The attraction effect and its explanations

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The attraction effect violates choice consistency, one of the central assumptions of economics. I present a risky choice experiment to test it and disentangle some of its explanations. I find the attraction effect, but in a smaller magnitude than previously thought. I uncover a 'range effect' that shows that people weight more attributes whose range increases. I also show that the aggregate results hide considerable heterogeneity between subjects.

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JEL codes: C91, D11, D80, D90

1 Introduction

The attraction effect[1] occurs when adding an option x' to a menu $\{x, y\}$, where x' is dominated by x but not by y, increases the probability of choosing x. One of the

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[1]Sometimes referred to as the asymmetric dominance effect or, rather confusingly, the decoy effect.

most popular topics in marketing research and psychology, it has been observed with consumer products, job candidates, political candidates, political issues, medication, investment opportunities, and environmental goods.[2] The attraction effect has even been observed among birds, bees, moulds, monkeys, and frogs.[3]

This body of research suggests that preferences are context-dependent and so challenges the principles of consistency and utility maximisation central to economics. For this reason it has served as a motivation for many economic papers.[4] Most of the evidence, however, comes from studies using hypothetical problems: of the 52 experiments in marketing reviewed by Lichters et al. (2015b) only one, Doyle et al. (1999), uses real incentives; and, in economics, one of the rare incentivised studies on the attraction effect is Herne (1999). Moreover, even in marketing where its study is widespread, there are still some debates about the replicability of the attraction effect.[5] Finally, after 30 years of research we still do not know how to explain the attraction effect (Simonson, 2015). There are two possibilities (Wedell, 1991): adding an asymmetrically dominated option could change the weighting of the different attributes, or it could change the choice process. These explanations have so far not been teased apart, which renders precarious any attempt to explain the attraction effect.

To solve these problems I setup a controlled, incentivised laboratory experiment aimed at testing and explaining the attraction effect in the context of choice under

[2]For consumer products, see Huber et al. (1982) for a seminal paper, Heath and Chatterjee (1995) and Milberg et al. (2014) for reviews, and Gomez et al. (2016) for a recent example. For job candidates, see, among others, Highhouse (1996), Slaughter et al. (1999) and Slaughter (2007). For political candidates, political issues, medications, investments opportunities, and environmental goods, see respectively Pan et al. (1995), Herne (1997), Schwartz and Chapman (1999), Schwarzkopf (2003), and Bateman et al. (2008). The attraction effect has even been observed in perceptual (Crosetto and Gaudeul, 2016; Trueblood et al., 2013) and inferential (Trueblood, 2012) tasks.

[3]The attraction effect has been observed among grey jays and honeybees (Shafir et al., 2002), slime moulds (Latty and Beekman, 2011), rhesus macaques (Parrish et al., 2015), and túngara frogs (Lea and Ryan, 2015). Note, however, that Cohen and Santos (2017) did not observe the effect with capuchin monkeys.

[4]See for example, among many others, Barbos (2010), Cherepanov et al. (2013), de Clippel and Eliaz (2012), Gerasimou (2016a), Manzini and Mariotti (2012a), Masatlioglu et al. (2012), and Ok et al. (2015).

[5]Frederick et al. (2014) and Yang and Lynn (2014) failed to replicate the attraction effect, which prompted replies by Huber et al. (2014) and Simonson (2014) in the same issue of the *Journal of Marketing Research*. Lichters et al. (2015b) and Lichters et al. (2015a) further added to the debate by providing guidelines for future attraction effect experiments.

risk. My first main finding is that, despite higher incentives, stricter controls, and a more refined design, I replicate the attraction effect. It is, however, smaller than previously reported. The second main finding is that none of the existing explanations is able to fully explain the attraction effect. In fact I observe another effect, the 'range effect', that runs against the attraction effect.

What previous studies have referred to as 'the attraction effect' actually encompasses two effects, each with a different implication: one violates the Weak Axiom of Stochastic Revealed Preference while the other violates the Regularity Condition.[6] Instead of focusing on one or the other, I study both in the same experiment; and, since the Weak Axiom of Stochastic Revealed Preference imposes more requirements on consistency I predict that we should observe its violations more often.

The results confirm that the attraction effect exists, and, as predicted, violations of the Weak Axiom of Stochastic Revealed Preference are observed more often. The effect I observe is, however, roughly half of what was previously reported. Yet, it cannot be explained by random errors and so is a systematic deviation from consistency.

One way of explaining the attraction effect is to assume that adding decoys changes people's relative weighting of the attributes constituting the options. This *weights explanation* supposedly stems from a *negative range effect*: increasing the range of an attribute makes people weight this attribute *less*. If this interpretation is correct then increasing the attribute ranges even more should generate more negative range effect and thus more attraction effect. To test this prediction I create new decoys which double the attribute ranges compared to the typical decoys. The results show that these new decoys do not cause more attraction effect and so reject the weights explanation.

Another way of explaining the attraction effect is to say that a decoy changes *how* people choose. As its name suggests, an asymmetrically dominated decoy is dominated by only one option and so, if people have weak or imprecise preferences, they might feel compelled to choose the dominating option. Thus this *process explanation* hinges on the decoys being asymmetrically dominated and removing the asymmetric dominance should eliminate the attraction effect. I test this by

[6]Both will be defined precisely in Section 2.

introducing a second class of new decoys which also double the attribute ranges but are *symmetrically* dominated. Because they double the ranges the weights explanation predicts more attraction effect, just like the previous new decoys. But because they are symmetrically dominated, the process explanation predicts no attraction effect.

In fact they trigger, not more, not none, but a *negative* attraction effect. This negative attraction effect results from a *positive range effect*: increasing the range of an attribute makes people weight it, not less, but *more*. It further invalidates the weights explanation and runs against the attraction effect.

This range effect shows that people weight more attributes whose range increases. A similar idea recently surfaced in economics with Kőszegi and Szeidl's (2013) focusing model, but it has a long tradition in psychology.[7] In the focusing model increasing the range of payoffs, say at a particular date in an intertemporal choice context, makes people weight more this date. Andersson et al. (2016) and Dertwinkel-Kalt et al. (2017) have verified this intuition experimentally and the range effect documented in the present experiment demonstrates that it can be extended to risky choice.

I use the data from the experiment to structurally estimate Tserenjigmid (2018) and Landry and Webb (2019), two recent promising models that explain the attraction effect. Tserenjigmid (2018) emerges as a clear winner. I find that the previous aggregate results mask considerable heterogeneity in how subjects react to decoys. While a single theory with a given set of parameters cannot explain all of the patterns, a flexible model such as Tserenjigmid (2018) and a flexible estimation method such as the method of maximum simulated likelihood simply attribute the different patterns to different subjects.

Apart from their implications for choice, these results confirm that firms can exploit the attraction effect to influence consumers[8] when risk matters, for example when selling financial products or insurance. Firms can similarly exploit the range effect to direct the attention of consumers, something that has not yet been considered. The results also demonstrate that we need to take into account the

[7]See the weight-change literature (Fischer, 1995; Goldstein, 1990; Mellers and Cooke, 1994; von Nitzsch and Weber, 1993; Wedell, 1998; Wedell and Pettibone, 1996) and the similarity literature (Mellers and Biagini, 1994; Mellers et al., 1992a,b).

[8]Eliaz and Spiegler (2011) and Ok et al. (2011) show in their models how this might happen.

range effect when trying to explain the attraction effect.

Compared to Herne (1999) the present experiment uses higher incentives, options with different expected values, and a more concrete and transparent procedure, so it constitutes a more robust test of the attraction effect. Crucially, it also introduces new manipulations to test its explanations. More details on the similarities and the differences are provided in the main text. Another close study is Soltani et al. (2012) who use context effects to test a new theory of context-dependent choice. They also find the attraction effect using simple binary gambles, but they do not differentiate between the two definitions of the attraction effect and between the weights and process explanations. Kroll and Vogt (2012) also study the attraction effect but they focus on its impact on certainty equivalents.

2 Definitions of the attraction effect

The attraction effect is a type of context effect whereby the introduction of a supposedly irrelevant option, the 'decoy', causes a choice reversal. In the attraction effect this decoy is asymmetrically dominated: it is dominated by only one of two options. Throughout this paper I will use superscripts to denote the decoys. For example x', that we have already encountered in the introduction, is the asymmetrically dominated decoy of x: it is dominated by x but not by y; similarly, y' is dominated by y but not by x.

There are two ways to define the attraction effect. The first one, used for example by Herne (1999), looks at the combined effect of x' and y' and so keeps constant the number of options:

Attraction Effect WASRP. *The probability of choosing x is greater in $\{x, y, x'\}$ than in $\{x, y, y'\}$, and the probability of choosing y is greater in $\{x, y, y'\}$ than in $\{x, y, x'\}$.*

The second way, more common in marketing research, focuses on the effect of one decoy at a time and so varies the number of options:

Attraction Effect Regularity.

1. *The probability of choosing x is greater in $\{x, y, x'\}$ than in $\{x, y\}$.*

2. *The probability of choosing y is greater in $\{x, y, y'\}$ than in $\{x, y\}$.*

As their names imply, Attraction Effect WASRP violates the Weak Axiom of Stochastic Revealed Preference (Bandyopadhyay et al., 1999) while Attraction Effect Regularity violates the Regularity Condition. These are stochastic versions of the Weak Axiom of Revealed Preference and of the Chernoff condition.[9] The Regularity Condition is the weakest consistency requirement of stochastic choice and is satisfied by all random utility models (Luce and Suppes, 1965, Theorem 41, p. 346). WASRP is a stronger requirement and necessarily implies the Regularity Condition (Dasgupta and Pattanaik, 2007).

Previous studies have used interchangeably the two definitions of the attraction effect, but since the Regularity Condition is a weaker consistency requirement, Attraction Effect Regularity is a more serious violation of consistency. We can therefore expect to observe more Attraction Effect WASRP than Attraction Effect Regularity.

Now that we know what is the attraction effect and what it implies, we can look at how it can be explained.

3 Explanations of the attraction effect

I follow Herne (1999) and study the attraction effect with simple binary gambles.[10] Figure 1, which I will use throughout, depicts the gambles and the different classes of decoys used in the experiment. The gambles offer a probability p of winning £x and a probability $1-p$ of winning £0, denoted by (x, p). In the Figure probabilities p are on the x-axis, and winning amounts x on the y-axis. Following the previous literature I focus on two types of gambles: $\omega_p = (x_p, p_p)$ and $\omega_£ = (x_£, p_£)$. As can be seen in the Figure, ω_p is better in the **p**robability attribute, $p_p > p_£$, while $\omega_£$ is better in the **£**x attribute, $x_£ > x_p$. As we have already seen the asymmetrically dominated decoys testing the classical attraction effect are denoted by a single prime: these are ω'_p and $\omega'_£$, also depicted in the Figure. All decoys will follow the same naming convention: the superscripted symbol denotes the class of decoy while the subscripted number denotes the option to which the decoy is attached to.

[9] See Appendix A for details on WASRP and the Regularity Condition.
[10] See Appendix B.1 for details on the use of gambles in attraction effect research.

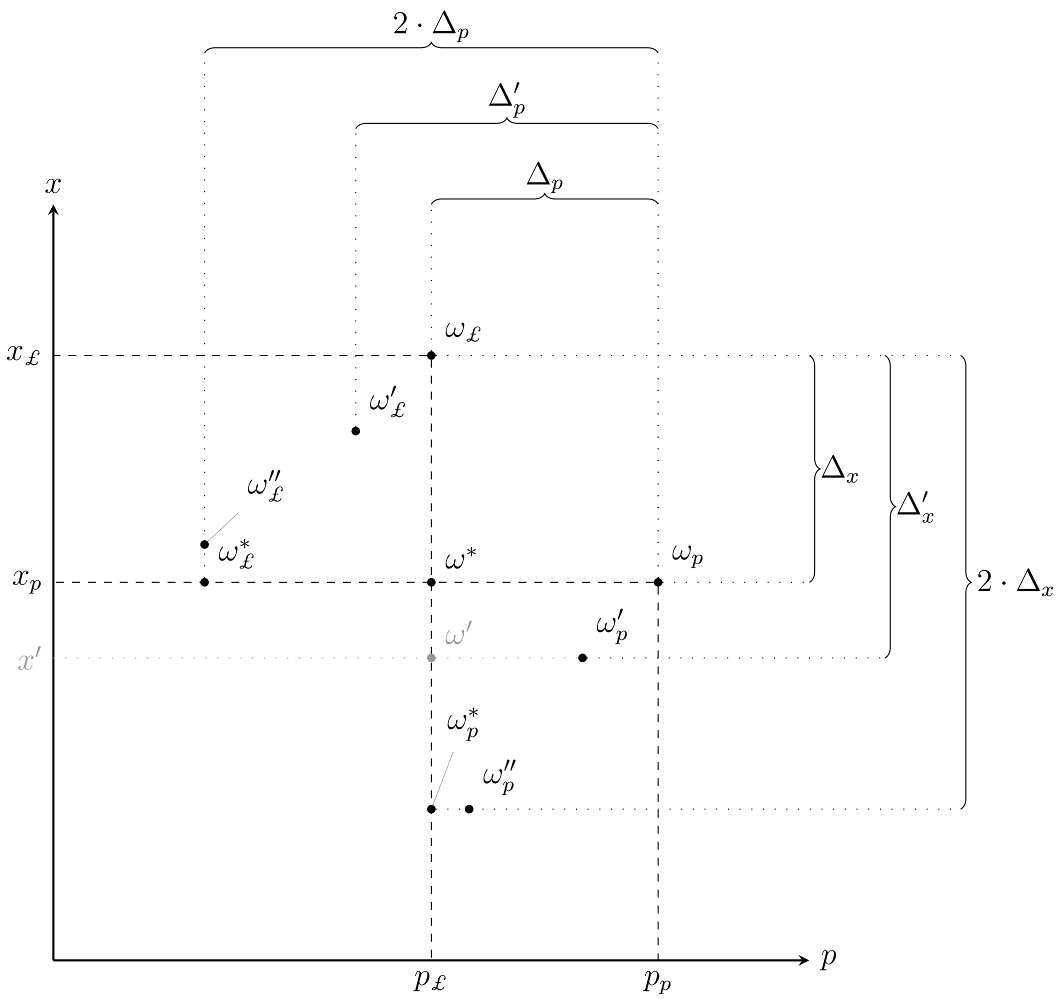

Figure 1: Decoys used to test the attraction effect and its explanations.

