	10 %
	<input type="checkbox"/> A <input type="checkbox"/> B	15 %
	<input type="checkbox"/> A <input type="checkbox"/> B	20 %
	<input type="checkbox"/> A <input type="checkbox"/> B	25 %
	<input type="checkbox"/> A <input type="checkbox"/> B	30 %
	<input type="checkbox"/> A <input type="checkbox"/> B	35 %
	<input type="checkbox"/> A <input type="checkbox"/> B	40 %
	<input type="checkbox"/> A <input type="checkbox"/> B	45 %
	<input type="checkbox"/> A <input type="checkbox"/> B	50 %
	<input type="checkbox"/> A <input type="checkbox"/> B	55 %
	<input type="checkbox"/> A <input type="checkbox"/> B	60 %
	<input type="checkbox"/> A <input type="checkbox"/> B	65 %
	<input type="checkbox"/> A <input type="checkbox"/> B	70 %
	<input type="checkbox"/> A <input type="checkbox"/> B	75 %
	<input type="checkbox"/> A <input type="checkbox"/> B	85 %
	<input type="checkbox"/> A <input type="checkbox"/> B	100 %

Imagine further that this question is selected for payment at the end of the experiment.

Imagine that the line corresponding to a chance to win of 10% is selected. If your choices are as described in the example above, which option would you play at the end of the experiment? *[Single choice]*

- Option A
- Option B

What happens if a red ball is drawn? *[Single choice]*

- I gain £0
- I gain £3
- It is irrelevant: how much I gain depends on the random number selected by the computer to play Option B.

Imagine that the line corresponding to a chance to win of 60% is selected. If your choices are as described in the example above, which option would you play at the end of the experiment? *[Single choice]*

- Option A
- Option B

What happens if a red ball is drawn? *[Single choice]*

- I gain £0
- I gain £3
- It is irrelevant: how much I gain depends on the random number selected by the computer to play Option B.

### E.2.2 Natural treatments

To test your understanding we have designed the following control questions.

Imagine one of the questions is as follows:

Option A You win £3 if the Dow evolves in one of the following ways:	Your choice	Option B You win £3 with the following chance:
<ul style="list-style-type: none"> <li>• The Dow decreases by more than 0.51%</li> <li>• The Dow increases by more than 0.11%</li> </ul>	A B	0 %
	A B	1 %
	A B	2 %
	A B	5 %
	A B	10 %
	A B	15 %
	A B	20 %
	A B	25 %
	A B	30 %
	A B	35 %
	A B	40 %
	A B	45 %
	A B	50 %
	A B	55 %
	A B	60 %
	A B	65 %
	A B	70 %
	A B	75 %
	A B	85 %
	A B	100 %

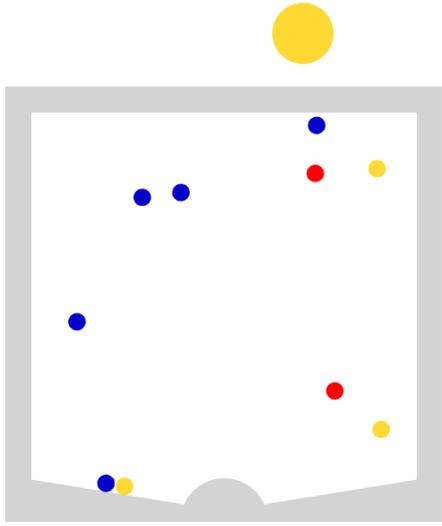
Imagine further that this question is selected for payment at the end of the experiment.

Imagine that the line corresponding to a chance to win of 10% is selected. If your choices are as described in the example above, which option would you play at the end of the experiment? *[Single choice]*

- Option A
- Option B

What happens if the Dow decreases by more than 0.51%? *[Single choice]*

- I gain £0
- I gain £3
- It is irrelevant: how much I gain depends on the random number selected by the computer to play Option B.

