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Do emotional carryover effects carry over?

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ABSTRACT

Existing research has demonstrated carryover effects whereby emotions generated in one context influence decisions in other, unrelated ones. We examine the carryover effect in relation to valuations of risky and ambiguous lotteries with a novel focus on the comparison of carryovers arising from a targeted stimulus (designed to elicit a specific emotion) with those arising from a naturalistic stimulus (designed to produce a more complex emotional response). We find carryover effects using both types of stimuli, but they are stronger for the naturalistic stimulus and in the context of ambiguity, providing a proof of concept that carryover effects can be observed when moving away from highly stylised settings. These effects are also gender specific with only males being susceptible. To probe the emotional foundations of the carryover effect, we conduct analysis relating individual self-reports of emotions to valuation behaviour. Our results cast doubt on some previously claimed links between specific incidental emotions and risk taking.

1. Introduction

This paper examines the role of *incidental* emotions which arise from one context but "carry over" to influence behaviour in a different, seemingly unrelated, context. Specifically, we report an experiment designed to compare the impact of different emotional priming tasks on individuals' subsequent decisions involving risk and ambiguity. The key novelty of our approach lies in testing whether carryover effects from a standard prime that elicits a single targeted emotion (fear) generalise when a more *naturalistic* prime from a real event is used, designed to generate a broader spectrum of negative emotional responses.

A literature dating back four decades has found strong evidence of carryover effects in settings characterised by risk.[1] This includes the seminal work of Johnson and Tversky (1983) who identified the influence of incidental mood on risk perceptions; a substantial literature in experimental psychology (e.g., Isen & Patrick, 1983; Nygren, 1998; Raghunathan & Pham, 1999; Yuen & Lee, 2003); and more recent work by economists (e.g., Drichoutis & Nayga, 2013; Stanton et al., 2014; Treffers et al., 2016; van Well et al., 2019). A feature of the more contemporary work generated in economics labs is that it has focused on carryover effects on financially incentivised risky choice, as opposed to self-reported risk perceptions or hypothetical risky decisions. This later work has also suggested more nuanced patterns in the carryover effect. These include sensitivity to different types of uncertainty, such as strategic risk and ambiguity (Kugler et al., 2010; Baillon et al., 2016), and gender differences in the effect of emotional primes on risky choice (Fessler et al., 2004; Fehr-Duda et al., 2011; Conte et al., 2018).

One of our primary contributions is to examine carryover effects associated with a novel 'naturalistic' emotional stimulus compared with a more conventional emotional prime. In the existing literature, the typical approach has been to use stimuli (such as fictional film clips) designed to target specific emotional responses such as fear. While it has been demonstrated that conventional stimuli can reliably generate fear responses (see Gross & Levenson, 1995; Hewig et al., 2005; Rottenberg, Ray, & Gross, 2007; Gabert-Quillen et al., 2015) and that subjects who have been primed this way sometimes exhibit carryover effects, questions have been raised about the representativeness of such stimuli. Specifically, emotional responses to natural events are likely to be more *complex* than those generated in experiments targeting a single emotion. For example, consider an individual's reaction to learning of a recent

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[1] Experimental studies have also found evidence for the effect of incidental emotions on other economic behaviours. These include spending and the willingness-to-pay gap (Lerner et al., 2004; Cryder et al., 2008), time preferences (Ifcher & Zarghamee, 2011), social preferences (Kirchsteiger et al., 2006; Andrade & Ariely, 2009; Drouvelis & Grosskopf, 2016), strategic behaviour in games (Castagnetti et al., 2023) and trading in financial markets (Lee & Andrade, 2011, 2015; Andrade et al., 2016).

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nearby terrorist event. It seems plausible that such knowledge might provoke a range of emotions including fear, anger, sadness, disgust and so on. While there is an established literature on complex emotions (see Berrios et al., 2015, Oh & Tong, 2022), their effects are not well understood, particularly regarding their impact on downstream behavioural outcomes such as the carryover effect. To date, there is no evidence exploring carryover effects on risky choice from stimuli designed to create more complex emotional responses. Our research breaks new ground through a proof-of-concept study exploring whether carryover effects can be observed when we depart from conventional primes in favour of more naturalistic ones: were we to find evidence for the existence of such effects, that would underpin more extensive study of them.

Our paper relates to a literature employing stimuli from real events to examine risk perceptions, for example, in the contexts of terrorism and natural disasters (Lerner et al., 2003; Västfjäll et al., 2008). A common finding amongst these studies is that stimuli related to real events can often have an impact on risk perceptions in other domains. We investigate related processes but with a focus on carryover effects to incentivised risky and ambiguous decisions in a controlled laboratory setting.

A further contribution of our paper is to explore the emotional foundations of the carryover effect by examining associations between emotional responses (as captured by self-reports) and economic decisions. In the study of carryover effects arising from specific emotions (e.g., examining the impact of fear on risk taking), a common approach has been to compare the behaviour of two groups of subjects who have been exposed to different emotional primes, for example, by looking at the willingness of subjects to take risks following either neutral or fear primes. Multiple studies have drawn the conclusion that 'fear affects risk taking' from the conjunction of observing both higher reports of fear and different willingness to take risks in the group that received the fear prime. While such findings – usually based on group-level comparisons of average responses – are interesting in their own right, they provide a limited window on the underlying connections between specific emotions and behaviour. For example, it is possible that other non-targeted and thus unmeasured emotions could be driving behaviour. In the case of a naturalistic stimulus that generates a complex mix of emotions, these may cancel or even reinforce each other. Our study probes this more deeply by seeking to disentangle the roles played by a wider range of emotions on individual-level decisions relating to risk. In addition, motivated by previous findings of gender differences in the carryover effect, we test the gender-specificity of different emotional channels. As such, our paper contributes directly to a relatively small literature investigating links between individual-level emotions and risky decision making (e.g., Bosman & Van Winden, 2010; Nguyen & Noussair, 2014; Cohn et al., 2015).

Our main findings are as follows. We observe significant carryover effects and they are stronger for the naturalistic stimulus (compared to the targeted) and for decision making under ambiguity (compared to risk), thereby providing a proof of concept that carryover effects can occur when moving away from highly stylised stimuli. These effects are gender specific with carryovers for both the targeted and naturalistic primes observed only for males. We find mixed support for an emotional basis of the carryover effect. For the targeted treatment, although the standard prime does, as expected, significantly increase reporting of fear we do not find an association between self-reports of fear and valuations for risky or ambiguous lotteries; we do, however, identify a different, but non-targeted, emotional mechanism. For the naturalistic case, although we observe a strong carryover effect, we are unable to find any reliable link between individual-level emotional responses and valuation behaviour. Given the range of emotions we elicit, this raises doubts about the carryover effect being understood as driven by *specific* emotions. The remainder of the paper is organised as follows. Section 2 outlines the experimental design. Section 3 reports the results of the experiment and the individual-level analysis. Section 4 discusses the broader implications of our results and concludes.

2. Experimental design

The main elements of the experimental design are summarised in Fig. 1. Subjects were randomly allocated to one of three treatments – *control, targeted* and *naturalistic*. In each treatment, subjects undertook one of three emotional priming tasks, each designed to produce a distinct profile of emotional responses. We elaborate on the expected emotional profiles and the emotional priming procedures for each treatment in Section 2.1. Following the priming task, we measured subjects' valuations for both a risky and an ambiguous lottery (details in Section 2.3). We test for carryover effects by looking for treatment differences in the average measured valuations. Self-reported emotions were measured twice for each subject in pre- and post-experimental questionnaires (details in Section 2.2). General experimental procedures are explained in Section 2.4.

2.1. Emotional priming task

Two of the three emotional primes used in our experiment are designed to replicate classic primes used in previous literature: a neutral prime in our control treatment and a prime designed to induce a specific emotion, fear, in our targeted treatment. A key novelty of our setup is the use of a naturalistic prime (in the naturalistic treatment), designed to produce a more complex emotional response relative to the targeted prime. In each of the three treatments, subjects were primed by watching a short video clip followed by a self-reflective writing task designed to make the emotional experiences more personally meaningful.[2] This procedure is based on standard protocols for inducing emotional states (examples include Lerner et al., 2004; Cryder et al., 2008; Andrade & Ariely, 2009).[3]

In the control treatment, subjects watched a video clip from a National Geographic Special about the Great Barrier Reef. This has been widely used in carryover experiments as a control prime (Lerner et al., 2004; Gino & Schweitzer, 2008; Han et al., 2012). In the writing task, subjects were asked for opinions about the suitability of the clip as a wildlife documentary.

Our targeted stimulus is based on that identified by Gross and Levenson (1995) as a successful prime to induce fear. We chose fear as the targeted emotion because this has received much attention in the literature as an emotion that affects risky choice (Kugler et al., 2010; Lee & Andrade, 2011, 2015; Cohn et al., 2015; Yang et al., 2020). Subjects watched a video clip from the film "The Shining". The clip depicts a boy looking for his mother in an empty corridor whilst tense music plays in the background. Gross and Levenson (1995) found that this stimulus generates a fear response that is both strong and clean (in the sense that no other negative emotions are induced).[4] In the writing task, subjects were asked about how they would feel if they were the person depicted in the video clip.

