The Context-Dependence of the Process of Risky Choice

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Abstract

The evaluation of risk is a fundamental aspect of decision-making and influences important outcomes, such as in the domain of financial and health behavior. In many economic applications, risk attitudes are assumed to be inherently stable. Nonetheless, there is strong evidence for temporal inconsistencies in risk preferences from both experimental and empirical research. This preference instability may result from the way information is presented (framing), personal experience, and emotions. We conduct four studies in this dissertation to shed light on the state dependency of risk attitudes and on the decision process of risky choice.

Chapter 2 examines, using a laboratory experiment, how high stakes in risky choices influence physiological arousal, as measured via skin conductance, pulse rate and pupil size, and attention, as measured via gaze bias and saccades. We link the changes in arousal and attention accompanying high stakes to changes in risk aversion. Moreover, we develop and test a Sequential Sampling Model (SSM), the arousal-modulated Attentional Drift Diffusion Model (aADDM), linking reaction time and choice while allowing attention and its interaction with arousal to modulate the evaluation process of risky alternatives. High stakes caused changes in attention toward the safe option's attributes, heightened physiological arousal, and increased risk aversion. Results from the aADDM, demonstrate that the values of the high attributes are discounted when participants attend to the low attributes, with arousal amplifying this process further.

Chapter 3, using a laboratory experiment, investigates how incentives and emotional experiences influence the adaptation process across high and low volatility contexts in risky choice. Due to the brain's computational capacity limitations, perception is optimized to detect differences within a narrow range of stimuli. We show that this adaptation process is itself context-dependent, with stronger incentives, heightened arousal, or more unpleasant feelings increasing payoff responsivity under high volatility.

Chapter 4, using survey data, focuses on fear responses during the COVID-19 pandemic and risk perception of the health- and financial-related consequences of the crisis. We show that women report higher fear of the COVID-19 pandemic compared to men, modulating the gender differences in preventative health behaviors. Women also perceive the health risks of COVID-19, and not financial risks, to be greater than men.

Chapter 5, using vignette experiments, demonstrates that betrayal aversion, or hesitancy regarding the risk of being betrayed in an environment involving trust, is an important preference construct in the decision to become vaccinated and is not accounted for by widely used vaccine hesitancy measures. We show that people are significantly less willing to get vaccinated when the associated risk involved the vaccine actively contributing to the cause of death. We also find that betrayal aversion is amplified with an active role of government or scientists. Moreover, we test an exogenous intervention that increases willingness to vaccinate without mitigating betrayal aversion.

JEL codes: D81, D83, D87, D91, I12, J16

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General Audience Abstract

Many decisions involve varying levels of uncertainty and perceived reward like investing in a risky asset or getting a vaccination during a pandemic. These risky decisions, however, require consuming scarce brain resources. In addition, one's own feelings that are altered by the decision context itself or are naturally occurring during daily activities may influence risky decision-making. The scientific mission of this dissertation is to advance our understanding on how the decision context and experienced emotions influence not only risky decisions but also the way by which the decisions are being made.

Our results show that real and high monetary rewards reduce financial risk-taking while altering attention and the perception of information. We also find that stronger incentives activate changes in the autonomous nervous system, such as a racing heart rate, increased sweating, or pupil dilation, and increase self-reports of emotional arousal. Importantly, we demonstrate, via computational modeling and experimental analysis, the role of emotional responses in modulating both attention and value perception of rewards in risky choice. In other words, we find that emotional experiences play an important role in adapting the process by which rewards are evaluated and perceived.

Since significant life events, such as experiencing the COVID-19 pandemic, can lead to substantial uncertainty and emotional distress, we collected survey data upon the crisis' onset to investigate the impact on different aspects of behavior including adherence to prevention measures and willingness to get vaccinated. We find that women, compared to men, reported higher fear of the COVID-19 pandemic and perceived greater negative health risks of the crisis. We attribute observed differences in adherence to prevention measures between men and women to gender differences in emotional responsivity to the pandemic. In addition, we demonstrate the importance of contextual factors, which drive feelings associated with the risk of betrayal, in the decision to become vaccinated. Taken together, the findings in this dissertation highlight the integral role of emotional experiences, which vary with incentives or because of previous experiences, in decision-making under risk.

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Attribution

One Published Journal Article (PJA) is embedded in this dissertation.

Chapter 4: Alsharawy A, Spoon R, Smith A and Ball S (2021) Gender Differences in Fear and Risk Perception During the COVID-19 Pandemic. *Front. Psychol.* 12:689467. doi: 10.3389/fpsyg.2021.689467

Chapter 1

1. Introduction

Risk attitudes are central to many important decisions, such as purchasing an insurance or getting a vaccine. The most widely used models of decision-making assume that risk attitudes are stable (Stigler & Becker, 1977). However, to fit historical data on asset prices, it is necessary to allow risk aversion to vary over time (Bekaert et al., 2019; Campbell & Cochrane, 1999; Cohn et al., 2015; Guiso et al., 2018). In other words, accounting for systematic variations in risk preferences within individuals (Frey et al., 2017; Loewenstein et al., 2001; Mata et al., 2018; Schildberg-Hörisch, 2018) is necessary for the advancement of behavioral modeling. This dissertation consists of four essays that investigate systematic deviations in attitudes toward risk across states and individuals, using both laboratory experiments and survey data. We investigate how stronger monetary incentives influence both the choice process and risk-taking. Importantly, we aim to link physiological and emotional responses to changes in attentional biases and in the perception of value. Since significant life events, such as experiencing the COVID-19 pandemic, can lead to substantial uncertainty and emotional distress, we collected survey data upon the crisis' onset to investigate the impact on different aspects of behavior including adherence to prevention measures and willingness to get vaccinated. We study whether fear of the pandemic is associated with adherence to prevention measures and whether it varies systematically across genders. In addition, we investigate the role of contextual factors that influence feelings associated with the risk of betrayal on vaccine hesitancy.

Chapter 2 investigates the physiological and information processing mechanisms underlying the effect of incentives on risk aversion. We acquired physiological (heart rate, skin conductance, pupil size) and gaze fixation data while participants are making risky choices involving large changes in monetary incentives to study the neurocomputational mechanisms underlying the effect of increased incentives on risk aversion. In this chapter, we develop the arousal-modulated Attentional Drift Diffusion model (aADDM) of the interaction of arousal and attention during evidence accumulation. Increased risk aversion under high real stakes was associated with changes in physiological arousal levels and in attention. In addition, high and low attributes for available options were attended differently. The aADDM results suggest that the values of the high attributes were discounted steeply when looking at the low attributes, with arousal amplifying this process further. No such effect was found for low attributes. These results demonstrate the value of integrating physiological and attention measures for understanding the decision process of risky choice.

Chapter 3 examines risky choice as it relates to the efficient coding hypothesis that posits that more frequently encountered payoffs are perceived more accurately (Barlow, 1961). In other words, value representations are context dependent due to the brain's computational constraints. We test how incentives (real vs. hypothetical) and emotional experiences (arousal and valence) modulate these value representations in financial decisions. Participants made risky choices under both low (LV) and high (HV) payoff volatility conditions, were assigned to receive real payment from either the LV or HV conditions, and regularly reported their emotional experience during the session. We find that stronger (real) incentives modulate the perception of value and increase self-reports of arousal. Real stakes, instead of hypothetical ones, interrupted the decline in perception sensitivity to small changes in payoffs when they are sampled from distributions with wider range. Moreover, participants experiencing heightened arousal or more unpleasant feelings under the wider range also experienced comparable sensitivities to changes in the risky payoff across volatility conditions. Thus, our study show that efficient coding seems to hold best under weak incentives, low levels of arousal and more pleasant feelings, suggesting that the range adaptation process itself is also context dependent.

Catastrophic events, such as experiencing a pandemic, may have different emotional and behavioral impacts across individuals (Callen et al., 2014; Huang et al., 2013; Ibuka et al., 2010). In Chapter 4, we investigate the differences in the perception of and emotional response to the COVID-19 pandemic between men and women residing in the United States. We administered an online survey to capture self-reported fear, expectations of negative health and economic consequences, and preventative measures taken during the early weeks of the pandemic. Women report higher fear of the COVID-19 pandemic compared to men. We further attribute the observed gender differences in adherence to preventative health behavior to fear of the pandemic. Moreover, women perceive the health risks of COVID-19 to be greater than men, despite the robust empirical finding that realized outcomes are worse for men. On the other hand, women have lower expectations of financial hardships due to COVID-19. We also argue that gender differences in negative emotional experiences are not unique to COVID-19 pandemic and can be generalized to other crises. Our findings are consistent with the affect heuristic: the notion that emotional experience shapes the perception of risk. Understanding gender differences in fear and risk perception can be useful to the design of targeted policy interventions in response to catastrophic events.

The determinants of vaccine hesitancy remain complex and context specific (MacDonald, 2015). Betrayal aversion occurs when an individual is hesitant to risk being betrayed in an environment involving trust (Koehler & Gershoff, 2003). Importantly, the disutility of betrayal can inhibit trust independent of risk or regret aversion (Bohnet et al., 2008; Lauharatanahirun et al., 2012). When choosing between safety products like vaccines, betrayal averse individuals may accept lower levels of protection from the primary risk in order to avoid a secondary risk of being harmed by the safety product itself. Current measures of vaccine hesitancy capture overall beliefs about the safety of vaccines without disassociating the source of the assumed risks. In Chapter 5, we document the importance of betrayal aversion in vaccination decisions and show that it is not captured by current vaccine hesitancy measures. We find that over a third of participants have betrayal averse preferences, resulting in an 8-26% decline in vaccine acceptance, depending on the betrayal source. We explore an exogenous message intervention and show that an otherwise effective message acts narrowly and fails to reduce betrayal aversion. Our results demonstrate the importance of betrayal aversion as a preference construct in the decision to vaccinate.

Together, these four studies shed light on the importance of the choice environment, emotional experiences, and previous experiences in shaping not only behavior and risk preferences but also the process by which the decisions are being made. We show how incentives influence physiological arousal and self-reports of emotional experiences as well as risk aversion, attention, and the perception of value. In addition, we demonstrate that significant events such as a pandemic influence emotional experiences and risk perception differently across sub-populations such as gender or across contexts that vary the framing of the potential risk. The findings in this dissertation, taken together, highlight the impact of contextual factors, such as incentives and previous experiences, on emotional experiences and in shaping both the choice process and behavior pertaining to decisions under risk.

Chapter 2

2. Incentives modulate arousal and attention in risky choice

Abdelaziz Alsharawy, Xiaomeng Zhang, Sheryl Ball, and Alec Smith

Abstract

We investigated the effect of large changes in financial incentives on the process of decision-making by measuring autonomic arousal and attention during a lottery-choice task. High real stakes caused increased risk aversion, increased physiological arousal, and shifted attention toward safer alternatives. These effects were manifested both within and between individuals. We also developed and fit a new arousal-modulated Attentional Drift Diffusion model (aADDM) to capture the interactions of arousal and attention with subjective value during evidence accumulation. The aADDM modeling demonstrates that arousal amplified discounting of high-valued outcomes when participants attended to low-valued outcomes. No such effect was found for low-valued outcomes. Our findings demonstrate that physiological changes and shifts in attention are integral to the process of decision-making under risk. Understanding how risk and incentives affect arousal and attention in value-based decisions can help explain not only individual behavior but also large-scale group dynamics such as bubbles and crashes in asset prices.

2.1. Introduction

Important decisions, such as whether to run from a bear or to sell stocks during a market crash, typically involve risk and high stakes. In the most widely used models of decision making under risk, choices are determined by exogenous, stable risk attitudes (Frey et al., 2017; Stigler & Becker, 1977). However, the decision environment may itself cause emotional and physiological reactions (Kang et al., 2011; Lerner et al., 2015; Loewenstein et al., 2001; Phelps et al., 2014) that in turn influence the choice process. Both uncertainty (Aston-Jones & Cohen, 2005; De Berker et al., 2016; Nassar et al., 2012; Urai et al., 2017; Yu & Dayan, 2005) and incentives (Anderson & Brown, 1984; Dix & Li, 2020; Eysenck, 1982; Richter & Gendolla, 2009) affect autonomic arousal, a key component of emotional responses. Arousal is regulated by the brain's locus coeruleus-norepinephrine (LC-NE) system, the activation of which results in widespread changes in physiology, affect, and cognition (Poe et al., 2020). For example, arousal has recently been shown to modulate retinal responses at the earliest levels of sensory input (Liang et al., 2020; Schröder et al., 2020). Arousal focuses attention on salient or goal-relevant stimuli, such as threats or losses(Eldar et al., 2013, 2016; Mather et al., 2016; Sutherland & Mather, 2018), amplifying their weight in decision-making (Causse et al., 2011; Hochman & Yechiam, 2011; Sheng et al., 2020; Sokol-Hessner et al., 2009), potentially through changes in attention (J. A. Aimone et al., 2016; Arieli et al., 2011; Fiedler & Glöckner, 2012; Karlsson et al., 2009; Pachur et al., 2018; Sheng et al., 2020; Sicherman et al., 2016). Thus, the same factors that determine choices in process-free models of decision-making may also change the way those choices are made.

In financial decision-making, high stakes typically lead to increased risk aversion (Binswanger, 1980; Holt & Laury, 2002; Kachelmeier & Shehata, 1992). This behavioral pattern is consistent with expected utility theory and thus could be a rational response to increased incentives (Bombardini & Trebbi, 2012; Rabin, 2000). In many settings, stronger incentives increase mental effort and improve cognitive performance (Botvinick & Braver, 2015; Frömer et al., 2021; Kool & Botvinick, 2014; Shenhav et al., 2017). However, in other settings high stakes also lead to increased arousal and mistakes (Ariely et al., 2009; Baumeister, 1984). Thus high-stakes risk aversion may be a rational response to increased incentives involving increased effort (Kahneman, 1973) and resource-constrained decision-making (Bhui et al., 2021; Lieder & Griffiths, 2020) or it might be a decision bias (Eldar et al., 2021) linked to narrowed attention (Easterbrook, 1959) and hyper-arousal (Ariely et al., 2009; Chib et al., 2014; Dunne et al., 2019).

To identify the effect of large changes in incentives on the process of making risky decisions, we measured arousal, attention, and attitudes towards risk in a within-subject design while experiment participants made choices between monetary lotteries involving hypothetical, low, and high stakes (*Figure 2.1*A). We hypothesized that high stakes decisions involving risk would generate a pronounced autonomic response, and that this response would be associated with both increased risk aversion and changes in the decision-making process.

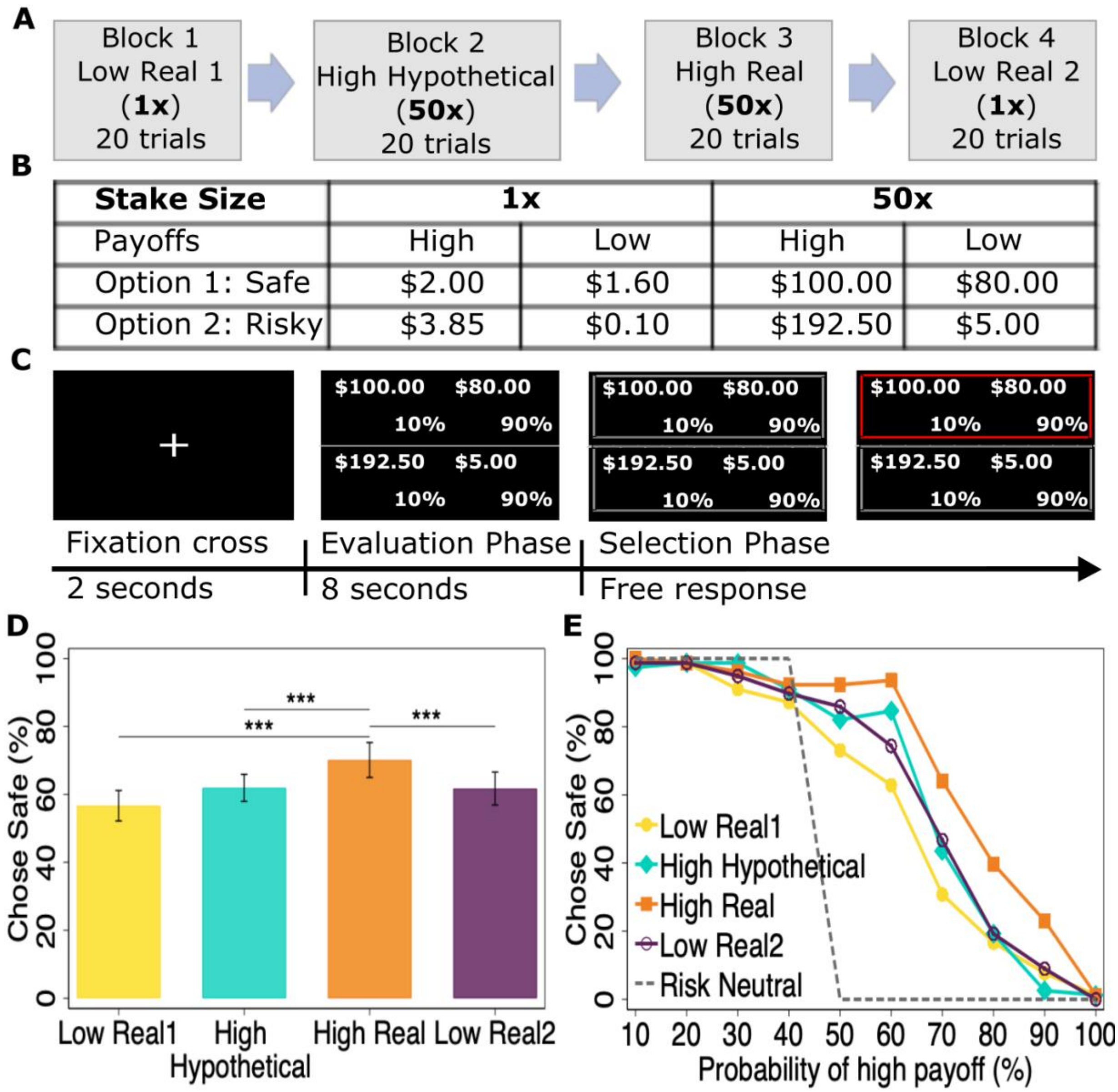

Figure 2.1 Task and Behavior. (A) Participants completed four ordered blocks of paired lottery-choice decisions. The probability of the high payoff varied between 10% to 100%. Each choice (see Table 2.S1) was presented twice. The presentation format (left vs. right; top vs. bottom) and the order of the lottery-choice decisions within each block were randomized across participants. (B) High payoffs (both hypothetical and real) were generated by multiplying the low payoffs by a scale factor of 50. (C) Illustration of a single decision round. (D) The rate of choosing the safe lottery across blocks and (E) for each lottery-choice decision ordered by the probability of the high payoff. Data points are participant averages. Risk aversion was greatest in the high real condition. Wilcoxon signed-rank test (N=39): *** P-value < 0.001. Error bars denote 95% confidence intervals.

2.2. Methods

Participants (N=46, median age=21, 28 males, 7 excluded due to data collection problems – see supplementary material) chose between two lotteries, one safe and one risky, each with two possible non-zero outcomes, while we recorded reaction time, gaze fixation, pupil dilation, pulse rate, and skin conductance. To investigate the influences of changes in autonomic arousal and attention on the evaluation of risky choice, we developed and tested a physiologically-plausible arousal-modulated Attentional Drift Diffusion model (aADDM) that captures the interaction of arousal and gaze bias during evidence accumulation.

The high stakes condition involved real monetary incentives that were 50 times greater than in the low real stakes condition (*Figure 2.1*B). In the hypothetical condition, choices were not incentivized. Each condition was presented in a separate block and participants learned the incentives before making choices in that block. Each of the ordered blocks consisted of 20 choice trials, randomized across participants. This design allowed us to capture physiological processes that govern tonic arousal, which take place on a longer time-scale than individual decisions (Aston-Jones & Cohen, 2005). We modified the lottery-choice decisions of the Holt & Laury (2002) task (*Figure 2.1*C), where the probability of the high payoff increases from 10% to 100% (see *Table 2.S1*), to record physiological measures for each lottery-choice presented sequentially (*Figure 2.1*D). The non-zero probability of choosing the safe option in decisions when the probability of the high payoff was greater than 40% is evidence of behavioral risk aversion.

2.3. Results

Participants displayed significantly increased risk aversion with high real stakes compared to each of the other three incentives schemes ($M_{difference}$>8%; Wilcoxon signed-rank test: N=39, all P<0.001; *Figure 2.1*D-E), supporting previously reported behavioral findings (Holt & Laury, 2002; Lévy-Garboua et al., 2012). Note that this finding provides opposing evidence to models involving scale invariance (Khaw et al., 2021).

To examine the causal role of incentives on arousal, we compared average levels of pretrial pulse rate, skin conductance and pupil dilation across blocks. Importantly, the set of stimuli in the high real and high hypothetical bocks were identical, except that in the high real block, participants were paid for one randomly selected choice. Tonic physiological arousal was measured prior to stimulus presentation (pretrial) while participants viewed a fixation cross (see *Figure 2.1*B and supplementary material for details on procedures and the computation of these measures). All three measures of pretrial arousal were significantly higher when stakes were high and real ($M_{difference}$>0.332; Wilcoxon signed-rank test: N=39, all P<0.010) (*Figure 2.2*A and *Figure 2.S2* in supplementary material). Because trial-by-trial pulse rate, skin conductance and pupil size on average were positively correlated (Spearman rank correlation: T=80; pulse and pupil ρ_s=0.4383; pulse and skin conductance ρ_s=0.670; pupil and skin conductance ρ_s=0.768, all P<0.0001) (Wang et al., 2018), we computed the first principal component (pc1) of our three measures to capture experienced arousal. Individual differences in the effect of high stakes on risk aversion (measured by the difference in the number of safe choices in the high real vs. the hypothetical conditions) were positively and significantly associated with concomitant changes in arousal (*Figure 2.2*B; Spearman rank correlation: N=39; ρ_s=0.441, P=0.005) (see supplementary material for phasic arousal -change from baseline- in the evaluation phase).