Option A You win £3 if one of the following balls is drawn:	Your choice	Option B You win £3 with the following chance:
	<input type="checkbox"/> A <input type="checkbox"/> B	0 %
	<input type="checkbox"/> A <input type="checkbox"/> B	1 %
	<input type="checkbox"/> A <input type="checkbox"/> B	2 %
	<input type="checkbox"/> A <input type="checkbox"/> B	5 %
	<input type="checkbox"/> A <input type="checkbox"/> B	10 %
	<input type="checkbox"/> A <input type="checkbox"/> B	15 %
	<input type="checkbox"/> A <input type="checkbox"/> B	20 %
	<input type="checkbox"/> A <input type="checkbox"/> B	25 %
	<input type="checkbox"/> A <input type="checkbox"/> B	30 %
	<input type="checkbox"/> A <input type="checkbox"/> B	35 %
	<input type="checkbox"/> A <input type="checkbox"/> B	40 %
	<input type="checkbox"/> A <input type="checkbox"/> B	45 %
	<input type="checkbox"/> A <input type="checkbox"/> B	50 %
	<input type="checkbox"/> A <input type="checkbox"/> B	55 %
	<input type="checkbox"/> A <input type="checkbox"/> B	60 %
	<input type="checkbox"/> A <input type="checkbox"/> B	65 %
	<input type="checkbox"/> A <input type="checkbox"/> B	70 %
<input type="checkbox"/> A <input type="checkbox"/> B	75 %	
<input type="checkbox"/> A <input type="checkbox"/> B	85 %	
<input type="checkbox"/> A <input type="checkbox"/> B	100 %	

**Figure E1:** Example of a choice task in A10, simple event.

Imagine that the line corresponding to a chance to win of 60% is selected. If your choices are as described in the example above, which option would you play at the end of the experiment? [*Single choice*]

- Option A
- Option B

What happens if the Dow decreases by more than 0.51%? [*Single choice*]

- I gain £0
- I gain £3
- It is irrelevant: how much I gain depends on the random number selected by the computer to play Option B.

## E.3 Tasks

Subjects saw 6 questions, randomised independently for each subject.

### E.3.1 A10 treatment

Table E1 gives an example of a task for a simple event, and Table E2, for a composite event

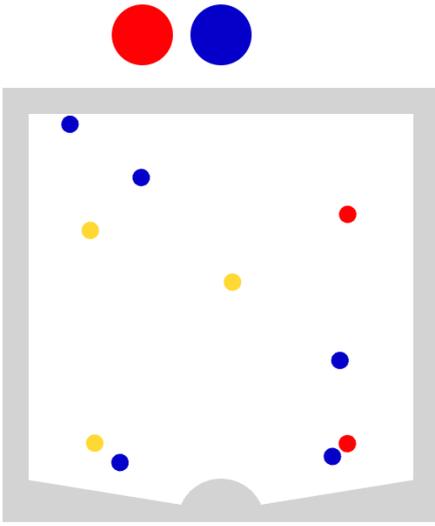
Option A You win £3 if one of the following balls is drawn:	Your choice	Option B You win £3 with the following chance:
 <p>The diagram shows a bingo blower containing 10 balls: 2 red, 2 blue, and 6 yellow. Above the blower are two large balls, one red and one blue, representing the winning balls for Option A. To the right is a table of probabilities for Option B, ranging from 0% to 100% in 5% increments. Each probability is associated with a choice between A and B.</p>	<input type="checkbox"/> A <input type="checkbox"/> B	0 %
	<input type="checkbox"/> A <input type="checkbox"/> B	20 %
	<input type="checkbox"/> A <input type="checkbox"/> B	35 %
	<input type="checkbox"/> A <input type="checkbox"/> B	40 %
	<input type="checkbox"/> A <input type="checkbox"/> B	45 %
	<input type="checkbox"/> A <input type="checkbox"/> B	50 %
	<input type="checkbox"/> A <input type="checkbox"/> B	55 %
	<input type="checkbox"/> A <input type="checkbox"/> B	60 %
	<input type="checkbox"/> A <input type="checkbox"/> B	65 %
	<input type="checkbox"/> A <input type="checkbox"/> B	70 %
	<input type="checkbox"/> A <input type="checkbox"/> B	75 %
	<input type="checkbox"/> A <input type="checkbox"/> B	80 %
	<input type="checkbox"/> A <input type="checkbox"/> B	85 %
	<input type="checkbox"/> A <input type="checkbox"/> B	90 %
	<input type="checkbox"/> A <input type="checkbox"/> B	93 %
	<input type="checkbox"/> A <input type="checkbox"/> B	95 %
<input type="checkbox"/> A <input type="checkbox"/> B	97 %	
<input type="checkbox"/> A <input type="checkbox"/> B	98 %	
<input type="checkbox"/> A <input type="checkbox"/> B	99 %	
<input type="checkbox"/> A <input type="checkbox"/> B	100 %	

Figure E2: Example of a choice task in A10, composite event.