For the naturalistic treatment, we used a video stimulus constructed from documentary and news reporting of real events connected to the 'BSE crisis' – a serious food safety issue prominent in the 1990s, following the discovery of apparent links between human consumption of beef infected with Bovine Spongiform Encephalopathy (BSE) and the rare but fatal degenerative disease CJD (human variant of Creutzfeldt-Jacob disease). In the writing task, subjects were asked how they felt about the risk of contracting a disease similar to what was depicted in

[2] Full details regarding the video stimuli used in the experiment are given in the electronic supplementary material (online resource 1).

[3] For a comprehensive comparison of affective priming procedures see Westermann et al. (1996).

[4] If you know this classic film scene, reader, we predict that the hairs on your spine are currently tingling as you bring the scene to mind.

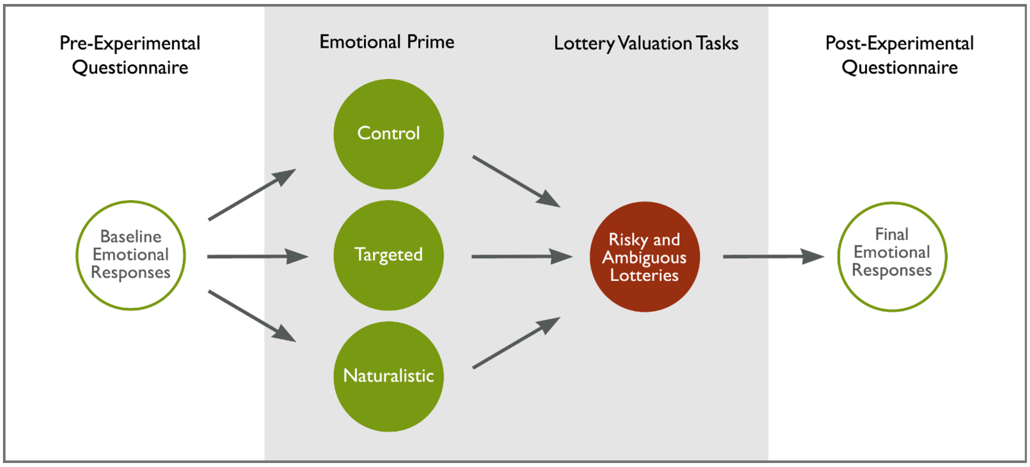

Fig. 1. Experimental design.

the video clip.

The control and targeted primes were selected as classic 'off the shelf' neutral and fear primes and our interest in them is partly as benchmarks: in relation to emotional responses, based on past literature, we expect to find relatively mild emotional responses for the control prime and, in the targeted treatment, we expect to find a fear response and few, if any, other significant negative emotions. By contrast, for the naturalistic prime, we sought a stimulus which would generate strong negative, but diverse emotions. To this end, we selected the BSE crisis as a good candidate in being both highly emotive and likely to produce a relatively complex spectrum of emotional responses. Food anxieties have long threatened consumers giving rise to food scares (see Beardsworth & Keil, 1997). The BSE scare is the most notorious food safety issue in recent times originating in the UK and spreading globally. Following a government announcement in 1996, consumers reacted dramatically with beef sales falling immediately by 40 % and an EU ban was imposed on UK beef products, leading to an estimated total economic loss of up to £980 million that year (DTZ Pieda Consulting, 1998). The media coverage was extensive with a sustained focus on several highly emotive issues including: fear about potential health risks, sadness associated with the consequences of contracting the disease, disgust from the visceral images of infected cows and food contamination; and anger against the beef industry and its oversight. For our experiment, we constructed a video stimulus using a selection of actual news reports from the time. We note that by using an event that was not prominent in the current news at the time of running the experiment, we ensured that the BSE issue was only salient to those subjects in the naturalistic treatment.[5]

2.2. Emotional responses and the circumplex representation

Relative to priming studies that have focused on a very limited range of specific emotions, our objectives require us to assess a broad spectrum of emotions generated by our naturalistic stimulus. Hence, we need some framework for determining both *which emotions to measure* as well as *how to measure them*. We address these issues in turn here.

We organise our selection of emotions to measure with reference to the Circumplex Model of Affect, a widely used model of emotions in psychology (Russell, 1980; Larsen & Diener, 1992). The Circumplex Model provides a visual representation of an affective space in which emotions are placed into octants arranged on a circle along two dimensions: pleasantness (left/right) and activation (top/bottom).[6] Pleasantness has positive valence emotions (e.g., happy) juxtaposed with negative ones (e.g., sad). Activation can be understood as arousal with high activation emotions (e.g., surprised) juxtaposed with low activation ones (e.g., passive).

One guiding principle for the selection of emotions was that we wanted some representation in all octants. Given our expectation that the targeted and naturalistic primes would produce differing emotional profiles in the negative affective space, we chose to over-represent the 'unpleasant' octants with negative emotions including sadness, disgust, fear and anger. Taking emotions from the standard circumplex literature appended by some additional items specifically for this study, our circumplex is presented in Fig. 2.

Here, the circumplex octants are labelled in the outer ring with corresponding emotions shown in the inner circle. Given the nature of our experimental primes, we are particularly interested in the 'activated unpleasant' octant and, so, we break this down into the three specific emotions: disgust, fear and (D, F, A - associated emotions in the key). We therefore have a total of 10 emotional groups: the three specific emotions D, F, A from the activated unpleasant octant plus the groups of emotions from the other seven octants of the circumplex. As well as providing structure for the selection of emotions, the circumplex framework also informs the subsequent analysis. At the treatment level, we use these 10 emotional groups in the circumplex array to visualise emotional profiles (see Section 3.1). At the individual level, we use the emotional groups as variables to probe the emotional basis of decisions (see Section 3.3).

We measured emotions using self-reports which is a standard approach in the literature (see Robinson & Clore, 2002). We took measures of emotions twice, recording baseline and final emotional responses for each subject.[7] To measure baseline responses, subjects were presented with the set of emotions and asked to indicate on a scale to what extent they had a particular feeling at that moment. Consistent with other studies, we used a response scale that ranged from 0 (do not have this feeling at all) to 8 (have this feeling more than ever before). To measure final responses, subjects were given the same emotions and scale and asked to indicate the extent to which the video clip and writing

[5] We further note that the experiment was conducted before the COVID-19 pandemic.

[6] This labelling of the dimensions is based on the version from Larsen and Diener (1992).

[7] In addition to the 25 emotions within the circumplex framework, following the literature on priming using film we also asked subjects to indicate the extent to which they felt confused (as a measure of general understanding of the video stimuli) as well as some emotionally neutral terms: neutral and indifferent.

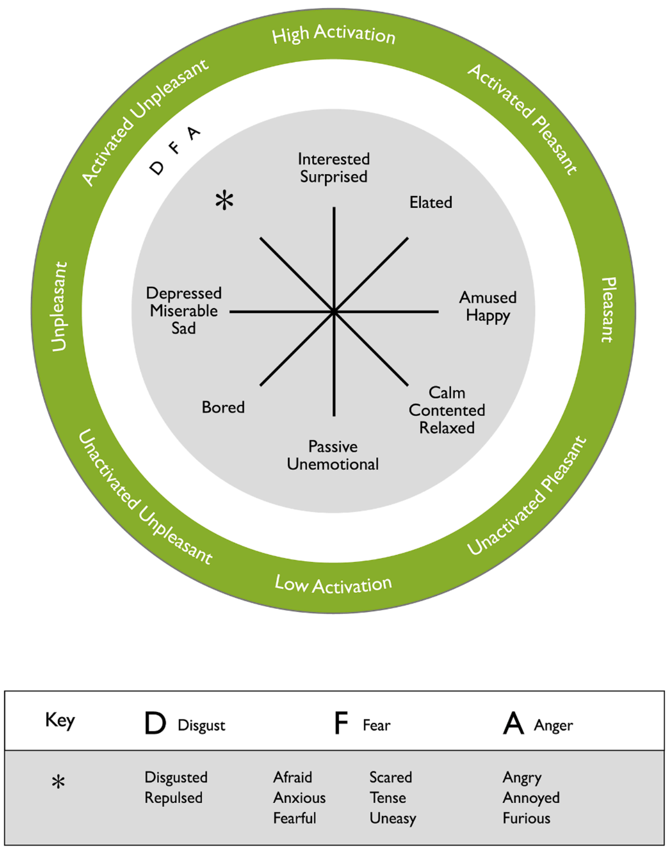

Fig. 2. Circumplex model of affect.

task had prompted each of these feelings.[8] We then calculated the within-subject difference between the two measures for each emotion. A positive difference indicates an increase relative to the baseline, whilst a negative difference indicates a decrease relative to the baseline. Via this strategy, we aim to measure changes in emotions associated with our treatment manipulations, across the full affective space of the circumplex model.