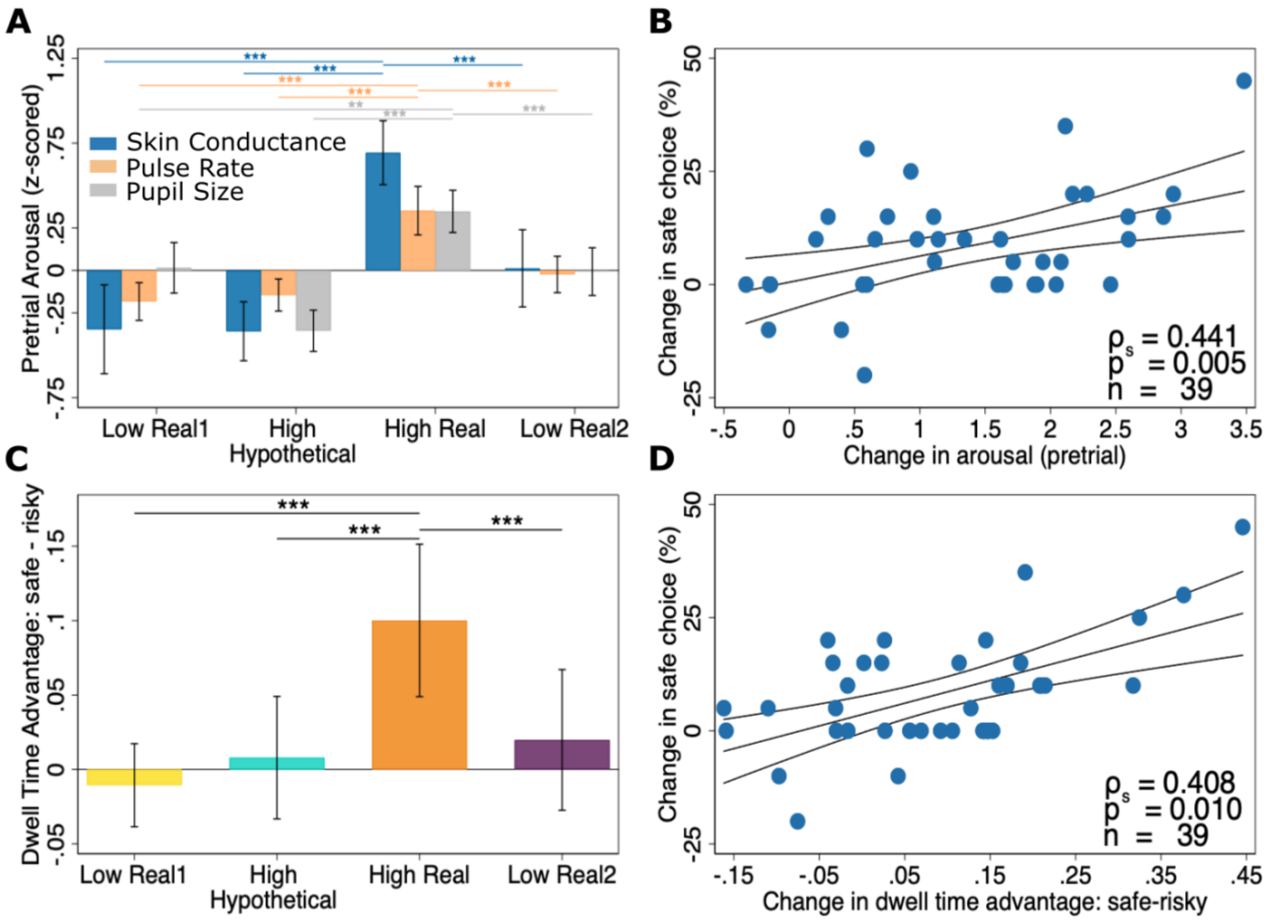

Figure 2.2 Incentives, arousal, and attention. (A) Skin conductance, pulse rate, and pupil diameter were all higher under high real stakes. (B) Individual differences in the effect of high stakes on generalized arousal were strongly associated with changes in risk aversion. Here the percentage difference in safe choices (y-axis) in the high stakes real vs. the hypothetical block is plotted against the individuals' difference in arousal in the high stakes real vs. the hypothetical block (x-axis). Experienced arousal is computed as the first principal component of the three pretrial arousal measures: skin conductance, pulse rate and pupil size (Spearman rank correlation reported). (C) Dwell time advantage during the evaluation phase for the safe option (relative fixation duration on safe outcomes minus risky outcomes) was highest during the high real block. (D) Individual differences in dwell time advantage for the safe option in the high real vs. the hypothetical block were strongly associated with changes in risk aversion. The percentage change in safe choices in the high real block relative to the hypothetical block (y-axis) is plotted against the individuals' difference in dwell time advantage (gaze on safe option minus gaze on risky option) during the evaluation phase in the high stakes real vs. the hypothetical block (x-axis) (Spearman rank correlation reported). Linear fits plotted in (B) and (D). Error bars and line bounds show 95% confidence intervals. For (A) and (C), Wilcoxon signed-rank test (N=39): ** P-value < 0.01; *** P-value < 0.001.

Gaze bias, where people tend to select the option that they have attended to the most, is a robust phenomenon in both simple and risky choice (Cavanagh et al., 2014; Fiedler & Glöckner, 2012; Krajbich et al., 2010; Krajbich & Rangel, 2011; Smith & Krajbich, 2018, 2019; Stewart et al., 2016). In our experiment, attentional patterns (measured during the evaluation phase) differed across all trials in the high real block compared to the hypothetical or the low real blocks. Under high real stakes, participants fixated significantly more on the safe option relative to the risky one ($M_{difference}$>0.080; Wilcoxon signed-rank test: N=39, all P<0.001) (*Figure 2.2*C and *Figure 2.S4* in supplementary material). Importantly, individual differences in risk aversion in the real vs. the hypothetical block were also positively and significantly associated with changes in dwell time advantage for the safe option from the hypothetical block to the high real one (Spearman rank correlation: N=39; ρ_s =0.408, P=0.010) (*Figure 2.2*D).

Certainly, the gaze bias differential effect under high real stakes (*Figure 2.2*C) was attributed to participants fixating less on the risky high outcome, and more on both outcomes of the safe option ($M_{difference}$>0.035; Wilcoxon signed-rank test: N=39, all P<0.002) (*Figure 2.3*A). Individual differences in changes in dwell time advantage on high outcomes (relative dwell time on safe high minus that on risky high) were also more strongly associated with the increased risk aversion between the hypothetical and the high real block (Spearman rank correlation: N=39; ρ_s =0.392, P=0.014) when compared to low outcomes (Spearman rank correlation: N=39; ρ_s = 0.169, P=0.304). In other words, in these instances, participants who attended more to the safe option's high outcome than the risky option's one were becoming more risk averse. Moreover, outcomes' evaluation differed when participants chose the risky option: there was an initial fixation bias toward the high outcomes of both available options with a greater duration spent on the risky high outcome until the end of the trial (*Figure 2.3*B-C, see *Figure 2.S5* and *Figure 2.S6* in supplementary material for gaze split by blocks and for gaze during selection phase).

Importantly, we find no evidence that increased risk aversion under high stakes is a mistake. On the contrary, the percentage of participants making inconsistent choices (selecting different options for the same decision within a block) was somewhat lower under high real stakes (High Real vs. High Hypothetical: $M_{difference}$=-4.103; Wilcoxon signed-rank test: N=39, P=0.066; High Real vs. Low Real 1: $M_{difference}$=12.051, P<0.001; High Real vs. Low Real 2: $M_{difference}$=2.564, P>0.100) (see *Figure 2.3*D). We also compute the Payne index that summarizes the search pattern with a greater score indicating more integrative evaluation, instead of a heuristic-dependent one (Payne & Braunstein, 1978). The average Payne index was significantly higher under high real stakes compared to high hypothetical and low real 2 blocks (High Real vs. High Hypothetical: $M_{difference}$=0.030; Wilcoxon signed-rank test: N=39, P=0.003; High Real vs. Low Real 1: $M_{difference}$=0.025, P>0.10; High Real vs. Low Real 2: $M_{difference}$=0.049, P<0.001) (see *Figure 2.3*E). Note however that the greatest increases in Payne index from the high hypothetical to the high real block was recorded for participants with intermediate increases in pretrial arousal (quadratic regression: $\beta_{pc1} = 0.054, P = 0.030$; $\beta_{pc1^2} = -0.021, P = 0.013$; see Fig S7), suggesting a differential impact of arousal on performance across participants (Eldar et al., 2021; Grueschow, 2018; Howells et al., 2012; Yerkes & Dodson, 1908) (see supplementary results).

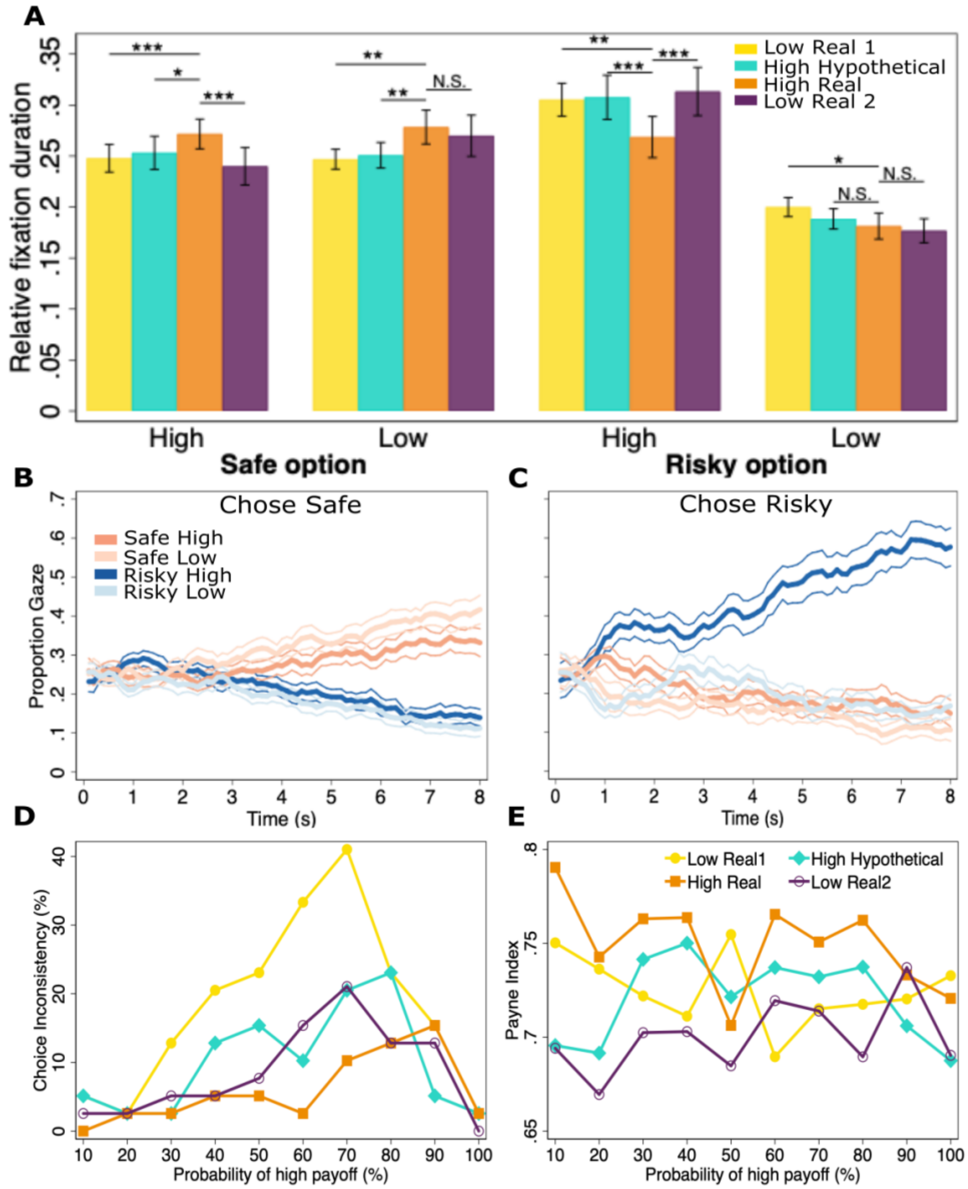

Figure 2.3 Differences in the information process. (A) Proportion of the evaluation phase fixated upon each outcome and associated probability. Fixation duration on the risky high outcome decreased in the high real block relative to the other three blocks while fixation duration on the risky low outcome remained relatively unchanged. Fixation duration for the safe high and low outcomes increased in the high real block relative to the other three blocks, while fixation duration for the safe low outcome increased. Error bars and line bounds show 95% confidence intervals. Wilcoxon signed-rank test (N=39): * P-value < 0.05; ** P-value < 0.01; *** P-value < 0.001; N.S. not significant. Cumulative proportion of the evaluation phase with gaze fixated on each outcome and associated probability when participants (B) chose the safe option and (C) chose risky option. When choosing the safe option, participants fixated more on both the high and low outcomes of the safe option. However, when choosing the risky option, participants fixated more on only the risky high outcome. Data shown are pooled across 100-millisecond windows (100 samples). (D) percentage of participants making inconsistent choices and (E) average Payne index in each decision for each block.

Computational models of decision-making processes such as Drift Diffusion Models (DDM), or, more broadly, Sequential Sampling Models (SSMs) describe the process of stochastic accumulation of information until enough evidence is built-up in support of one of the alternatives to reach its decision boundary (Ratcliff, 1978). In two-alternative choice problems, DDM models link reaction time and choice data in order to infer parameters that pertain to a noisy process of decision making (Ratcliff et al., 2016). The decision threshold represents the amount of information required before making a choice, while the drift rate represents the speed by which a decision maker accumulates information. We ran a simple DDM that allows the threshold to vary with the first principal component of our pretrial arousal measures. Increased trial-to-trial arousal levels increased the amount of information needed to arrive at a decision signifying higher response caution ($\beta = 0.051, P < 0.0001;$ –where P= 1-pd (posterior probability of direction)–(*Figure 2.4*A)). This finding is consistent with the higher average reaction time, de-trended using quadratic time trend, under high real stakes ($M_{difference}$>0.480; Wilcoxon signed-rank test: N=39, all P<0.050) (see Figure 2.S8).

Attentional Drift Diffusion Models (ADDMs (Krajbich et al., 2010; Krajbich & Rangel, 2011)) extend the DDM to incorporate the effect of attention on choice. These models demonstrate that gaze amplifies the effect of information on decisions – choices are biased in the direction of attended information (Cavanagh et al., 2014; Krajbich et al., 2010; Krajbich & Rangel, 2011; Smith & Krajbich, 2018, 2019; Westbrook et al., 2020). Particularly, evidence accumulated in favor of the fixated option receives higher weight relative to that of the non-fixated one both independently and when multiplied with respective values. Similarly, autonomic arousal is thought to amplify the gain in information processing (Aston-Jones & Cohen, 2005; Krishnamurthy et al., 2017; Mather et al., 2016). Therefore, we hypothesized that arousal might amplify the effect of attentional gaze bias. We develop an arousal-modulated Attentional Drift Diffusion model (aADDM) that captures the interaction of arousal and attention during evidence accumulation.

The aADDM allows us to investigate how pre-trial arousal levels interact with gaze to influence the drift rate of the decision process. We fit our model using hierarchical drift diffusion modeling – HDDM (Wiecki et al., 2013) (see supplementary material for details on estimation procedure and model specification). Our model is flexible in incorporating different attentional biases split by whether the high or low outcomes were being evaluated (as shown in equation SE6PC1). Since we find evidence that attention to particular outcomes differs with choice and across blocks (see *Figure 2.3*), our model allows the subjective value difference for high outcomes (H) to be evaluated differently from low outcomes (L) depending on the participant's gaze location (g) on safe high (SH), safe low (SL), risky high (RH) or risky low (RL). Importantly, model parameters in our aADDM vary with pretrial arousal levels (pc1) allowing arousal to modulate attentional biases.

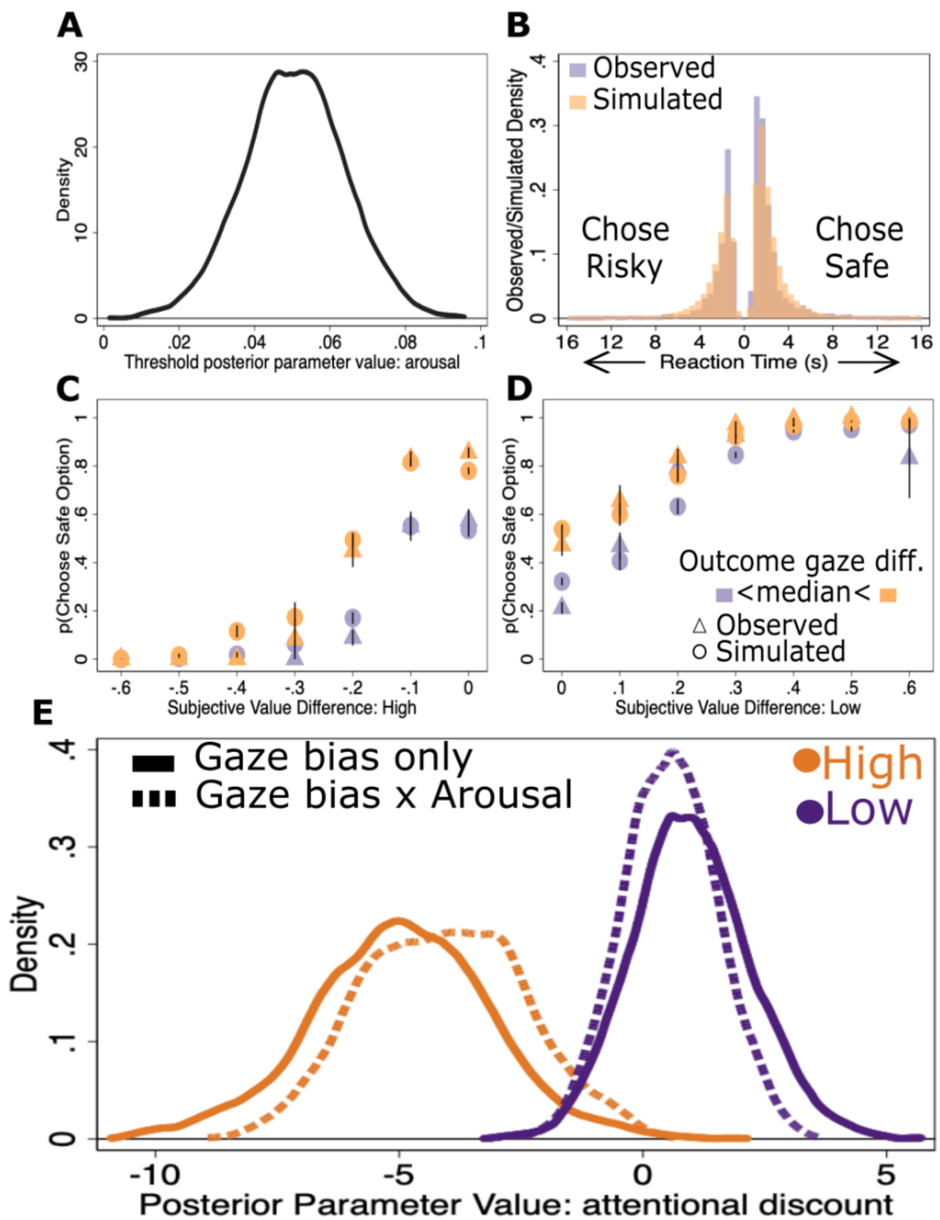

Figure 2.4 Arousal-modulated Attentional Drift Diffusion Model. (A) Arousal increased the decision threshold ($\beta = 0.051, P < 0.0001$) in a simple drift-diffusion model. (B-D) Simulated choices from the attribute-wise model (which includes both additive and multiplicative gaze) predicted (B) reaction time and (C) observed choices relative to high outcomes' value difference, and (D) low outcomes' value difference. Error spikes denote standard error of the mean. (G) Gaze on the opposite outcome during evaluation phase discounted the value of high outcomes only (γ_{High}= -4.96, P=0.005). Generalized arousal amplified the high outcomes' attentional bias during the evaluation phase ($\gamma_{pc1tonic*High}$= -4.09, P=0.002) (see supplementary material for additive gaze bias and for model fits using selection phase gaze). Extreme outlier reaction times are not shown in (B), less than 1.3% of the data points are omitted.

We estimated the aADDM twice, once for gaze recorded during the evaluation phase (EP: passive exposure phase) and another time for that recorded during selection phase (SP) (see *Figure 2.1*). The question of whether gaze bias takes an additive/independent or a multiplicative (with value) form has been debated in the literature with evidence for both approaches (Cavanagh et al., 2014; Smith & Krajbich, 2019; Westbrook et al., 2020). Multiplicative gaze bias for high-valued outcomes, for example, would be present if the safe high and risky high subjective values have a greater influence on drift rate while looking at high outcomes rather than on low outcomes. Including both additive and multiplicative gaze effects and employing an attribute-wise model specification provided the best model fits (see Fig S9) and closely matches observed data (see *Figure 2.4*B-D). Attribute-wise models had also been found to provide better model fits compared to option-wise models in temporal decision-making (Amasino et al., 2019) and in willingness to expend cognitive effort (Westbrook et al., 2020).

High-valued outcomes were discounted steeply when attending to low outcomes, with pretrial arousal levels amplifying this bias during the evaluation phase (γ_{High}= -4.96, P=0.005; $\gamma_{\text{pc1*High}}$= -4.09, P=0.002 –where P=1-pd (posterior probability of direction)– see supplementary material for additional details). On the other hand, the low outcomes' subjective values were not discounted when attending to high outcomes, and arousal had no role in creating such a bias (see *Figure 2.4*E and *Table 2.S2*; see *Figure 2.S10* for model derived using selection phase gaze). Thus, attending to the low outcomes in presented lotteries discount steeply the values of the high outcomes, with arousal further exacerbating this effect. Attending to high outcomes, however, does not alter the evaluation of low outcomes.

This study shows that high real stakes caused increased risk aversion, increased autonomic arousal, and shifted attention toward safer options, both within and between individuals. We find no evidence, however, that increased risk aversion is a mistake. Model-based analysis further demonstrated that arousal and attention amplify subjective value in the evaluation of risky options. Our findings demonstrate that physiological changes and shifts in attention are integral to the process of decision-making under risk.

2.4. Supplementary Material A

2.4.1. Subjects

All procedures were approved by Virginia Tech Institutional Review Board, and each participant provided informed consent prior to participation. There was no deception involved in this study. The average payment received by participants was $108.58, which includes $10 show-up fee. Each participant made a total of 80 lottery choices, using Holt & Laury (2002) lotteries (see Table 2.S1). Initially we recruited 46 participants but data from 39 were used in our final analysis, as seven participants from our original sample were excluded due to either poor eye tracking data (5 participants), stimulus computer crash (1 participant) or non-responsive skin conductance measurement (1 participant). Thus, our analysis sample included 24 males and 15 females with an average age of 22 (minimum age: 18, maximum age: 33).