### E.3.2 A60 treatment

Tasks in the A60 treatments were identical as those in the A10 treatment except that that the virtual bingo blower contained 60 balls.

### E.3.3 Natural treatment

Table E3 gives an example of a task for a simple event, and Table E4, for a composite event

Option A You win £3 if the Dow evolves in one of the following ways:	Your choice	Option B You win £3 with the following chance:
<ul style="list-style-type: none"> <li>The Dow decreases by more than 0.51%</li> <li>The Dow decreases by less than 0.51% or increases by less than 0.11%</li> </ul>	<input type="checkbox"/> A <input type="checkbox"/> B	0 %
	<input type="checkbox"/> A <input type="checkbox"/> B	20 %
	<input type="checkbox"/> A <input type="checkbox"/> B	35 %
	<input type="checkbox"/> A <input type="checkbox"/> B	40 %
	<input type="checkbox"/> A <input type="checkbox"/> B	45 %
	<input type="checkbox"/> A <input type="checkbox"/> B	50 %
	<input type="checkbox"/> A <input type="checkbox"/> B	55 %
	<input type="checkbox"/> A <input type="checkbox"/> B	60 %
	<input type="checkbox"/> A <input type="checkbox"/> B	65 %
	<input type="checkbox"/> A <input type="checkbox"/> B	70 %
	<input type="checkbox"/> A <input type="checkbox"/> B	75 %
	<input type="checkbox"/> A <input type="checkbox"/> B	80 %
	<input type="checkbox"/> A <input type="checkbox"/> B	85 %
	<input type="checkbox"/> A <input type="checkbox"/> B	90 %
	<input type="checkbox"/> A <input type="checkbox"/> B	93 %
	<input type="checkbox"/> A <input type="checkbox"/> B	95 %
	<input type="checkbox"/> A <input type="checkbox"/> B	97 %
	<input type="checkbox"/> A <input type="checkbox"/> B	98 %
	<input type="checkbox"/> A <input type="checkbox"/> B	99 %
	<input type="checkbox"/> A <input type="checkbox"/> B	100 %

**Figure E3:** Example of a choice task in Natural, simple event.

Option A You win £3 if the Dow evolves in one of the following ways:	Your choice	Option B You win £3 with the following chance:
<ul style="list-style-type: none"> <li>The Dow decreases by less than 0.51% or increases by less than 0.11%</li> </ul>	<input type="checkbox"/> A <input type="checkbox"/> B	0 %
	<input type="checkbox"/> A <input type="checkbox"/> B	1 %
	<input type="checkbox"/> A <input type="checkbox"/> B	2 %
	<input type="checkbox"/> A <input type="checkbox"/> B	5 %
	<input type="checkbox"/> A <input type="checkbox"/> B	10 %
	<input type="checkbox"/> A <input type="checkbox"/> B	15 %
	<input type="checkbox"/> A <input type="checkbox"/> B	20 %
	<input type="checkbox"/> A <input type="checkbox"/> B	25 %
	<input type="checkbox"/> A <input type="checkbox"/> B	30 %
	<input type="checkbox"/> A <input type="checkbox"/> B	35 %
	<input type="checkbox"/> A <input type="checkbox"/> B	40 %
	<input type="checkbox"/> A <input type="checkbox"/> B	45 %
	<input type="checkbox"/> A <input type="checkbox"/> B	50 %
	<input type="checkbox"/> A <input type="checkbox"/> B	55 %
	<input type="checkbox"/> A <input type="checkbox"/> B	60 %
	<input type="checkbox"/> A <input type="checkbox"/> B	65 %
	<input type="checkbox"/> A <input type="checkbox"/> B	70 %
	<input type="checkbox"/> A <input type="checkbox"/> B	75 %
	<input type="checkbox"/> A <input type="checkbox"/> B	85 %
	<input type="checkbox"/> A <input type="checkbox"/> B	100 %

**Figure E4:** Example of a choice task in Natural, composite event.