2.3. Lottery valuation tasks

The existence of carryover effects is tested by comparing valuations of (risky and ambiguous) lotteries in the targeted and naturalistic treatments relative to corresponding valuations in the control treatment. Following their emotional prime, all subjects undertook two lottery valuation tasks, one for a risky lottery and the other for an ambiguous lottery. For the risky task, the lottery gave a 50 % probability of winning £12 or nothing. For the ambiguous task, the lottery gave an unknown probability of winning £12 or nothing. We used physical devices to operationalise these lotteries in order to make differences between the risky and ambiguous tasks salient and easy to understand. For the risky lottery, subjects drew a disc out of a bag, which contained 10 blue and 10 red discs. Subjects were shown the discs being placed into the bag beforehand and verified the composition of the discs. For the ambiguous lottery, subjects did not see the discs being placed into the bag: they knew that the bag contained a mix of blue and red discs but not their relative proportions. In each experimental session, the order of the two lottery valuation tasks was randomised.

We elicited certainty equivalent (CE) valuations for these lotteries using a simple price list design. For each task, subjects were presented with a decision sheet containing 25 rows, as shown in Fig. 3. In each row, subjects chose whether they preferred to play the lottery (option A) or take a certain amount of money for sure (option B). These certain amounts of money increased moving down the rows and were set so that individuals would prefer the lottery in the top row but prefer the certain amount by the bottom row. Hence, we expected each subject to switch from A to B as they moved down the table revealing the lower bound of an interval capturing their certainty equivalent valuation of the lottery. For the risky task, this valuation can be further interpreted as reflecting the individual's risk attitude.[9] Risk-neutral subjects prefer the lottery in rows 1–12 (where its expected value is higher than the sure amount) but prefer the sure amount in all rows after row 13 (where the lottery's expected value is less than the sure amount). Switching to B before row 13 indicates risk-averse behaviour. For the ambiguous task, the switch point reflects attitudes towards uncertainty as well as risk.[10] If, as is plausible, experimental subjects are averse to the source of ambiguity in our setup, then we would expect average valuations for the ambiguous lottery to be lower than those for the risky lottery within a given treatment.

Subjects' decisions in the two valuation tasks were motivated by financial incentives: subjects knew in advance that the experimenter would select one row at random from either decision sheet to be rewarded for real according to the subjects' decisions (see Bardsley et al., 2010, ch.6, for discussion and defence of such standard random incentive procedures).

2.4. Experimental procedures

186 student subjects (100 female, 86 male) from the University of Nottingham took part in the experiment.[11] Subjects were recruited using ORSEE (Greiner, 2015). Upon entering the laboratory, subjects were seated in private booths equipped with computers and headphones with no visual access to other participants. Subjects first completed the pre-experimental questionnaire to measure their baseline emotional responses. To minimise experimenter demand, the emotional prime and lottery valuation tasks were framed as separate from each other.[12] Before watching their video clip, subjects were asked to sit back, relax and take a couple of deep breaths to help them focus fully on the stimulus. The main lights were turned off and the subjects were prompted to start the video clip.[13] After completing the valuation tasks, subjects completed the post-experimental questionnaire which measured the final emotional responses and demographic information. Each session

[8] Final emotional responses were measured after the lottery valuation tasks as it has been shown that labelling one's feelings after an emotional prime reduces its effect on the variable of interest (Schwarz & Clore, 1983; Keltner et al., 1993; Yip & Côté, 2013).

[9] Consider, for example, an expected utility model in which a single parameter α controls the curvature of the utility function. An individual's switch point can then be used to impute bounds on their α.

[10] Various models of ambiguity attitudes provide alternative interpretations of ambiguity-sensitive preferences. We do not rely on any specific theoretical model, but for discussions of alternative models see Wakker (2010); Etner et al., (2012) and Gilboa and Marinacci (2016).

[11] The sample size was chosen to be comparable to other lab studies on incidental emotions and economic behaviour. Gender balance tests indicate no significant differences in the percentage of females between the control (58%) and targeted (42%, $p = 0.086$), and naturalistic treatments (62%, $p = 0.658$) at the 5% level.

[12] Subjects were not explicitly told that the two tasks were independent, but rather materials and payment for each task were treated as separate. Subjects received a fixed payment for watching the video clip conditional on completion of the writing task. All paper materials were then collected in before subjects undertook the lottery valuation tasks. Full transcripts of the experimental instructions and materials are given in the electronic supplementary material (online resource 2).

[13] The video clips were played using z-Tree (Fischbacher, 2007). All subjects saw identical screens and the video clips played at the same time.

1	Play Option A	○	Receive £3.00 for sure	○
2	Play Option A	○	Receive £3.25 for sure	○
3	Play Option A	○	Receive £3.50 for sure	○
4	Play Option A	○	Receive £3.75 for sure	○
5	Play Option A	○	Receive £4.00 for sure	○
6	Play Option A	○	Receive £4.25 for sure	○
7	Play Option A	○	Receive £4.50 for sure	○
8	Play Option A	○	Receive £4.75 for sure	○
9	Play Option A	○	Receive £5.00 for sure	○
10	Play Option A	○	Receive £5.25 for sure	○
11	Play Option A	○	Receive £5.50 for sure	○
12	Play Option A	○	Receive £5.75 for sure	○
13	Play Option A	○	Receive £6.00 for sure	○
14	Play Option A	○	Receive £6.25 for sure	○
15	Play Option A	○	Receive £6.50 for sure	○
16	Play Option A	○	Receive £6.75 for sure	○
17	Play Option A	○	Receive £7.00 for sure	○
18	Play Option A	○	Receive £7.25 for sure	○
19	Play Option A	○	Receive £7.50 for sure	○
20	Play Option A	○	Receive £7.75 for sure	○
21	Play Option A	○	Receive £8.00 for sure	○
22	Play Option A	○	Receive £8.25 for sure	○
23	Play Option A	○	Receive £8.50 for sure	○
24	Play Option A	○	Receive £8.75 for sure	○
25	Play Option A	○	Receive £9.00 for sure	○

Fig. 3. Decision sheet for lottery valuation tasks.

took approximately 1 hour to complete, including instructions and payment and subjects earned on average £9.48.

3. Results

We structure the results in the following way. In Section 3.1, we present the emotional profiles for our three treatments. In Section 3.2, we test for carryover effects by comparing valuations of the risky and ambiguous lotteries across treatments. In Section 3.3, we examine relationships between emotional responses and valuations.

3.1. Emotional profiles across treatments

Examining emotional profiles serves two key purposes. First, we can check whether our implementations of the off-the-shelf priming tasks (control and targeted treatments) produce the patterns expected, based on the extant literature. Second, we can check whether our novel naturalistic prime produces, as we conjectured, a broader spectrum of emotional responses. Both can be considered as manipulation checks, but the second is particularly important given our research objectives.

Fig. 4 visualises the emotional profiles on the circumplex diagram. For each treatment, the spokes radiating from the centre are used as axes to locate data for each emotional group. Each circle represents the mean difference (MD) between the first and second measurement of the individual emotions for that group, averaged across subjects, for a particular treatment. The diameter of each circle is an indication of the relevant effect size.[14] A dark circle indicates an increase in the mean reported emotion for a group; a light circle indicates a decrease. Since we have separate observations for disgust, fear and anger, these lie on/close to the activated unpleasant axis and are labelled D, F, A respectively. We test whether the mean of each emotional group significantly increased or decreased within a particular treatment using a paired *t*-test. The distance from the origin denotes the t-ratio with the dotted circles representing thresholds of significance at the 5 % and 1 % levels (the 1 % threshold being the one further out from the centre).

Looking first at the emotional profile for the control treatment (left-hand panel of Fig. 4), we see that, as expected, the stimulus generated only mild emotional responses, compared with the other two treatments. A significant increase (5 % level) is found for just one emotional group, high activation (MD=0.518, $p = 0.035$). Note that this is mirrored by a significant decrease in low activation (MD=−0.616, $p = 0.001$). A similar pattern of increases in high activation and decreases in low activation is observed for all three treatments; a finding which we interpret as evidence that subjects were engaged in the experiment. Significant decreases are found amongst the unpleasant emotional groups, though the effect sizes are small compared to the other two treatments (unpleasant: MD=−0.524, $p = 0.006$; disgust: MD=−0.232, $p = 0.046$; fear: MD=−0.557, $p = 0.011$; anger: MD=−0.512, $p = 0.006$). The mild emotional responses observed in this treatment enable us to use the risk behaviour observed in this treatment as a control when we test for carryover effects (see Section 3.2).

Turning to the emotional profile for the targeted treatment (middle panel of Fig. 4), we are able to replicate the findings of Gross and Levenson (1995) that this stimulus provides a strong and clean fear response, at least insofar as we focus on the negative emotions located in the north-west quadrant of the circumplex. Increases in fear are the largest of all emotion groups in all treatments (MD=2.189, $p < 0.001$), whereas effect sizes for other unpleasant emotions are low and insignificantly different from zero (unpleasant: MD=−0.055, $p = 0.724$; disgust: MD=0.159, $p = 0.06$; anger: MD=−0.030, $p = 0.781$). That said, large and significant decreases are found amongst the pleasant groups. In particular, we observe a very large reduction for unactivated pleasant, similar in magnitude to the change in fear but with the opposite sign (MD=−2.048, $p < 0.001$). We also find significant but smaller reductions for activated pleasant (MD=−0.871, $p < 0.001$) and pleasant (MD=−1.136, $p < 0.001$). Since this emotional prime produces a strong fear response, we will use it to retest existing claims (see Section 3.2) that incidental fear influences risk attitudes.