2.4.2. Task and procedures

We only used two stake sizes from Holt & Laury's (2002) original lottery choices: the low stake size (1X) and a high-stake size of 50X (the exact payoffs in each stake size condition are shown in Figure 2.*1*B of the main text). Our experiment employs a within-subject design in which each participant completes four blocks in the following order (see Figure 2.*1*A of the main text):

1) Low Real1 (1X): 20 low stakes choices with one choice randomly selected for payment.
2) High Hypothetical (50X): 20 hypothetical choices of the high payoffs.
3) High Real (50X): 20 high stakes choices with one choice randomly selected for payment.
4) Low Real2 (1X): 20 low stakes choices with one choice randomly selected for payment.

Participants in our experiment were presented with the lottery choices sequentially. The order of the lotteries within a block is randomized across participants who see each decision problem twice, once in the first 10 trials and once again in the second 10 trials. To help ensure that participants scan all the information on the screen and that the presentation format is not causing a bias, we add variation in the presentation format as follows: for each of the first 10 trials, a random number determines which of the presentation formats is used with an equal chance of each of the following: 1) the safe lottery up and the high payoffs to the left, 2) the safe lottery up and the high payoffs to the right, 3) the safe lottery down and the high payoffs to the left, and 4) the safe lottery down and the high payoffs to the right. In the second 10 trials in a block, we show the same 10 payoffs and associated probabilities again but with the opposite presentation format. A participant, for example, who sees one of the decision problems with the safe lottery up and the large payoffs to the left during the first 10 trials, would be presented with the same decision problem but with the safe lottery down and the large payoffs to the right during the second 10 trials. The order of the lottery choice within a block is randomized for the first 10 rounds and again for the next 10 trials. The order of the four blocks, however, is the same for all participants.

Prior to moving to the next block, one lottery from the completed block is randomly selected and played out to determine the payoff for that block. In order to proceed to the high real block and to control for wealth effects, participants had to agree to forfeit the first block's payment before they proceeded. Unsurprisingly, all participants elected to do forfeit their first block's payment. For the high hypothetical block, we asked participants to acknowledge that the payoffs in that block were hypothetical and will not be paid. Also, to familiarize participants with the payoff structure associated with that upcoming block, one random trial from the block was presented during the instruction phase of that block and prior to making decisions.

After participants arrive in the lab and complete the consent phase, we first connect the transducers that measure heart rate and skin conductance to three fingers on their non-dominant hand. The next step is the calibration and validation process for the EyeLink 1000 plus eye tracker, which typically takes 5 to 10 minutes. This step is important in accurately collecting gaze data. Next, participants are presented with the instructions that are specific to the block they will see. During each trial, a fixation cross appears at the center of the screen for 2 seconds before the two options are presented on the screen for 8 seconds (Evaluation Phase: EP) (see Figure 2.1C in the main text). Pretrial psychophysiological measured during the presentation of the fixation cross reflect tonic level of arousal, and arousal measured during the Evaluation Phase reflect phasic arousal level (Murphy et al., 2011). Pupillometry studies, for example, show that drugs that induce low arousal decrease baseline pupil diameter (for example, Hou et al., 2005) whereas responding to stimuli in cognitive tasks rapidly increases pupil size (for example, Beatty, 1982). After 8 seconds, two rectangular grey boxes appear on the screen, one for each option. Participants had unlimited time to use the arrow keys on the keyboard, causing the box on the selected option to become red, until selecting the option that they prefer by pressing the Enter button (Selection Phase: SP). Once an option is submitted, a fixation cross appears again before the next round is presented. Reaction time was recorded once the rectangular grey boxes appear on the screen. Each participant was informed of each block's outcome before reading the instructions for the next block. The average duration of the experimental session was around 50 minutes.

2.4.3. Eye-tracking and physiological measurements

Presentation of the gambles and the selection of options were programmed using Matlab, employing Psychophysics and Eyelink toolbox extensions (http://psychtoolbox.org/) to record eye movements and pupil dilation. We collected eye tracking data using the EyeLink 1000 Plus eye tracker, which consists of a High-Speed Camera that records 1000 samples per second and a Host PC that is dedicated to receiving and processing the collected data (see http://www.sr-research.com/mount_desktop_1000plus.html for more information). We used a desktop mount that sits in front of the stimulus monitor, and we employ an adjustable head stabilizer (chin rest) to improve data quality. Participants face the camera, which is placed in front of the monitor. Prior to the presentation of each decision, a fixation cross appears on the monitor for 2 seconds. Tonic pupil dilation is measured as the baseline average pupil size 1 second before stimulus presentation while phasic pupil dilation is measured as the difference between maximum pupil size recorded in the evaluation phase and the tonic (baseline) pupil size (Figure 2.S1) (Bradley et al., 2008; Eldar et al., 2013; Murphy et al., 2011). We then compute pretrial pupil size and evaluation phase pupil dilation z-scores for each participant.

Physiological data on heart rate and skin conductance were collected using the software Aqcknowledge version 5.0.4, BIOPAC MP160WSW data acquisition system and BioNomadix PPG & EDA system. The data was recorded at 2000 samples per second (see www.biopac.com for details). The following physiological measures were collected via wireless devices worn on the left hand: Electrodermal Activity (EDA) and Pulse Photoplethysmogram (PPG) (Fowles et al., 1981; Allen, 2007). EDA (also known as Galvanic Skin Response (GSR) or Skin Conductance Activity (SCA)) is a measure of eccrine activity or skin sweating. EDA signal can be obtained from placing two electrodes (Ag-AgCl) on two different fingers of the hand while very low constant voltage is applied (which is not felt by the participant). The constant voltage is maintained between the two electrodes such that current flow is proportional to skin conductance (Braithwaite et al., 2013). We placed the (disposable) electrodes on the ring and middle fingers of the non-dominant hand (between the middle and distal phalanges). Before exporting the data for analysis in Stata 15.1, we used the software Aqcknowledge version 5.0.4 to filter and smooth the data and to mark skin conductance responses.

EDA data were down sampled to 250 Hz before further analysis. We derived pretrial Skin Conductance Level (SCL) as a one second average of skin conductance before stimulus presentation and during fixation cross presentation (Bradley et al., 2008; Braithwaite et al., 2013). Moreover, we set a minimal response criterion at 0.02 µS (microSiemens), and we measured evaluation phase skin conductance response (SCR) as the maximum recorded response by trough-to-peak amplitude difference in the time window 1 second after the presentation of the lotteries in a trial till 8 seconds from onset (Figure 2.S1). SCL relates to the general level of skin conductance, which reacts slowly, while SCR reacts faster to presented stimuli (Braithwaite et al., 2013). For processing the data, we applied the following: low-pass filtering (25 Hz), smoothing (3 sample kernel), and applying a square root transformation (Sokol-Hessner et al., 2009). We then estimate a z-score for each participant to facilitate comparisons within and across participants. Thus, we derive our two measures (z-score) of skin conductance: 1) pretrial skin conductance level and 2) evaluation phase skin conductance responses.

PPG provides measurements for heart rate and is measured via a wireless transducer that monitors changes in infrared reflectance resulting from varying blood flow. The pulse transducer was placed on the index finger's distal phalange of the same hand where the electrodes were placed. The PPG signal was down sampled (250 Hz) and smoothed (3 sample kernel) before deriving the pulse rate using a minimum threshold of 0.05 volts. The pulse rate signal was also smoothed (3 sample kernel). Similar to skin conductance, we computed an average pretrial measure of heart rate as a one second average before stimulus presentation (Jennings et al., 1981; Bradley et al., 2008). We then compute the average pulse rate recorded during the first 8 seconds from stimuli presentation onset (Figure 2.S1). And, we generate an analogous phasic (change from baseline) pulse rate measure by subtracting the pretrial measure of pulse rate from the average evaluation phase measure of pulse rate. We refer to this measure as evaluation phase pulse rate. Last, we derived pretrial and evaluation phase pulse rate z-scores for each participant.

2.4.4. HDDM estimation

HDDM involves Markov Chain Monte-Carlo (MCMC) sampling to estimate DDM parameters for both individual and group-level. To avoid an explosion in the number of parameters and to aid in convergence, we only estimate individual estimates for the intercept in the drift rate regression and we obtain group estimates for the remaining regression coefficients (Frank et al., 2015). In the HDDM estimation for all our models, we used 6000 samples drawn from the posterior and discarded the first 1000 samples as burn-in. In our models, we fit participant's choice (safe/risky) along with reaction time and we fit regression models for drift rate as outlined in the subsequent section. To investigate how trial-to-trial changes in arousal levels influence the decision threshold, we run a separate model that fits a regression model for threshold with pretrial arousal levels as a regressor (DIC=11864).

2.4.5. aADDM

Our arousal-modulated Attentional Drift Diffusion Model (aADDM) integrates arousal to previously developed sequential sampling models (Krajbich et al., 2010; Cavanagh et al., 2014; Sheng et al., 2020; Westbrook et al., 2020). Estimated subjective utilities have been used to substitute objective values when the latter cannot always be identified and has been implemented in an application to risky choice experiments (Smith & Krajbich, 2018). Thus, we resort to estimating subjective utilities for each outcome, and each option, using power-expo utility function ($U(x) = \frac{1-\exp(-\alpha x^{1-r})}{\alpha}$) given the functional form's superiority in modelling increased risk aversion with increased stakes (Saha, 1993; Holt & Laury, 2002). Note that both constant relative risk aversion and constant absolute risk aversion are special cases in the power-expo model when α and r converge to zero, respectively. Power-expo utility function allows for the common finding of increasing relative risk aversion and decreasing absolute risk aversion.

Using observations from real blocks only, we fit a nonlinear mixed effects model using maximum likelihood (menl function in Stata 15.1) to estimate each participant's α and r parameters in the power-expo function while including an individual level noise parameter μ (Luce, 1959). We specify an unstructured covariance structure between the random intercepts α, r and μ, and we estimate an exchangeable covariance structure for within-subject errors. For μ approaching zero, the option with the higher expected utility is chosen with certainty while for larger values of μ, the probability of choosing that option converges to one-half. The trial likelihood function involved estimating the probability of choosing the top option presented on the screen such that: $pr(choosing\ top\ option) = \frac{U_{top}^{\frac{1}{\mu}}}{U_{top}^{\frac{1}{\mu}} + U_{bottom}^{\frac{1}{\mu}}}$ and $U_{\{top,bottom\}}$ are formulated using the power-expo utility function weighted by the probabilities of each outcome. Note that decisions from the hypothetical block were omitted during the estimation procedure. The individual estimates of α and r were then used to compute subjective utilities for each outcome that were later used in the HDDM estimation: subjective values (sv) for the safe high (SH), risky high (RH), safe low (SL) and risky low (RL) ($\mathrm{sv}_{\mathrm{SH}}$, $\mathrm{sv}_{\mathrm{RH}}$, $\mathrm{sv}_{\mathrm{SL}}$, $\mathrm{sv}_{\mathrm{RL}}$, respectively). We normalize the subjective values for each individual between 0 (lowest value) and 1 (highest value). Outcomes' subjective values were then summed up to derive the subjective value for each of the options ($\mathrm{sv}_{\mathrm{safe}}$, $\mathrm{sv}_{\mathrm{risky}}$) that were used in the option-wise models. Two participants (out of 39) had estimates of *r* that were greater than 1. For both participants, we divided their subjective values by 1-*r* before adding twice the lowest subjective value estimated for each participant. This helped us ensure that for all participants, a more positive value indicates higher subjective value with a subjective value of zero given only when the probability of receiving the payoff is zero. These steps were necessary for applying our normalization technique that is consistent across our participants. Our results remain the same if we, instead, exclude these two participants from our analysis.

We estimate both option-wise and attribute-wise models to analyze the decision process of choosing the safe option while allowing for attentional bias to influence evidence accumulation. Equations SE1-SE3 outline the option-wise models' specification for the drift rate (v_{ij}, participant i in trial j), while equations SE4-SE6 outline that of the attribute-wise models. Equations SE1PC1-SE6PC1 outline the drift rate specifications that allow pretrial arousal (first principal component of the arousal measures – $pc1$) to modulate all of the included parameters.

In model SE1 (option-wise additive), we allow the drift rate to vary with the value difference between the safe (sv_{safe}) and risky (sv_{risky}) options. Also, we include additive (simple) gaze bias: relative fixation duration spent on the safe option (g_{safe}) minus that spent on the risky one (g_{risky}). In model SE2 (option-wise multiplicative), we allow the values of the fixated option (fix) to be integrated differently from the values of non-fixated option ($nonfix$). In model SE3 (option-wise additive and multiplicative), we allow both additive and multiplicative gaze to influence the decision process.

Model SE1: $v_{ij} = \beta_{0i} + \beta_{sv}(sv_{safe} - sv_{risky})_j + \beta_{\Delta g}(g_{safe} - g_{risky})_j$

Model SE1PC1: $v_{ij} = \beta_{0i} + \beta_{pc1}pc1_j + \beta_{sv}(sv_{safe} - sv_{risky})_j + \beta_{sv*pc1}(sv_{safe} - sv_{risky})_j * pc1_j + \beta_{\Delta g}(g_{safe} - g_{risky})_j + \beta_{\Delta g*pc1}(g_{safe} - g_{risky})_j * pc1_j$

Model SE2: $v_{ij} = \beta_{0j} + \beta_{fix}(g_{safe} * sv_{safe} - g_{risky} * sv_{risky})_j + \beta_{nonfix}(g_{risky} * sv_{safe} - g_{safe} * sv_{risky})_j$

Model SE2PC1: $v_{ij} = \beta_{0j} + \beta_{pc1}pc1_j + \beta_{fix}(g_{safe} * sv_{safe} - g_{risky} * sv_{risky})_j + \beta_{fix*pc1}(g_{safe} * sv_{safe} - g_{risky} * sv_{risky})_j * pc1_j + \beta_{nonfix}(g_{risky} * sv_{safe} - g_{safe} * sv_{risky})_j + \beta_{nonfix*pc1}(g_{risky} * sv_{safe} - g_{safe} * sv_{risky})_j * pc1_j$

Model SE3 $v_{ij} = \beta_{0j} + \beta_{fix}(g_{safe} * sv_{safe} - g_{risky} * sv_{risky})_j + \beta_{nonfix}(g_{risky} * sv_{safe} - g_{safe} * sv_{risky})_j + \beta_{\Delta g}(g_{safe} - g_{risky})_j$

Model SE3PC1 $v_{ij} = \beta_{0j} + \beta_{pc1}pc1_j + \beta_{fix}(g_{safe} * sv_{safe} - g_{risky} * sv_{risky})_j + \beta_{fix*pc1}(g_{safe} * sv_{safe} - g_{risky} * sv_{risky})_j * pc1_j + \beta_{nonfix}(g_{risky} * sv_{safe} - g_{safe} * sv_{risky})_j + \beta_{nonfix*pc1}(g_{risky} * sv_{safe} - g_{safe} * sv_{risky})_j * pc1_j + \beta_{\Delta g}(g_{safe} - g_{risky})_j + \beta_{\Delta g*pc1}(g_{safe} - g_{risky})_j * pc1_j$

We also run attribute-wise variant models where attention to the high outcomes (high payoffs and their associated probabilities) in the presented lotteries are allowed to influence the decision process differently compared to attention to the low outcomes. These models are useful in examining whether visual attention directed at particular attributes in decision problems influence evidence accumulation differently (Westbrook et al., 2020). Equations SE4-SE5 and SE6 outline the specification models for the drift rate (v_{ij}) in our attribute-wise models for the decision process of choosing the safe option. In model SE4 (attribute-wise additive), we allow the drift rate to differ across high and low outcomes. In particular, the evaluation of the high outcomes of the safe ($sv_{safe_{High}}$) and that of the risky option ($sv_{Risky_{High}}$) influence the drift rate differently compared to the evaluation of the low outcome of the safe option ($sv_{safe_{Low}}$) and that of the risky option ($sv_{Risky_{Low}}$). In addition, we include a term for the gaze difference of attending to the safe option's high outcome ($g_{safe_{High}}$) instead of the risky option's high outcome ($g_{Risky_{High}}$) and another analogous term for attending to the safe option's low outcome ($g_{safe_{Low}}$) instead of the risky option's low outcome ($g_{Risky_{Low}}$). This represents simple (additive) gaze bias that is independent of the particular attribute value but is again allowed to influence drift rate differently for high and low outcomes. In model SE5 (attribute-wise multiplicative), we allow the subjective values to be evaluated at different rate when fixating at each of the four regions in our presentation: safe high (g_{SH}), risky high (g_{RH}), safe low (g_{SL}) and risky low (g_{RL}). Importantly, we estimate different weights for the evaluation of the high outcomes compared to that of the low outcomes. In model SE6 (attribute-wise additive and multiplicative), we allow both additive and multiplicative gaze to influence evidence accumulation. Each variable in this last model (SE6) is then interacted with arousal (SE6PC1) and yields the results reported in main text. This is the model that provides the best model fits for both evaluation phase and selection phase gaze (see Figure 2.S9).

Model SE4: $v_{ij} = \beta_{0j} + \beta_{High}\left(sv_{safe_{High}} - sv_{Risky_{High}}\right)_j + \beta_{Low}\left(sv_{safe_{Low}} - sv_{Risky_{Low}}\right)_j + \beta_{\Delta g_{High}}\left(g_{safe_{High}} - g_{Risky_{High}}\right)_j + \beta_{\Delta g_{Low}}\left(g_{safe_{Low}} - g_{Risky_{Low}}\right)_j$

Model SE4PC1: $v_{ij} = \beta_{0j} + \beta_{pc1}pc1_j + \beta_{High}\left(sv_{safe_{High}} - sv_{Risky_{High}}\right)_j + \beta_{High*pc1}\left(sv_{safe_{High}} - sv_{Risky_{High}}\right)_j * pc1_j + \beta_{Low} * \left(sv_{safe_{Low}} - sv_{Risky_{Low}}\right)_j + \beta_{Low*pc1}\left(sv_{safe_{Low}} - sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{\Delta g_{High}}\left(g_{safe_{High}} - g_{Risky_{High}}\right)_j + \beta_{\Delta g_{High}*pc1}\left(g_{safe_{High}} - g_{Risky_{High}}\right)_j * pc1_j + \beta_{\Delta g_{Low}}\left(g_{safe_{Low}} - g_{Risky_{Low}}\right)_j + \beta_{\Delta g_{Low}*pc1}\left(g_{safe_{Low}} - g_{Risky_{Low}}\right)_j * pc1_j$

Model SE5: $v_{ij} = \beta_{0j} + \beta_{H_{sameO_{sameA}}}\left(g_{SH}sv_{safe_{High}} - g_{RH}sv_{Risky_{High}}\right)_j + \beta_{H_{sameO_{otherA}}}\left(g_{SL}sv_{safe_{High}} - g_{RL}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{sameA}}}\left(g_{RH}sv_{safe_{High}} - g_{SH}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{otherA}}}\left(g_{RL}sv_{safe_{High}} - g_{SL}sv_{Risky_{High}}\right)_j + \beta_{L_{sameO_{sameA}}}\left(g_{SL}sv_{safe_{Low}} - g_{RL}sv_{Risky_{Low}}\right)_j + \beta_{L_{sameO_{otherA}}}\left(g_{SH}sv_{safe_{Low}} - g_{RH}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{sameA}}}\left(g_{RL}sv_{safe_{Low}} - g_{SL}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{otherA}}}\left(g_{RH}sv_{safe_{Low}} - g_{SH}sv_{Risky_{Low}}\right)_j$

Model SE5PC1: $v_{ij} = \beta_{0j} + \beta_{pc1}pc1_j + \beta_{H_{sameO_{sameA}}}\left(g_{SH}sv_{safe_{High}} - g_{RH}sv_{Risky_{High}}\right)_j + \beta_{H_{sameO_{sameA}}*pc1}\left(g_{SH}sv_{safe_{High}} - g_{RH}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{H_{sameO_{otherA}}}\left(g_{SL}sv_{safe_{High}} - g_{RL}sv_{Risky_{High}}\right)_j + \beta_{H_{sameO_{otherA}}*pc1}\left(g_{SL}sv_{safe_{High}} - g_{RL}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{H_{otherO_{sameA}}}\left(g_{RH}sv_{safe_{High}} - g_{SH}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{sameA}}*pc1}\left(g_{RH}sv_{safe_{High}} - g_{SH}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{H_{otherO_{otherA}}}\left(g_{RL}sv_{safe_{High}} - g_{SL}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{otherA}}*pc1}\left(g_{RL}sv_{safe_{High}} - g_{SL}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{L_{sameO_{sameA}}}\left(g_{SL}sv_{safe_{Low}} - g_{RL}sv_{Risky_{Low}}\right)_j + \beta_{L_{sameO_{sameA}}*pc1}\left(g_{SL}sv_{safe_{Low}} - g_{RL}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{L_{sameO_{otherA}}}\left(g_{SH}sv_{safe_{Low}} - g_{RH}sv_{Risky_{Low}}\right)_j + \beta_{L_{sameO_{otherA}}*pc1}\left(g_{SH}sv_{safe_{Low}} - g_{RH}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{L_{otherO_{sameA}}}\left(g_{RL}sv_{safe_{Low}} - g_{SL}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{sameA}}*pc1}\left(g_{RL}sv_{safe_{Low}} - g_{SL}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{L_{otherO_{otherA}}}\left(g_{RH}sv_{safe_{Low}} - g_{SH}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{otherA}}*pc1}\left(g_{RH}sv_{safe_{Low}} - g_{SH}sv_{Risky_{Low}}\right)_j * pc1_j$