Over the years, researchers in psychology and marketing research have proposed many explanations to the attraction effect, which can be grouped into two categories (Herne, 1996; Köhler, 2007; Wedell, 1991).

3.1 Weights explanation

The first, the oldest one,[11] is a preference-based explanation: it argues that adding decoys changes the weights people attach to the attributes. For example, according

[11]It was first proposed by Huber et al. (1982) and is based on Parducci's (1974) range-frequency theory. Simonson and Tversky (1992) and Tversky and Simonson (1993) have a similar explanation.

to this *weights explanation* people choose ω_p following the introduction of ω'_p because they weight less the money attribute x. They weight it less because, as the explanation goes, the attribute range changes: Figure 1 shows that ω'_p increases the range of money from Δ_x to Δ'_x. Thus the attraction effect as explained by the weights explanation arises from a *negative range effect*: increasing an attribute range makes people weight less this particular attribute.

If this weights explanation is correct then increasing even more the ranges should cause more negative range effect and so more attraction effect. To test this prediction I created the decoys ω''_p and $\omega''_£$. As can be seen in the Figure, these new decoys are also asymmetrically dominated (hence the prime symbols), but compared to ω'_p and $\omega'_£$ they double the ranges, from Δ_x and Δ_p to $2 \cdot \Delta_x$ and $2 \cdot \Delta_p$ (hence the double primes). So, ω''_p and $\omega''_£$ should cause more attraction effect due to an increased negative range effect. They also test one of the findings of Heath and Chatterjee's (1995) meta-analysis: the greater the range extension, the more pronounced the attraction effect.

3.2 Process explanation

The second category of explanations is a heuristic-based explanation: it argues that adding a decoy changes *how* people make a choice. This *process explanation* hinges on the decoys being asymmetrically dominated. For example, ω_p dominates ω'_p but $\omega_£$ does not; one could then feel that ω'_p gives good reason to choose ω_p.[12] So, the process explanation explains the attraction effect as a change of decision process triggered by the introduction of an asymmetrically dominated option.

To test for this explanation, I remove the asymmetric dominance from ω''_p and $\omega''_£$ to create ω^*_p and $\omega^*_£$ (the star symbol replacing the prime symbol should help the reader remember that the star decoys are symmetrically dominated). As Figure 1 shows, ω^*_p and $\omega^*_£$ have the same range extension as ω''_p and $\omega''_£$, at $2 \cdot \Delta_x$ and $2 \cdot \Delta_p$, so the weights explanation predicts the same attraction effect. On the other hand, since ω^*_p and $\omega^*_£$ are *symmetrically* dominated the process explanation predicts that the attraction effect will disappear. In other words, if the attraction effect disappears the process explanation can be ruled out; if it holds it has to come from

[12] This is Simonson's (1989) 'choice based on reasons' approach. For a similar reasoning, see Ariely and Wallsten (1995) and Hedgcock and Rao (2009).

the weights explanation alone. For this reason ω_p^* and $\omega_£^*$ are the important decoys that allow me to discriminate between the two explanations. They are intentionally close to the double prime decoys, the only real difference being the removal of the asymmetric dominance.

Wedell (1991, Experiment 2) followed a similar approach and used the decoy ω' (also represented in Figure 1) which removes the asymmetric dominance from ω_p'. He found that adding ω' has no effect and so concluded against the weights explanation, which subsequent studies confirmed (Wedell, 1998; Wedell and Pettibone, 1996). But he used, for example, $\omega_p = (\$20, 0.5)$, $\omega_£ = (\$33, 0.3)$ and $\omega' = (\$18, 0.3)$. With these, the increase in the range of winning amounts is minimal, from $\Delta_x = 33 - 20 = \$13$ to $\Delta_x' = 33 - 18 = \$15$. The weights explanation might work but only for greater range extensions, hence why I am doubling the ranges.

3.3 Relation to choice models

Most models have followed the weights explanation. For example, the negative range effect is the backbone of Bushong et al.'s (2017) 'model of relative thinking', which thus predicts that we should see more attraction effect at ω_p'' and $\omega_£''$ than at ω_p' and $\omega_£'$. Kőszegi and Szeidl (2013), by contrast, build their 'model of focusing' on the *positive* range effect, according to which one puts more weight on an attribute when this attribute range *increases*. They thus predict that, when introducing ω_p', we should observe more choice of $\omega_£$, which is in contradiction to the attraction effect.

Tserenjigmid's (2018) 'choosing with the worst in mind' model explains the attraction effect using reference dependence where the reference point is determined by the minimum of the attributes. For example, in Figure 1, ω^* is the reference point when facing the menu $\{\omega_p, \omega_£\}$ since it is composed of the minimal probability $p_£$ and of the minimal amount of money x_p. Introducing ω_p' changes the reference point to ω', which decreases the reference of x from x_p to x'. Because of decreasing sensitivity the marginal value of x decreases, which increases the relative marginal value of p, leading to more choice of ω_p and thus causing the attraction effect. Introducing ω_p'' decreases further down the reference of x and creates even more attraction effect.

Landry and Webb's (2019) 'pairwise normalization model' is also related to the weights explanation. In their model, inspired by the neuroscience of perception, attribute levels are first compared in a pairwise fashion before being normalised. But since it does not rely on ranges or on a reference point the model is more general.

These last two models are particularly promising candidates to capture the attraction effect in that they formalise earlier approaches. Tserenjigmid (2018) shows that his model encompasses Huber et al.'s (1982) early explanation of the attraction effect based on Parducci's (1974) range-frequency theory. Landry and Webb show that their model explains context effects better than all existing models, among them Bushong et al. (2017).

Since all of these models are closely tied to the weights explanation, they predict that the removal of the asymmetric dominance, when we move from ω_p'' and $\omega_£''$ to ω_p^* and $\omega_£^*$, should not change choice. In fact the D-WARP condition in Tserenjigmid (2018) explicitly prevents it. Therefore, ω_p^* and $\omega_£^*$ further allow me to test this class of models.

Gerasimou (2016b) is the only economic model explicitly built on the process explanation. In this model, preferences are incomplete and the asymmetric dominance of the decoy helps the decision-maker break ties between alternatives that are otherwise incomparable. It could thus be seen as the theoretical underpinning of Simonson's (1989) 'choice based on reason' argument. To be applied, however, one needs to elicit indifference between ω_p and $\omega_£$, which is uncommon in attraction effect research.

3.4 Other explanations

Bordalo et al.'s (2013) 'salience model' is another popular model, but it cannot be directly applied to the present experiment. In this model salience emerges from the comparison of the payoff of a lottery in a given state of the world to the payoffs of other lotteries in the same state of the world. Given that in the present experiment each and every gamble will give a different amount of money with a different probability, and given the incentive mechanism which picks a gamble pair or triple at random, it can be argued that the payoffs are all in different states of the world, so salience theory would be silent. Even if we tweaked the theory to allow it to make predictions, it would not capture the attraction effect generated by the manipulation of the range of probabilities. Landry and Webb (2019) further show that Bordalo et al. (2012, 2013) can only explain the attraction effect in very specific cases and that the pairwise normalization model performs better.

Other models, for example Eliaz et al. (2011), de Clippel and Eliaz (2012), Manzini and Mariotti (2012b), Masatlioglu et al. (2012) and Manzini et al. (2013), introduce weakenings of the consistency requirements of rational choice to capture context effects such as the attraction effect. These models are abstract and do not make clear predictions; they do not try to pin down a particular mechanism behind the attraction effect and so could fit in either category.

Finally, ω^* in Figure 1 tests for the possibility that simply introducing a third option in itself causes an effect, even if it is neither asymmetrically dominated nor increasing the attribute ranges.

3.5 Summary

To summarise, I use four classes of decoys, each asking a different question:

- The prime decoys ω'_p and $\omega'_£$ test for the classical attraction effect.
- The double prime decoys ω''_p and $\omega''_£$ keep the asymmetric dominance but double the attribute ranges. The weights explanation predicts that we will observe a stronger attraction effect due to the negative range effect.
- The star decoys ω^*_p and $\omega^*_£$ also double the attribute ranges but remove the asymmetric dominance. The weights explanation predicts that we will observe the same attraction effect compared to the previous decoys, while the process explanation predicts that the attraction effect will disappear. These star decoys also allow me to test most existing models.
- ω^* does not increase attribute ranges and is symmetrically dominated, so both explanations predict that it will have no effect.

The next Section presents the experimental design implementing these decoys in the laboratory.

Table 1: Parameter sets.

Set	ω_p		$\omega_£$		ω^*		ω'_p		$\omega'_£$		ω''_p		$\omega''_£$		ω^*_p		$\omega^*_£$	
	p_p	x_p	$p_£$	$x_£$	p^*	x^*	p'_p	x'_p	$p'_£$	$x'_£$	p''_p	x''_p	$p''_£$	$x''_£$	p^*_p	x^*_p	$p^*_£$	$x^*_£$
a	0.8	7	0.55	12.5	0.55	7	0.75	6	0.5	11.5	0.6	1.5	0.3	8	0.55	1.5	0.3	7
b	0.75	7.5	0.55	12.5	0.55	7.5	0.7	6.5	0.5	11.5	0.6	2.5	0.35	8.5	0.55	2.5	0.35	7.5
c	0.75	7.5	0.5	14	0.5	7.5	0.7	6.5	0.45	13	0.55	1	0.25	8.5	0.5	1	0.25	7.5
d	0.7	8	0.5	14	0.5	8	0.65	7	0.45	13	0.55	2	0.3	9	0.5	2	0.3	8
e	0.7	8	0.45	15.5	0.45	8	0.65	7	0.4	14.5	0.5	0.5	0.2	9	0.45	0.5	0.2	8
f	0.65	8.5	0.5	14	0.5	8.5	0.6	7.5	0.45	13	0.55	3	0.35	9.5	0.5	3	0.35	8.5
g	0.65	8.5	0.45	15.5	0.45	8.5	0.6	7.5	0.4	14.5	0.5	1.5	0.25	9.5	0.45	1.5	0.25	8.5
h	0.6	9.5	0.5	14	0.5	9.5	0.55	8.5	0.45	13	0.55	5	0.4	10.5	0.5	5	0.4	9.5
i	0.6	9.5	0.45	15.5	0.45	9.5	0.55	8.5	0.4	14.5	0.5	3.5	0.3	10.5	0.45	3.5	0.3	9.5
j	0.6	9.5	0.4	17	0.4	9.5	0.55	8.5	0.35	16	0.45	2	0.2	10.5	0.4	2	0.2	9.5
k	0.5	11.5	0.3	22.5	0.3	11.5	0.45	10.5	0.25	21.5	0.35	0.5	0.1	12.5	0.3	0.5	0.1	11.5
l	0.75	13.5	0.5	25	0.5	13.5	0.7	12.5	0.45	24	0.55	2	0.25	14.5	0.5	2	0.25	13.5
m	0.7	14.5	0.45	27.5	0.45	14.5	0.65	13.5	0.4	26.5	0.5	1.5	0.2	15.5	0.45	1.5	0.2	14.5
n	0.65	15.5	0.5	24.5	0.5	15.5	0.6	14.5	0.45	23.5	0.55	6.5	0.35	16.5	0.5	6.5	0.35	15.5

Note. The gambles not used in the experiment have been greyed out.

4 Experimental design

4.1 Parameter sets, between- and within-subject comparisons

I started by creating 14 sets of gambles. To account for risk aversion and test the robustness of the attraction effect, in each set the expected value of $\omega_£$ is 20% higher than the one of ω_p.[13] For the first 11 sets, the expected values of ω_p and $\omega_£$ are approximately £5.8 and £7; for the remaining 3 sets, they are £10 and £12.[14] By contrast, Herne's (1999) gambles were all of the same expected value of 30 Finnmarks, which was approximately £3.3 in 1999.

Each set accommodates all decoys previously mentioned to ensure that all sets have the same underlying structure and so can be compared. Accommodating ω^*_p and $\omega^*_£$ imposes the most restrictions because the probabilities of ω_p and $\omega_£$ should be such that the range of probabilities can be doubled. For example, $\omega_p = (£7.2, 0.8)$ and $\omega_£ = (£23, 0.3)$ cannot be part of a valid set because they cannot accommodate $\omega^*_£$: the probability range is $\Delta_p = 0.8 - 0.3 = 0.5$ and it is impossible to introduce a $\omega^*_£$ that doubles it. Table 1 presents the resulting 14 sets.

Then, of the first 11 low-stake sets (sets a to k), I randomly selected 3 to study

[13] Most studies on the attraction effect have used options with the same expected value, an approach criticised by Frederick et al. (2014) and Crosetto and Gaudeul (2016).

[14] At the time of the experiment, £1 $\simeq$ \$1.42.

the decoys $\{\omega'_p, \omega'_£\}$, 3 to study $\{\omega''_p, \omega''_£\}$ and, since these are the most important ones, 5 to study $\{\omega^*_p, \omega^*_£\}$, making sure that the sets assigned to a class of decoys were not too similar. I also randomly assigned one of the 3 remaining high-stake sets to each class.

The experiment is setup to study Attraction Effect WASRP within- and between-subject; and Attraction Effect Regularity, due to concerns about experimenter demand effects,[15] only between-subject. Note that Wedell (1991) and Herne (1999) only studied Attraction Effect WASRP within-subject, while most studies in psychology and marketing research only studied Attraction Effect Regularity between-subject. The combination of the two approaches allows me to study the effect from both angles. And, if the effect were to appear only in one context, I would be suspicious of the reality of the effect.

Table 2 describes how I combined the two types of attraction effect and within- and between-subject comparisons in the same experiment. As can be seen in the Table, subjects are split into 4 groups. All subjects encounter the 14 parameter sets in the same order in the first booklet but they see different decoys depending on their group. For example, the first line of the Table corresponds to parameter set g. Subjects in the first group choose between ω_p and $\omega_£$; while subjects in the second, third and fourth groups have the decoys ω^*, ω^*_p and $\omega^*_£$ added to their menu. Comparing Group 1 and 3, and Group 1 and 4, addresses between-subject Attraction Effect Regularity, while comparing Group 3 and 4 addresses between-subject Attraction Effect WASRP. The menus $\{\omega_p, \omega_£\}$ and $\{\omega_p, \omega_£, \omega^*\}$ act as fillers between parameter sets so that subjects: *(a)* do not face the same class of decoy twice in a row; *(b)* do not face decoys favouring the same option twice in a row.