The fact that our implementation of two standard priming tasks both produce the expected emotional profiles in line with existing evidence,

[14] This is operationalised in the figure by constructing the size of each circle as a percentage of the largest data point in the dataset.

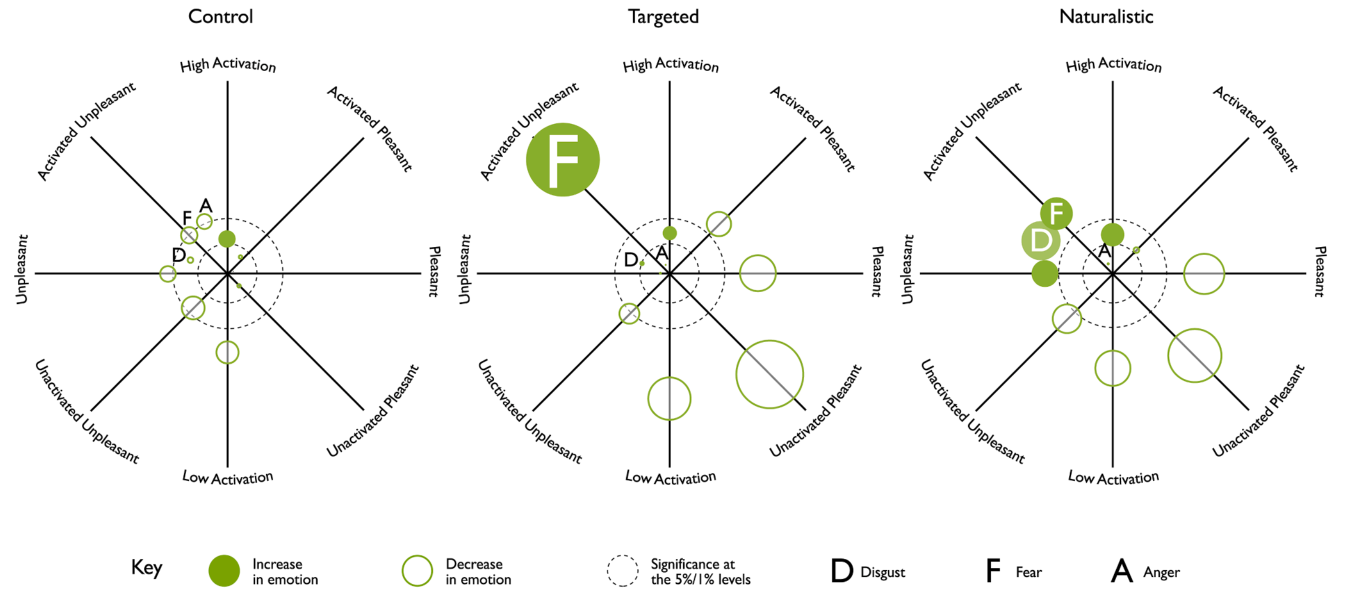

Fig. 4. Emotional profiles across treatment.

provides reassurance that our priming procedure and measurement of emotions have some degree of internal validity. Against this backdrop, we now consider the emotional profile of subjects exposed to our novel prime.

Examining the emotional profile of the naturalistic treatment (right-hand panel of Fig. 4), we find marked differences compared to the targeted treatment. Specifically, as hypothesised, this stimulus generates a more diverse emotional response within the unpleasant dimension of the circumplex. Significant increases are observed for unpleasant (MD=0.790, $p < 0.001$), disgust (MD=1.153, $p < 0.001$), fear (MD=0.956, $p < 0.001$), although not anger (MD=0.086, $p = 0.715$). These increases are of similar magnitude and considerably less than the fear response from the targeted treatment. Like the targeted treatment, we observe significant decreases in the pleasant groups (pleasant: MD=−1.242, $p < 0.001$; unactivated pleasant: MD=−1.630, $p < 0.001$). So, in line with our expectations, this emotional prime, based on reporting of real events, produces an emotional profile in which multiple emotions have been influenced. Hence, as we hoped, we are in a position to assess the impact of a prime generating a more complex emotional response.

3.2. Carryover effects on lottery valuations

In this section, we test for carryover effects by comparing mean valuations of the risky and ambiguous lotteries in the targeted and naturalistic treatments relative to valuations in the control. Treatment differences (d) are tested using a two-sample *t*-test and are reported in monetary units.[15]

Mean lottery valuations across treatment are summarised in Fig. 5. Focusing first on whether our results are consistent with the existing literature that a targeted fear stimulus influences risk attitudes, we do not find evidence to support this with valuations in the targeted and control treatments statistically similar to each other (d=−0.161, p = 0.532). For ambiguous decision making, valuations are lower in the targeted treatment compared to the control, though insignificant

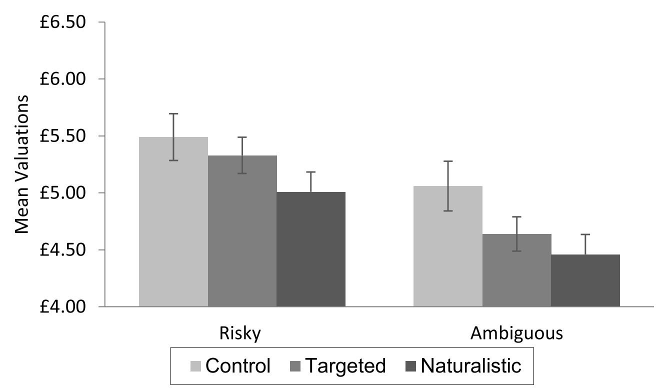

Fig. 5. Mean lottery valuations. Error bars indicate mean ± standard error.

(d=−0.418, p = 0.110). Turning now to the naturalistic treatment, we observe carryover effects both for risky valuations (d=−0.481, p = 0.074) and more strongly for ambiguous valuations (d=−0.594, p = 0.034). So, although we are unable to replicate existing findings of carryover effects from a targeted fear stimulus, we do find carryover effects for the naturalistic stimulus, and these are stronger for ambiguous valuations.

As discussed earlier, several studies have found gender differences in the carryover effect for risky choice. To explore this possibility in our data, we evaluate mean lottery valuations across treatment and gender, summarised in Fig. 6. Focusing first on risky valuations in the left-hand panel, we do observe gender-specific treatment effects: for males, compared to the control, risky valuations are lower in the targeted treatment (d=−0.493, p = 0.179) and even lower in the naturalistic treatment (d=−0.907, p = 0.030). Female behaviour, on the other hand, does not exhibit this pattern: risky valuations are not significantly different from the control in both the targeted (d = 0.036, p = 0.897) and naturalistic treatments (d=−0.102, p = 0.770). This leads to the following key result – *we observe carryover effects on risky decision making and these effects are stronger for the naturalistic stimulus, but only males are susceptible.*

Turning now to ambiguous valuations in the right-hand panel of Fig. 6, we observe a similar pattern. Compared to the control, male ambiguous valuations are significantly lower in the targeted treatment (d=−0.755, p = 0.043) and are again even lower in the naturalistic

[15] Before proceeding with the analysis, we excluded lottery valuation data from subjects who indicated multiple switching between the lottery and sure amount. For risky valuations, 19 out of 186 observations were dropped. For ambiguous valuations, 20 out of 186 were dropped. Multiple switching was not related to treatment.

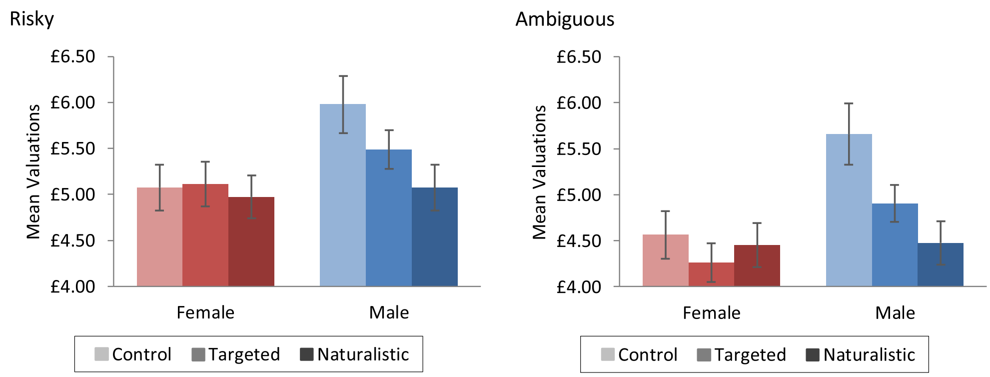

Fig. 6. Mean lottery valuations split by gender. Error bars indicate mean ± standard error.

treatment (d=−1.182, p = 0.006). However, female ambiguous valuations are similar across all treatments, and we do not see any carryover effects for them (targeted: d=−0.304, p = 0.373; naturalistic: d=−0.112, p = 0.756). This gives us another main result – *for males, carryover effects on ambiguous decision making follow a similar pattern to those for risky decisions, but the treatment differences are even stronger.*

Although in the control treatment we replicate the standard finding that males are more risk-seeking than females (d = 0.904, p = 0.026), these gender differences diminish when female valuations in the control are compared to male valuations in the other treatments. Gender differences are insignificant when compared to male valuations in the targeted treatment (d = 0.412, p = 0.21). Furthermore, female valuations in the control and male valuations in the naturalistic treatment are indistinguishable (d=−0.003, p = 0.994). This pattern is also observed with ambiguous valuations. Ambiguous valuations are higher for males compared to females in the control treatment (d = 1.094, p = 0.011), but these gender differences disappear when we compare male valuations in the other treatments to female valuations in the control (targeted: d = 0.340, p = 0.294; naturalistic: d=−0.088, p = 0.808). The carryover effect therefore eradicates commonly observed gender differences in risky and ambiguous decisions.