Model SE6: $v_{ij} = \beta_{0j} + \beta_{H_{sameO_{sameA}}}\left(g_{SH}sv_{safe_{High}} - g_{RH}sv_{Risky_{High}}\right)_j + \beta_{H_{sameO_{otherA}}}\left(g_{SL}sv_{safe_{High}} - g_{RL}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{sameA}}}\left(g_{RH}sv_{safe_{High}} - g_{SH}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{otherA}}}\left(g_{RL}sv_{safe_{High}} - g_{SL}sv_{Risky_{High}}\right)_j + \beta_{L_{sameO_{sameA}}}\left(g_{SL}sv_{safe_{Low}} - g_{RL}sv_{Risky_{Low}}\right)_j + \beta_{L_{sameO_{otherA}}}\left(g_{SH}sv_{safe_{Low}} - g_{RH}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{sameA}}}\left(g_{RL}sv_{safe_{Low}} - g_{SL}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{otherA}}}\left(g_{RH}sv_{safe_{Low}} - g_{SH}sv_{Risky_{Low}}\right)_j + \beta_{\Delta g_{High}}\left(g_{safe_{High}} - g_{Risky_{High}}\right)_j + \beta_{\Delta g_{Low}}\left(g_{safe_{Low}} - g_{Risky_{Low}}\right)_j$

Model SE6PC1: $v_{ij} = \beta_{0j} + \beta_{pc1}pc1_j + \beta_{H_{sameO_{sameA}}}\left(g_{SH}sv_{safe_{High}} - g_{RH}sv_{Risky_{High}}\right)_j + \beta_{H_{sameO_{sameA}}*pc1}\left(g_{SH}sv_{safe_{High}} - g_{RH}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{H_{sameO_{otherA}}}\left(g_{SL}sv_{safe_{High}} - g_{RL}sv_{Risky_{High}}\right)_j + \beta_{H_{sameO_{otherA}}*pc1}\left(g_{SL}sv_{safe_{High}} - g_{RL}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{H_{otherO_{sameA}}}\left(g_{RH}sv_{safe_{High}} - g_{SH}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{sameA}}*pc1}\left(g_{RH}sv_{safe_{High}} - g_{SH}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{H_{otherO_{otherA}}}\left(g_{RL}sv_{safe_{High}} - g_{SL}sv_{Risky_{High}}\right)_j + \beta_{H_{otherO_{otherA}}*pc1}\left(g_{RL}sv_{safe_{High}} - g_{SL}sv_{Risky_{High}}\right)_j * pc1_j + \beta_{L_{sameO_{sameA}}}\left(g_{SL}sv_{safe_{Low}} - g_{RL}sv_{Risky_{Low}}\right)_j + \beta_{L_{sameO_{sameA}}*pc1}\left(g_{SL}sv_{safe_{Low}} - g_{RL}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{L_{sameO_{otherA}}}\left(g_{SH}sv_{safe_{Low}} - g_{RH}sv_{Risky_{Low}}\right)_j + \beta_{L_{sameO_{otherA}}*pc1}\left(g_{SH}sv_{safe_{Low}} - g_{RH}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{L_{otherO_{sameA}}}\left(g_{RL}sv_{safe_{Low}} - g_{SL}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{sameA}}*pc1}\left(g_{RL}sv_{safe_{Low}} - g_{SL}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{L_{otherO_{otherA}}}\left(g_{RH}sv_{safe_{Low}} - g_{SH}sv_{Risky_{Low}}\right)_j + \beta_{L_{otherO_{otherA}}*pc1}\left(g_{RH}sv_{safe_{Low}} - g_{SH}sv_{Risky_{Low}}\right)_j * pc1_j + \beta_{\Delta g_{High}}\left(g_{safe_{High}} - g_{Risky_{High}}\right)_j + \beta_{\Delta g_{High}*pc1}\left(g_{safe_{High}} - g_{Risky_{High}}\right)_j * pc1_j + \beta_{\Delta g_{Low}}\left(g_{safe_{Low}} - g_{Risky_{Low}}\right)_j + \beta_{\Delta g_{Low}*pc1}\left(g_{safe_{Low}} - g_{Risky_{Low}}\right)_j * pc1_j$

In the main text, we report multiplicative attentional discounting of high and low outcomes. This bias was examined by computing the posterior parameter density for the following terms in equation SE6PC1: $\gamma_{\mathrm{High}} = \beta_{\mathrm{H}_{\mathrm{sameO}_{\mathrm{otherA}}}} + \beta_{\mathrm{H}_{\mathrm{otherO}_{\mathrm{otherA}}}} - \beta_{\mathrm{H}_{\mathrm{sameO}_{\mathrm{sameA}}}} - \beta_{\mathrm{H}_{\mathrm{otherO}_{\mathrm{sameA}}}}$. Note negative γ_{High} provides evidence that high outcome values are being discounted when fixating on the other low outcomes. Similarly, $\gamma_{\mathrm{Low}} = \beta_{\mathrm{L}_{\mathrm{sameO}_{\mathrm{otherA}}}} + \beta_{\mathrm{L}_{\mathrm{otherO}_{\mathrm{otherA}}}} - \beta_{\mathrm{L}_{\mathrm{sameO}_{\mathrm{sameA}}}} - \beta_{\mathrm{L}_{\mathrm{otherO}_{\mathrm{sameA}}}}$ computes the attentional discounting low outcome evaluation while fixating on high outcomes. We then derive analgous posterior parameter densitites to investigate arousal's modulatory influence on attentional discounting across outcomes: $\gamma_{\mathrm{pc1*High}} = \beta_{\mathrm{pc1*H}_{\mathrm{sameO}_{\mathrm{otherA}}}} + \beta_{\mathrm{pc1*H}_{\mathrm{otherO}_{\mathrm{otherA}}}} - \beta_{\mathrm{pc1*H}_{\mathrm{sameO}_{\mathrm{sameA}}}} - \beta_{\mathrm{pc1*H}_{\mathrm{otherO}_{\mathrm{sameA}}}}$ and $\gamma_{\mathrm{pc1*Low}} = \beta_{\mathrm{pc1*L}_{\mathrm{sameO}_{\mathrm{otherA}}}} + \beta_{\mathrm{pc1*L}_{\mathrm{otherO}_{\mathrm{otherA}}}} - \beta_{\mathrm{pc1*L}_{\mathrm{sameO}_{\mathrm{sameA}}}} - \beta_{\mathrm{pc1*L}_{\mathrm{otherO}_{\mathrm{sameA}}}}$.

2.4.6. Posterior predictive checks for aADDM

Posterior predictive checks help in gauging the reliability of our model in producing observed behavioral patterns. We simulate 500 samples based on model estimates for each trial in our dataset. We generate two quantiles for evaluation phase 1) gaze bias on the safe option's high outcome instead of that of the risky option and 2) gaze bias on the safe option's low outcome instead of that of the risky option (Figure 2.*4* in the main manuscript). We analogously generate two quantiles using selection phase gaze to test the latter models (Figure 2.S10). Then, we compare the frequency of choosing the safe option across both observed and simulated datasets for both evaluation phase and selection phase models. The results provide visual evidence that our model simulations fare well in predicting behavior with regard to attribute-wise subjective value difference and for reaction time (Figure 2.*4* and Figure 2.S10).

2.4.7. Physiological recordings and gaze bias within trials and across blocks

We investigated how the trial's milli-second to milli-second arousal differed across blocks. Even though the general pattern of arousal was similar across blocks, the greatest arousal levels were recorded during the high real block (Figure 2.S1). Note that under high real stakes, the phasic arousal measures, except for skin conductance response, did not significantly increase (see Figure 2.S3). By construct, the average pupil size and pulse rate phasic measures are inversely associated with their tonic or baseline measures (Eldar et al., 2013). The mild changes in phasic arousal under the high real stakes are in line with the Adaptive Gain Hypothesis, suggesting that high stakes may had instead induced a tonic high gain mode narrowing attention on the most strongly represented features of the lotteries (Aston-Jones & Cohen, 2005; Eldar et al., 2013). The increased attention toward the safe option's attributes that we report in the main manuscript seems to suggest that the safe option is the pre-disposed sensory stimuli (see Figure 2.*3* in the main text).

Gaze bias (dwell time advantage for the safe option relative to the risky one) spiked at the beginning of the high real block before declining over time (Figure 2.S2 and Figure 2.S4). Moreover, individual differences in changes in selection phase dwell time advantage from high hypothetical to high real block were strongly associated with increased risk aversion (Spearman rank correlation: n=39; ρ_s =0.873, p=4.3$\times 10^{-13}$). Similar to fixations during the evaluation phase (see Figure 2.*3* in main manuscript and Figure 2.S5), participants were attending more to the risky option's high payoff during selection phase when choosing the risky option (see Figure 2.S6).

2.4.8. Additive gaze bias

People are both influenced by what they look at but they also look at what they will choose (Armel et al., 2008; Westbrook et al., 2020). The former is accounted for by multiplicative gaze where attention boosts the value of fixated attributes, as reported in main text. The latter is accounted for by additive gaze where attention correlates to choice through a simple attention bias that is independent from value.

We find that simple gaze bias holds for both high and low outcomes, with the former having a larger impact on drift rate and with arousal interacting with evaluation phase gaze to widen this gap. For additive gaze terms, an overall similar pattern prevails for both evaluation phase and selection gaze, where more time spent fixating on high (low) outcomes of the safe option instead of the risky option's high (low) outcomes increases drift rate (EP: $\beta_{\Delta g_{high}} = 0.85, p < 0.0001;\ \beta_{\Delta g_{low}} = 0.79, p < 0.0001;$ SP: $\beta_{\Delta g_{high}} = 1.39, p < 0.0001;\ \beta_{\Delta g_{low}} = 1.20, p < 0.0001$) with the former having a greater influence (EP:$\beta_{\Delta g_{high}} - \beta_{\Delta g_{low}} = 0.06, p = 0.028;$ SP: $\beta_{\Delta g_{high}} - \beta_{\Delta g_{low}} = 0.19, < 0.019$) (Figure 2.S10). Interestingly, we find that pretrial arousal does modulate additive EP gaze by enhancing its effect for high outcomes and weakening it for low outcomes ($\beta_{pc1*\Delta g_{high}} = 0.12, p = 0.053$; $\beta_{pc1*\Delta g_{low}} = -0.22, p = 0.01$). We thus find that arousal modulates both multiplicative and additive gaze bias during the evaluaton phase of decision-making, amplifying attentional bias for high outcomes' value integration while also modulating additive gaze terms.

2.4.9. Direction of search

Standard models of risky choice assume that agents employ a particular cognitive processing patterns (expectation models) where people weigh the subjective value (utility) of the available option by its likelihood of occurrence to compute an expected utility associated with each option for choosing the one that maximizes welfare (Loewenstein et al., 2001). In lottery choices, a strategy to choose the option with the higher expected utility is likely to involve more option-wise transitions (looking between attributes of the same alternative) rather than attribute-wise transitions (comparing probabilities or comparing payoffs across alternatives) that are typically associated with the usage of decision heuristics (Payne & Braunstein, 1978; Arieli et al., 2011). Manipulating search strategy by presenting information that encourage within alternative-based transitions had been found to increase risk tolerance, establishing causal relationship between attention and risk decision making (J. A. Aimone et al., 2016). We compute the Payne index, which has a larger score when transitions are more consistent with option-wise scan of information instead of attribute-wise ones (Payne & Braunstein, 1978).

Using a median split, we created two groups based on the change in the average first principal component for the pretrial arousal measures from hypothetical to high real block. Then, we investigate how the change in information acquisition patterns altered behavior differently across participants who had low changes in arousal compared to those experiencing high changes. In the subsequent analysis, we focus our attention on the hypothetical and high real blocks and on decision numbers 5 to 9 (see Table 2.S1) in which behavior differs the most during the high real stakes block (see fig 1E in main text) and where the expectation value model predicts choosing the risky option. We find a negative and significant association between the change in Payne index from high hypothetical to the high real block and the change in risk aversion for the highly aroused participants (Spearman rank correlation: N=19; ρ_S =-0.737; P=0.0003) while no relationship was found for the modestly aroused group (Spearman rank correlation: N =20; ρ_S =0.136; P =0.568). Thus, the change in information acquisition patterns are strong predictors for adhering with the expectation model for participants experiencing heightened arousal only, where more option-wise scans were strongly associated with choosing the risky option. In addition, we examine whether changes in evaluation phase arousal impact information acquisition and risk aversion differently across the two groups. Interestingly, we find that only highly (pretrial) aroused participants had a positive and significant relationship between the change in arousal during the evaluation phase (first principal component of evaluation phase arousal measures) and increased risk aversion (Spearman rank correlation: N =19; ρ_S =0.566; P=0.012) and a negative and significant relationship between the change in evaluation phase arousal and the change in Payne index (Spearman rank correlation: N =19; ρ_S = -0.528; P =0.020). Changes in evaluation phase arousal did not systematically vary with changes in the frequency of choosing the safe option (Spearman rank correlation: N =20; ρ_S =-0.004; P=0.987) or with the changes in Payne index (Spearman rank correlation: N =20; ρ_S =-0.208; P=0.380) for the group that experienced low changes in pretrial arousal from the high hypothetical to the high real block. Our results provide support for the synergy between tonic (pretrial arousal) and phasic (evaluation phase) arousal (Howells et al., 2012).

2.5. Supplementary material B

2.5.1. Supplementary figures

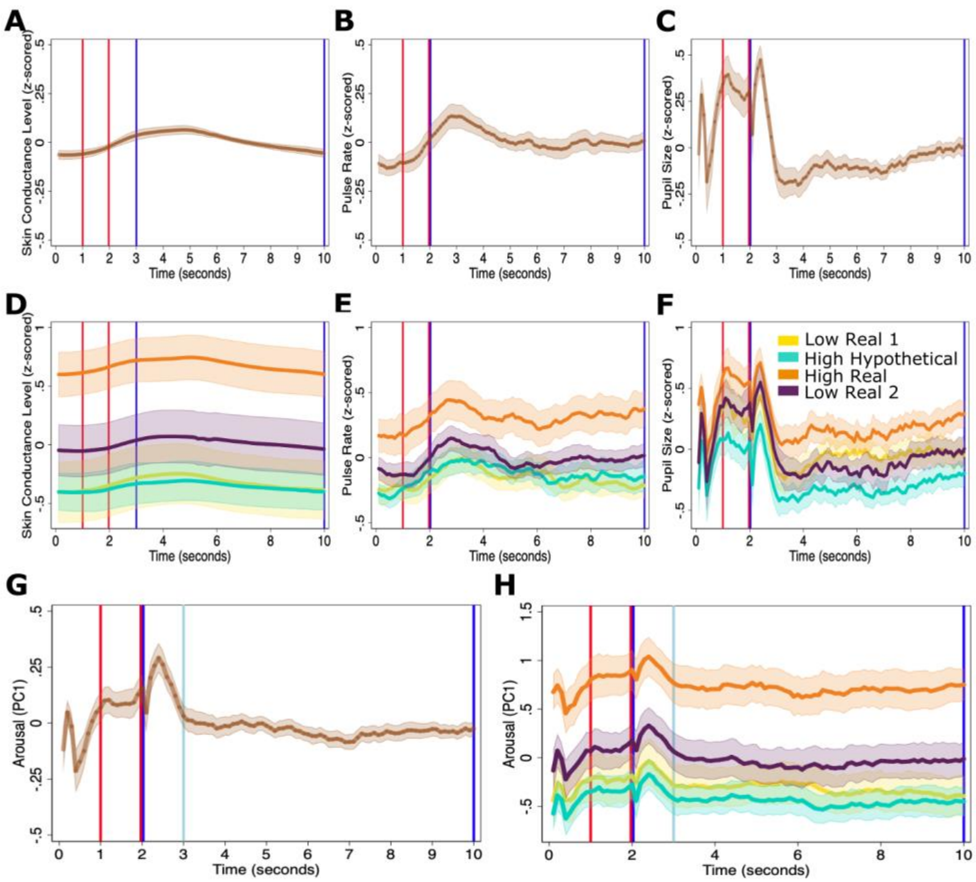

Figure 2.S1 Physiological measurements recorded during a trial round. (A) Average skin conductance level and (B) pulse rate across time in a trial for all participants and trials. (A-B) For each 100 milli-seconds, one datapoint is extracted by taking the average across 25 samples recorded. (C) Average pupil size across time in a trial for all participants and trials. For each 100 milli-seconds, one datapoint is extracted by taking the average across 100 samples recorded. Average (D) skin conductance level, (E) pulse rate and (F) pupil size across time in a trial for each block. All arousal measures are z-scored at the individual level across all trials. Average (G) first principal component of the three arousal measures across time in a trial (G) for all participants and trials and (H) for each block. Pretrial measures are obtained as the one second average pre-stimulus presentation (red bounds) while evaluation phase measures are obtained post-stimulus presentation and prior to the selection phase (blue bounds). Evaluation phase pulse rate is derived by taking the 8 second average post-stimulus presentation and prior to selection phase. Evaluation phase skin conductance (skin conductance response-SCR) is derived as the maximum recorded response by trough-to-peak amplitude difference (squared-root transformation applied) in the time window 1 second after stimuli presentation till 8 seconds from onset (blue bounds starting at the light blue edge). Evaluation phase pupil size is derived as the maximum pupil size during the 8 seconds post-stimulus presentation and prior to selection phase. The shaded region shows 95% confidence intervals around the mean value for each measure.

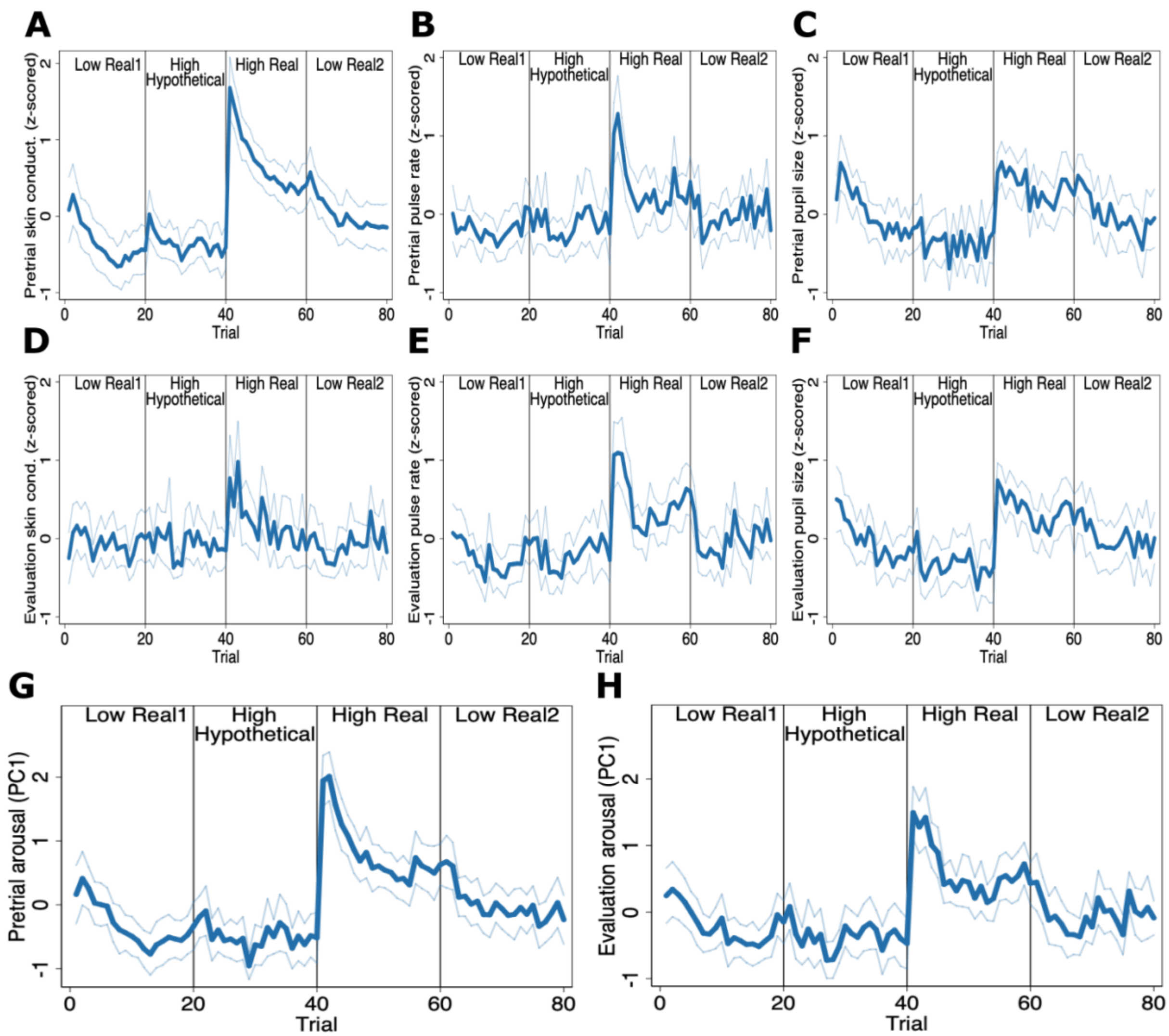

Figure 2.S2 Physiological measures across trials. Average pretrial (A) skin conductance level, (B) pulse rate, and (C) pupil size are plotted against trials during the experimental session. Average evaluation phase (D) skin conductance response, (E) pulse rate, and (F) maximum pupil size are plotted against trials during the experimental session. Decisions within a block were randomized across participants. (G) Average first principal component across pretrial skin conductance level, pulse rate and pupil size and (H) average first principal component across evaluation phase skin conductance response, pulse rate and maximum pupil size are plotted decisions during the experimental session. All measures are z-scored at the individual level across all trials. Line bounds show 95% confidence intervals.