Subjects face again the 14 parameter sets in the second decision booklet (second part of Table 2) but with different decoys. Keeping the example of parameter set g, subjects in Group 3 who faced the menu $\{\omega_p, \omega_£, \omega^*_p\}$ in the first booklet

[15]Within-subject designs have more statistical power, are less noisy, and are more natural when one wants to study preferences (Charness et al., 2012). But they are also more prone to elicit spurious effects due to sensitisation (Greenwald, 1976) or even experimenter demand (Zizzo, 2010). Experimenter demand effects are especially a problem for Attraction Effect Regularity: since it requires to add a single, asymmetrically dominated option to the choice between two original options, it signals what the experiment is about and subjects can easily find out what is expected from them.

Table 2: Decoys added to $\{\omega_p, \omega_{\pounds}\}$ and explanation tested for each parameter set, in order of presentation.

Set	Group 1		Group 2		Group 3		Group 4	
				Booklet 1				
g	—	No decoy	ω^*	Neutral decoy	ω^*_p	Weights/Process	$\omega^*_{\pounds}$	Weights/Process
c	ω^*_p	Weights/Process	$\omega^*_{\pounds}$	Weights/Process	—	No decoy	ω^*	Neutral decoy
f	ω^*	Neutral decoy	—	No decoy	$\omega'_{\pounds}$	Standard decoy	ω'_p	Standard decoy
k	$\omega'_{\pounds}$	Standard decoy	ω'_p	Standard decoy	ω^*	Neutral decoy	—	No decoy
j	—	No decoy	ω^*	Neutral decoy	ω''_p	Weights	$\omega''_{\pounds}$	Weights
m	ω''_p	Weights	$\omega''_{\pounds}$	Weights	—	No decoy	ω^*	Neutral decoy
b	ω^*	Neutral decoy	—	No decoy	$\omega^*_{\pounds}$	Weights/Process	ω^*_p	Weights/Process
h	$\omega^*_{\pounds}$	Weights/Process	ω^*_p	Weights/Process	ω^*	Neutral decoy	—	No decoy
a	—	No decoy	ω^*	Neutral decoy	ω'_p	Standard decoy	$\omega'_{\pounds}$	Standard decoy
n	ω'_p	Standard decoy	$\omega'_{\pounds}$	Standard decoy	—	No decoy	ω^*	Neutral decoy
i	ω^*	Neutral decoy	—	No decoy	$\omega''_{\pounds}$	Weights	ω''_p	Weights
e	$\omega''_{\pounds}$	Weights	ω''_p	Weights	ω^*	Neutral decoy	—	No decoy
d	—	No decoy	ω^*	Neutral decoy	ω^*_p	Weights/Process	$\omega^*_{\pounds}$	Weights/Process
l	ω^*_p	Weights/Process	$\omega^*_{\pounds}$	Weights/Process	—	No decoy	ω^*	Neutral decoy
				Booklet 2				
g	ω^*	Neutral decoy	—	No decoy	$\omega^*_{\pounds}$	Weights/Process	ω^*_p	Weights/Process
c	$\omega^*_{\pounds}$	Weights/Process	ω^*_p	Weights/Process	ω^*	Neutral decoy	—	No decoy
f	—	No decoy	ω^*	Neutral decoy	ω'_p	Standard decoy	$\omega'_{\pounds}$	Standard decoy
k	ω'_p	Standard decoy	$\omega'_{\pounds}$	Standard decoy	—	No decoy	ω^*	Neutral decoy
j	ω^*	Neutral decoy	—	No decoy	$\omega''_{\pounds}$	Weights	ω''_p	Weights
m	$\omega''_{\pounds}$	Weights	ω''_p	Weights	ω^*	Neutral decoy	—	No decoy
b	—	No decoy	ω^*	Neutral decoy	ω^*_p	Weights/Process	$\omega^*_{\pounds}$	Weights/Process
h	ω^*_p	Weights/Process	$\omega^*_{\pounds}$	Weights/Process	—	No decoy	ω^*	Neutral decoy
a	ω^*	Neutral decoy	—	No decoy	$\omega'_{\pounds}$	Standard decoy	ω'_p	Standard decoy
n	$\omega'_{\pounds}$	Standard decoy	ω'_p	Standard decoy	ω^*	Neutral decoy	—	No decoy
i	—	No decoy	ω^*	Neutral decoy	ω''_p	Weights	$\omega''_{\pounds}$	Weights
e	ω''_p	Weights	$\omega''_{\pounds}$	Weights	—	No decoy	ω^*	Neutral decoy
d	ω^*	Neutral decoy	—	No decoy	$\omega^*_{\pounds}$	Weights/Process	ω^*_p	Weights/Process
l	$\omega^*_{\pounds}$	Weights/Process	ω^*_p	Weights/Process	ω^*	Neutral decoy	—	No decoy

face $\{\omega_p, \omega_\pounds, \omega_\pounds^*\}$ in the second booklet, and the the other way round for subjects in Group 4. Comparing the choices across booklets for a given parameter set addresses within-subject Attraction Effect WASRP. This way subjects see a given parameter set only twice, once in each booklet with different decoys, which minimises experimenter demand and sensitisation effects.

A consequence of this design is that half of the subjects see the decoy related to ω_p first (ω_p^* in the example) while the others see the decoy related to $\omega_\pounds$ first ($\omega_\pounds^*$), so the design also allows me to study the directionality of within-subject Attraction Effect WASRP. Previous studies, on the other hand, studied the effect only in one direction for a given parameter set.

4.2 Procedure and incentives

To achieve concreteness the experiment made use of pairs of 10-sided dice to describe and play the gambles. All subjects had the dice on their desk throughout the experiment, they were encouraged to examine them and they knew that these would be the dice used to play their chosen gamble at the end of the experiment. The choice tasks themselves also referred to the dice (see Appendix B.2 for a sample). By contrast, previous experiments on the attraction effect using gambles, such as Herne (1999), relied on a random number generator on the computer and described the probabilities in abstract terms.

The experiment was incentivised using the PRINCE mechanism (Johnson et al., 2015). It adds transparency to the traditional random incentive system by asking subjects entering the laboratory to draw a sealed envelope that contains a piece of paper describing the entire choice task (of the 28 they face in the experiment) that will matter to determine their earnings. At the end of the experiment the subject and the experimenter open the envelope and flip through the booklets to find the task described on the piece of paper. The subject then plays the gamble she has chosen in this particular choice task and is paid accordingly, plus a show-up fee. Appendix B.3 details exactly how the experiment was conducted and how PRINCE was implemented.

Finally, the instructions (Appendix B.4) featured detailed examples, none using the gambles that the subjects would encounter in the experiment, and control questions.

5 Results

The experiment took place across five sessions between the end of April and the beginning of June 2016 at the CeDEx laboratory in Nottingham. 207 subjects were recruited randomly using ORSEE (Greiner, 2015). A session lasted about 1 hour for an average payment of £11.37 (SD = £7.43). Each subject made 28 choices (14 in each booklet) and two subjects left a task blank, which leaves 5794 choices to exploit. Across the whole experiments subjects chose decoys only 10 times, so in what follows I will not mention decoy choices.

Denote by $\tilde{\omega}_i$ the decoy associated with ω_i, $i, j \in \{p, £\}$ $i \neq j$, $c(\cdot)$ the observed choice in a menu, and $\Pr(\cdot)$ the proportion of subjects exhibiting a particular pattern. Within-subject Attraction Effect WASRP is characterised by

$$\begin{aligned} &\Pr\Big(\omega_i = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_i\}\Big) \text{ and } \omega_j = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_j\}\Big)\Big) \\ &- \Pr\Big(\omega_j = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_i\}\Big) \text{ and } \omega_i = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_j\}\Big)\Big) > 0, \end{aligned} \tag{1}$$

which I will test using a one-sided McNemar test. Note that this test rules out explanations of the attraction effect based on random errors: If random errors were present, they would affect both choice patterns in (1) equally, and there is no reason to believe that one pattern would be affected more than the other. Looking at the difference between the two patterns thus rules out random errors and reveals truly anomalous behaviour.[16]

Between-subject Attraction Effect WASRP is characterised by

$$\Pr\Big(\omega_i = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_i\}\Big)\Big) - \Pr\Big(\omega_i = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_j\}\Big)\Big) > 0, \tag{2}$$

and between-subject Attraction Effect Regularity by

$$\Pr\Big(\omega_i = c\Big(\{\omega_p, \omega_£, \tilde{\omega}_i\}\Big)\Big) - \Pr\Big(\omega_i = c\Big(\{\omega_p, \omega_£\}\Big)\Big) > 0, \tag{3}$$

both tested using a one-sided χ^2 test.

The neutral decoy ω^* is in principle associated with neither ω_p nor $\omega_£$. I choose

[16] Cubitt et al. (2004) used the same argument in the context of preference reversals.

to look at its impact on ω_p and define the within-subject effect of ω^* by

$$\begin{aligned}&\Pr\Big(\omega_p \in c\big(\{\omega_p, \omega_£\}\big) \text{ and } \omega_£ \in c\big(\{\omega_p, \omega_£, \omega^*\}\big)\Big)\\ &- \Pr\Big(\omega_£ \in c\big(\{\omega_p, \omega_£\}\big) \text{ and } \omega_p \in c\big(\{\omega_p, \omega_£, \omega^*\}\big)\Big) \neq 0,\end{aligned} \tag{4}$$

tested using a two-sided McNemar test; and its between-subject effect, by

$$\Pr\Big(\omega_p \in c\big(\{\omega_p, \omega_£, \omega^*\}\big)\Big) - \Pr\Big(\omega_p \in c\big(\{\omega_p, \omega_£\}\big)\Big) \neq 0. \tag{5}$$

tested using a two-sided χ^2 test.

Figure 2 reports the aggregate results of the experiment. I will comment on parameter-set irregularities when appropriate. Disaggregated and detailed results can be found in Appendix C.

5.1 There is a (small) attraction effect

I start with the classical attraction effect, using the decoys ω'_p and $\omega'_£$. The top-left graph of Figure 2 focuses on within-subject Attraction Effect WASRP, when ω'_p is seen first ($\omega'_p \to \omega'_£$, first row) or when $\omega'_£$ is seen first ($\omega'_£ \to \omega'_p$, second row). We see that the attraction effect is significant in both cases so the experiment replicates the results from Wedell (1991) and Herne (1999); but note that when $\omega'_£$ is seen first the effect is in the right direction for all parameter sets but significant in only one. The top-right graph of Figure 2 shows that Attraction Effect WASRP carries-over to between-subject comparisons.

Moving to Attraction Effect Regularity, the bottom-left graph of Figure 2 shows that the effect appears with ω'_p but not with $\omega'_£$. The effect ω'_p causes, however, is small, and a closer inspection shows that this effect stems primarily from only one parameter set.

So, I replicate the two types of attraction effects, but with two new observations. As predicted, Attraction Effect Regularity appears to be weaker than Attraction Effect WASRP. Second, the attraction effect I observe is considerably smaller than previously reported. For example, the within-subject Attraction Effect WASRP observed by Herne (1999, Experiment 1) varies, depending on the parameter set, between 16% and 35.2%, averaging at about 24.1%. Mine, by contrast, varies

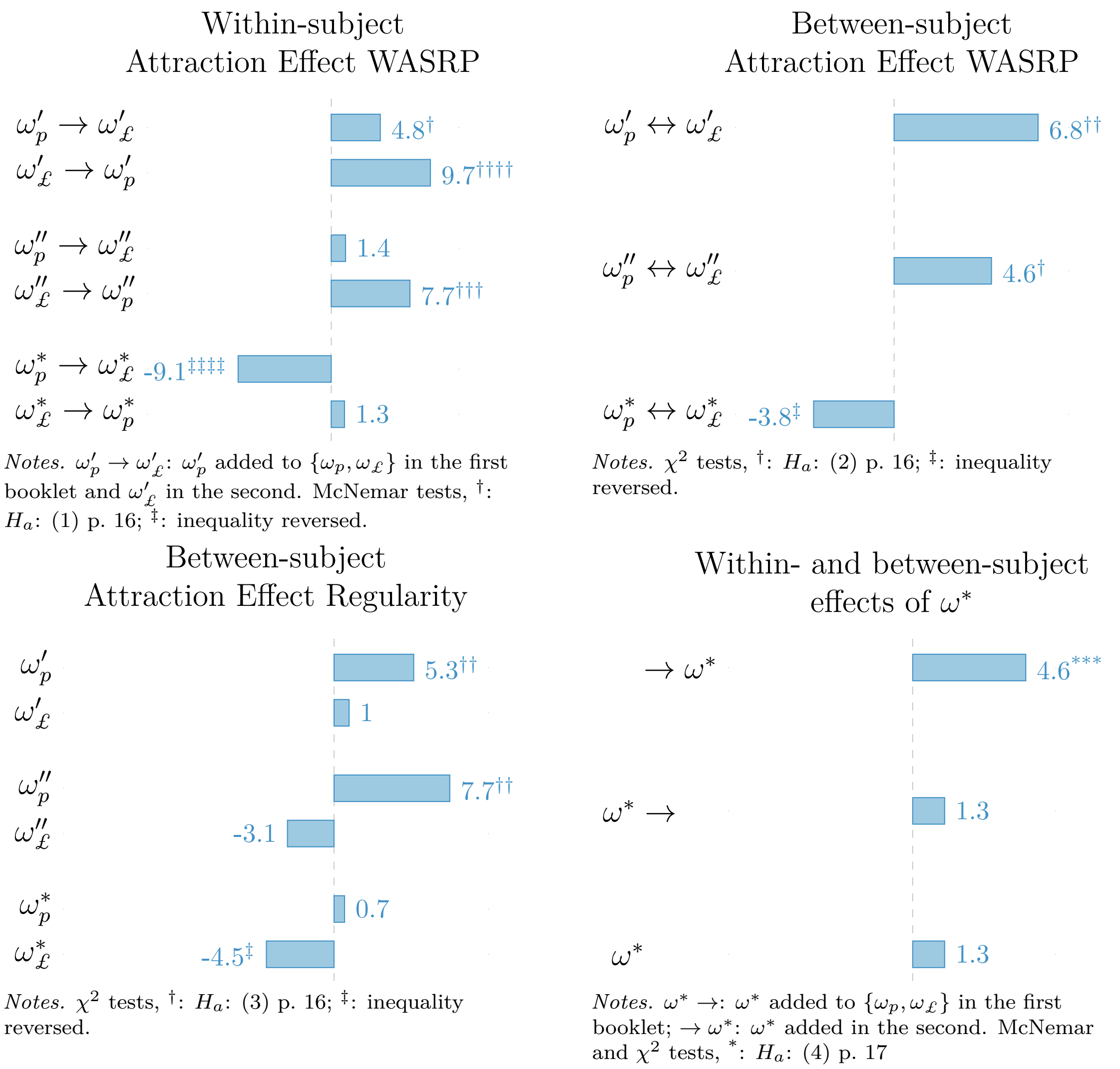

Figure 2: Attraction effects (in percent) at the aggregate level. One, two, three and four symbols indicate significance at $\alpha = 0.1$, 0.05, 0.01 and 0.001.

between 2% and 23.5%, averaging at about 7.2%. Still, it is significant, and it survives to the higher incentives, the gambles with different expected values, the more transparent incentive mechanism, and the increased concreteness of the choice situation.