As a robustness check, we pool the data across all three treatments and run OLS regressions to assess the impact of these treatments on valuations. We estimate separate models for risky and ambiguous lotteries, and in each case, we run versions with and without a set of additional controls. Model 1 contains the experimental treatment variables (targeted and naturalistic), treatment-gender interactions and task ordering ambiguous → risky=1). Model 2 incorporates additional demographic control variables from the post-experimental questionnaire.[16]

The regression analysis presented in Table 1 shows a consistently significant negative effect for males in the naturalistic treatment. The size of the effect means that these subjects, on average, switch between 4 and 6 rows earlier in the price list table indicating an average reduction in valuation of £1.00 – £1.50 (recall that the expected value of the risky lottery is £6). The effects are larger and more strongly significant for the case of the ambiguous lottery and become slightly larger when additional controls are added. Notice that the coefficient on the gender interaction (Naturalistic x Female) is similar in size to the non-interacted Naturalistic coefficient but with the opposite sign – indicating that the treatment effect occurs only for males and not females. We also identify similar effects of lower valuations in the targeted treatment, but this effect is only significant in the ambiguity case. Task order is found to be consistent with standard findings of anchoring with the risky lottery seen as more attractive when evaluated after the ambiguous lottery and vice versa. Overall, the regression results confirm the main finding of our analysis: relative to the control treatment, the naturalistic prime has a stronger and more consistent impact on behaviour than the targeted prime, although these carryover effects are gender specific with only males being susceptible.

Table 1
OLS regression models for risky and ambiguous valuations.

	Risky		Ambiguous	
Dependent variable: Lottery valuations	Model 1	Model 2	Model 1	Model 2
Targeted	−0.548	−0.406	−0.831**	−0.743**
	(0.350)	(0.346)	(0.352)	(0.341)
Naturalistic	−1.012**	−1.028**	−1.298***	−1.449***
	(0.397)	(0.422)	(0.389)	(0.409)
Targeted X Female	0.676	0.837*	0.657	0.943
	(0.508)	(0.501)	(0.509)	(0.497)
Naturalistic X Female	0.970	0.854	1.245**	1.218**
	(0.520)	(0.527)	(0.509)	(0.504)
Female	−0.983***	−1.031***	−1.207***	−1.267***
	(0.371)	(0.377)	(0.371)	(0.372)
Task Order	0.404**	0.445**	0.511**	0.548***
	(0.206)	(0.206)	(0.203)	(0.200)
Constant	5.803***	5.605***	5.450***	5.341***
	(0.285)	(0.293)	(0.285)	(0.288)
Controls	No	Yes	No	Yes
Adj. R-Squared	0.051	0.097	0.102	0.175
Observations	167	166	166	165

Standard errors are in parentheses. *p < 0.10, **p < 0.05, ***p < 0.01.

3.3. Testing the emotional foundations of the carryover effect

Having observed carryover effects, we now examine whether variation in emotional responses can explain differences in lottery valuations. Given our finding of gender-specific carryover effects, a natural question to ask is whether there are differences in emotions across treatment *and* gender. Our data show that although measured female emotional responses tend to be larger in magnitude than males (a consistent finding in the literature), emotional profiles for each treatment are otherwise qualitatively very similar across gender (See Appendix, Figs. A.1 and A.2, which reproduce the circumplex representation of Fig. 4 separately for males and females).

The fact that comparing males and females, we see broadly similar patterns of emotional responses yet markedly different propensities for carryover provides some reason to doubt whether individual-level emotional responses can explain the carryover effect. To explore this issue further, we conduct a mediation analysis. The proposed mediation model is shown as a path diagram in Fig. 7. The observed treatment effect is denoted by path c. The model decomposes this treatment effect

[16] One subject did not fully complete the post-experimental questionnaire leading to one less observation in the regression models that include additional controls. A full list of the controls used in these models is given in the Appendix, Table A.1.

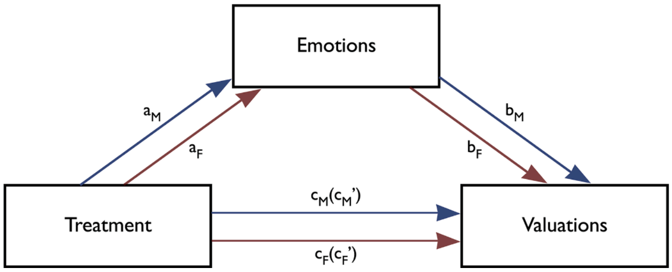

Fig. 7. Path diagram linking emotions and lottery valuations.

into (i) an indirect effect (emotional) via paths marked *a* and *b*; and (ii) a direct effect (non-emotional) indicated by paths marked *c'*. Path *a* indicates how much an emotion responds to a treatment (targeted or naturalistic) relative to the control, and path *b* indicates the impact of that emotion on a given type of valuation (risky or ambiguous). Separate paths are constructed for males and females, denoted with subscripts *M* and *F*, respectively.

Since we are interested in the behavioural effects of emotions across the whole emotional space, we operationalise the 'emotions' part of the model using the emotional groups from the circumplex. Specifically, for each subject, we use the difference between the first and second measurement for each of the 10 emotional groups, forming 10 individual-level emotion variables for the analysis. For given pairs of treatments (see below), we then estimate paths *a* and *b* for each emotion individually, conditional on the effect of the other emotions in the model. To formally test the impact of each emotion, we test the significance of the product of coefficients (POC) of path *a* and path *b* for that emotion.[17] Thus, a key feature of our testing strategy is to allow multiple emotions to have an impact on individual valuations. Furthermore, in our models, an emotion can still be identified as being a determinant of valuations even when the effects of one emotion are offset by another and no overall treatment effects are observed. For this reason, we do not limit our analysis to where we find significant treatment effects but examine the effect of emotions in all treatments, for males and females.

We use structural equation methods to simultaneously estimate coefficients for the paths in Fig. 7 based on equations (1)–(3). V_i represents subject i's valuation, $Treat_i$ is the experimental treatment experienced by i, Fem_i is a dummy for gender, ΔEmo_{ij} is the within-subject difference of the j^{th} emotion $j = 1...k$, $Order_i$ is task order for subject *i*. Equation (1) estimates the treatment effect (path *c*). Equations (2.1) – (2.k) estimate path *a* of the indirect effect for each emotion 1…*k* associated with each treatment. Equation (3) estimates path *b* of the indirect effect for each emotion and the direct effect (path *c'*). All paths include gender interactions to examine whether any emotional effects on valuations are gender specific.[18]

$$V_i = c_0 + c_1 Treat_i + c_2 Treat_i \cdot Fem_i + c_3 Fem_i + c_4 Order_i + \varepsilon_{i1} \tag{1}$$

$$\Delta Emo_{i1} = a_{0,1} + a_{1,1} Treat_i + a_{2,1} Treat_i \cdot Fem_i + a_{3,1} Fem_i + \varepsilon_{i2,1} \tag{2.1}$$
$$\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots$$

$$\Delta Emo_{ik} = a_{0,k} + a_{1,k} Treat_i + a_{2,k} Treat_i \cdot Fem_i + a_{3,k} Fem_i + \varepsilon_{i2,k} \tag{2.k}$$

$$V_i = b_0 + c'_1 Treat_i + c'_2 Treat_i \cdot Fem_i + c'_3 Fem_i + c'_4 Order_i + \sum_{j=1}^{k} b_{1,j} \Delta Emo_{ij} + \sum_{j=1}^{k} b_{2,j} \Delta Emo_{ij} \cdot Fem_i + \varepsilon_{i3} \tag{3}$$

We estimate these models separately for each specific treatment effect (targeted vs control and naturalistic vs control) and separately for risky and ambiguous valuations.