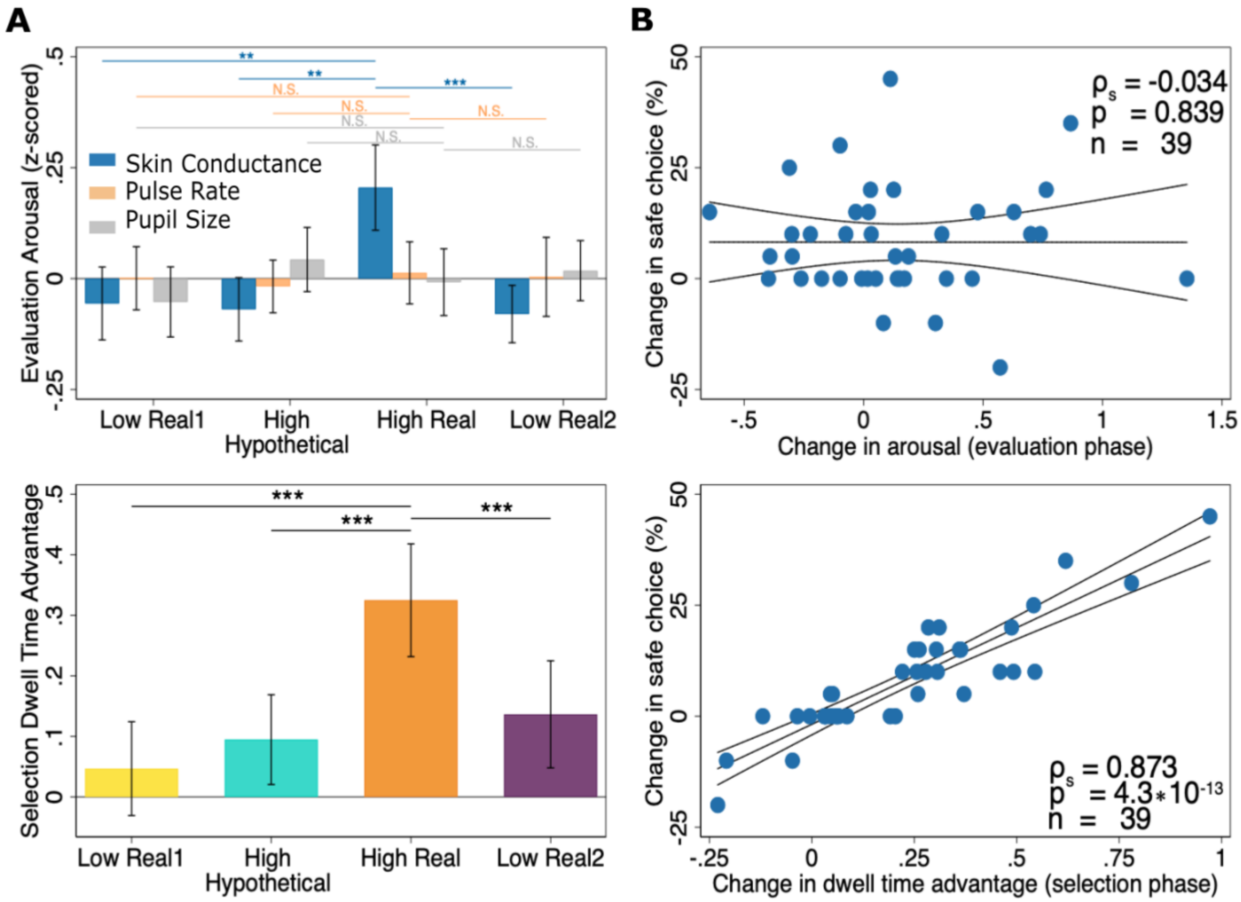

Figure 2.S3 Arousal during evaluation phase and attention during selection phase. (A) Only skin conductance response was higher under high real stakes while (phasic) pulse rate and pupil diameter from evaluation phase did not significantly differ across blocks. (B) Individual differences in the effect of high stakes on generalized evaluation phase arousal were not associated with changes in risk aversion. Here the percentage difference in safe choices (y-axis) in the high stakes real vs. the hypothetical block is plotted against the individuals' difference in arousal in the high stakes real vs. the hypothetical block (x-axis). Experienced arousal is computed as the first principal component of the three phasic arousal measures: skin conductance response, pulse rate and pupil size (Spearman rank correlation reported). (C) Dwell time advantage during the selection phase for the safe option (relative fixation duration on safe outcomes minus risky outcomes) was highest during the high real block. (D) Individual differences in dwell time advantage for the safe option in the high real vs. the hypothetical block were strongly associated with changes in risk aversion. The percentage change in safe choices in the high real block relative to the hypothetical block (y-axis) is plotted against the individuals' difference in dwell time advantage (gaze on safe option minus gaze on risky option) during the selection phase in the high stakes real vs. the hypothetical block (x-axis) (Spearman rank correlation reported). Linear fits plotted in (B) and (D). Error bars and line bounds show 95% confidence intervals. For (A) and (C), Wilcoxon signed-rank test (N=39): ** P-value < 0.01; *** P-value < 0.001.

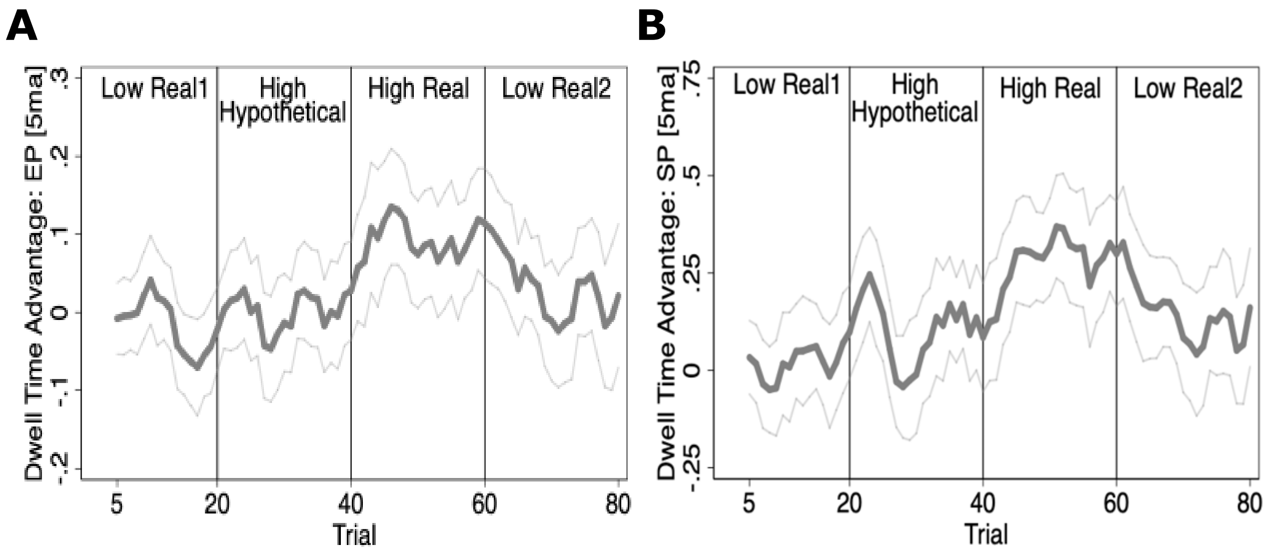

Figure 2.S4 Gaze bias across trials. Five trial moving average of dwell time advantage for the safe option during (A) evaluation phase and (B) selection phase are plotted against trials during the experimental session and spike in high real block.

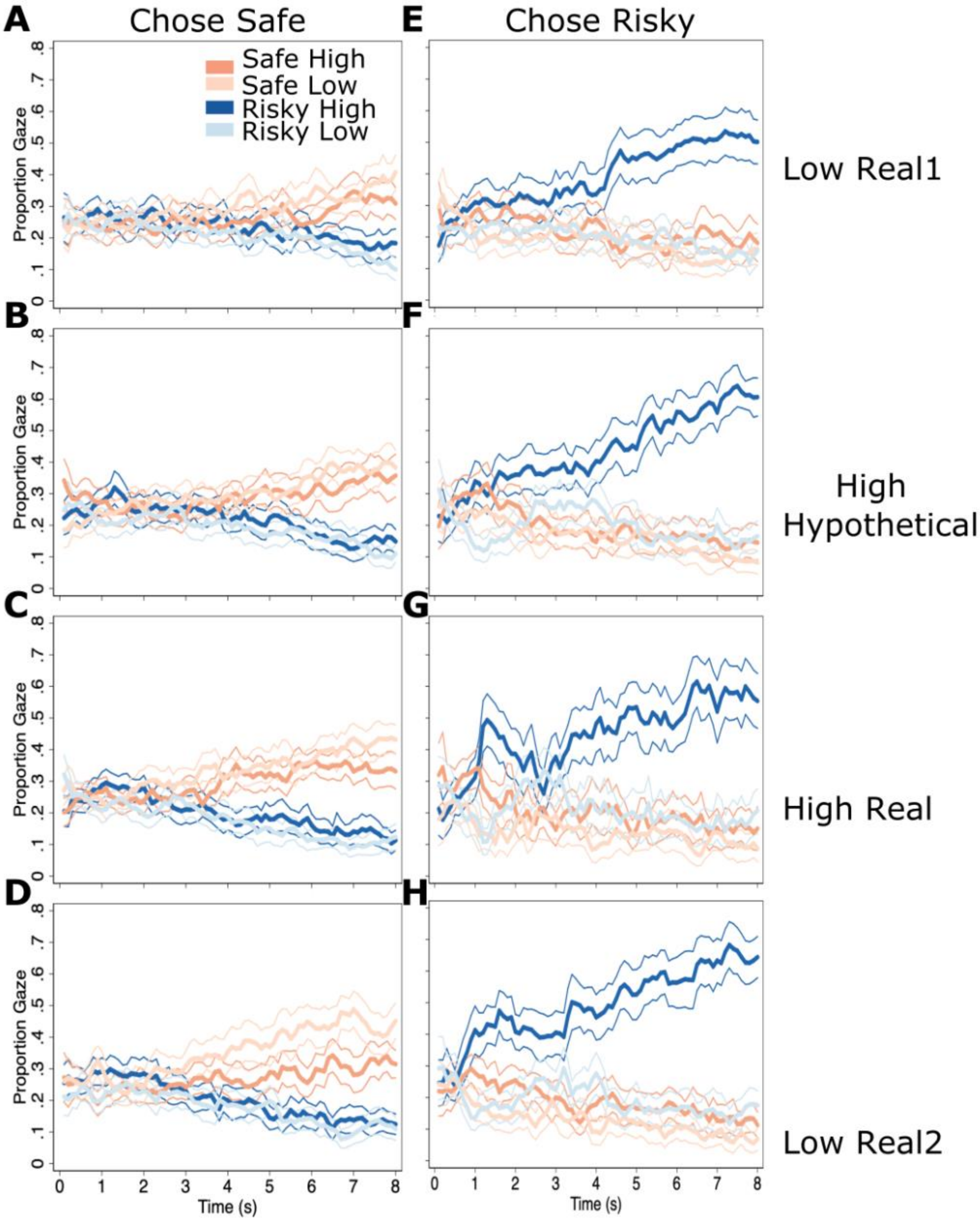

Figure 2.S5 Attention during evaluation phase. Cumulative proportion by block of the selection phase with gaze fixated on each outcome and associated probability when participants choosing the safe option (A-D) and when choosing the risky option (E-H). Data shown are pooled across 100-millisecond windows (100 samples). Error bars and line bounds show 95% confidence intervals.

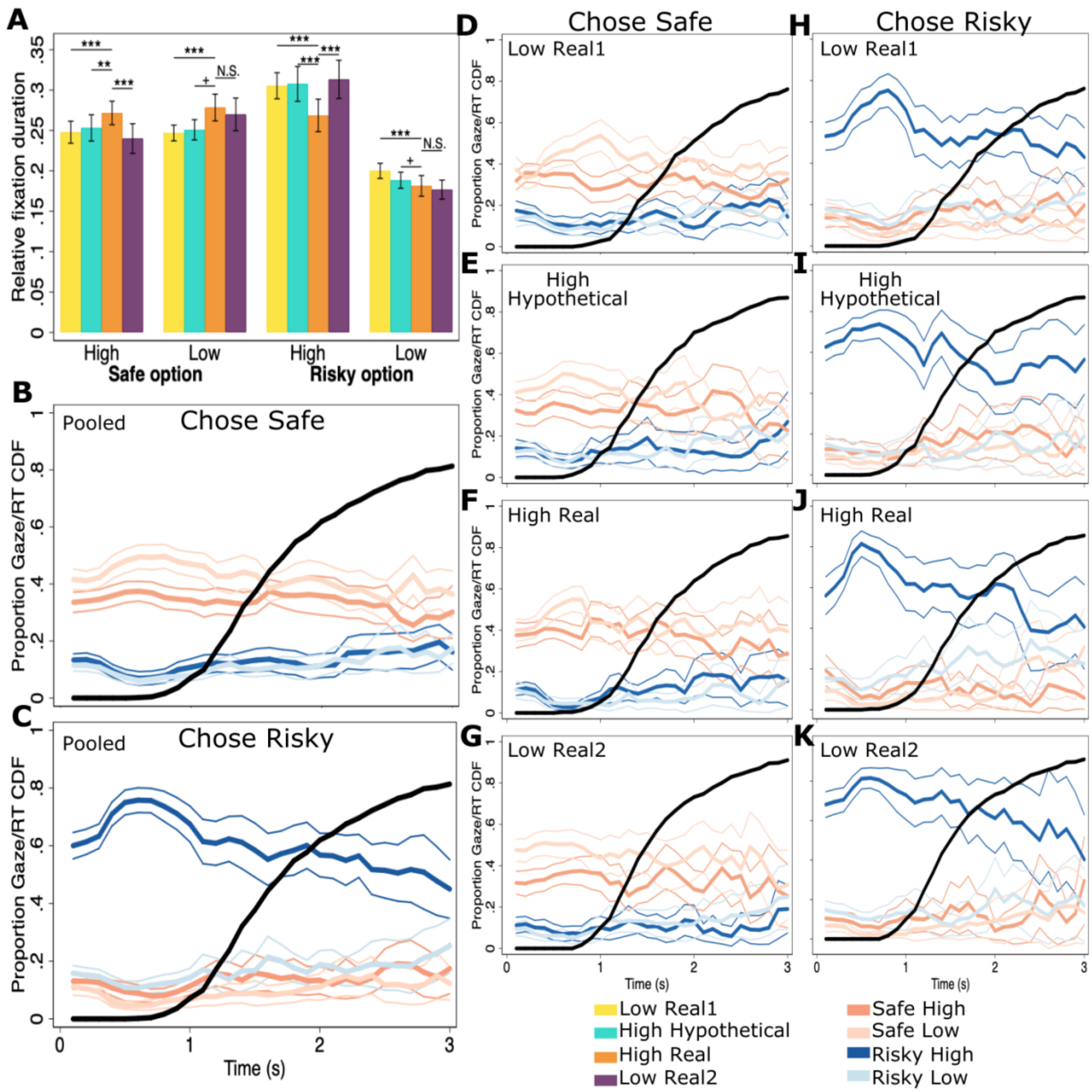

Figure 2.S6 Attention during selection phase. (A) Proportion of the selection phase fixated upon each outcome and associated probability. Cumulative proportion of the selection phase with gaze fixated on each outcome and associated probability when participants (B) chose the safe option and (C) chose risky option across all blocks. Cumulative proportion by block of the selection phase with gaze fixated on each outcome and associated probability when participants choosing the safe option (D-G) and when choosing the risky option (H-K). Data shown are pooled across 100-millisecond windows (100 samples). Reaction time (RT) cumulative distribution function (CDF) is shown. Error bars and line bounds show 95% confidence intervals. Wilcoxon signed-rank test (N=39): + P-value <0.10; * P-value < 0.05; ** P-value < 0.01; *** P-value < 0.001; N.S. not significant.

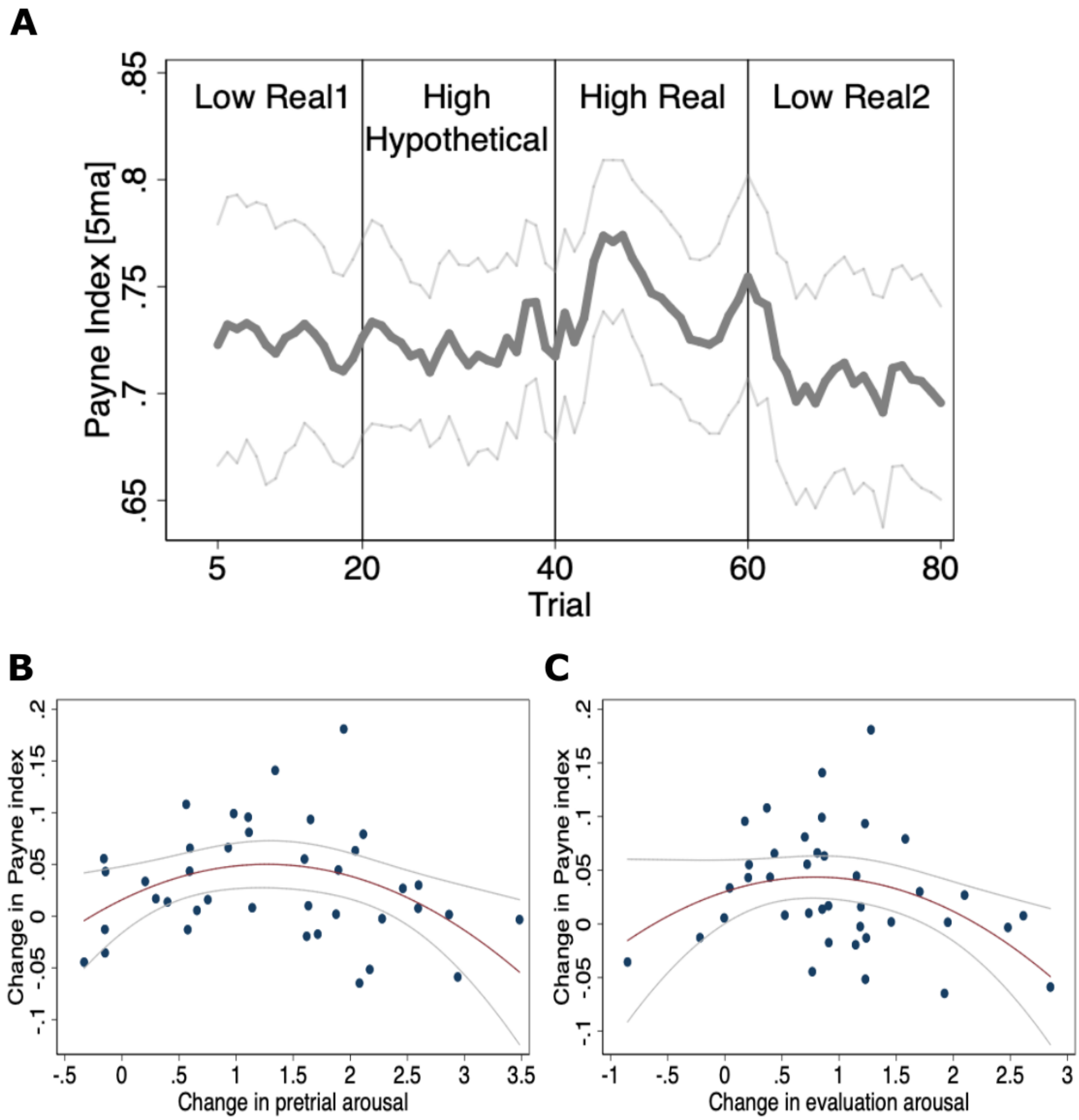

Figure 2.S7 Payne Index. (A) Five trial moving average of Payne index during evaluation phase is plotted against trials during the experimental session and spike in high real block. Change in Payne index in the high real block compared to hypothetical block is plotted against change in the first principal component of the three (A) pretrial and (B) evaluation phase arousal measures: pulse rate, pupil size and skin conductance (Quadratic fits and 95% bounds displayed).

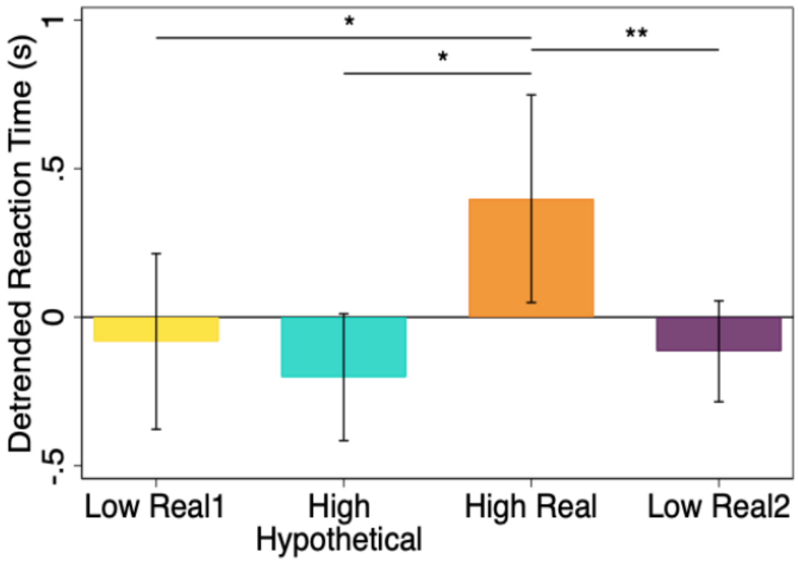

Figure 2.S8 Detrended reaction time. Average detrended reaction time across blocks. Quadratic time trend is applied. Error bars and spikes denote 95% confidence intervals. Wilcoxon signed-rank test (N=39): * P-value < 0.05; ** P-value < 0.01.

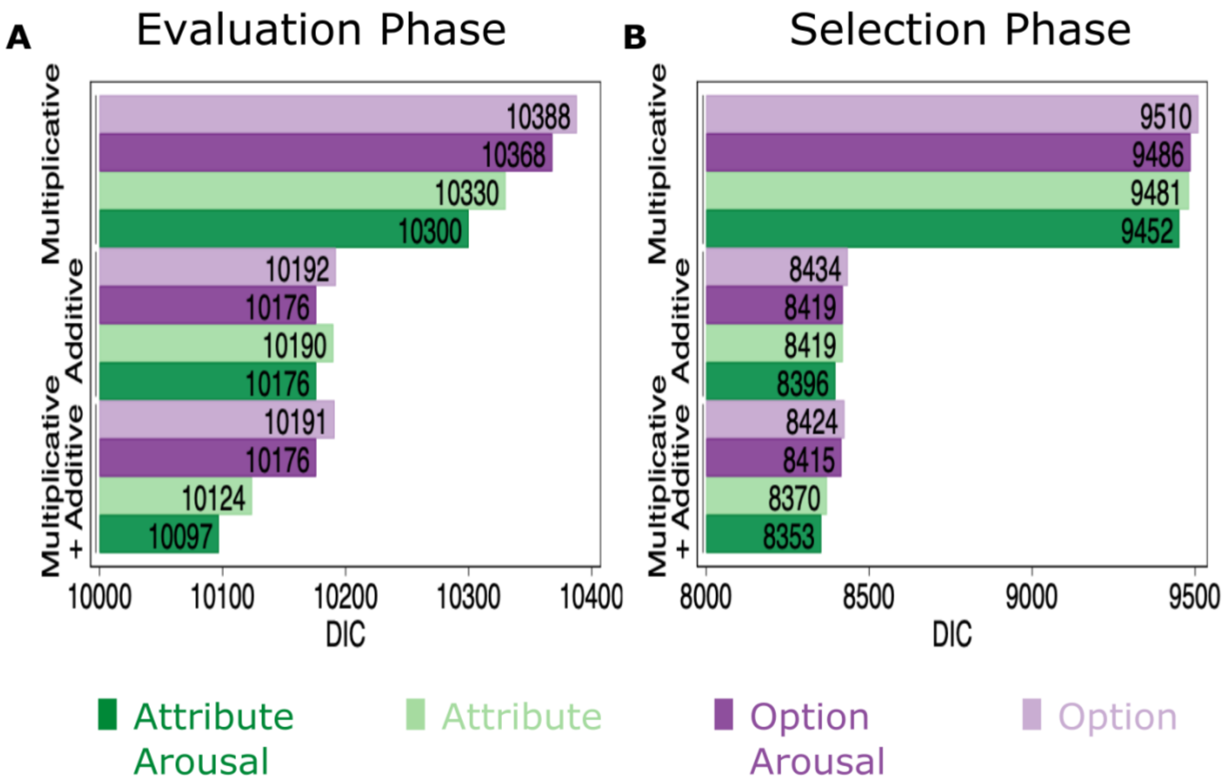

Figure 2.S9 Model fits for drift diffusion models. DIC for attribute-based and option-based models (A) with gaze recorded during evaluation phase and (B) with gaze recorded during the selection phase.