5.2 There is no clear support for the weights explanation

Consider then ω''_p and $\omega''_{£}$. As we saw, these decoys are also asymmetrically dominated but they double the range of the weakest attribute of their associated option. The weights explanation predicts that they will cause a stronger attraction effect, while the process explanation predicts no change at all.

The results provide mixed evidence. Within-subject Attraction Effect WASRP now appears in one direction only, when subjects are first exposed to $\omega''_{£}$, but at a higher significance level (top-left, third and fourth row); and so for 3 out of 4 parameter sets, compared to only one when subjects were first exposed to $\omega'_{£}$. Between-subject, Attraction Effect WASRP is less pronounced than before (top-right, second row).

For Attraction Effect Regularity (bottom-left, fourth row), ω''_p has more incidence than ω'_p: introducing ω''_p increases the proportion of subjects choosing ω_p by almost 8 percentage points, compared to 5 for ω'_p (bottom-left, third row). $\omega''_{£}$, just as $\omega'_{£}$, has no effect .

Therefore, ω''_p and $\omega''_{£}$ do cause an attraction effect, which reinforces the results obtained with ω'_p and $\omega'_{£}$; but increasing the attribute ranges does not seem to cause a stronger attraction effect, which invalidates the weights explanation and the entire class of models built on it.[17]

5.3 A positive range effect operates against the attraction effect

The real test, however, comes from ω^*_p and $\omega^*_{£}$. Remember that according to the weights explanation, we should observe the same attraction effect; but according to the process explanation, the effect should vanish.

[17] Mann-Whitney U tests further show that ω''_p does not cause more between-subject attraction effect than ω'_p ($U = 6$, $p = 0.686$), and $\omega''_{£}$, than $\omega'_{£}$ ($U = 7$, $p = 0.886$). Given that these tests compare different parameters sets, however, they should be interpreted with caution.

Neither is correct: Looking at within-subject Attraction Effect WASRP (top-left, rows 5 and 6) introducing ω_p^* in the first booklet and $\omega_£^*$ in the second causes a *negative* attraction effect whereby subjects switch from $\omega_£$ to ω_p and not from ω_p to $\omega_£$. This effect is highly significant at the aggregate level, significant for 3 out of 6 parameter sets, and always in this direction. Introducing $\omega_£^*$ first has no effect. This negative attraction effect carries over to between-subject Attraction Effect WASRP (top-right, last row).

Between-subject Attraction Effect Regularity resulting from the introduction of $\omega_£^*$ is also negative, which makes the effect clearer: introducing $\omega_£^*$ *decreases* the choice of $\omega_£$ and so increases the choice of ω_p (bottom-left, last row). So, instead of favouring $\omega_£$ as would predict the weights explanation, $\omega_£^*$ actually favours ω_p. Recall from Figure 1 that $\omega_£^*$ increases the range of the probability attribute. When the probability range is increased, subjects tend to chose ω_p, the superior option in terms of the probability attribute: it is a *positive range effect*. Note that ω_p^* causes no between-subject Attraction Effect Regularity at the aggregate level.

This result further invalidates the models that follow the weights explanation and are built on the negative range effect, for example Bushong et al. (2017). If anything, when the asymmetric dominance is removed subjects behave closer to Kőszegi and Szeidl (2013), which relies on the positive range effect.

5.4 Order effects and diverging results

The first two rows of the bottom-right graph in Figure 2 report the within-subject effect of introducing the neutral decoy ω^*. As explained in equation (4), here a positive within-subject effect means that subjects switched more from $\omega_£$ to ω_p than the opposite. Figure 2 shows that this happened when ω^* was introduced only in the second booklet (first row), but not when it was added in the first booklet then removed (second row). It is unlikely that this pattern comes from ω^* itself, since the last row of the same graph shows that it had no between-subject effect. Instead, the pattern might reveal a simple order effect, by which subjects tended to choose ω_p more often as the experiment progressed. Since ω_p is less risky than $\omega_£$, one way to explain this finding is that subjects became more risk averse over the course of the experiment. This is a common observation in risky choice experiments (see for example Loomes et al., 2002).

This order effect partially explains the directionality of within-subject Attraction Effect WASRP (top-left), where introducing $\omega'_£$, $\omega''_£$ or ω^*_p in the second booklet caused less or no effects. As we saw, these decoys are supposed to favour $\omega_£$, either through the normal attraction effect or through the positive range effect; but the order effect works against $\omega_£$ and pushes subjects to pick the less risky option ω_p. Without the order effect, we might have observed a similar reactivity to decoys.

The order effect, however, cannot explain everything. The between-subject results are immune to it because subjects faced the parameter sets in the same order; yet we saw that, even between-subject, decoys had less grip on $\omega_£$ than on ω_p. It might be that subjects had imprecise preferences (Butler and Loomes, 2007) for $\omega_£$ and thus had difficulty to interpret a decoy that supposedly favoured it.[18] It might also be that they perceived $\omega_£$ to be particularly unattractive and tried to avoid it even in the presence of a decoy. Meta-analyses (e.g. Heath and Chatterjee, 1995; Milberg et al., 2014) have consistently found that low-quality options are less responsive to decoys than high-quality ones. If we assimilate a probability to a quality attribute, this would explain why ω_p and $\omega_£$ responded differently to decoys. Malkoc et al. (2013) have also shown that attraction effect is attenuated when the options are unattractive. In their setting, however, both target options are unattractive—they are for example losses—whereas in the present experiment only $\omega_£$ can be said to be unattractive.

5.5 Reduced-form regression results

Table 3 reports the results of a logistic regression looking at the impact of the different classes of decoy on the probability of choosing ω_p or $\omega_£$. This regression reproduces the analysis leading to the between-subject Attraction Effect Regularity in Figure 2, but further controls for subject fixed-effects, option order within a task, and task order.

We see that the results presented above carry through: ω'_p and ω''_p increase the probability of choosing ω_p while ω^*_p does not, which lends support to the process explanation. On the other hand, decoys do not affect $\omega_£$ except for $\omega^*_£$ which actually decreases the probability of choosing it and so favours ω_p, which is the positive range effect. ω^* does not affect choice in this between-subject setting.

[18] I thank Robert Sugden for this observation.

Table 3: Impact of the different classes of decoy on the probability of choosing ω_p or $\omega_£$, logit model.

	ω_p		$\omega_£$	
Decoy type				
ω_i'	0.20	0.36**	0.06	0.08
	(0.13)	(0.18)	(0.13)	(0.18)
ω_i''	0.31**	0.58***	−0.10	−0.23
	(0.13)	(0.19)	(0.13)	(0.19)
ω_i^*	0.06	0.09	−0.20*	−0.43***
	(0.11)	(0.15)	(0.11)	(0.15)
ω^*	0.05	0.08	−0.07	−0.15
	(0.08)	(0.11)	(0.08)	(0.11)
Controls				
Parameter set group	✓	✓	✓	✓
Subject dummy		✓		✓
Option order		✓		✓
Task order		0.02***		−0.01**
		(0.01)		(0.01)
Observations	4347	3507	4347	3402
Pseudo R^2	0.01	0.32	0.01	0.30
Log-likelihood	−2960.60	−1649.70	−2978.70	−1650.20
Wald χ^2	83.31	1548.00	51.17	1407.10
Prob > χ^2	0.00	0.00	0.00	0.00

Note. Coefficients, standard errors in parentheses.
Constant omitted.
Option order: the position of the gamble on the page: first, second or third.
Parameter set group: a dummy identifies the parameter set used to test a class of decoy: sets $\{a, f, k, n\}$ for ω_i', $\{e, i, j, m\}$ for ω_i'', and $\{b, c, d, g, h, l\}$ for ω_i*.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

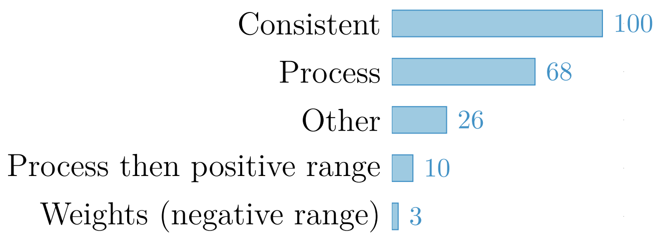

Figure 3: Number of subjects classified into the different patterns of choice.

Finally, the order of the task affects positively the probability of choosing ω_p, which is the order effect previously mentioned.

5.6 Heterogeneity of choice behaviour

Up to now we have looked at the effects only at the aggregate; we can get a better sense of subjects' heterogeneity by grouping them into different classes. To do so, I say that for a given subject a decoy $\tilde{\omega}_i$ affects ω_i if it does so in at least half of the parameter sets for which it is involved. For example, ω_i^* affects ω_j, thus creating a positive range effect, if a subject switches to ω_j following the introduction of the decoy in at least 3 of the 6 parameter sets where this type of decoy is present.

I then define classes of choice behaviour. Subjects can

- fit in the process explanation class if ω_i' and ω_i'' affect ω_i but not ω_i^*;
- fit in the weights explanation class if ω_i', ω_i'' and also ω_i^* affect ω_i;
- fit in the 'process then positive range effect' class if ω_i' and ω_i'' affect ω_i, but ω_i^* affects ω_j;
- and finally, fit in the consistent class is they choose the same, or almost always the same, option between the two booklets.

Figure 3 shows the results from this classification. We see that almost half of the subjects, 100, can be classified as consistent. Of these 100 subjects, 46 are perfectly consistent—they always choose the same option between the booklets; 9 are affected only by ω^* but are otherwise perfectly consistent; and 45 choose the same option more than 85% of the time and never exhibit one of the other effects. The attraction effect, while present, thus leaves many subjects unaffected.

The second most popular class, with 68 subjects, is the process class. Of them, 30 exhibit more attraction effect at ω_i' than at ω_i'': for these subjects the decoy benefits from being close to its target. In contrast, 28 subjects exhibit more effect at ω_i'' than at ω_i': for them the decoy needs to be asymmetrically dominated, but within the asymmetric dominance decoys that increase the range create more effect; this is a 'process + negative range effect' class. There remains 10 subjects who exhibit as much effect at ω_i' than at ω_i''.

These two classes encompass more than 80% of the subjects. Then, 10 subjects fit in the 'process then positive range effect' class: they exhibit the classical attraction effect as long as the asymmetric dominance is maintained, and then switch to the positive range effect.

Only 3 subjects fit in the weight class,. This was expected since, as Figure 2 showed us, the star decoys never created an attraction effect. Finally, 26 subjects do not fit in any of these classes.

These results suggest a different interpretation of the shift observed between $\omega_{£}''$ and $\omega_{£}^*$. At the aggregate $\omega_{£}''$ favours $\omega_{£}$ and $\omega_{£}^*$ favours ω_p, not because the introduction of $\omega_{£}^*$ makes subjects shift from $\omega_{£}$ to ω_p, but because *some* subjects—the ones in the process class—stop choosing $\omega_{£}$ while *others*—the ones in the process then positive range class—start choosing ω_p. Such heterogeneity should thus be taken into account when studying the attraction effect, something that was lacking in previous studies.

6 Structural estimation

To close this paper, and in order to gain further insight, I estimate two of the most promising models mentioned in Section 3, Landry and Webb (2019) and Tserenjigmid (2018), using the data generated in the experiment.

6.1 The models under consideration

Expected utility As a baseline I use expected utility. Assume throughout a power utility function $u(x) = x^\alpha$. So, for a binary gamble $\omega_i = (x_i, p_i)$ we have

$$\mathrm{EU}(\omega_i) = p_i x_i^\alpha.$$

Landry and Webb (2019) The model of Landry and Webb (2019) considers options with N attributes $x = (x_1, \ldots, x_N)$ and $y = (y_1, \ldots, y_N)$. The utility of an option in a menu A is

$$U_{LW}(x, A) = \sum_{n=1}^{N} \sum_{y \in A \setminus x} \frac{x_n}{x_n + y_n}. \tag{6}$$

To apply the model we need to translate it to choice under risk. To do so, when the options are $\omega = (x, p)$, I choose the attributes to be probabilities and money utilities so that (6) becomes

$$U_{LW}(\omega_i, A) = \sum_{\omega_j \in A \setminus \omega_i} \left(\frac{p_i}{p_i + p_j} + \frac{x_i^\alpha}{x_i^\alpha + x_j^\alpha} \right),$$

This way, the model reduces to expected utility when there are only two options, $A = \{\omega_i, \omega_j\}$ (Landry and Webb, 2019, Lemma 1).

Tserenjigmid (2018) In the 'choosing with the worst in mind' model we first look at the vector that consists of the minimum of each attribute in menu A, $m_A = (\min_{\omega \in A} x, \min_{\omega \in A} p) = (x_{min}, p_{min})$. Then, applying the model to simple binary gambles we have[19]

$$U_T(\omega_i, A) = \Big(\alpha \ln(x) - \alpha \ln(x_{min})\Big)^{\gamma_x} + \Big(\ln p - \ln p_{min}\Big)^{\gamma_p}.$$

This model is a reference-dependent model where the minimum of the attribute is the reference point. γ_x and γ_p then capture how the decision-maker reacts to the change in the reference for a particular attribute. When there are only two options, $A = \{\omega_i, \omega_j\}$, and $\gamma_x = \gamma_p = 1$, the model reduces to expected utility.