As a further bifurcation designed to avoid collinearity problems, we separately estimate 'increases' and 'decreases' versions of the model: 'increases' models include only those emotions that increased in the relevant treatments; and vice versa for 'decreases' models.[19] Hence in total, we estimate eight model variants.[20]

Table 2 reports the *a* and *b* path coefficients for each emotion in models comparing the targeted treatment vs control for males. We observe similar patterns for both risky and ambiguous models and therefore report them together. Focusing first on the 'increases' model, the *a* path for fear is large, positive and highly significant, supporting the result that for males, the targeted treatment produces a clean fear response. Rather surprisingly, however, the *b* path coefficient for fear is extremely small and not significantly different from zero for either risky or ambiguous valuations. This gives us a striking result – *in our model, the carryover effect observed for males in the targeted treatment is not explained by variation in fear.* In fact, since none of the *b* paths in this model are significant, no emotion in the 'increases' model is able to explain the carryover effect.

Table 2
SEM path coefficients: males – targeted vs control.

	Risky		Ambiguous	
	a	b	a	b
Increases Model				
High Activation	0.078	0.006	0.078	−0.060
	(0.438)	(0.132)	(0.438)	(0.129)
Disgust	0.353*	−0.240	0.353*	−0.156
	(0.197)	(0.334)	(0.197)	(0.315)
Fear	1.960***	0.063	1.960***	0.088
	(0.453)	(0.100)	(0.453)	(0.097)
Anger	0.264	0.079	0.264	0.152
	(0.288)	(0.182)	(0.288)	(0.171)
Unpleasant	0.194	−0.128	0.194	−0.303
	(0.340)	(0.194)	(0.340)	(0.183)
Observations	123	109	123	106
Decreases Model				
Activated Pleasant	−0.640	−0.142	−0.640	−0.070
	(0.429)	(0.125)	(0.429)	(0.127)
Pleasant	−1.302***	−0.133	−1.302***	−0.095
	(0.427)	(0.103)	(0.427)	(0.101)
Unactivated Pleasant	−1.286***	0.415***	−1.286***	0.384***
	(0.445)	(0.130)	(0.445)	(0.130)
Low Activation	−0.716*	−0.107	−0.716*	−0.165
	(0.395)	(0.129)	(0.395)	(0.130)
Unactivated Unpleasant	0.281	−0.252***	0.281	−0.142
	(0.560)	(0.095)	(0.560)	(0.097)
Observations	123	108	123	105

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

[17] Our approach is similar to the mediation frameworks put forward by Preacher and Hayes (2008) and Fairchild and MacKinnon (2009).

[18] Our models do not include interaction effects between different emotions. While it is possible that the effect of one emotion could vary with another emotion, we do not wish to over-parameterise the models.

[19] Increases in circumplex groups were typically counterbalanced with reductions in their polar opposite groups (see Fig. 4) so inclusion of the full set of variables creates severe collinearity problems.

[20] Although we have taken care not to complicate the models, we acknowledge that our sample size may limit statistical power. As such, we view the mediation analysis to be a more exploratory aspect of our study.

Turning to the 'decreases' model, we find significant *a* paths for pleasant emotions indicating that these emotions significantly decreased in the targeted treatment relative to the control. Furthermore, we find a significant, positive, *b* path for unactivated pleasant showing a relationship between this emotion and valuations. The POC coefficient is significant for risky valuations (POC=−0.534, $p = 0.032$), and its size corresponds to 96 % of the treatment effect. The POC coefficient for ambiguous valuations is also significant (POC=−0.493, $p = 0.039$), and corresponds to 58 % of the treatment effect. In short, we have found an emotional basis to the carryover effect in the targeted treatment, although the emotion driving this is a non-targeted emotion that decreased in the experiment.[21]

Fig. 8 provides a path diagram - separated by gender - to visualise the effect of unactivated pleasant on valuations. We find that although this emotion significantly decreases in the targeted treatment for both males and females (path *a*), it is the relationship between this emotion and valuations where the gender differences lie (path *b*). Specifically, for males, there is a significant positive relationship between unactivated pleasant and valuations, whilst for females this relationship is very close to zero. We also see that the observed treatment effect (path *c*) is reduced in size after the inclusion of unactivated pleasant, as shown by the direct effect (path *c'* in parentheses). This is further evidence that, based on our data, this emotion appears a key part of the mechanism driving the carryover effect for males in the targeted treatment.

We now investigate whether there is an emotional basis to the carryover effect observed in the naturalistic treatment. Table 3 reports the *a* and *b* path coefficients for each emotion in models comparing the naturalistic treatment vs control for males. Looking at the 'increases' model, we find a number of *a* paths significant – disgust, fear and unpleasant, confirming that the naturalistic treatment produced a negative and diverse emotional response relative to the control. However, no *b* paths are significant for either risky or ambiguous valuations. Furthermore, we see similar results for the 'decreases' model with several significant *a* paths, but no significant *b* paths. This brings us to our final key result of the paper – *although we observe stronger carryover effects in the naturalistic treatment, we cannot attribute this to variation in any of the emotions that we measured via self-reports.*[22]

Given the rather surprising results we find from the mediation analysis that the targeted emotion fear cannot explain the carryover effect observed for males in the targeted treatment and no emotions appear to be associated with the carryover effect in the naturalistic treatment, it is natural to consider whether this finding is robust. In relation to this, one key departure we make from the bulk of related literature is to measure emotional responses twice and then use the within-subject difference of these responses in the analysis. An alternative method would be to only use our second emotions measure (i.e., final emotional state) thereby allowing the model to capture emotional effects beyond those attributable to our treatment manipulations (for example, this might better capture 'dispositional emotions' that may affect risk attitudes, see Fehr-Duda et al., 2011). As a robustness check, we re-estimated the models using the same econometric specifications as before, except for using final emotions, rather than changes in emotions. We present the results of this analysis in the Appendix, Tables A.4 and A.5, seeking to explain the treatment differences for males in terms of final emotions. We find very similar results with the *b* path close to zero for fear in the targeted treatment for both risk and ambiguous valuations (Table A.4) as well as insignificant *b* paths for emotions in the naturalistic treatment (Table A.5). These results provide reassurance that our findings are robust to how emotional responses are defined.[23]

4. Discussion and conclusion

An established literature in psychology and more recently in economics, demonstrates the existence of emotional carryover effects. Our study contributes to the literature in two ways. Firstly, we examine whether carryover effects generalise from those associated with highly targeted emotional stimuli to more complex profiles of emotions associated with a naturalistic stimulus, based on reporting of real events. Secondly, we test whether we can identify an emotional foundation to carryover effects by examining individual-level relationships between emotional responses and decisions.

We identify clear carryover effects, but they are highly gender specific: only men are susceptible. Among males, they are also stronger in the naturalistic treatment and stronger in the context of ambiguity. For the targeted treatment, although we identify an emotional mechanism that explains the gender differences in the carryover effect, this is actually driven by a non-targeted emotion rather than the targeted emotion fear. While we cannot definitively rule out that fear plays some role – partly because of strong correlations between emotions in the circumplex – our finding adds weight to doubts about any generic claim that fear influences risk attitudes.

We note that a variety of previous studies that provide evidence for the influence of fear emotions on risky decision making do not directly associate measured fear emotions with risky decisions at the individual level – instead they infer this relationship through observations of average levels of reported fear and risk-taking across treatments. While a prima facie interpretation of such data is that changes in fear are causing changes in risk, our results which dig down from treatment level averages, fail to find corresponding support at the individual level. We recognise that some work has succeeded in finding some individual level connections from fear emotions to risk behaviours and a prominent example is Cohn et al. (2015), who primed fear responses among investment professionals. We note, however, that others have failed to replicate their results (see König-Kersting & Trautmann, 2018; Alempaki et al., 2019) albeit with different subject pools. Notwithstanding the use of different subject pools, however, it is notable that Alempaki et al. (2019) were unable to observe differences in risky decisions across treatments even when fear was successfully manipulated between the treatments. Our study adds evidence to this ongoing debate about the emotional foundations of risky decisions, partly by further questioning the role of fear emotions and partly by identifying a new contender as an emotional driver. Specifically, in terms of the circumplex classifications, we identify a low activation-pleasant dimension as the uniquely significant emotional correlate of risky and ambiguous valuations in the targeted treatment (at least amongst males).

Despite measuring a full spectrum of emotions, we are unable to explain the carryover effect, generated among males by the naturalistic prime, through any of our measured emotions. We consider our contribution here to be tentative and exploratory. Emotions are only ever measured imperfectly. Future research could apply methods proposed by Gillen et al. (2019) to reduce possible measurement error in emotion elicitation. Furthermore, promising new approaches for studying emotions are emerging: for example, combining self-reports

[21] Corresponding analysis for females is presented in the Appendix, Table A.2. We do not find any significant relationships between emotions and valuations in the targeted treatment models.

[22] Corresponding analysis is presented for females in the Appendix, Table A.3, and here too we find little evidence to support connections between variations in valuations and our measured emotions. We note that we do find some effect of anger on ambiguous valuations, although this is not large enough to show any observable change in valuations (POC=0.330, $p < 0.10$).

[23] One difference from the final emotional states analysis is that the effect of unactivated pleasant in the targeted treatment is considerably weaker. This is due to the inclusion of the dispositional component of the variable, which we found to correlate with risk differently compared with the component attributed to the treatment manipulation, therefore having potentially confounding effects. We see this as evidence to support our choice of using the within-subject difference in the analysis.