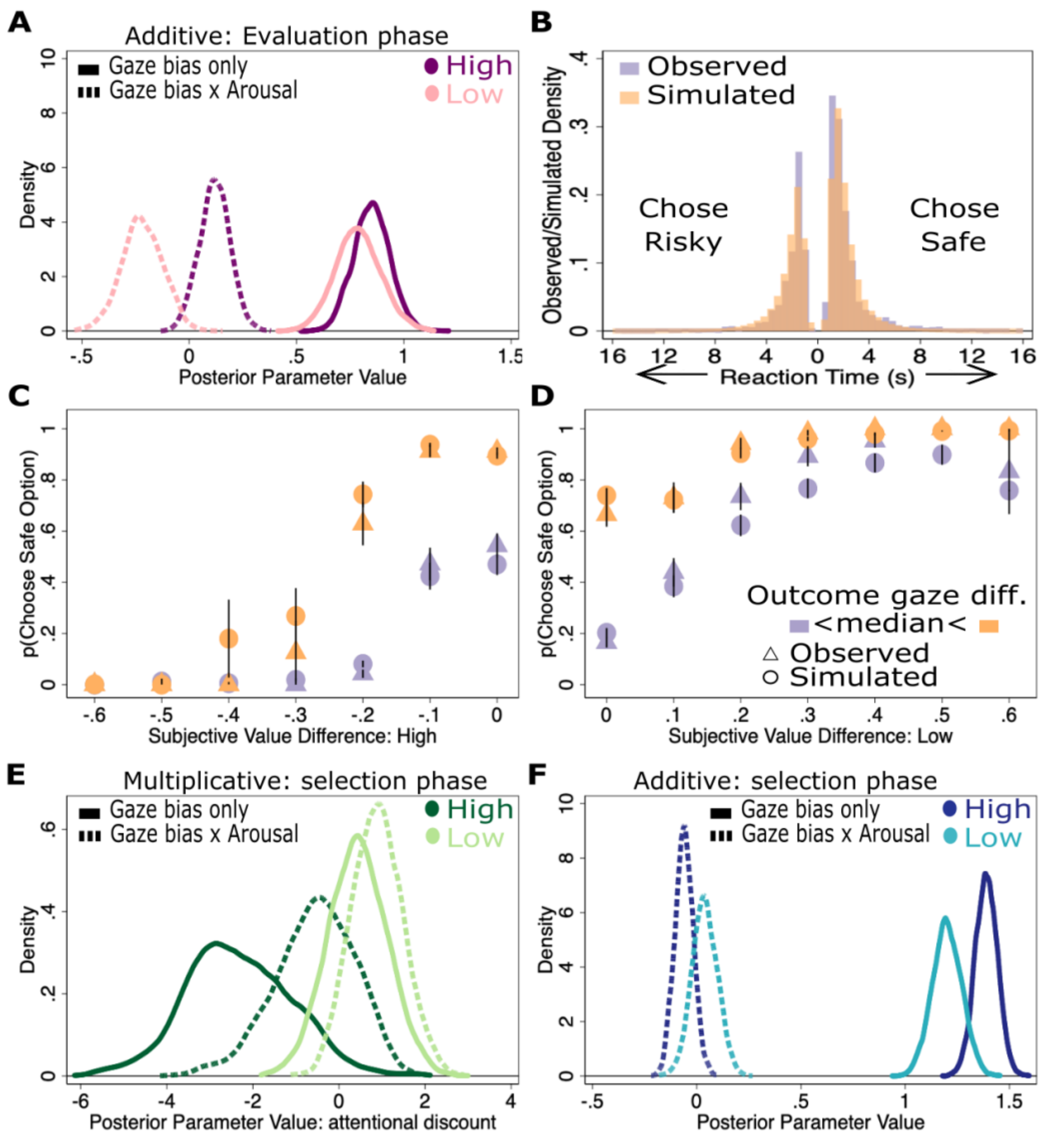

Figure 2.S10 Additive gaze bias and model with selection phase gaze. (A) Additive gaze bias holds for high and low attributes during evaluation phase ($\beta_{\Delta g_{high}} = 0.85, p < 0.0001$; $\beta_{\Delta g_{low}} = 0.79, p < 0.0001$), with arousal strengthening it for high attributes and weakens it for low attributes ($\beta_{pc1*\Delta g_{high}} = 0.12, p = 0.053$; $\beta_{pc1*\Delta g_{low}} = -0.22, p = 0.01$). Selection phase attribute-wise model simulations (including both additive and multiplicative gaze) predicted (B) reaction time and (C) observed choices relative to high outcomes' and (D) low outcomes' value difference. Extreme outlier reaction times are not shown in (B), less than 1.3% of the data points are omitted. (E) Selection phase gaze on the opposite outcomes discount the value of high outcomes only (γ_{high}= -2.32, p=0.032). Arousal has no significant effect when interacted with multiplicative selection phase gaze. (F) Additive selection phase gaze bias holds for high and low outcomes ($\beta_{\Delta g_{high}} = 1.39, p < 0.0001$; $\beta_{\Delta g_{low}} = 1.20, p < 0.0001$), with arousal having no significant effect when interacted with additive selection phase gaze.

2.5.2. Supplementary tables

Decision	**Option A: Safe**				**Option B: Risky**				**EV diff.**
Outcome	**High**		**Low**		**High**		**Low**		
#	**%of A1**	**$A1**	**%of A2**	**$A2**	**%of B1**	**$B1**	**%of B2**	**$B2**	
1	10%	2	90%	1.6	10%	3.85	90%	0.1	1.165
2	20%	2	80%	1.6	20%	3.85	80%	0.1	0.830
3	30%	2	70%	1.6	30%	3.85	70%	0.1	0.495
4	40%	2	60%	1.6	40%	3.85	60%	0.1	0.160
5	50%	2	50%	1.6	50%	3.85	50%	0.1	-0.175
6	60%	2	40%	1.6	60%	3.85	40%	0.1	-0.510
7	70%	2	30%	1.6	70%	3.85	30%	0.1	-0.845
8	80%	2	20%	1.6	80%	3.85	20%	0.1	-1.180
9	90%	2	10%	1.6	90%	3.85	10%	0.1	-1.515
10	100%	2	0%	1.6	100%	3.85	0%	0.1	-1.850

Table 2.S1 Holt & Laury (2002) choices (lowest stakes: 1X), expected value difference was not provided to participants.

		High outcomes				Low outcomes				Additive		Arousal
Model	$\boldsymbol{\beta_0}$	$\boldsymbol{\beta_{H_{sameO_{sameA}}}}$	$\boldsymbol{\beta_{H_{sameO_{otherA}}}}$	$\boldsymbol{\beta_{H_{otherO_{sameA}}}}$	$\boldsymbol{\beta_{H_{otherO_{otherA}}}}$	$\boldsymbol{\beta_{L_{sameO_{sameA}}}}$	$\boldsymbol{\beta_{L_{sameO_{otherA}}}}$	$\boldsymbol{\beta_{L_{otherO_{sameA}}}}$	$\boldsymbol{\beta_{L_{otherO_{otherA}}}}$	$\boldsymbol{\beta_{\Delta g_{high}}}$	$\boldsymbol{\beta_{\Delta g_{low}}}$	$\boldsymbol{\beta_{pc1}}$
1A: Evaluation Phase	0.09 (0.03)	4.68 (0.41)	1.47 (0.61)	4.06 (0.45)	2.32 (0.58)	3.22 (0.33)	2.18 (0.34)	2.38 (0.43)	4.41 (0.38)	0.85 (0.09)	0.79 (0.11)	0.04 (0.02)
		Variables interacted with group arousal indicator										
		0.39 (0.35)	-1.20 (0.54)	0.75 (0.37)	-1.76 (0.51)	-0.51 (0.28)	-0.41 (0.34)	-0.27 (0.28)	-0.09 (0.29)	0.12 (0.07)	0.22 (0.10)	
1B: Selection Phase	0.10 (0.03)	2.38 (0.24)	0.90 (0.52)	2.24 (0.28)	1.40 (0.52)	1.69 (0.20)	1.28 (0.23)	1.73 (0.27)	2.57 (0.26)	1.28 (0.03)	1.05 (0.04)	-0.02 (0.02)
		Variables interacted with group arousal indicator										
		-0.39 (0.19)	-0.57 (0.39)	-0.27 (0.21)	-0.65 (0.40)	-0.39 (0.18)	0.10 (0.19)	-0.46 (0.20)	-0.06 (0.22)	-0.08 (0.03)	0.07 (0.03)	

Table 2.S2 Drift rate regression estimates for model SE6 including non-decision time gaze (1A) and decision time gaze (1B) Mean (SD)

Chapter 3

3. Incentives and emotional experiences modulate the perception of value in risky choice

Abdelaziz Alsharawy, Sheryl Ball, and Alec Smith

Abstract

The brain must use limited computational resources to make decisions. The principle of efficient coding posits that value representations are context dependent. In particular, more frequently encountered payoffs are perceived more accurately. Our objective was to test how incentives (real vs. hypothetical) and emotional experiences (arousal and valence) modulate payoff representations and value perception in risky choice. We recruited 70 participants to complete a series of 600 decisions choosing between two options: 1) a lottery with a 50% chance of a positive payoff and a 50% of a zero payoff and 2) a sure payoff. The payoffs were sampled from a distribution with a narrow range (low volatility – LV– condition) in half of the trials and from a distribution with the same mean but a wider range (high volatility– HV– condition) in the other half of the trials. Crucially, participants were assigned to receive real payment, based on a randomly determined decision, from either the LV or HV conditions and regularly reported their emotional experience (arousal/valence). Our findings confirm the efficient coding hypothesis only for participants assigned to receive real payment from the LV condition, with perception sensitivity to changes in payoffs declining in the HV condition relative to the LV one. On the other hand, participants assigned to receive real payment from the HV condition displayed comparable sensitivities to changes in payoffs across volatility conditions. Moreover, self-reports of arousal, and not valence, were significantly higher in the real payment condition. Sensitivity to changes in the risky option's payoffs did not decline for participants experiencing amplified arousal levels or greater unpleasant feelings in the HV condition. In addition, reaction time and risk aversion were higher in the real payment condition. Our results demonstrate the importance of incentives and emotional experiences in the adaptation of perceptual processing of value.

3.1. Introduction

Perception of information is bounded by the brain's limited computational resources (Marois & Ivanoff, 2005). This limitation reduces the precision by which environmental stimuli are represented by the brain (Woodford, 2020) and, importantly, yields costs of cognition that are overlooked by classical economic models of expected utility maximization (Gershman et al., 2015). The information process, as a result, in both perceptual-based and value-based decision-making is inherently noisy (Khaw et al., 2021; Wei & Stocker, 2017). Indeed, people factor in the internal costs of cognition, which are associated with perception, when making decisions rendering these costs highly pertinent to observed behavior (Kool et al., 2010; Kool & Botvinick, 2014; McGuire & Botvinick, 2010).

The efficient coding hypothesis implies that the brain organizes information in a way to reduce redundancy when perceiving and transmitting sensory signals, maximizing the usage of the scarce resources (Barlow, 1961). When a series of stimuli share common features, the brain selectively ignores shared components of stimuli to devote resources only to statistically independent features. This process maximizes the perceived information given the computational constraints (Ganguli & Simoncelli, 2014; Wei & Stocker, 2017). If the nature of the stimuli changes, for example moving from a dark room to a lit one, this resource allocation may however result in perceptual errors such as temporary blindness (Frydman & Jin, 2020). Thus, perception at a given time is optimized only for specific statistical characteristics of the presented stimuli (Ganguli & Simoncelli, 2014; Wei & Stocker, 2017). Efficient coding naturally then extends to the accuracy of value perception, a fundamental building block of decision making (Frydman & Jin, 2020; Heng et al., 2020; Louie et al., 2015; Polania et al., 2019; Rustichini et al., 2017; Tymula & Plassmann, 2016; Webb et al., 2021).

Given the limitations on, and the efficient allocation of, computational resources, the context-dependence of value encoding lies at the core of the study of behavior, judgment, and decision-making. An important component of efficient coding in a temporal context is range adaptation, where the number of action potentials in the brain adjust to match the range of possible values (for a review, see Louie & Glimcher, 2012). Particularly, neuronal sensitivity to value adapts to the reward distribution: the greater the range of reward values, the lower is the neuronal sensitivity (Kobayashi et al., 2010; Padoa-Schioppa, 2009). Range adaptation was recently tested in the domain of risky choice (Frydman & Jin, 2020), where participants made a series of risky choices with payoffs sampled across conditions from distributions with different volatilities but identical means. A unitary change in the available payoffs yielded stronger change in risk taking in the low volatility condition relative to the high volatility one. In other words, sensitivity to payoff values is greater for commonly presented stimuli under the low volatility condition.

Despite the success of efficient coding in describing how and why neural representations differ across contexts in risky choice, the mechanism of the adaptation process itself remains unclear (Frydman & Jin, 2020; Polania et al., 2019). A risky decision context involving real, rather than hypothetical, consequences increases risk aversion (Binswanger, 1980; Bombardini & Trebbi, 2012; Holt & Laury, 2002). The exertion of mental effort also increases with stronger incentives (Botvinick & Braver, 2015; Frömer et al., 2021; Kool & Botvinick, 2014; Shenhav et al., 2017). Importantly, real choices between consumer goods were linked to stronger neuronal activity of brain reward encoding regions when compared to hypothetical choices (Kang et al., 2011).

In addition, the Risk as Feelings Hypothesis posits that experienced emotions are integral to the evaluation of risky scenarios (Loewenstein et al., 2001). Causal manipulations of emotional experiences instigated changes in risk preferences (see for example, Kugler et al., 2012; Lee & Andrade, 2015; Stanton et al., 2014). The brain's amygdala, with its activity robustly linked to (unpleasant) emotion processing, is also believed to modulate value representation and reward learning rate (Baxter & Murray, 2002). On the other hand, positive mood induction, relative to a sad induction condition, increased risk-taking and the magnitude of the framing effect (Stanton et al., 2014).

Arousal is another dimension of emotional experiences that has been widely connected with task performance (Yerkes & Dodson, 1908). The locus coeruleus-norepinephrine (LC-NE) system, which modulates one's wakefulness, is also believed to influence the learning rate of unexpected uncertainty in the environment (Yu & Dayan, 2005). Pupillary arousal, for example, has been shown to facilitate learning in a predictive-inference task with an inverted U-shaped relationship (Nassar et al., 2012), following the Yerkes-Dodson Law (Yerkes & Dodson, 1908). The Adaptative Gain Theory postulates that the LC-NE system is highly implicated in information processing (Aston-Jones & Cohen, 2005). In particular, the high gain mode (high tonic arousal) narrows attention, while increasing the specificity of neural processing on the strongly represented (most salient) features of the stimuli, while the low gain mode (low tonic arousal) instead broadens the scope of attention and weakens the input from specific stimuli (Eldar et al., 2013, 2016).

In this study, our objective is two-fold. First, we investigate how the information-processing dynamics, in particular range adaptation, vary when risky choices involve real instead of hypothetical choices. Second, we examine the role of emotional experiences, namely arousal and valence, in the modulation of value perception of risk. In doing so, we propose integrating the well-established neuroscience model of perception captured by the efficient coding hypothesis with the rich literature in affective science that links emotions and behavior (Roberts & Hutcherson, 2019). We recruited 70 participants to make risky choices under both low and high payoff volatility conditions. Participants regularly reported their emotional experiences and were assigned to receive real payment from either the low or high volatility conditions. We hypothesized that value representations would be influenced by incentives (real vs. hypothetical) and by affective states (arousal and valence).

Our results confirm the efficient coding hypothesis in risky choice (Frydman & Jin, 2020) but, importantly, sheds light on the adaptation process. Particularly, we find that risk-taking behavior is less responsive to unitary changes in payoffs under high volatility for participants who were weakly incentivized, or those who reported low arousal levels or more pleasant feelings. In contrast, participants who were informed that the outcome of one random trial will be paid out, or those who reported high arousal levels and more unpleasant feelings, exhibited comparable behavior to unitary changes in payoffs across volatility conditions. Our results highlight the role of incentives in range adaptation, while also demonstrating that emotional experiences can modulate these effects.

3.2. Methods

A total of 70 participants completed our risky choice task, after being trained to report their emotional experiences on unpleasant/pleasant and low arousal/high arousal dimensions, followed by a survey that captures individual characteristics such as age, gender, and ethnicity (39 identified as men and 31 identified as women; average age: 24, minimum=18, maximum=65). The experiment was conducted at the Virginia Tech Econ Lab in April/May of 2021, and participants were recruited from the university's community. All procedures were approved by Virginia Tech's Institutional Review Board, and participants provided informed consent prior to their participation. We ran 17 sessions with the number of participants ranging between 3 and 5. The average payment per participant was $20.8, which included a $10 show-up payment. All parts of the experiment were conducted on a computer terminal (Chen et al., 2016).

We use a risky choice task designed to test efficient coding (Frydman & Jin, 2020). This task involves a series of 600 decisions to choose between a sure payoff and a lottery with 50% chance of a positive payoff and a 50% of a zero payoff (see *Figure 3.1*D). The 600 decisions are divided into two conditions that differ in terms of the underlying distribution from which the (positive) payoffs are sampled (see *Figure 3.1*E-F). In the low volatility (LV) condition, the payoffs are sampled independently for each participant from uniform narrow distributions (sure payoff range: 8 to 12; risky option's positive payoff: 16 to 24). On the other hand, the high volatility (HV) condition payoffs are sampled independently from uniform broad distributions (sure payoff range: 4 to 16; risky option's positive payoff: 8 to 32). Note that the mean values across the volatility conditions' payoffs are constant (10 for the sure payoff and 20 for the risky positive payoff). The order of the conditions was randomized across participants.

An important feature of this task is the common trials, in which 30 trials were selected a priori (matching those in Frydman & Jin, 2020) to fall in the support of both the low and high volatility conditions and to be presented across both conditions. These identical trials were sampled to span the low volatility payoff distributions, and in which all our analyses in this study are based, enable us to exploit within-subject choice variation across volatility conditions. To maintain the statistical properties of the underlying payoff distributions, the sampled payoffs in the HV conditions were thus re-drawn if they fell in the support of LV condition. After a short adaptation phase of 30 trials with the payoffs sampled independently from the underlying distributions, the common trials were presented in a random order in the remaining 270 trials of each volatility condition across participants.

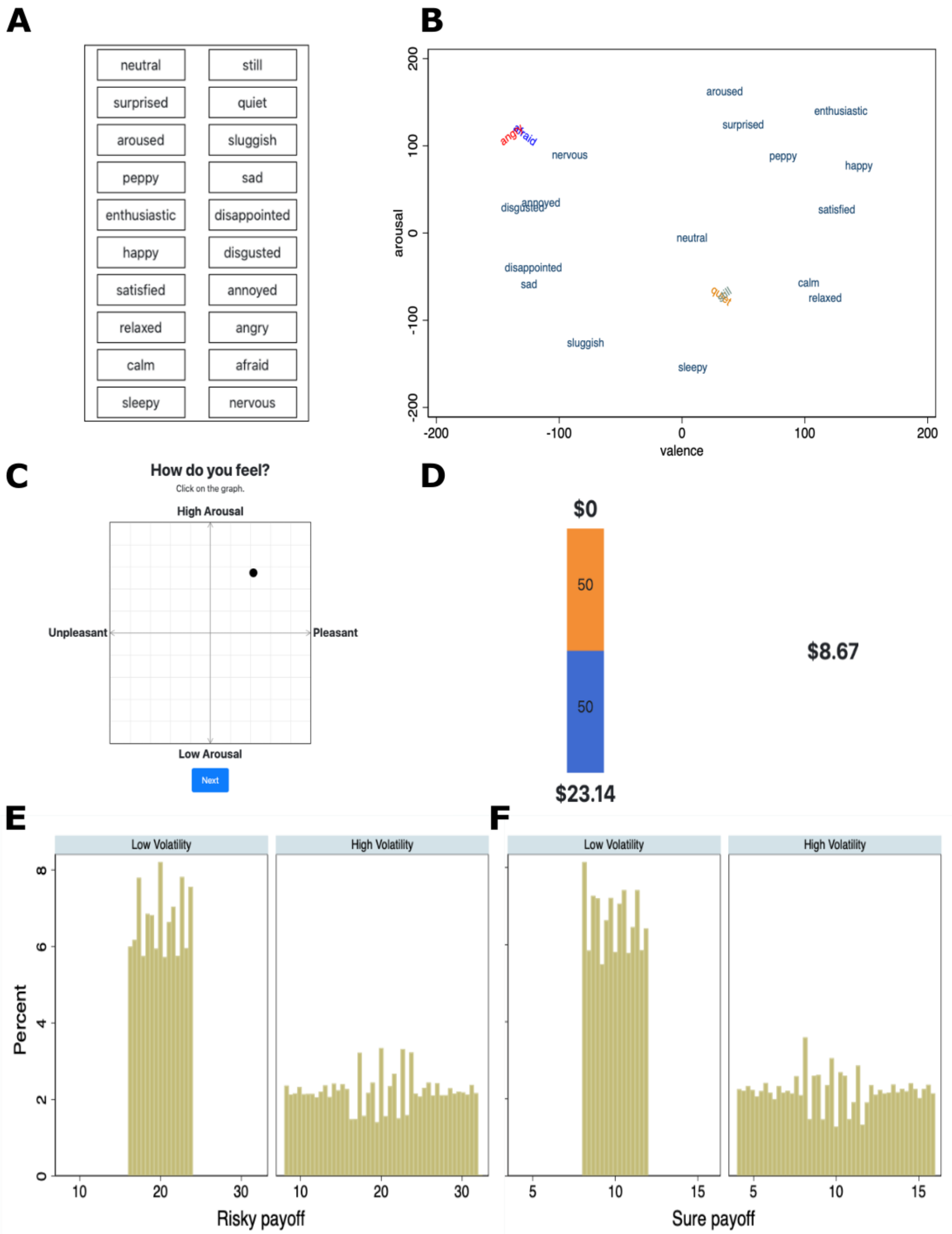

Figure 3.1 Emotion Classification and Risky Choice Tasks. (A) The list of emotions presented in the Emotion Classification Task. (B) The average location of each of the 20 emotions across participants. (C) Procedure for elicitation of emotional experiences. (D) Risky choice task. Note that the location of the risky option varied across trials and participants. (E-F) The distributions of the (E) risky payoffs and (F) sure payoffs across low and high volatility conditions. Note that the spikes in the narrow (low volatility) range are due to the common trials presented to all participants and in both volatility conditions (see Frydman & Jin, 2020)).