In order to explain the attraction effect, Tserenjigmid restricts to $\gamma_i < 1$, which implies diminishing sensitivity: a decrease in the reference value for attribute i, or in other words an increase in the range of i, makes the marginal value of this attribute decrease. This effect is similar to the negative range effect.

We could, however, also have $\gamma_i > 1$, implying that a decrease in the reference value of attribute i makes the marginal value of this attribute *increase*, which would

[19] I thank Gerelt Tserenjigmid for suggesting this formulation. See also the Online Appendix of Tserenjigmid (2018) for more details.

be the positive range effect. This model is thus flexible enough to capture all of the effects identified in the previous Section.

6.2 Noise and tremble

Denote by $\tilde{U}(\omega, A)$ one of these utility functions. These models are deterministic: subjects choose $\omega_£$ over ω_p if and only if $\tilde{U}(\omega_£, A) - \tilde{U}(\omega_p, A) > 0$.

To apply them to the data we need to introduce a stochastic component. The simplest way is to assume that subjects evaluate their preferences with some additive error: they choose $\omega_£$ if and only if $\tilde{U}(\omega_£, A) - \tilde{U}(\omega_p, A) + \epsilon > 0$. Different assumptions on the distribution of ϵ imply different stochastic structures. I use the strong utility story—the so-called Frechner errors (Hey and Orme, 1994)—whereby $\epsilon \sim \mathcal{N}(0, \sigma^2)$. σ represents the noisiness in choice.

Further, as mentioned before some subjects chose the decoys. Frechnian errors could explain these decoy choices but would require, since the decoys are obviously dominated, large evaluation error. It is more natural to assume that subjects had some concentration lapse and chose randomly. Under this tremble story (Loomes et al., 2002; Moffatt and Peters, 2001) subjects choose the option with the highest utility, taking into account the evaluation error, with probability $1 - \kappa$, and choose something else with probability κ. When they tremble, subjects have a probability $\kappa/2$ to choose any given option when there are two options, and $\kappa/3$ when there are three options. The tremble probability would also capture more general erratic behaviour difficult to reconcile with any of the theories..

6.3 Between-subject variation

To sum up, all models have the following parameters:

- α, the degree of risk aversion;
- σ, the noise in choice; and
- κ, the tremble parameter, the probability a subject loses concentration and chooses randomly.

Tserenjigmid (2018) adds two parameters:

- γ_p, which captures the response to a change in the reference of attribute p; and

- γ_x, the response to a change in the reference of x.

To account of subject heterogeneity, I assume that the parameters vary across subjects according to some distribution. In principle any of these parameters can be a random parameter, but given that we have only 28 observations per subject we need to be parsimonious. Therefore I assume that α_n, $\gamma_{x,n}$ and $\gamma_{p,n}$ are independently normally distributed over the population, and I estimate their mean and standard deviation. On the other hand I assume that σ and κ are constant.

Random parameters call for the method of maximum simulated likelihood. Conte et al. (2011) and Von Gaudecker et al. (2011) are other recent example of the use of maximum simulated likelihood to capture heterogeneity. To keep the exposition concise the full details, such as the derivation of choice probabilities, the log-likelihoods and different specifications, are relegated to Appendix D.

6.4 Estimation results

The estimation results are presented in Table 4. We see that the estimates are fairly stable across models: The mean of α oscillates around 0.6, which is slightly lower than in other experiments but reflects that, as explained in Section 4, subjects making decisions had not received a show-up fee and so faced the full risk of leaving the experiment empty-handed. Its standard deviation is significantly different from 0 in the three models (χ^2 tests, $p < 0.001$), which shows the importance of the method of maximum simulated likelihood to capture the heterogeneity in the data. From the tremble parameter κ we infer that the a probability of subjects choosing at random is negligible, at around 0.75%.

Looking at the maximised log-likelihoods Landry and Webb (2019) and Tserenjigmid (2018) fit the data better than expected utility. Both have lower σ, indicating that they rely less on noise to explain the data. Of the two Tserenjigmid (2018) is the one with the largest log-likelihood. Clarke's (2003) sign test gives a preference to Tserenjigmid (2018) compared to expected utility ($p = 0.0122$) and Landry and Webb (2019) ($p < 0.001$). On the other hand, Landry and Webb (2019) cannot be distinguished from expected utility ($p > 0.1$). Therefore, Tserenjigmid (2018) emerges as the clear winner.

For the remaining, since it is the best fitting model I will concentrate on Tserenjigmid (2018). The mean of γ_x and of γ_p are not different from 1 ($\chi^2(1) = 0.55$ and

Table 4: Estimates and standard errors from maximum simulated likelihood estimation of the structural models.

		EU	U_{LW}	U_T
α	mean	0.5885	0.6139	0.5928
		(0.0136)	(0.0193)	(0.0157)
	s.d.	0.1810	0.3022	0.2394
		(0.0111)	(0.0189)	(0.0161)
γ_x	mean	-	-	0.9954
		-	-	(0.0063)
	s.d.	-	-	0.0232
		-	-	(0.0125)
γ_p	mean	-	-	0.9984
		-	-	(0.0078)
	s.d.	-	-	0.0279
		-	-	(0.0142)
σ		0.1648	0.0691	0.0829
		(0.0045)	(0.0025)	(0.0035)
κ		0.0070	0.0078	0.0074
		(0.0025)	(0.0027)	(0.0025)
$\log \mathcal{L}$		-2847.4175	-2834.6110	-2737.4307

Notes. EU: expected utility model; U_{LW}: Landry and Webb (2019); U_T: Tserenjigmid (2018).
Standard errors in parentheses.
200 subjects, 28 observations per subject.
Number of Halton draws used: 50.

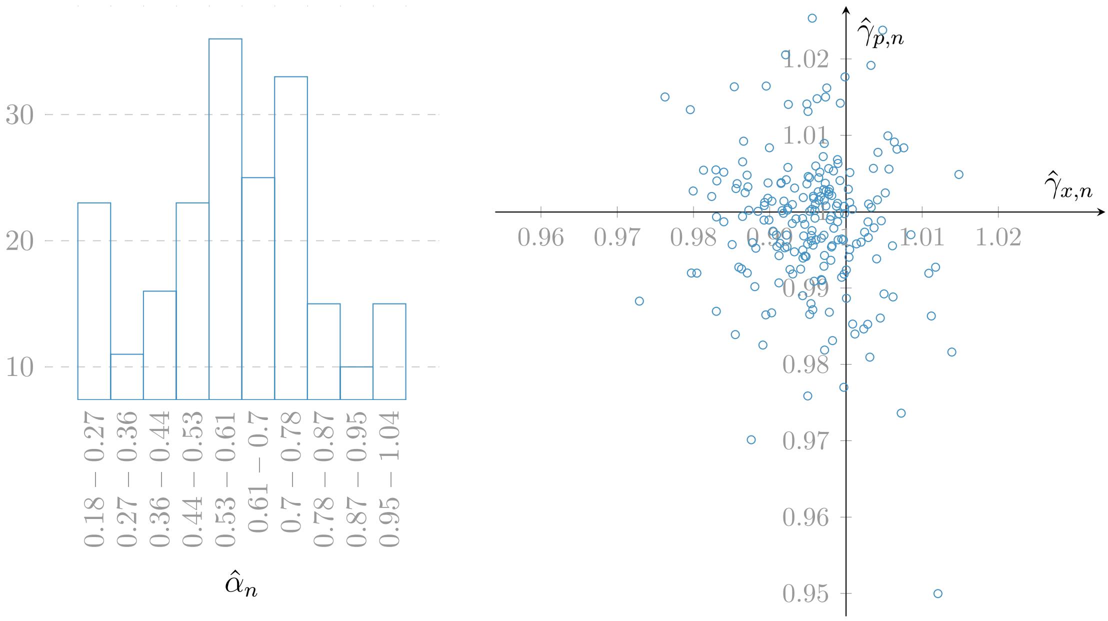

Figure 4: Distribution of the posterior estimates from Tserenjigmid (2018).

0.04, $p = 0.4585$ and 0.8376), and in this case the model boils down to expected utility. The standard deviation of γ_p, however, is significantly different from 0 at the 5% level ($\chi^2(1) = 3.87$, $p = 0.0490$), and the standard deviation of γ_x, at the 10% level ($\chi^2(1) = 3.41$, $p = 0.0648$). So, while the average subject follows expected utility, for some subjects $\gamma_{i,n} < 1$ while for others $\gamma_{i,n} > 1$.

To look at heterogeneity into more detail, I obtain for each subjects posterior estimates that I denote by $\hat{\alpha}_n$, $\hat{\gamma}_{x,n}$ and $\hat{\gamma}_{p,n}$. Their distribution is presented in Figure 4. The left graph shows that subjects range from extreme risk aversion to risk neutrality and slight risk lovingness.

Regarding the $\hat{\gamma}_{i,n}$, the right graph shows that there is also considerable heterogeneity. Most subjects, 81 out of 207, are in the lower left quadrant: they exhibit decreasing sensitivity for both attributes and so are susceptible to the attraction effect for both ω_p and $\omega_{£}$. The second most popular category, almost at a tie with 80 subjects, is in the upper left quadrant: these subjects exhibit decreasing sensitivity for the winning amounts, and increasing sensitivity for probabilities. They would thus be susceptible to the attraction effect with decoys under ω_p, while decoys under $\omega_{£}$, such as $\omega''_{£}$ and $\omega^*_{£}$, would create a positive range effect and so also favour ω_p. 28 subjects, in the lower right quadrant, do the opposite: they instead exhibit decreasing sensitivity for probabilities and increasing sensitivity for winning amounts. Finally, 18 subjects fit in the upper right quadrant: they show increasing sensitivity, so positive range effect, to both attributes.

As we saw, models built on the weights explanation cannot explain all phenomena at the aggregate, because if they predict the attraction effect with ω''_p and $\omega''_{£}$ they have to predict it with ω^*_p and $\omega^*_{£}$ as well, since the ranges remain the same. But a model such as Tserenjigmid (2018), flexible enough to pick up both the positive and the negative range effect, and an estimation allowing for heterogeneity, in which subjects receive different parameter values, indicate that ω''_p affecting the choice ω_p but $\omega^*_{£}$ also affecting the choice of ω_p happens because subjects are affected differently by the decoys. Still, this model cannot explain the Process class in Figure 3, because the reference does not change between the prime-prime and the star decoys.

7 Conclusion

I have presented an experiment to test the attraction effect and its explanations. The experiment finds it to be smaller than previously reported, but still detectable despite the more robust test. I have also found that the aggregate results mask substantial heterogeneity in how people react to decoys.

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Appendices

Appendix A Weak Axiom of Stochastic Revealed Preference and Regularity Condition

To see how Attraction Effect WASRP violates the Weak Axiom of Revealed Preference, denote by $\mathbb{P}_A(B)$ the probability that the choice from the set A lies in B. WASRP holds if and only if, for all A and B, $\mathbb{P}_B(C) - \mathbb{P}_A(C) \leq \mathbb{P}_A(A - B)$ for all $C \subseteq A \cap B$. For us, $A = \{x, y, x'\}$ and $B = \{x, y, y'\}$. $\mathbb{P}_A(A - B)$ boils down to $\mathbb{P}_{\{x,y,x'\}}(x')$, which is always 0 in properly setup attention effect experiments. With $C = \{x\}$, WARSP becomes $\mathbb{P}_{\{x,y,y'\}}(x) \leq \mathbb{P}_{\{x,y,x'\}}(x)$, and with $C = \{y\}$, $\mathbb{P}_{\{x,y,y'\}}(y) \leq \mathbb{P}_{\{x,y,x'\}}(y)$, a condition that Attraction Effect WASRP violates.[20]

Then, for the Attraction Effect Regularity and with the same notation, we know that the Regularity Condition is satisfied if and only if, for all A, B, C such that $C \subseteq B \subseteq A$, $\mathbb{P}_B(C) \geq \mathbb{P}_A(C)$. For us, $B = \{x, y\}$, and, for example, $A = \{x, y, x'\}$ and $C = \{x\}$. The Condition becomes $\mathbb{P}_{\{x,y\}}(x) \geq \mathbb{P}_{\{x,y,x'\}}(x)$, which Attraction Effect Regularity 1 violates; and similarly for Attraction Effect Regularity 2 with $A = \{x, y, y'\}$ and $C = \{y\}$.

As said in the main text, WASRP and the Regularity Condition are stochastic generalisations of the the Weak Axiom of Revealed Preference (WARP) and of the Chernoff Condition[21] (Dasgupta and Pattanaik, 2007). If we were to use these, we would use a similar reasoning: We know that the Chernoff Condition is necessary for the existence of *any* preferences, while WARP is necessary and sufficient for the existence of *rational* preferences, so WARP necessarily implies the Chernoff Condition.[22] Thus, violations of WARP should be observed more often, since there should be more people with non-rational preferences than people without preferences at all.

Appendix B Details of the experiment

This Appendix provides additional details on the experiment. Appendix B.1 explains more in depth why I used simple binary gambles to test the attraction effect. Appendix B.2 gives a sample of a choice task found in a decision booklet.

[20] On the WASRP, see also Bandyopadhyay et al. (2002), Bandyopadhyay et al. (2004) and Dasgupta and Pattanaik (2007).

[21] From Chernoff (1954); also called Sen's α (Sen, 1969), basic contraction consistency (Sen, 1977) or the independence of irrelevant alternatives (Nash, 1950).

[22] On Chernoff, see Sen (1969, Lemma 2, p. 384). On WARP, see Mas-Colell et al. (1995, Proposition 1.D.1 and 1.D.2, pp. 12-13). On WARP implying Chernoff, see Sen (1971, T.8 and Corollary, p. 314).

Appendix B.3 describes how the experiment was conducted and how the PRINCE mechanism was implemented. Appendix B.4 reproduces the instructions.