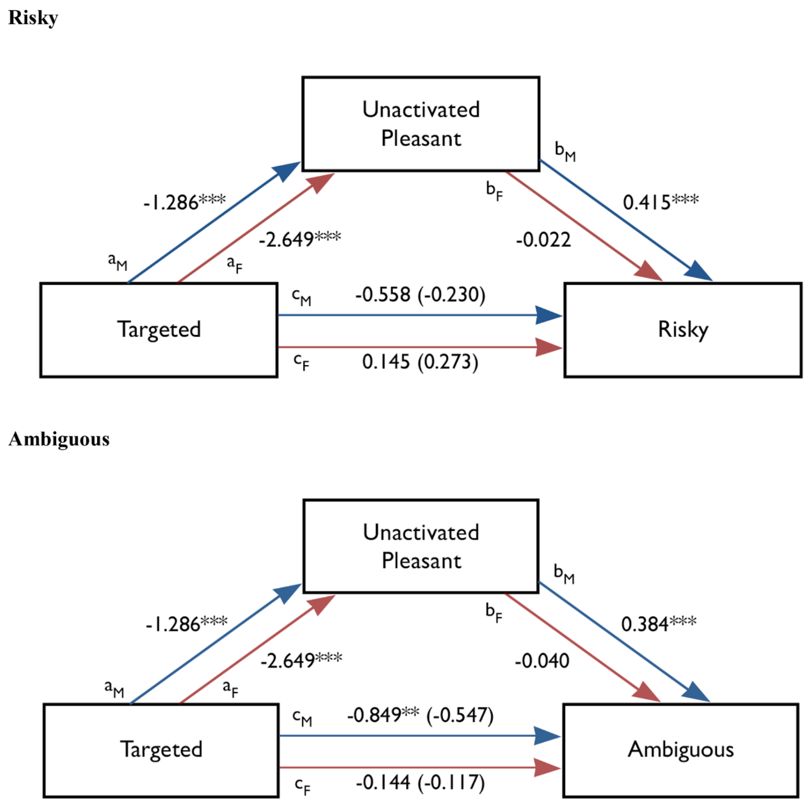

Fig. 8. Path diagrams for the effect of unactivated pleasant on risky and ambiguous valuations between the targeted treatment vs control, conditional on the other emotional variables in the model (indirect effects of other emotions not shown). Regression coefficients and significance for each path are reported above each arrow. Direct effect is given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3
SEM path coefficients: males – naturalistic vs control.

	Risky		Ambiguous	
	a	b	a	b
Increases Model				
High Activation	−0.146	0.025	−0.146	−0.056
	(0.535)	(0.169)	(0.535)	(0.159)
Disgust	1.078**	−0.112	1.078**	−0.007
	(0.473)	(0.200)	(0.473)	(0.192)
Fear	0.864*	0.069	0.864*	−0.003
	(0.477)	(0.177)	(0.477)	(0.149)
Anger	0.054	0.075	0.054	0.043
	(0.464)	(0.146)	(0.464)	(0.154)
Unpleasant	1.057**	−0.215	1.057**	−0.203
	(0.458)	(0.189)	(0.458)	(0.179)
Observations	119	105	119	106
Decreases Model				
Activated Pleasant	−0.254	0.046	−0.254	−0.093
	(0.467)	(0.147)	(0.467)	(0.152)
Pleasant	−1.256***	0.056	−1.256***	0.104
	(0.479)	(0.143)	(0.479)	(0.140)
Unactivated Pleasant	−1.275***	0.111	−1.275***	0.123
	(0.490)	(0.143)	(0.490)	(0.147)
Low Activation	−0.610	−0.085	−0.610	−0.161
	(0.450)	(0.153)	(0.450)	(0.140)
Unactivated Unpleasant	−0.123	−0.119	−0.123	−0.043
	(0.676)	(0.112)	(0.676)	(0.109)
Observations	119	105	119	106

Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

with more advanced technological methods, such as deep learning facial expression recognition software could enhance real-time emotion detection. In particular, developments in the identification of emotional blends i.e., emotional states formed from simultaneously experiencing a combination of basic emotions (Du et al., 2014), could pave the way for a better understanding of the behavioural effects of more complex emotional stimuli.

Our study also sheds new light on another dimension of the literature. Consider, for example, Fessler et al. (2004), who also observe gender differences in the carryover effect on risk but find little difference in emotional responses across gender. By digging down to examine individual-level responses, we demonstrated that even in the absence of gender differences in emotional responses to priming (i.e., along path *a* in our mediation model), there are gender differences in the behavioural responses to emotions (i.e., along response path *b* in our model). The natural question to ask is why these gender differences in the carryover effect occur. Although we can not fully answer this question, we note an interesting paper by Yip and Côté (2013), who find that individuals with higher emotional intelligence can accurately identify the source of their emotions, making them less susceptible to emotional carryover. With much of the literature finding that females generally score higher on emotional intelligence scales than males (see Joseph & Newman, 2010, for a meta-analysis), this could offer a potential explanation for why females in our experiment did not exhibit emotional carryover and provides a promising avenue of research.

Whatever the role of emotions in driving the carryover effects observed in our data – we *do* identify carryover effects and they are sizeable in magnitude for those prone to them (i.e., the males in our study). The finding that these effects are even larger for the naturalistic (versus targeted) prime and larger for ambiguity compared to risk is a result of some potential practical significance. While previous research has demonstrated that targeted primes influence risk taking, our findings provide proof of concept that such effects can be even stronger as we move from highly stylised settings to incorporate closer approximations to the richness of the stimuli that arise in the wild.

CRediT authorship contribution statement

Nikhil Masters: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Tim Lloyd:** Writing – review & editing, Visualization, Validation, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Chris Starmer:** Writing – review & editing, Visualization, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

none

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2024.102312.

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Appendix

Table A.1
List of variables in OLS regression models (from Table 1).

Variable	Description
Dependent Variables	
Risky	Valuations of risky lottery
Ambiguous	Valuations of ambiguous lottery
Experimental Treatment Variables	
Targeted	1 if in the targeted treatment, 0 otherwise
Naturalistic	1 if in the naturalistic treatment, 0 otherwise
Female	1 if female, 0 otherwise
Order	1 if ambiguous-risky task ordering, 0 otherwise
Controls (plus Naturalistic interactions)	
Health Science	1 if study medicine/health sciences, 0 otherwise
Non-European	1 if non-European nationality, 0 otherwise
Vegetarian	1 if vegetarian, 0 otherwise
BSE	1 if changed food habits due to BSE, 0 otherwise

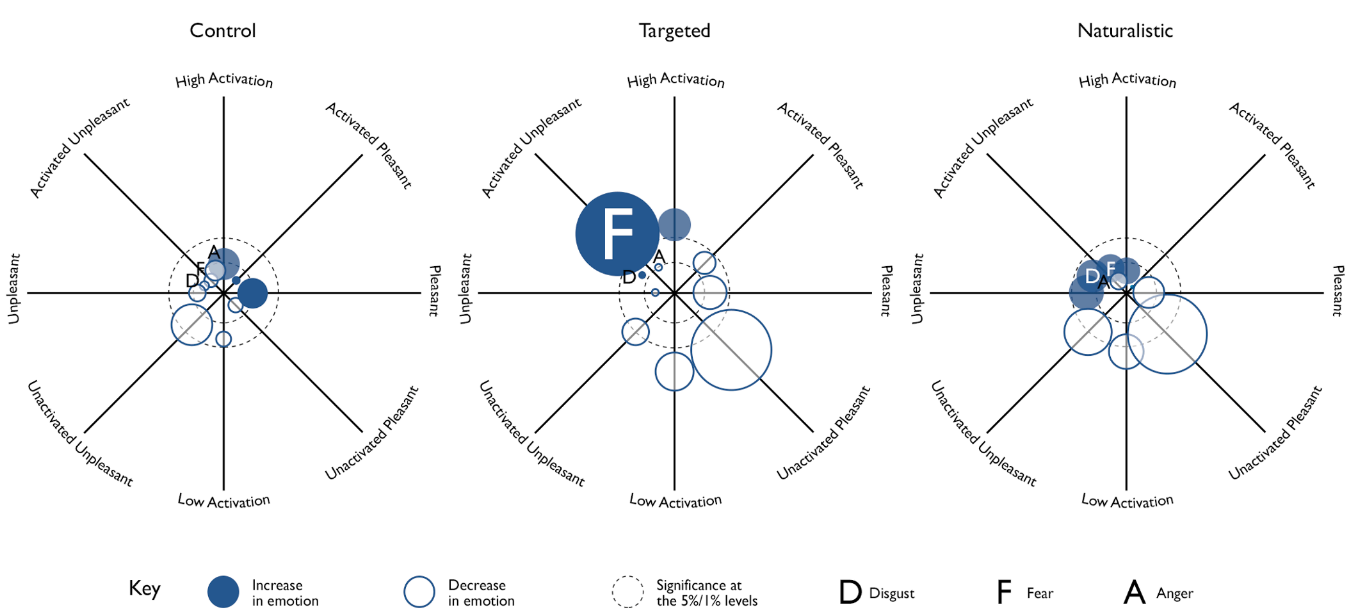

Fig. A.1. Emotional profiles across treatment - males.