We adapt this risky choice in two ways. First, half of the participants were assigned to receive real payment from the LV condition only with the payment from the high volatility condition yielding a hypothetical consequence. The other half of participants were instead assigned to receive real payment from the high volatility condition and hypothetical payment from the low volatility condition. One randomly determined trial was selected at the end of the session as the paying trial for each volatility condition with participants only receiving real payment from either the HV or LV conditions. Second, we ask participants to report their emotional experiences at regular intervals using the dynamic Affective Representation Mapping (dARM) (Heffner et al., 2021). Particularly, at the beginning of the session and prior to the risky choice task, participants were trained to classify emotional experiences on an unpleasant/pleasant and low/high arousal dimensions (Russell et al., 1989) simultaneously on a 200 by 200-pixel grid (see *Figure 3.1*A-B). Then, participants were asked to report their feelings (valence and arousal) regularly during the risky choice task (see *Figure 3.1*C).

Here is a summary of how the experimental session proceeded. After participants provided informed consent and learned how to classify emotional experiences, they completed the risky choice task starting with either the low volatility condition or the high volatility one (order counter-balanced across participants). Participants were not informed of the underlying distribution of payoffs prior to making their decisions. Instead, participants were only informed whether the payment received from the upcoming decisions were in the real or hypothetical conditions. Moreover, the 300 trials within a treatment condition were divided into blocks of 50 decisions, in which participants were allowed short breaks in between blocks. Participants were also reminded whether this condition involved the real or the hypothetical payment in the beginning of each block. Finally, participants reported their feelings in the beginning of each block and every 10 trials thereafter. Two keys on the keyboard were used for making decisions between the left and right options, in which the sure and risky options were displayed (the presentation format - left vs. right - of the options was randomized). A two-seconds fixation preceded the presentation of the options in each trial, and response time was recorded in addition to which option was selected.

3.3. Results

We confirmed the efficient coding hypothesis in risky choice (Frydman & Jin, 2020) via our pooled sample analysis on the common trials, including both participants receiving real payment from the HV condition and those receiving it from the LV condition. As shown in *Figure 3.2*, sensitivity to changes in expected value differences (and payoff values) is lower under the HV condition relative to the LV one. In other words, risk taking was more responsive to changes in payoffs when the underlying sampling distribution was narrow (steeper slope under LV). Thus, under LV, perception is optimized for the payoffs that were more commonly presented, providing evidence in favor of range adaptation.

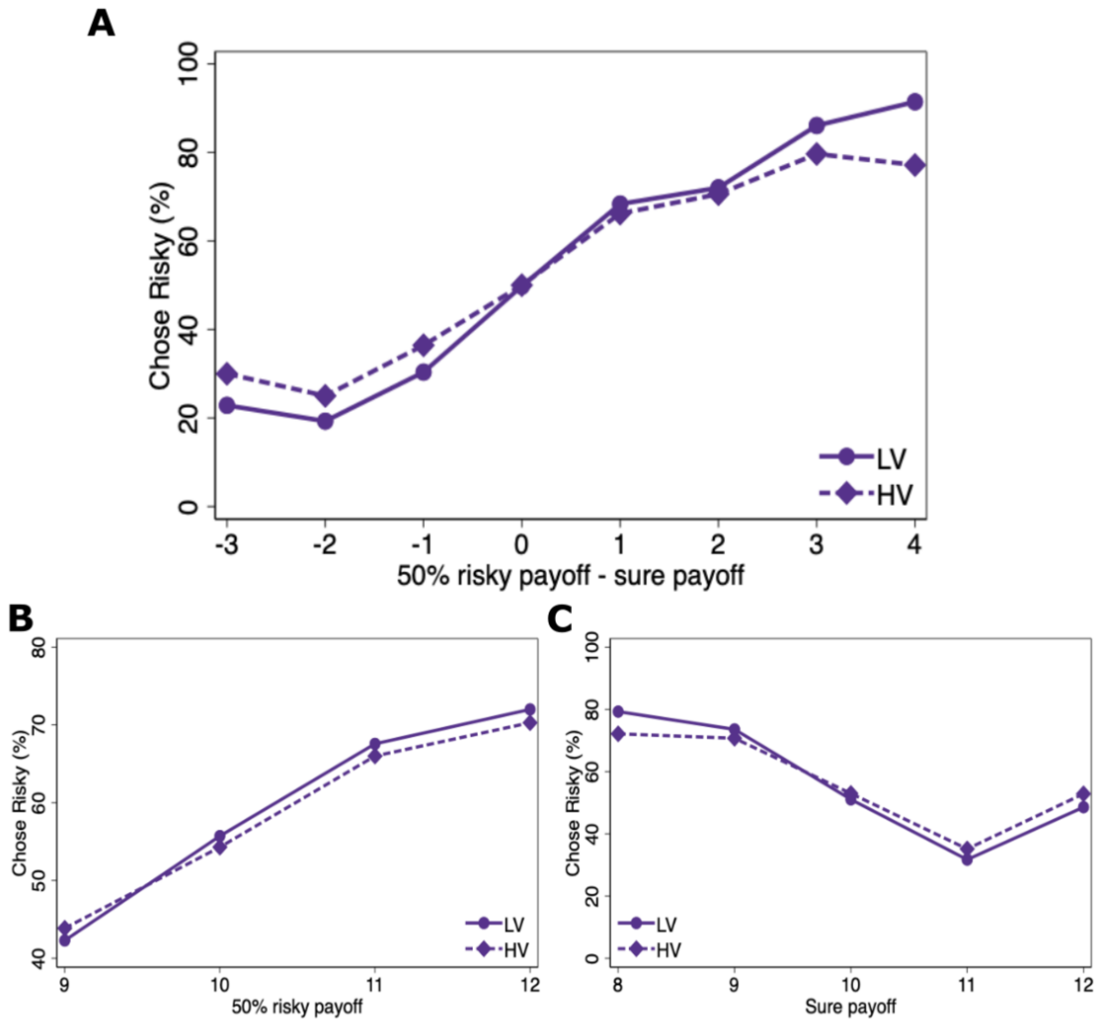

Figure 3.2 Risky choice in pooled sample. The frequency of choosing the risky option for the common trials across volatility conditions are plotted against (A) the difference in expected value of the risky option and that of the sure payoff, (B) the expected value of the risky payoff, and (C) the value of the sure payoff. Risk-taking is less responsive to changes in expected value differences (and payoff values) under high volatility.

These results are also confirmed formally using a mixed effect logistic regression (see *Table 3.1*). In our specification here, and in subsequent models, the dependent variable is choosing the risky option (taking a value of 1 and zero otherwise), and we include a random intercept and a random effect for both the risky and sure payoffs. The level of risk-taking did not differ between the HV and LV conditions ($\beta_{High\ Volatility} = -1.054, p = 0.274$). The value of the risky payoff was positively and significantly associated with choosing the risky option ($\beta_{Risky} = 0.449, p < 0.001$) while the value of the sure payoff was negatively and significantly associated with choosing the risky option ($\beta_{Sure} = -1.139, p < 0.001$). Notably, the coefficient for the interaction between the risky payoff and the HV condition moved in the opposite direction ($\beta_{Risky*HV} = -0.088, p = 0.020$) confirming range adaptation and suggesting that sensitivity to changes in the payoffs had declined under high volatility. The same holds for the sure payoff, with a positive and significant coefficient for the interaction between the sure payoff and the HV condition ($\beta_{Sure} = 0.291, p < 0.001$).

Table 3.1 Mixed effects logistic regressions: pooled sample and split by payment conditions.

	(a)	(b)	(c)
Dependent variable:	Pooled	LV	HV
Chose the risky option	Sample	Real	Real
High Volatility (HV)	-1.054	-.177	-2.414
	(.963)	(1.301)	(1.489)
Risky payoff	.449***	.425***	.500***
	(.042)	(.053)	(.069)
Sure payoff	-1.139***	-1.059***	-1.306***
	(.085)	(.108)	(.142)
Risky payoff × HV	-.088**	-.149***	-.024
	(.038)	(.051)	(.06)
Sure payoff × HV	.291***	.398***	.203*
	(.075)	(.101)	(.118)
Constant	2.319***	1.543	3.547***
	(.752)	(.986)	(1.179)
Observations	4200	2100	2100
Common trials only	Yes	Yes	Yes

*Standard errors of the fixed effects are in parentheses. High volatility takes a value of 1 for the condition with distributions sampled from the wider distributions. The models include a random intercept and a random effect on the risky and sure payoffs' variables. (Tables created using asdoc, a Stata program written by Shah (2020)) *** p<.01, ** p<.05, * p<.1*

We next investigate the impact of incentives on range adaptation. We split our sample into groups based on the random assignment to payment conditions. As shown in *Figure 3.3*, participants who were assigned to receive real payment in the LV condition were the ones who displayed the greatest decline in sensitivity to changes in expected value differences (and payoff values) across volatility conditions (flatter slope in the HV condition). On the other hand, participants assigned to receive real payment in the HV condition maintained comparable sensitivities to changes in expected value difference and payoff values in the HV condition to that in the LV one. In other words, a unitary increase in the expected value difference between the risky option and the sure payoff yielded a greater increase in risk taking in the LV condition when compared to the HV condition for participants who were assigned to receive real payment in the LV condition only. This unitary change in the expected value difference, however, yielded a similar increase in risk taking across both LV and HV conditions for participants assigned to receive real payment in the HV condition.

As shown in *Table 3.1*, the mixed effects logistic regression confirmed these results. Under both payment conditions, the coefficients for the risky payoff were positively and significantly associated with choosing the risky option ($LV\ real\colon \beta_{Risky} = 0.425, p < 0.001; HV\ real\colon \beta_{Risky} = 0.500, p < 0.001$) while that of the sure payoff was instead negatively and significantly associated with risk-taking ($LV\ real\colon \beta_{Sure} = -1.059, p < 0.001; HV\ real\colon \beta_{Sure} = -1.306, p < 0.001$).

Even though the coefficients for the interaction between the risky and sure payoffs and HV condition were consistent with the efficient coding hypothesis for participants assigned to receive real payment in LV condition ($\beta_{Risky*HV} = -0.149, p = 0.004$; $\beta_{Sure*HV} = 0.398, p < 0.001$), the coefficients of these interactions were not significantly different from zero for those assigned to receive real payment in the HV condition instead ($\beta_{risky*HV} = -0.024, p = 0.688$; $\beta_{sure*HV} = 0.203, p = 0.085$). Thus, our results suggest that perception to changes in payoffs across the narrow and wide ranges did not differ for participants assigned to receive a real payment from the HV condition: no evidence for range adaptation.

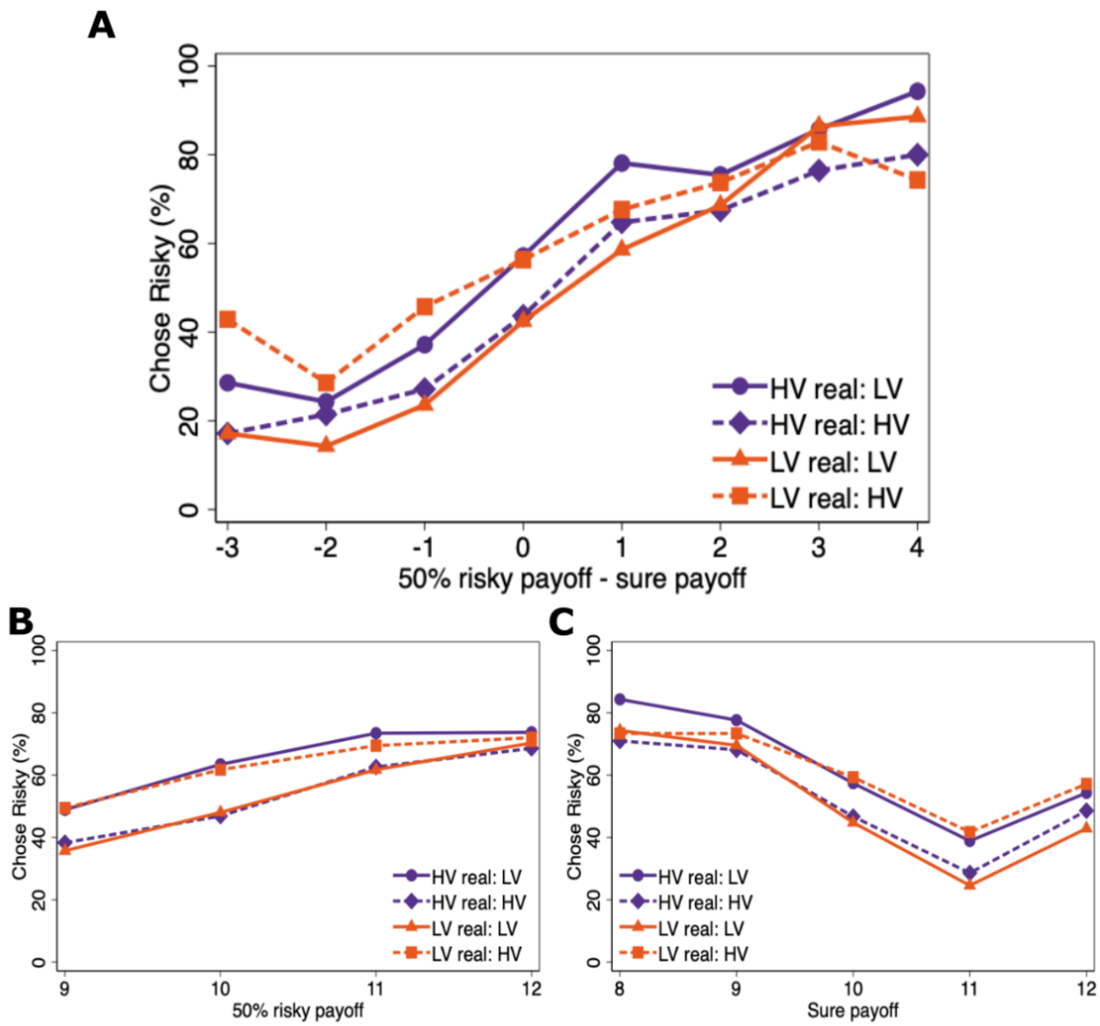

Figure 3.3 Risky choice split by payment conditions. The frequency of choosing the risky option for the common trials across volatility conditions for the two groups split by real payment condition (HV real vs. LV real) are plotted against (A) the difference in expected value of the risky option and that of the sure payoff, (B) the expected value of the risky payoff, and (C) the value of the sure payoff. Risk-taking is more responsive to changes in expected value differences (or, payoff values) under high volatility for participants assigned to receive real payment in the LV condition (LV real). The decline in sensitivity to changes in expected value difference (and payoffs) are milder for the HV real group.

We turn next to the relationship between (self-reported) emotional experiences and the perception of value in risky choice. As a manipulation check, we tested whether (z-scored) arousal and valence differed across payment conditions (see *Figure 3.4*). Indeed, we find that arousal, on average, was significantly higher in the real payment condition ($M_{diff} = 0.450; Wilcoxon\ signed - rank\ test;\ N = 70, p < 0.001$). Valence, however, did not differ significantly across payment conditions ($M_{diff} = 0.072; Wilcoxon\ signed - rank\ test;\ N = 70,\ p = 0.576$).

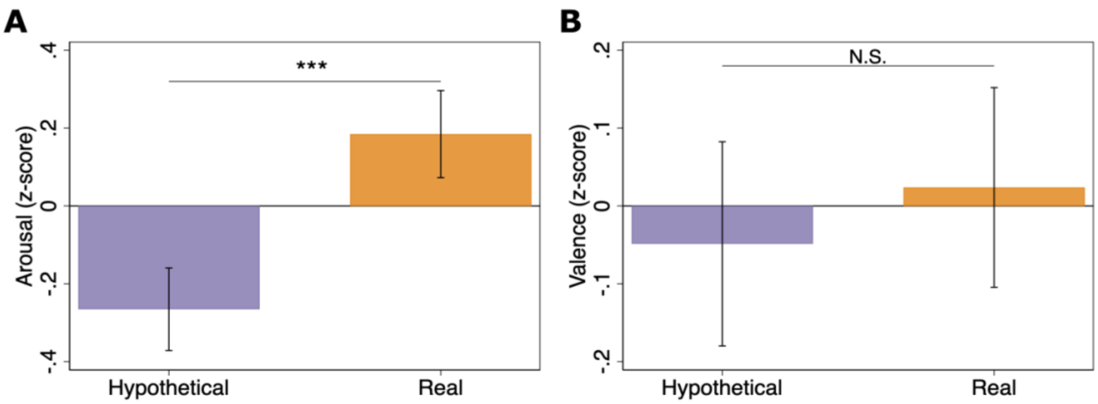

Figure 3.4 Arousal and valence across payment conditions. (A-B) Average self-reported (A) arousal and (B) valence (both z-scored within participant) across real payment conditions. Arousal was significantly higher under real stakes. Valence did not significantly differ between payment conditions. Wilcoxon signed-rank test (N=70): *** P-value < 0.01, N.S. not significant.

We use median splits to divide our sample into two groups based on changes in arousal across volatility conditions. The first group included participants who reported low or small differences in (mean) z-scored arousal in the HV condition relative to the LV one (HV Lower Arousal, N=35). The second group included participants who reported an above median difference in (mean) z-scored arousal in the HV condition relative to the LV one (HV Higher Arousal, N=35). Note that the change in arousal for 7 out of 35 participants assigned to receive real payment in the HV condition (in the LV condition) was higher (lower) than the sample median. As shown in *Figure 3.5*, the HV Lower Arousal group exhibited differences in sensitivity to changes in expected value differences (and payoff values) across volatility conditions (flatter slope under HV condition). For the HV Higher Arousal group, however, the decline in responsivity of risky taking to a unitary change in expected value differences (and, payoff values) in the wider range (HV) condition was milder when compared to that of the HV Lower Arousal group.

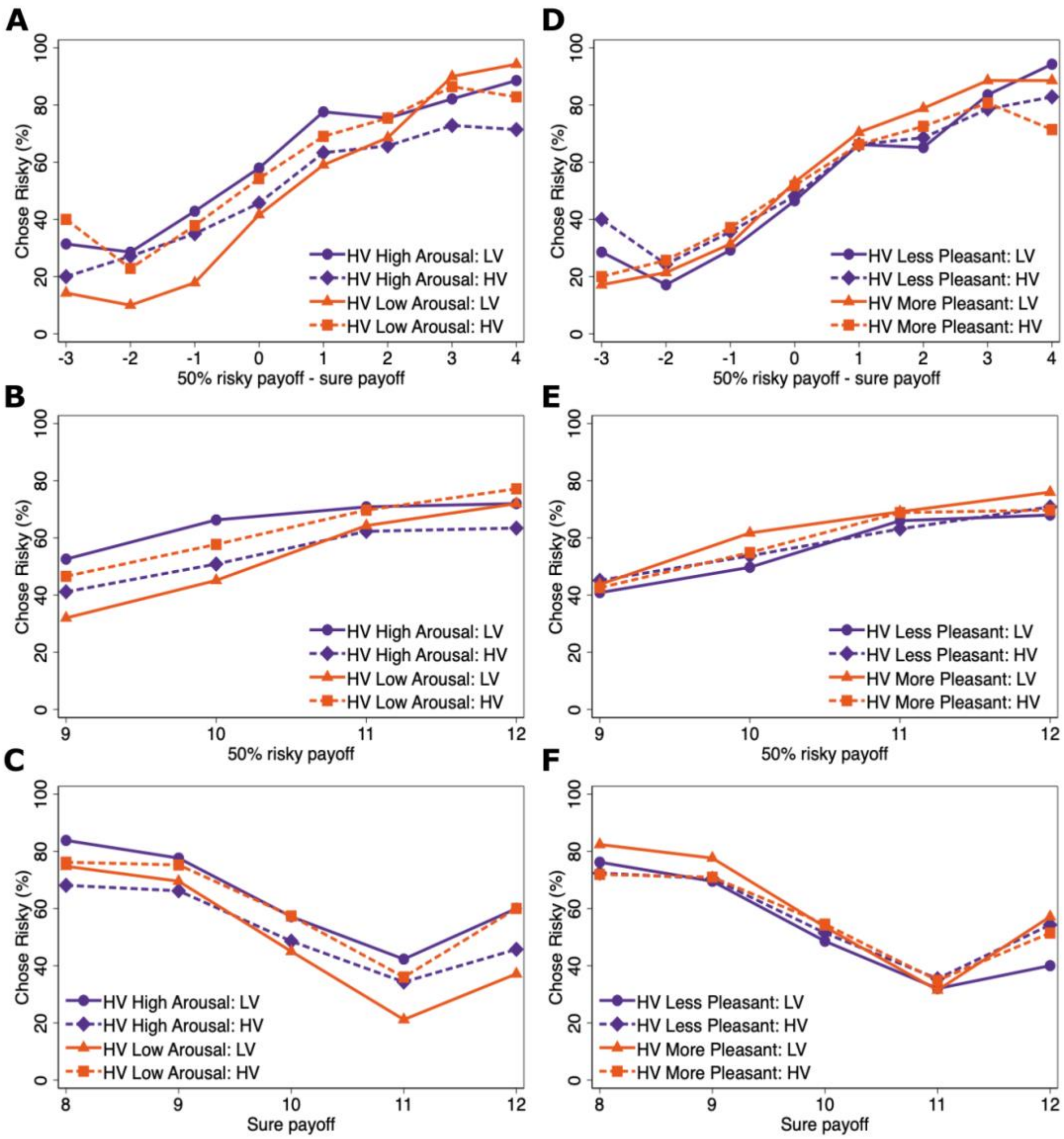

Figure 3.5 Risky choice split by arousal and valence groupings. (A-C) The frequency of choosing the risky option for the common trials across volatility conditions for the two groups split based on the difference in arousal across volatility conditions (above median, HV High Arousal; below median, HV low Arousal) are plotted against (A) the difference in expected value of the risky option and that of the sure payoff, (B) the expected value of the risky payoff, and (C) the value of the sure payoff. Risk-taking is more responsive to changes in expected value differences (and payoff values) under high volatility for the HV Low Arousal group. The decline in sensitivity to changes in expected value differences (and payoff values) are milder for the HV High Arousal group. (D-F) The frequency of choosing the risky option for the common trials across volatility conditions for the two groups split based on the difference in valence across volatility conditions (above median, HV More Pleasant; below median, HV Less Pleasant) are plotted against (D) the difference in expected value of the risky option and that of the sure payoff, (E) the expected value of the risky payoff, and (F) the value of the sure payoff. Risk-taking was less responsive to changes in expected value differences (or, payoff values) for the HV More Pleasant group. The decline in sensitivity under high volatility is milder for the HV Less Pleasant group.