B.1 Gambles in attraction effect experiments

I relied on simple binary gambles to test the attraction effect for mainly two reasons. The first one is practical: gambles maximise internal validity. To understand why, note that in principle the attraction effect holds with any option, so the only criteria to consider when choosing an option is that it renders the experiment internally valid. A recent debate[23] has clarified which options do so. The options should allow for economic consequences (Lichters et al., 2015a), which rules out hypothetical options as well as options that are costly and difficult to implement, such as the cars, TV sets and apartments routinely used in the consumer research literature. The researcher should also have good reason to believe that subjects perceive the options as intended. For example, not everyone knows that the T-bone steaks used by Yang and Lynn (2014) are dominated by Porterhouse steaks (Simonson, 2014); some might even prefer the supposedly dominated T-bone decoys. The problem here stems from the use of complex options with many attributes, which requires the researcher to arbitrarily select two attributes out of all potential ones (an approach criticised by Frederick et al., 2014). People, however, might have preferences for the attributes not selected (Huber et al., 2014). Simple binary gambles easily solve these issues: they can be incentivised, since subjects can play their chosen gamble at the end of the experiment and be paid accordingly; and there is no need to arbitrarily select two attributes because simple binary gambles have two natural attributes, probability and money.

The second reason to use gambles is that they hold a special place for economists. They have proven to be a popular proving ground for theories (Starmer, 2000) and knowing whether the attraction effect might manifest itself when one tries to, say, elicit risk preferences, is important for the design of experiments and the interpretation of results. Further, testing the explanations to the attraction effect might give us hints on what to incorporate in future theories of risky choice.

As for external validity, gambles readily appear in domains such as financial and medical decision-making. The results obtained with gambles can thus be directly applied to these domains. It is true that the abstractness of gambles might dampen our ability to generalise to other domains; nonetheless, more concrete options, such as medical coverage or loans, would in turn hinder internal validity, since the requirements outlined above would be hard to satisfy; and for any selected option one could always ask how much exactly the results generalise. All in all, in the

[23]Frederick et al. (2014) and Yang and Lynn (2014) failed to replicate the attraction effect, which prompted replies by Huber et al. (2014) and Simonson (2014) in the same issue of the *Journal of Marketing Research*. Lichters et al. (2015a,b) added to the debate by providing guidelines for future attraction-effect experiments.

tension between internal and external validity (Schram, 2005; Starmer, 1999) I have favoured the former.

B.2 Sample choice task

In one of the envelopes, the options are:

	1 80	81 100
P	£7	£0

	1 55	56 100
Q	£12.5	£0

If these options are the ones in my envelope, give me option: (write P or Q in the box)

- writing **P** means that I will receive £7 if the dice throw yields a number from 1 to 80, and £0 otherwise;
- writing **Q** means that I will receive £12.5 if the dice throw yields a number from 1 to 55, and £0 otherwise.

B.3 Procedure

Subjects waited outside the laboratory in line. An experimenter controlled their student card against the list generated by ORSEE and let them enter. Once inside the laboratory (Picture 5a) they were greeted by a second experimenter who asked them to draw a number from a pouch. This number determined their seat number as well as their group, as defined in Table 2 of the main text. They were then directed to take an envelope from the box corresponding to their group (Picture 5b). In each box were approximately 190 envelopes (Picture 5c). Inside each envelope was a piece of paper describing one of the 28 choice tasks that a member of the group assigned to this box could encounter in the experiment. Subjects were instructed to take this envelope with them but to not open it – all subjects obeyed this instruction. The draw of the envelope was without replacement.

Subjects then went to their assigned desk. There they found the instructions, a pen and two 10-sided dice (Picture 5d). Once everyone was seated the experimenter started reading the instructions, which are found in Appendix B.4. The experimenters also controlled subjects' answers to the control questions. Then, the experimenters distributed the first decision booklet and the subjects started completing the 14 tasks contained inside. Depending on their seat number and so their group, subjects received different booklets. The booklets differed in the decoys seen, again as described in Table 2 of the main text. Appendix B.2 provides a sample of a choice task found in the booklets.

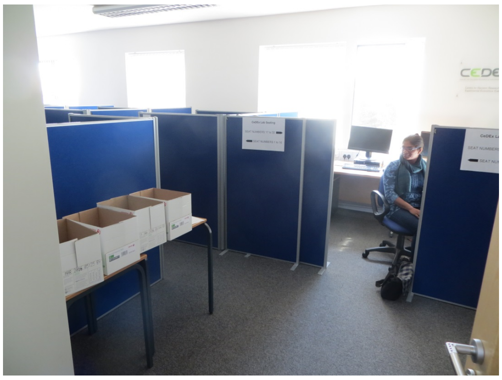
In the instructions subjects were instructed to raise their hand when they would finish the first booklet. As soon as a subject did the experimenters went to see her, collected the first booklet and gave her the second booklet containing 14 additional choice tasks. On average subjects took 15 minutes to complete each booklet.

Subjects were further instructed to raise their hand when they would finish the second booklet. Once everyone had finished the experimenters started the payment phase. When an experimenter came to a subject the experimenter gave her her first booklet. Then, the experimenter asked the subject to open the envelope and they flipped through the two booklets to find the choice task described on the piece of paper. Together they looked at the gamble the subject chose in this particular choice task and the experimenter read out loud the text at the bottom of the choice task (Appendix B.2) describing what would happen depending on the result of the dice. The experimenter asked the subject to draw her dice and, depending on the result, the subject won or lost. In any case the subject also received a show-up fee, of which they were not aware before this moment. The experimenter wrote the final payoff of the subject on a piece of paper, which the subject took to the centre of the room where a third experimenter collected it and paid the subject accordingly. Finally the subject exited the room

In total the experiment took about 1 hour.

B.4 Instructions

The next pages reproduces the instructions as they were seen by the subjects – they are here reproduced two-pages-on-one to save space.



(a) Entering the laboratory.

(b) Boxes containing the envelopes.

(c) Inside a box.

(d) A subject's desk.

Figure 5: Pictures of the experiment.

Instructions

Welcome to the experiment. Please switch off your electronic devices and remain silent. If you have a question at any time, raise your hand and an experimenter will come to your desk to answer it.

* * *

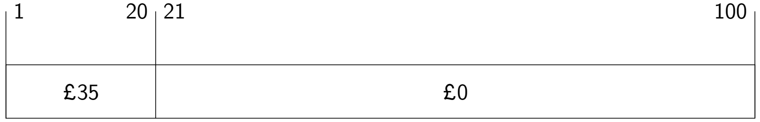
In this experiment, you will face options that give you chances to win amounts of money. An option is for example a 20%-chance of winning £35.

To represent the chances of winning, we will refer to the dice placed on your desk, which you are welcome to examine as much as you want throughout the experiment. One die is used for the tens and the other for the units. Throwing the dice together and adding the results yields a number from 1 to 100. For example, the throw below is 31:

The next one is 8:

100 is obtained by getting zeros on both dice. Each ten and each unit is equally likely, so *each number from 1 to 100 is also equally likely.*

In terms of the dice, the 20%-chance of winning £35 is equivalent to £35 for numbers from 1 to 20, and £0 for numbers from 21 to 100. We will represent it as follows:



This means that, if the dice throw yields a number from 1 to 20, you will receive £35. If it yields a number from 21 to 100, you will receive £0.

* * *

All tasks in this experiment will ask you to select one from a set of two or three such options. The options in these tasks are always gambles which will feature different chances of winning various amounts of money. You will record your selected option in each of these tasks in decision booklets, which we will distribute soon. There will be a different task of this form on each page.

You will play one of the gambles that you select for real at the end of the experiment, meaning that you might win some money in this real task. The task that is real for you has already been selected in the following way: When you entered the room, you picked one from a set of envelopes. Each envelope contains a piece of paper describing one of the tasks that you will face in your booklet. Any one of the tasks that you face could be for real, but you will not know which one is for real until the end of the experiment.

At the end of the experiment, an experimenter will come to your desk and open your envelope. The piece of paper in the envelope will show the task that will be real for you. The experimenter will then look in your decision booklet to see which option you picked in this task. That option will be a gamble which will specify an amount of money that you can win depending on the throw of the dice. You will then roll the dice to see whether you earn money from the real task or not. If you win, you will be paid in cash the amount specified in your chosen option.

So, as you respond to the tasks remember that for each task, the option that you pick could turn out to be the one that you play for real at the end of the experiment. Because of this, we suggest that you treat each task as if it is for real and as if it is the only task you face since at the end of the experiment you will only face one task for real (i.e. the one contained in the envelope you now have).

Let us illustrate this with an example.

Imagine that one of the pages of the decision booklet is as follows: (The presentation will be the same, but the options will be different.)

Page A

In one of the envelopes, the options are:

	1 – 60	61 – 100
P	£12	£0

	1 – 40	41 – 100
Q	£25	£0

If these options are the ones in my envelope, give me option: (write P or Q in the box)

$\boxed{P}$

- writing **P** means that I will receive £12 if the dice throw yields a number from 1 to 60, and £0 otherwise;
- writing **Q** means that I will receive £25 if the dice throw yields a number from 1 to 40, and £0 otherwise.

This example assumes that you chose option P.
Then, imagine that another page of the decision booklet is:

Page B

In one of the envelopes, the options are:

	1 – 30	31 – 100
P	£20	£0

	1 – 50	51 – 100
Q	£10	£0

	1 – 20	21 – 100
R	£40	£0

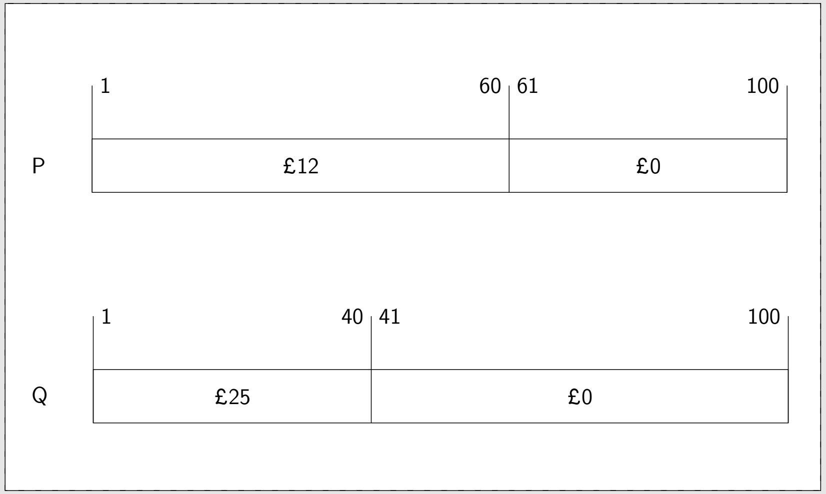
If these options are the ones in my envelope, give me option: (write P, Q or R in the box)

$\boxed{R}$

- writing **P** means that I will receive £20 if the dice throw yields a number from 1 to 30, and £0 otherwise;
- writing **Q** means that I will receive £10 if the dice throw yields a number from 1 to 50, and £0 otherwise;
- writing **R** means that I will receive £40 if the dice throw yields a number from 1 to 20, and £0 otherwise.

Here, we assume that you chose option R.

At the end of the experiment, the experimenter comes to your desk and opens your envelope. Suppose that your envelope contains:



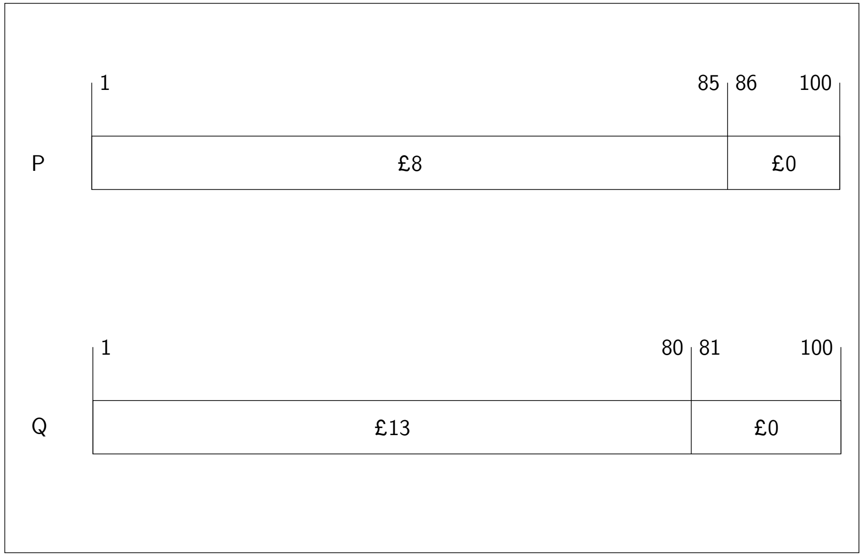
The experimenter will look for these options in your decision booklet. They were in Page A above and we assumed that you chose option P. The experimenter will then throw the dice. In accordance with what is written in the decision booklet, you would get £12 if the throw yields a number from 1 to 60, and £0 if it yields a number from 61 to 100.

Questions

We want to make sure you understand the procedure fully, so we have designed two questions to test your understanding. These questions have no bearing on the rest of the experiment. Please answer them and raise your hand when you have finished; an experimenter will come to verify your responses.

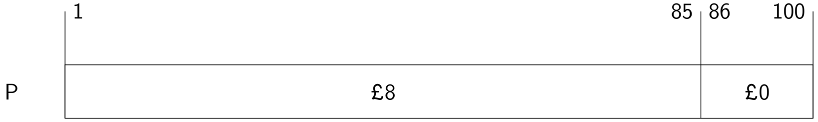
Question 1

Imagine that the options in your envelope are:



These two options are the ones on the following page of the decision booklet:

In one of the envelopes, the options are:



If these options are the ones in my envelope, give me option: (write P or Q in the box)

- writing **P** means that I will receive £8 if the dice throw yields a number from 1 to 85, and £0 otherwise;
- writing **Q** means that I will receive £13 if the dice throw yields a number from 1 to 80, and £0 otherwise.

What happens if:

- you write **P** and the dice throw yields **81**? ....
- you write **P** and the dice throw yields **91**? ....
- you write **Q** and the dice throw yields **81**? ....
- you write **Q** and the dice throw yields **10**? ....

Question 2

Suppose that you encounter the next two pages in your decision booklet and make the following choices:

Page A

In one of the envelopes, the options are:

	1–70	71–100
P	£14	£0

	1–20	21–100
Q	£35	£0

If these options are the ones in my envelope, give me option: (write P or Q in the box)

Q

- writing **P** means that I will receive £14 if the dice throw yields a number from 1 to 70, and £0 otherwise;
- writing **Q** means that I will receive £35 if the dice throw yields a number from 1 to 20, and £0 otherwise.