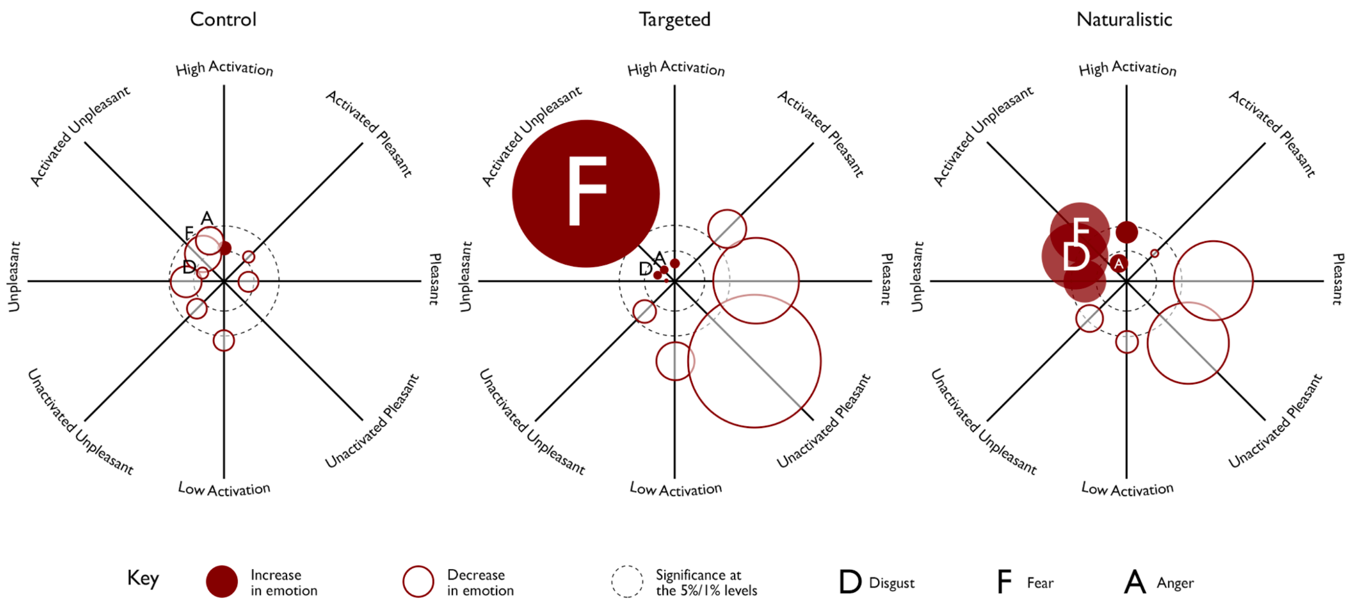

Fig. A.2. Emotional profiles across treatment – females.

Table A.2
SEM path coefficients: females – targeted vs control.

	Risky		Ambiguous	
	a	b	a	b
Increases Model				
High Activation	−0.228*	0.125	−0.228*	0.100
	(0.432)	(0.107)	(0.432)	(0.102)
Disgust	0.429**	−0.264	0.429**	−0.441*
	(0.195)	(0.244)	(0.195)	(0.234)
Fear	3.655***	−0.116	3.655***	−0.112
	(0.450)	(0.128)	(0.450)	(0.121)
Anger	0.728**	−0.061	0.728**	0.122
	(0.285)	(0.210)	(0.285)	(0.203)
Unpleasant	0.741**	0.320*	0.741**	0.260
	(0.338)	(0.189)	(0.338)	(0.178)
Observations	123	109	123	106
Decreases Model				
Activated Pleasant	−0.825*	−0.007	−0.825*	0.027
	(0.435)	(0.103)	(0.435)	(0.103)
Pleasant	−1.308***	0.087	−1.308***	−0.055
	(0.421)	(0.135)	(0.421)	(0.133)
Unactivated Pleasant	−2.649***	−0.022	−2.649***	−0.004
	(0.439)	(0.132)	(0.439)	(0.126)
Low Activation	−0.545	−0.109	−0.545	−0.100
	(0.392)	(0.137)	(0.392)	(0.137)
Unactivated Unpleasant	0.281	−0.025	0.281	0.073
	(0.560)	(0.067)	(0.560)	(0.065)
Observations	123	108	123	105

Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.3
SEM path coefficients: females – naturalistic vs control.

	Risky		Ambiguous	
	a	b	a	b
Increases Model				
High Activation	0.281	0.033	0.281	−0.067
	(0.434)	(0.087)	(0.434)	(0.076)
Disgust	1.571***	0.048	1.571***	−0.018
	(0.386)	(0.114)	(0.386)	(0.115)
Fear	1.942***	0.037	1.942***	0.007
	(0.390)	(0.148)	(0.390)	(0.145)

(*continued on next page*)

Table A.3 (*continued*)

	Risky		Ambiguous	
	a	b	a	b
Anger	0.932**	0.195	0.932**	0.376**
	(0.380)	(0.164)	(0.380)	(0.147)
Unpleasant	1.492***	−0.028	1.492***	−0.051
	(0.374)	(0.140)	(0.374)	(0.135)
Observations	119	105	119	106
Decreases Model				
Activated Pleasant	0.124	−0.077	0.124	−0.043
	(0.382)	(0.118)	(0.382)	(0.117)
Pleasant	−1.166***	−0.038	−1.166***	0.048
	(0.388)	(0.114)	(0.388)	(0.113)
Unactivated Pleasant	−1.650***	−0.026	−1.650***	−0.095
	(0.397)	(0.107)	(0.397)	(0.106)
Low Activation	−0.056	0.016	−0.056	−0.030
	(0.368)	(0.118)	(0.368)	(0.119)
Unactivated Unpleasant	−0.216	0.038	−0.216	0.156**
	(0.552)	(0.065)	(0.552)	(0.066)
Observations	119	105	119	106

Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.4
SEM path coefficients: final emotional states – males – targeted vs control.

	Risky		Ambiguous	
	a	b	a	b
Increases Model				
High Activation	0.070	0.057	0.070	−0.028
	(0.404)	(0.098)	(0.404)	(0.124)
Disgust	0.304	0.098	0.304	−0.023
	(0.210)	(0.257)	(0.210)	(0.255)
Fear	1.413***	−0.024	1.413***	−0.004
	(0.423)	(0.104)	(0.423)	(0.106)
Anger	−0.086	−0.029	−0.086	0.033
	(0.223)	(0.242)	(0.223)	(0.240)
Unpleasant	−0.642**	−0.354*	−0.642**	−0.267
	(0.354)	(0.183)	(0.354)	(0.181)
Observations	123	110	123	107
Decreases Model				
Activated Pleasant	−0.309	−0.104	−0.309	−0.147
	(0.364)	(0.124)	(0.364)	(0.120)
Pleasant	−1.104***	−0.039	−1.104***	−0.011
	(0.411)	(0.112)	(0.411)	(0.110)
Unactivated Pleasant	−0.896**	0.211	−0.896**	0.235
	(0.429)	(0.153)	(0.429)	(0.149)
Low Activation	−0.443	−0.114	−0.443	−0.154
	(0.472)	(0.138)	(0.472)	(0.135)
Unactivated Unpleasant	−0.235	−0.072	−0.235	0.021
	(0.467)	(0.114)	(0.467)	(0.110)
Observations	123	109	123	106

Standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A.5
SEM path coefficients: final emotional states – males – naturalistic vs control.

	Risky		Ambiguous	
	a	b	a	b
Increases Model				
High Activation	0.464	0.120	0.464	0.197
	(0.484)	(0.160)	(0.484)	(0.170)
Disgust	1.374***	−0.313*	1.374***	−0.171
	(0.414)	(0.187)	(0.414)	(0.199)
Fear	0.729	0.029	0.729	−0.118
	(0.471)	(0.170)	(0.471)	(0.177)
Anger	0.542	−0.222	0.542	−0.031
	(0.396)	(0.149)	(0.396)	(0.137)
Unpleasant	0.501	−0.131	0.501	−0.021
	(0.459)	(0.143)	(0.459)	(0.144)
Observations	120	106	120	107

(*continued on next page*)

Table A.5 (*continued*)

	Risky		Ambiguous	
	a	b	a	b
Decreases Model				
Activated Pleasant	−0.082	−0.183	−0.082	−0.273
	(0.408)	(0.143)	(0.408)	(0.150)
Pleasant	−0.973**	0.218	−0.973**	0.160
	(0.462)	(0.115)	(0.462)	(0.142)
Unactivated Pleasant	−0.153	−0.115	−0.153	0.220
	(0.504)	(0.131)	(0.504)	(0.135)
Low Activation	−0.199	−0.104	−0.199	−0.231*
	(0.481)	(0.127)	(0.481)	(0.133)
Unactivated Unpleasant	−0.100	0.002	−0.100	0.067
	(0.565)	(0.104)	(0.565)	(0.107)
Observations	120	106	120	107

Standard errors are in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

Data availability

The data and the analysis files are available via the Open Science Framework https://doi.org/10.17605/OSF.IO/DHRPB.

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