Page B

In one of the envelopes, the options are:

	1–20	21–100
P	£50	£0

	1–50	51–100
Q	£12	£0

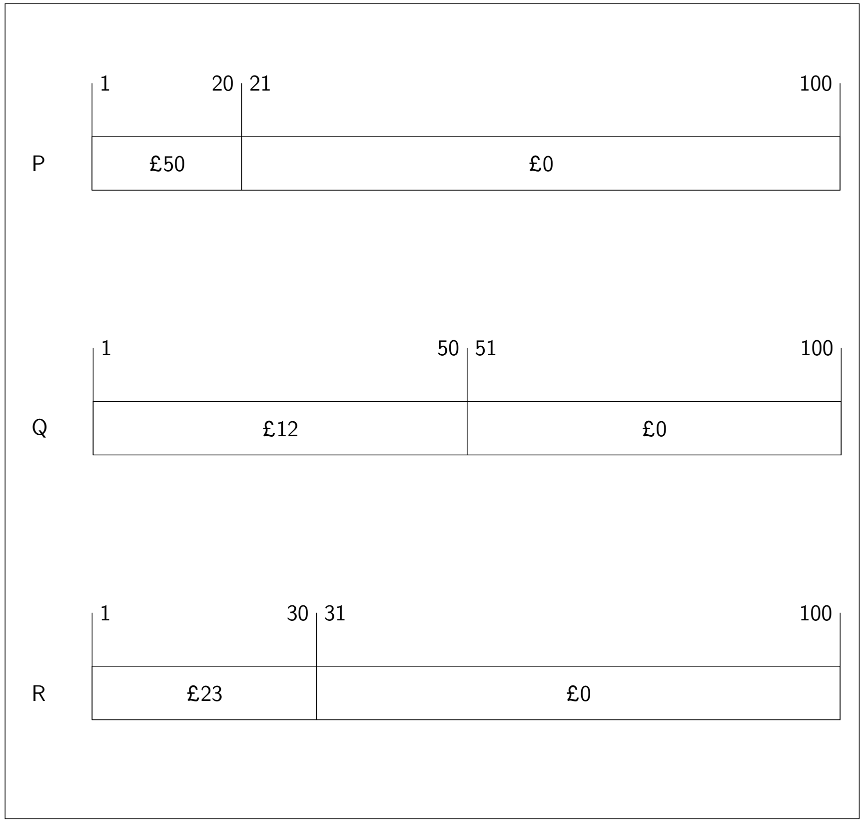
	1–30	31–100
R	£23	£0

If these options are the ones in my envelope, give me option: (write P, Q or R in the box)

R

- writing **P** means that I will receive £50 if the dice throw yields a number from 1 to 20, and £0 otherwise;
- writing **Q** means that I will receive £12 if the dice throw yields a number from 1 to 50, and £0 otherwise;
- writing **R** means that I will receive £23 if the dice throw yields a number from 1 to 30, and £0 otherwise.

If the options in your envelope are:



Which option is going to be played for real? ....

If the dice throw yields 24, what happens? ....
....

We are now ready to distribute the first decision booklet. You can start completing it as soon as you get it. When you have finished, raise your hand; we will collect your booklet and give you a second one for you to complete.

Appendix C Result tables

This Appendix provides disaggregated and detailed results corresponding to all aggregated results encountered in the main text. The Tables are as follows:

- Table 5 reports within-subject results corresponding Figure 2 top-left in the main text;
- Table 6 reports between-subject results corresponding Figure 2 top-right and bottom-left in the main text;
- Table 7 reports within-subject results with ω^*;
- Table 8 reports between-subject results with ω^*;

The different Attraction Effects are computed as follows:

- *Within-subject Attraction Effect WASRP*: from Table 5,
  - when the decoy of ω_p is seen first (e.g. $\omega'_p \to \omega'_£$), it is the percentage of subjects who switch from ω_p to $\omega_£$ (column ω_p then $\omega_£$) minus the percentage of subjects who switch from $\omega_£$ from ω_p (column $\omega_£$ then ω_p);
  - when the decoy of $\omega_£$ is seen first (e.g. $\omega'_£ \to \omega'_p$), it is the percentage of subjects who switch from $\omega_£$ to ω_p (column $\omega_£$ then ω_p) minus the percentage of subjects who switch from ω_p from $\omega_£$ (column ω_p then $\omega_£$).

  Table 7 uses a similar definition but the test is two-sided since there is no expected effect.
- *Between-subject Attraction Effect WASRP*: from Table 6,
  - it is the percentage of subjects who choose ω_p when the decoy is related to ω_p (column Decoy under ω_p) minus the percentage of subjects who choose ω_p when the decoy is related to $\omega_£$. *Note that this last percentage is not displayed directly on the Table*: it is roughly 100 minus the percentage of subjects who choose $\omega_£$ when the decoy is related to $\omega_£$ (column Decoy under $\omega_£$) but not exactly since some subjects chose the Decoy and these subjects are not displayed on the Table. However since the Decoy was very rarely chosen (less than 10 times across the whole experiment) this has a small impact on the numbers. The Figures in the main text report exact percentages, that is they take care of these few subjects who chose the Decoy.
  - It is also the percentage of subjects who choose $\omega_£$ when the decoy is related to $\omega_£$ (column Decoy under $\omega_£$) minus the percentage of subjects who choose $\omega_£$ when the decoy is related to ω_p. The same remark applies.

  The result of the χ^2 test is reported in the rightmost column.
- *Between-subject Attraction Effect Regularity*: from Table 6,
  - when the decoy is related to ω_p (e.g. ω'_p), it is the percentage of subjects who choose ω_p when there is a decoy (column Decoy under ω_p) minus the

percentage of subjects who choose ω_p when there is no decoy (column No decoy under ω_p);

– when the decoy is related to $\omega_£$ (e.g. $\omega'_£$), it is the percentage of subjects who choose $\omega_£$ when there is a decoy (column Decoy under $\omega_£$) minus the percentage of subjects who choose $\omega_£$ when there is no decoy (column No decoy under $\omega_£$).

Table 8 uses a similar definition but here the test is two-sided since there is no expected effect.

Table 5: Percentage (n) of choice patterns by class of decoy and presentation order (within-subject).

Set		ω_p then ω_p		$\omega_£$ then $\omega_£$		ω_p then $\omega_£$		$\omega_£$ then ω_p		χ^2		ω_p then ω_p		$\omega_£$ then $\omega_£$		ω_p then $\omega_£$		$\omega_£$ then ω_p		χ^2
a	$\omega'_p \to \omega'_£$	43.1	(22)	33.3	(17)	11.8	(6)	9.8	(5)	0.09	$\omega'_£ \to \omega'_p$	36.5	(19)	40.4	(21)	7.7	(4)	15.4	(8)	1.33
f		32.7	(17)	46.1	(24)	11.5	(6)	3.9	(2)	2.00†		41.2	(21)	29.4	(15)	2.0	(1)	25.5	(13)	10.29††††
k		61.1	(33)	11.1	(6)	20.4	(11)	7.4	(4)	3.27††		72.0	(36)	12.0	(6)	6.0	(3)	10.0	(5)	0.50
n		34.0	(17)	46.0	(23)	8.0	(4)	12.0	(6)	0.40		42.6	(23)	46.3	(25)	3.7	(2)	7.4	(4)	0.67
Aggregate		43.0	(89)	33.8	(70)	13.0	(27)	8.2	(17)	2.27†		47.8	(99)	32.4	(67)	4.8	(10)	14.5	(30)	10.00††††
e	$\omega''_p \to \omega''_£$	51.9	(28)	25.9	(14)	13.0	(7)	9.3	(5)	0.33	$\omega''_£ \to \omega''_p$	56.0	(28)	22.0	(11)	6.0	(3)	16.0	(8)	2.27†
i		42.3	(22)	38.5	(20)	13.5	(7)	5.8	(3)	1.60		60.8	(31)	11.8	(6)	7.8	(4)	19.6	(10)	2.57†
j		62.8	(32)	17.7	(9)	11.8	(6)	7.8	(4)	0.40		53.9	(28)	34.6	(18)	1.9	(1)	9.6	(5)	2.67†
m		48.0	(24)	30.0	(15)	6.0	(3)	16.0	(8)	2.27‡		46.3	(25)	25.9	(14)	13.0	(7)	14.8	(8)	0.07
Aggregate		51.2	(106)	28.0	(58)	11.1	(23)	9.7	(20)	0.21		54.1	(112)	23.7	(49)	7.3	(15)	15.0	(31)	5.57†††
b	$\omega^*_p \to \omega^*_£$	31.4	(16)	47.1	(24)	7.8	(4)	13.7	(7)	0.82	$\omega^*_£ \to \omega^*_p$	43.1	(22)	33.3	(17)	7.8	(4)	15.7	(8)	1.33
c		36.0	(18)	52.0	(26)	2.0	(1)	10.0	(5)	2.67‡		37.0	(20)	44.4	(24)	9.3	(5)	9.3	(5)	0.00
d		60.8	(31)	27.5	(14)	3.9	(2)	7.8	(4)	0.67		44.2	(23)	40.4	(21)	5.8	(3)	9.6	(5)	0.50
g		49.0	(25)	25.5	(13)	2.0	(1)	23.5	(12)	9.31‡‡‡		40.4	(21)	42.3	(22)	3.9	(2)	13.5	(7)	2.78††
h		29.6	(16)	50.0	(27)	5.6	(3)	14.8	(8)	2.27‡		10.0	(5)	54.0	(27)	22.0	(11)	14.0	(7)	0.89
l		38.0	(19)	44.0	(22)	6.0	(3)	12.0	(6)	1.00		44.4	(24)	35.2	(19)	13.0	(7)	7.4	(4)	0.82
Aggregate		40.7	(125)	41.0	(126)	4.6	(14)	13.7	(42)	14.00‡‡‡‡		36.7	(115)	41.5	(130)	10.2	(32)	11.5	(36)	0.24

Notes. Subjects choosing the decoy not shown.
ω_p then ω_p: subject chooses ω_p in the first booklet and ω_p in the second booklet.
$\omega'_p \to \omega'_£$: ω'_p added to $\{\omega_p, \omega_£\}$ in the first booklet and $\omega'_£$ in the second.
McNemar tests. One, two, three and four symbols indicate significance at $\alpha = 0.1$, 0.05, 0.01 and 0.001.
†: H_a: (1) p.16; ‡: inequality reversed.

Table 6: Percentage (n) choosing a gamble type as a function of the decoy (between-subject).

Set		ω_p						$\omega_{£}$					χ^2
		No decoy		Decoy		χ^2		No decoy		Decoy		χ^2	
a		51.0	(53)	53.4	(55)	0.18		49.0	(51)	50.5	(52)	0.04	0.40
f		36.5	(38)	56.3	(58)	$8.98^{\dagger\dagger\dagger}$		63.5	(66)	56.3	(58)	0.78	4.46^{**}
k	ω'_p	79.6	(82)	81.7	(85)	0.15	$\omega'_{£}$	20.4	(21)	26.9	(28)	1.22	2.23^{*}
n		49.5	(51)	46.2	(48)	0.23		50.5	(52)	53.9	(56)	0.23	0.00
Aggregate		54.1	(224)	59.4	(246)	$2.78^{\dagger\dagger}$		45.9	(190)	46.9	(194)	0.12	4.03^{**}
e		64.1	(66)	68.3	(71)	0.41		35.9	(37)	38.5	(40)	0.14	1.03
i		54.8	(57)	68.0	(70)	$3.78^{\dagger\dagger}$		45.2	(47)	41.8	(43)	0.25	2.09^{*}
j	ω''_p	54.8	(57)	68.9	(71)	$4.37^{\dagger\dagger}$	$\omega''_{£}$	45.2	(47)	36.9	(38)	1.47	0.78
m		58.3	(60)	57.7	(60)	0.01		41.8	(43)	38.5	(40)	0.23	0.32
Aggregate		58.0	(240)	65.7	(272)	$5.24^{\dagger\dagger}$		42.0	(174)	38.9	(161)	0.85	1.88^{*}
b		41.4	(43)	49.0	(50)	1.22		58.7	(61)	52.4	(54)	0.81	0.04
c		52.4	(54)	42.3	(44)	$2.13^{\ddagger}$		47.6	(49)	53.9	(56)	0.81	0.31
d		43.7	(45)	59.2	(61)	$4.98^{\dagger\dagger}$		56.3	(58)	40.8	(42)	$4.98^{\ddagger\ddagger}$	0.00
g	ω^*_p	47.1	(49)	52.4	(54)	0.58	$\omega^*_{£}$	52.9	(55)	41.8	(43)	$2.57^{\ddagger}$	0.71
h		37.9	(39)	29.8	(31)	1.50		62.1	(64)	61.5	(64)	0.01	1.73^{*}
l		54.4	(56)	48.1	(50)	0.82		45.6	(47)	46.2	(48)	0.01	0.69
Aggregate		46.1	(286)	46.8	(290)	0.05		53.9	(334)	49.4	(307)	$2.44^{\ddagger}$	$1.78^{\star}$

Notes. χ^2 tests. One, two and three symbols indicate significance at $\alpha = 0.1$, 0.05 and 0.01.
†: H_a: (3) p. 16; ‡: inequality reversed.
*: H_a: (2) p. 16; *: inequality reversed.

Table 7: Percentage (n) of choice patterns with ω^* by presentation order (within-subject).

$\{\omega_p, \omega_{\pounds}\} \rightarrow \{\omega_p, \omega_{\pounds}, \omega^*\}$

Set	ω_p then ω_p		$\omega_{\pounds}$ then $\omega_{\pounds}$		ω_p then $\omega_{\pounds}$		$\omega_{\pounds}$ then ω_p		χ^2
a	36	(18)	38	(19)	10	(5)	16	(8)	0.69
b	29.6	(16)	44.4	(24)	14.8	(8)	11.1	(6)	0.29
c	51.0	(26)	33.3	(17)	3.9	(2)	11.8	(6)	2.00
d	34.7	(17)	40.8	(20)	10.2	(5)	14.3	(7)	0.33
e	50	(26)	38.5	(20)	7.7	(4)	3.9	(2)	0.67
f	27.8	(15)	38.9	(21)	13.0	(7)	20.4	(11)	0.89
g	32	(16)	44	(22)	4	(2)	20	(10)	5.33^{**}
h	25	(13)	59.6	(31)	7.7	(4)	7.7	(4)	0.00
i	46.3	(25)	29.6	(16)	9.3	(5)	14.8	(8)	0.69
j	42	(21)	40	(20)	4	(2)	14	(7)	2.78^{*}
k	63.5	(33)	23.1	(12)	7.7	(4)	5.8	(3)	0.14
l	45.1	(23)	27.5	(14)	13.7	(7)	11.8	(6)	0.08
m	56.9	(29)	23.5	(12)	3.9	(2)	11.8	(6)	2.00
n	45.1	(23)	31.4	(16)	5.9	(3)	17.7	(9)	3.00^{*}
Aggregate	41.8	(301)	36.6	(264)	8.3	(60)	12.9	(93)	7.12^{***}

$\{\omega_p, \omega_{\pounds}, \omega^*\} \rightarrow \{\omega_p, \omega_{\pounds}\}$

Set	ω_p then ω_p		$\omega_{\pounds}$ then $\omega_{\pounds}$		ω_p then $\omega_{\pounds}$		$\omega_{\pounds}$ then ω_p		χ^2
a	46.3	(25)	38.9	(21)	5.6	(3)	9.3	(5)	0.50
b	32	(16)	52	(26)	10	(5)	6	(3)	0.50
c	30.8	(16)	48.1	(25)	1.9	(1)	19.2	(10)	7.36^{***}
d	40.7	(22)	42.6	(23)	14.8	(8)	1.9	(1)	5.44^{**}
e	62.8	(32)	19.6	(10)	9.8	(5)	7.8	(4)	0.11
f	26.0	(13)	54	(27)	14	(7)	6	(3)	1.60
g	40.7	(22)	35.2	(19)	7.4	(4)	14.8	(8)	1.33
h	27.5	(14)	47.1	(24)	9.8	(5)	15.7	(8)	0.69
i	48	(24)	34	(17)	12	(6)	6	(3)	1.00
j	50	(27)	27.8	(15)	9.3	(5)	13.0	(7)	0.33
k	76.5	(39)	7.8	(4)	3.9	(2)	11.8	(6)	2.00
l	38.5	(20)	48.1	(25)	3.9	(2)	7.7	(4)	0.67
m	46.2	(24)	42.3	(22)	5.8	(3)	5.8	(3)	0.00
n	42.3	(22)	46.2	(24)	5.8	(3)	5.8	(3)	0.00
Aggregate	43.5	(316)	38.8	(282)	8.1	(59)	9.4	(68)	0.64

Notes. Subjects choosing the decoy not shown.
ω_p then ω_p: subject chooses ω_p in the first booklet and ω_p in the second booklet.
McNemar tests. One, two and three symbols indicate significance at $\alpha = 0.1$, 0.05 and 0.01.
*: H_a: (4) p. 17

Appendix D Details on the structural model

D.1 Deriving the log-likelihood

Here I will derive the log-likelihood for Tserenjigmid's (2018) model; the other models are simpler and can be similarly derived by following the same steps. Denote by i, j, k the options, n the subjects and t the tasks. Collect the the subject-specific parameters—α_n, $\gamma_{x,n}$ and $\gamma_{p,n}$—in a vector θ_n. As we saw in the main text, and omitting A to simplify the notation, a subject n chooses ω_{it} over ω_{jt} if and only if

$$\mathrm{U_T}(\omega_{it}|\theta_n) - \mathrm{U_T}(\omega_{jt}|\theta_n) = \nabla^{ij}_{nt}(\theta_n) > 0.$$

The strong utility model is obtained by appending ϵ_{nt}:

$$\nabla^{ij}_{nt}(\theta_n) + \epsilon_{nt} > 0,$$

with ϵ_{nt} a realisation of $\epsilon \sim \mathcal{N}(0, \sigma^2)$. Therefore, conditional on θ_n, the probability of observing a subject n in task t choosing ω_{it} over ω_{jt} when there are two options is

$$\Pr(\omega_{it}|\theta_n) = \Phi\Big(\frac{\nabla^{ij}_{nt}(\theta_n)}{\sigma}\Big)$$

with Φ the standard normal c.d.f.

When there are three options, the subject chooses ω_{it} if ω_{it} wins over both ω_{jt} and ω_{kt}, so the probability becomes

$$\Pr(\omega_{it}|\theta_n) = \Phi\Big(\frac{\nabla^{ij}_{nt}(\theta_n)}{\sigma}\Big)\Phi\Big(\frac{\nabla^{ik}_{nt}(\theta_n)}{\sigma}\Big).$$

Assume further that the subject trembles with probability κ, so the probability is

$$\Pr(\omega_{it}|\theta_n) = (1-\kappa)\Phi\Big(\frac{\nabla^{ij}_{nt}(\theta_n)}{\sigma}\Big) + \frac{\kappa}{2}$$

when there are two options and

$$\Pr(\omega_{it}|\theta_n) = (1-\kappa)\Phi\Big(\frac{\nabla^{ij}_{nt}(\theta_n)}{\sigma}\Big)\Phi\Big(\frac{\nabla^{ik}_{nt}(\theta_n)}{\sigma}\Big) + \frac{\kappa}{3}$$

when there are three.

Denote by ω_t the option actually chosen in task t. The probability to observe

Table 8: Percentage (n) choosing ω_p with ω^* (between-subject).

Set		No decoy		Decoy		χ^2
a	ω^*	51.0	(53)	51.9	(54)	0.02
b		41.4	(43)	41.4	(43)	0.00
c		52.4	(54)	47.6	(49)	0.49
d		43.7	(45)	51.9	(54)	1.41
e		64.1	(66)	63.1	(65)	0.01
f		36.5	(38)	44.2	(46)	1.28
g		47.1	(49)	50.0	(52)	0.24
h		37.9	(39)	35.0	(36)	0.19
i		54.8	(57)	60.6	(63)	0.71
j		54.8	(57)	57.7	(60)	0.18
k		79.6	(82)	74.8	(77)	0.69
l		54.4	(56)	49.5	(51)	0.31
m		58.3	(60)	60.2	(62)	0.21
n		49.5	(51)	55.3	(57)	0.70
Aggregate		51.8	(750)	53.1	(769)	0.62

Notes. χ^2 tests. One, two and three symbols indicate significance at $\alpha = 0.1$, 0.05 and 0.01.
H_a: (5) p. 17

the subject making the sequence of choices $\{\omega_t\}_{t=1}^{28}$, given our assumptions on ϵ, is

$$\Pr(\{\omega_t\}_{t=1}^{28}|\theta_n) = \prod_{t=1}^{28} \Pr(\omega_t|\theta_n), \tag{7}$$

which is the likelihood of subject n conditional on θ_n

We do not know θ_n; we assume it is distributed over the population according to

$$\theta_n = \begin{pmatrix} \alpha \\ \gamma_x \\ \gamma_p \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} \mu_\alpha \\ \mu_{\gamma_x} \\ \mu_{\gamma_p} \end{pmatrix}, \Omega\right)$$

where Ω is the covariance matrix,

$$\Omega = \begin{pmatrix} \eta_\alpha^2 & \mathrm{Cov}(\alpha, \gamma_x) & \mathrm{Cov}(\alpha, \gamma_p) \\ \mathrm{Cov}(\alpha, \gamma_x) & \eta_{\gamma_x}^2 & \mathrm{Cov}(\gamma_x, \gamma_p) \\ \mathrm{Cov}(\alpha, \gamma_p) & \mathrm{Cov}(\gamma_x, \gamma_p) & \eta_{\gamma_p}^2 \end{pmatrix}.$$

Denote the joint density by $f(\theta_n|\mu_\alpha, \mu_{\gamma_x}, \mu_{\gamma_p}, \Omega)$.

We could keep the full covariance matrix Ω, but as mentioned in the main text we need to be parsimonious. So assume that α, γ_x, and γ_p are uncorrelated, so Ω is a diagonal matrix. The joint density thus boils down to $f(\theta_n|\mu_\alpha, \mu_{\gamma_x}, \mu_{\gamma_p}, \eta_\alpha, \eta_{\gamma_x}, \eta_{\gamma_p})$.

We can now derive from the conditional likelihood (7) the marginal likelihood by integrating over θ_n:

$$\mathcal{L}_n = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} \prod_{t=1}^{28} \Pr(\omega_t|\theta_n) f(\theta_n|\mu_\alpha, \mu_{\gamma_x}, \mu_{\gamma_p}, \eta_\alpha, \eta_{\gamma_x}, \eta_{\gamma_p})\, \mathrm{d}_\alpha\, \mathrm{d}_{\gamma_x}\, \mathrm{d}_{\gamma_p}\, .$$

For the sample log-likelihood we take the log and sum over subjects:

$$\log \mathcal{L} = \sum_{n=1}^{207} \ln \mathcal{L}_n\, .$$

D.2 Maximum simulated likelihood

Because of the integrals, $\log \mathcal{L}$ often does not have a closed-form solution. There are two approaches: quadrature and simulation. Quadrature allows one to write down an analytical approximation (see Wilcox, 2008, for an example), but it becomes cumbersome when we have more than one integral, and for Tserenjigmid (2018) we have three. Simulation can be used with any number of integrals and this is the approach I follow.

Approaching integrals with simulation leads to the method of simulated likelihood. In short, it amounts to taking random draws to simulate the distribution, then taking the mean over all draws to approximate the integral. The draws are typically Halton draws, which have better properties than purely random draws. Further details can be found in Train (2009) and Moffatt (2016, Chapters 10 and 13).

D.3 Contextual errors

In the main text I followed the strong error story and assumed that $\epsilon \sim \mathcal{N}(0, \sigma^2)$. Here I consider the contextual error story whereby the standard deviation of ϵ is instead $\sigma\sqrt{u(x_{max}) - u(x_{min})}$, with x_{max} and x_{min} the largest and smallest outcomes in A. Wilcox (2008), in his comparison of the different stochastic models, found the contextual error story to be the winner. It is particularly fitting here: it could be that the decoys do not change preferences but, by changing the difference between the smallest and the largest outcome, create more choice error.

The new estimates are shown in Table 9. They are similar to the ones found in Table 4 in the main text. The standard deviation of γ_x is negative, but it is not significantly different from 0 ($\chi^2(1) = 1.88$, $p = 0.1706$).

There are two interesting observations. First, the noise σ is lower with contextual errors than with strong errors, which indicates that the former captures something that is missing from the latter.

Second, the fit of expected utility dramatically improves with contextual errors, but the one of Landry and Webb (2019) and Tserenjigmid (2018) worsens. It is not entirely clear why this happens. Wilcox (2008) found that contextual errors improve the fit of all theories, but the theories he considered are not theories aimed at capturing context-dependent choice. One possibility is that applying contextual errors to a context-dependent model is ill-founded. Context-dependent models such as Landry and Webb (2019) and Tserenjigmid (2018) already have the apparatus to take into account choice that varies with the context, and so might not need the help of context-dependent errors. Another possibility is that the error term is misspecified. As I wrote above I have used $\sigma\sqrt{u(x_{max}) - u(x_{min})}$ for all theories. It is clear that u is the utility of money in expected utility, but it is not clear what is the utility of money irrespective of the context in Landry and Webb (2019) and Tserenjigmid (2018). It might be that, for this class of models, the error term needs to be specified differently.

D.4 Adding experience

As we saw in Section 5.4 of the main text there are some order effects, and we could be concerned about the robustness of the estimation results if we do not take them into account. Here I introduce experience and show this is not a major concern.

Order effects could in principle affect any of the parameters mentioned so far. Since the results from ω^* strongly suggest that subjects' risk preference change

Table 9: Results from the maximum simulated likelihood estimation, with contextual errors.

		EU	U_{LW}	U_T
α	mean	0.5860	0.6424	0.6614
		(0.0174)	(0.0166)	(0.0154)
	s.d.	0.2514	0.2539	0.2255
		(0.0174)	(0.0172)	(0.0155)
γ_x	mean	-	-	1.0043
		-	-	(0.0068)
	s. d.	-	-	-0.0168
		-	-	(0.0122)
γ_p	mean	-	-	0.9931
		-	-	(0.0077)
	s. d.	-	-	0.0356
				(0.0126)
σ		0.1638	0.0384	0.0507
		(0.0070)	(0.0013)	(0.0019)
κ		0.0067	0.0120	0.0125
		(0.0024)	(0.0032)	(0.0032)
$\log \mathcal{L}$		-2758.4181	-2887.8610	-2805.6535

Notes. EU: expected utility model; U_{LW}: Landry and Webb (2019); U_T: Tserenjigmid (2018).
Standard errors in parentheses.
200 subjects, 28 observations per subject.
Number of Halton draws used: 50.

Table 10: Results from the maximum simulated likelihood estimation, with experience.

		EU	Landry and Webb (2019)
α_0	mean	0.6002	0.6306
		(0.0140)	(0.0209)
	s.d.	0.1844	0.3092
		(0.0113)	(0.0196)
α_d		-0.0014	-0.0020
		(0.0004)	(0.0008)
α_{28}		0.5772	0.5972
		(0.0135)	(0.0198)
σ		0.1638	0.0687
		(0.0045)	(0.0025)
κ		0.0074	0.0078
		(0.0026)	(0.0027)
$\log \mathcal{L}$		-2841.6334	-2831.5511

Notes. EU: expected utility model; U_{LW}: Landry and Webb (2019); U_T: Tserenjigmid (2018).
Standard errors in parentheses.
200 subjects, 28 observations per subject.
Number of Halton draws used: 50.
α_0: risk aversion at the start of the experiment; α_d: task-to-task decay of risk aversion; α_{28}: risk aversion at the end of the experiment.

through the experiment, I look at the effect of order on α. More specifically, still denoting by $t \in \{1, \ldots, 28\}$ the task order, describe the change in risk aversion with $\alpha = \alpha_0 \exp(\alpha_d \times t)$. α_0 is the risk aversion at the beginning of the experiment, and α_d indicates its task-to-task decay.

I then re-estimate the simple expected utility model and Landry and Webb (2019), adding only this experience element.[24] The results are displayed in Table 10. Compared to Table 4 in the main text, we see that the estimates are similar, and that the log-likelihoods are almost the same, indicating that the order effect, while present, plays only a marginal role. As expected, the α reported in Table 4 is essentially the average of α_0 and α_{28} reported in Table 10.

[24] The addition of experience to Tserenjigmid (2018) did not result in a converging model.

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