We use mixed effects logistic regressions to formally test and confirm these observations (see *Table 3.2*). For both groups, we again find that the risky payoff is positively and significantly associated with risk taking ($HV\ Lower\ Arousal$: $\beta_{Risky} = 0.487, p < 0.001$; $HV\ Higher\ Arousal$: $\beta_{Risky} = 0.375, p < 0.001$) while the sure payoff is negatively and significantly associated with risk taking ($HV\ Lower\ Arousal$: $\beta_{Safe} = -1.108, p < 0.001$; $HV\ Higher\ Arousal$: $\beta_{Safe} = -1.134, p < 0.001$). For the HV Lower Arousal group, behavior is consistent with the efficient coding hypothesis with the coefficients of the payoffs' interactions with the HV condition attenuating responsivity to changes in payoffs ($\beta_{Risky*HV} = -0.150, p = 0.004$; $\beta_{sure*HV} = 0.359, p = 0.001$). For the HV Higher Arousal group, however, the evidence in favor of range adaptation is somewhat weaker ($\beta_{Risky*HV} = -0.025, p = 0.656$; $\beta_{Sure*HV} = 0.256, p = 0.020$). Even though risk-taking was less sensitive to changes in the sure payoff values, the risky payoffs influenced behavior similarly across HV and LV conditions for participants in the Higher Arousal group. These results provide support for the Adaptive Gain Hypothesis (Aston-Jones & Cohen, 2005), suggesting that high arousal increases neural gain for specific stimuli: the risky payoff in our task.

Table 3.2 Mixed effects logistic regressions: sample split by change in arousal and valence groupings.

	(a)	(b)	(c)	(d)
Dependent variable:	HV	HV	HV	HV
Chose the risky option	Low Arousal	High Arousal	More Pleasant	Less Pleasant
High Volatility (HV)	.23	-2.809*	-1.481	-.645
	(1.295)	(1.438)	(1.36)	(1.368)
Risky payoff	.487***	.375***	.479***	.422***
	(.041)	(.065)	(.059)	(.059)
Sure payoff	-1.108***	-1.134***	-1.225***	-1.061***
	(.082)	(.136)	(.12)	(.121)
Risky payoff × HV	-.15***	-.025	-.106**	-.077
	(.053)	(.055)	(.054)	(.054)
Sure payoff × HV	.359***	.256**	.354***	.242**
	(.104)	(.11)	(.107)	(.106)
Constant	.695	4.371***	2.655**	2.007*
	(.92)	(1.084)	(1.036)	(1.1)
Observations	2100	2100	2100	2100
Common trials only	Yes	Yes	Yes	Yes

*Standard errors of the fixed effects are in parentheses. High volatility takes a value of 1 for the condition with distributions sampled from the wider distributions. The models include a random intercept and a random effect on the risky and sure payoffs' variables. *** p<.01, ** p<.05, * p<.1*

In a similar vein, we split our sample into two groups based on the change in valence across volatility conditions (median splits). The HV Less Pleasant group (N=35) included participants who reported low or small differences in (mean) z-scored pleasant feelings in the HV condition relative to the LV one while the HV More Pleasant group (N=35) included participants who instead reported an above median change in z-scored pleasant feelings. For valence, the change 16 out of 35 participants assigned to receive real payment in the HV condition (in the LV condition) reported more (less) pleasant feelings than the sample median. As shown in *Figure 3.5*, risk-taking in the HV condition was more sensitive to changes in expected value differences (and payoff values) for the HV More Pleasant group. This result did not extend to the HV Less Pleasant group with participants exhibiting comparable sensitivities across volatility conditions. Again, our observations are confirmed via mixed effects logistic regressions (see *Table 3.2*). The risky payoff was again positively and significantly associated with choosing the risky option $(HV\ More\ Pleasant{:}\ \beta_{Risky} = 0.479, p < 0.001; HV\ Less\ Pleasant{:}\ \beta_{Risky} = 0.422, p < 0.001)$ while the sure payoff moved in the opposite direction $(HV\ More\ Pleasant{:}\ \beta_{Sure} = -1.225, p < 0.001; HV\ Less\ Pleasant{:}\ \beta_{Sure} = -1.106, p < 0.001)$. Despite the overall similarity in self-reported valence across real and hypothetical payment conditions, we confirm that the HV More Pleasant group had a greater decline in sensitivity to changes in payoffs in the HV condition $(\beta_{Risky*HV} = -0.106, p = 0.049;\ \beta_{Sure*HV} = 0.354, p = 0.001)$. Evidence in favor of range adaptation are again weaker for the HV Less Pleasant group $(\beta_{Risky*HV} = -0.077, p = 0.152;\ \beta_{Sure*HV} = 0.242, p = 0.022)$: perception sensitivity to risky payoff changes did not significantly decline across volatility conditions This finding seems consistent with the aversiveness of mental effort exertion (Shenhav et al., 2017).

We also investigate how overall risk taking differed across payment conditions. Interestingly, we find that risk aversion increased in the real payment condition $(M_{diff} = 10.238; Wilcoxon\ signed-rank\ test;\ N = 70,\ p = 0.001)$. Moreover, reaction time was greater in the condition with a real payment $(M_{diff} = 0.192; Wilcoxon\ signed-rank\ test;\ N = 70,\ p = 0.040)$ (see *Figure 3.6*). This latter finding provides further evidence that incentives do not only bias behavior but also the choice process by which participants arrive at their decisions.

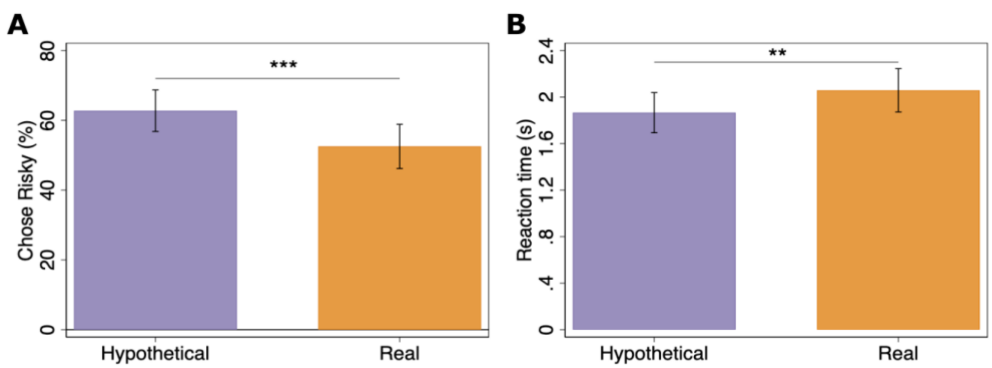

Figure 3.6 Risk aversion and reaction time across payment conditions. (A) frequency of choosing the risky option and (B) average reaction time across real payment conditions for the common trials. Risk-taking dropped under high stakes while reaction time increased. Wilcoxon signed-rank test (N=70): ** P-value<0.05, *** P-value < 0.01

Last, we examine whether changes in arousal between the LV and HV conditions vary systematically with changes in risk-taking and reaction time. Interestingly, we find that participants who reported higher arousal levels in the HV condition, relative to the LV one, were less likely to choose the risky option (Spearman rank correlation, $\rho_s = -0.338;\ \mathrm{N} = 70,\ \mathrm{p} = 0.004$) and more likely to spend longer time to choose an alternative (Spearman rank correlation, $\rho_s = 0.343;\ \mathrm{N} = 70,\ \mathrm{p} = 0.004$) (see *Figure 3.7*). On the other hand, changes in valence across volatility conditions were not significantly associated with changes in risk-taking (Spearman rank correlation, $\rho_s = 0.044;\ \mathrm{N} = 70,\ \mathrm{p} = 0.718$) or with changes in reaction time (Spearman rank correlation, $\rho_s = 0.180;\ \mathrm{N} = 70, p = 0.136$).

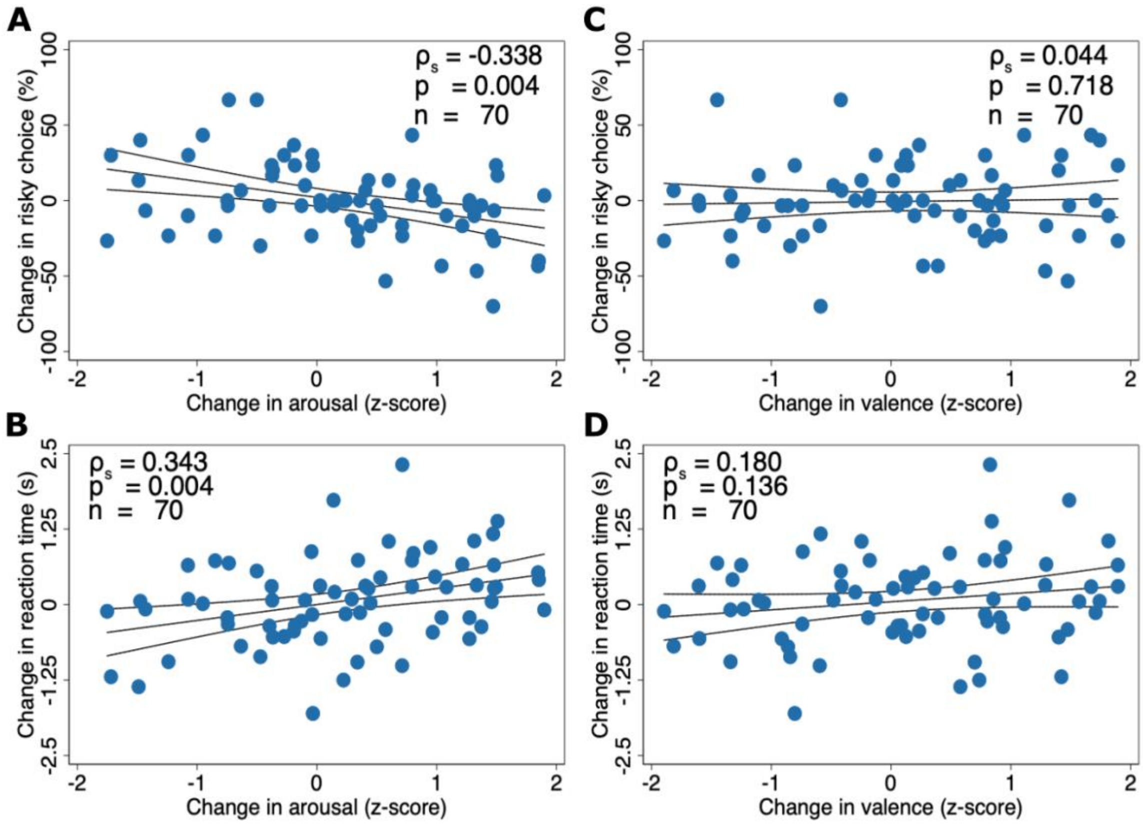

Figure 3.7 Individual differences in risk aversion and reaction time to changes in arousal and valence. (A-B) The change (A) the frequency of choosing the risky option (y-axis) and (B) reaction time (y-axis) in the high volatility vs. the low volatility condition are plotted against the individuals' difference in (z-scored) arousal in the high volatility vs. the low volatility condition (x-axis). (C-D) The change in (C) the frequency of choosing the risky option (y-axis) and (D) reaction time (y-axis) in the high volatility vs. the low volatility condition are plotted against the individuals' difference in (z-scored) valence in the high volatility vs. the low volatility condition (x-axis). Individual differences in arousal during the high volatility condition were positively and strongly associated with changes in risk aversion and reaction time while differences in valence were only significantly associated with changes reaction time.

3.4. Discussion

Our findings are consistent with the efficient coding hypothesis for participants assigned to receive real payment from the low volatility condition only. In particular, perception adapted across ranges and was more sensitive to changes in payoffs under the low volatility condition relative to the high volatility one. In contrast, participants assigned to receive real payment from the high volatility condition displayed comparable sensitivities to changes in payoffs across the two volatility conditions. Consistent with previous findings on incentives and arousal (see findings from Chapter 2 and Anderson & Brown, 1984; Richter & Gendolla, 2009), we find that self-reported arousal is higher under real stakes. Valence, however, did not differ across the real and hypothetical conditions. Importantly, we find that both arousal and valence seem to play an important role in range adaptation.

Participants who experienced modest or declining changes in arousal or more pleasant feelings in the high volatility condition, relative to the low volatility one, displayed lower sensitivity to changes in payoffs. In contrast, participants reporting amplified arousal levels in the high volatility condition or less pleasant feelings displayed comparable sensitivities to changes in the risky option's payoffs across volatility conditions. Our findings also confirm the amplification of risk aversion under real stakes (see Chapter 2 and Holt & Laury, 2002). In addition, we find that reaction time, which is commonly used to investigate the choice-process (Cooper et al., 2019; Konovalov & Krajbich, 2019), increased under real stakes. Interestingly, individual differences in arousal across the low volatility and high volatility conditions were strongly associated with changes in both risk aversion and reaction time between conditions.

Stronger (real) incentives modulate the perception of value and increase self-reports of arousal. The higher sensitivity to changes in payoff values in the high volatility condition under real stakes is consistent with the greater brain activation of value encoding regions in real, instead of hypothetical, consumer good choices (Kang et al., 2011). In addition, heightened self-reports of arousal results in higher sensitivity to changes in a specific stimulus, the risky payoff, when the range of the underlying payoff distribution increases. This finding seems consistent with the Adaptive Gain Theory (Aston-Jones & Cohen, 2005), high neuronal gain to particular inputs, and with the link between arousal levels and mental effort (Howells et al., 2010). On the other hand, our results lie in contrast with key assumptions in adaptation models such as fixed neural activity range (Kobayashi et al., 2010; Padoa-Schioppa, 2009) or fixed capacity constraints (Frydman & Jin, 2020). Moreover, the valence dimension of affect seems to also play an integral role in information processing, similar to previous findings on the framing effect (Stanton et al., 2014) and potentially through activations of brain regions that are associated with emotion processing (Baxter & Murray, 2002). These results demonstrate the importance of incentives and emotional experiences in the adaptation of perceptual processing of value, potentially by modulating the neuronal activity range or the capacity constraint that are typically assumed fixed in adaptation models (see Kobayashi et al., 2010, Padoa-Schioppa, 2009, and Frydman & Jin, 2020). The efficient coding hypothesis seems to hold best under weak incentives, low levels of arousal and more pleasant feelings, suggesting that the range adaptation process itself is also context dependent.

Chapter 4

4. Gender differences in fear and risk perception during the COVID-19 pandemic

Abdelaziz Alsharawy, Ross Spoon, Sheryl Ball, and Alec Smith

Abstract

The COVID-19 pandemic has led many people to suffer from emotional distress. Previous studies suggest that women process and express affective experiences, such as fear, with a greater intensity compared to men. We administered an online survey to a sample of participants in the United States that measures fear of COVID-19, perceptions about health and financial risks, and preventative measures taken. Despite the empirical fact that men are more likely to experience adverse health consequences from COVID-19, women report greater fear and more negative expectations about health-related consequences of COVID-19 than men. However, women are more optimistic than men regarding the financial consequences of the pandemic. Women also report more negative emotional experiences generally during the pandemic, particularly in situations where other people or the government take actions that make matters worse. Though women report taking more preventative measures than men in response to the pandemic, gender differences in behavior are reduced after controlling for fear. These results shed light on how differences in emotional experiences of the pandemic may inform policy interventions.

4.1. Introduction

The consequences of COVID-19 transcend public health. The pandemic has profoundly affected economic activity, social interactions, and emotional well-being. Despite the universality of the pandemic, experience with previous natural disasters suggests that its impact may vary across individuals. Gender, age, socioeconomic status, and affective responses all influence how people are affected by catastrophic events (Neumayer & Plümper, 2007; M. R. Taylor et al., 2008; Eckel et al., 2009; Ibuka et al., 2010; Huang et al., 2013; Callen et al., 2014; Jang et al., 2020). For example, among earthquake victims in Turkey, women were more likely to recall panicking during the crisis (Yilmaz et al., 2005). Moreover, women were also more likely to report fear of disasters such as landslide or flooding in Taiwan (Ho et al., 2008) and to worry about serious negative consequences of climate change in Sweden (Sundblad et al., 2007).

Gender differences are common in self-reported emotional experiences. Women report greater affective intensity (Fujita et al., 1991) and experience negative emotions such as fear more frequently (Brebner, 2003; A. H. Fischer et al., 2004). The COVID-9 pandemic is no exception. In recent surveys conducted in the US, Cuba, and China, women reported greater fear and stress associated with the pandemic (Fitzpatrick et al., 2020; Broche-Pérez et al., 2020; Park et al., 2020; Liu et al., 2020). Early research on the impact of the COVID-19 pandemic suggests that local COVID-19 infection rates (Bu et al., 2020) and fear of the virus decrease risk taking (Alsharawy et al., 2020), and predict adherence to prevention measures (Harper et al., 2020; Müller & Rau, 2021). In addition, across eight different countries, women had a greater perception of the severity of the COVID-19 pandemic and greater adherence to prevention measures (Galasso et al., 2020).

Interestingly, these differences run counter to sex differences in the health consequences of the pandemic. Though disease prevalence is roughly equal between males and females, males are more likely to experience serious health consequences and to die from COVID-19 (Bhopal & Bhopal, 2020; Gebhard et al., 2020; Jin et al., 2020; Peckham et al., 2020). A recent meta-analysis indicates that, conditional on a positive diagnosis, males have roughly a 40% greater mortality risk from COVID-19, and are nearly 3 times more likely to be admitted to hospital intensive treatment units (Peckham et al., 2020).

We surveyed nearly 1500 people across the United States to measure emotions, behaviors and expectations associated with the COVID-19 pandemic. We hypothesized that women would report higher levels of fear, and this would motivate higher adherence to COVID-19 prevention measures, such as washing hands or physical distancing. Similarly, we explore whether pro-sociality increase adherence to mitigation strategies. Finally, based on previous studies of natural disasters, we also expected that women would report greater concern about the negative consequences of the crisis.

4.2. Methods

In April of 2020, we administered a repeated cross-sectional survey to a random sample of around 1500 people residing in the United States on Amazon Mechanical Turk (MTurk). We collected a third of our data every two weeks starting on April 2nd, 2020. There were approximately 200,000 confirmed COVID-19 cases in the United States at the time of our first sample; this number was tripled in the following two weeks and reached over 1 million cases by our third wave. The number of US deaths from COVID-19 was less than 4000 at the time of our initial sample, reached about 26,000 two weeks later, and passed 50,000 around the time of our third sample wave (*Coronavirus Disease 2019 (COVID-19) Situation Report – 73*, 2020; *Coronavirus Disease 2019 (COVID-19) Situation Report – 87*, 2020; *Coronavirus Disease 2019 (COVID-19) Situation Report – 101*, 2020). To determine local COVID-19 infection rates, we matched participants ZIP codes to counties (using a publicly available ZIP code database: www.unitedstateszipcodes.org/zip-code-database) and obtained county-level data on population and COVID-19 related deaths from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University (https://github.com/CSSEGISandData/COVID-19) (Dong et al., 2020).

Our survey captured self-reported fear of COVID-19 and adherence to preventative health behavior. Participants also indicated their perceptions of health and financial risks in the form of probabilistic beliefs about the percent chance that 1) they or a household member will lose a job due to the pandemic, 2) total household income will decrease over the next 12 months, 3) they or someone close will develop COVID-19, and 4) they or someone close will die from COVID-19. To elicit these beliefs, we adapted question formats that were validated against realizations of the same events (Manski, 2004). We also elicited anticipated negative emotions after people or institutions make decisions that make matters worse during a crisis. The full list of survey questions is provided in the supplementary material (see section 4.6.5). The survey included other measures that are discussed in a companion paper on fear of COVID-19 and economic preferences, which finds that risk and time preferences varied significantly with fear of COVID-19 and the association weakening over time (Alsharawy et al., 2020). We designed this survey in the early weeks of the pandemic to capture individual and socioeconomic characteristics (22 questions), economic preferences from the Global Preference Survey (10 questions; Falk et al., 2016, 2018), unincentivized risky lottery preference (Eckel & Grossman, 2002), and trust (9 questions adapted from Global Preference Survey, Socio-Economic Panel Study and World Value Survey, Inglehart, 2004; Wagner et al., 2007; Falk et al., 2016, 2018). In addition, we surveyed participants on their behavior and beliefs with regard to the pandemic (14 questions), and expectations about the emotions they would experience if people/institutions made wrong decisions in response to a crisis (4 questions). In this study, we explore gender differences in behavior, beliefs and expectations with regard to the pandemic.

We set an initial criterion in our first wave of master status for MTurk workers. For subsequent waves, we then dropped this requirement, due to difficulties in collecting our pre-determined sample size of 500 per wave, while still requiring a 99% or higher approval rating and at least 5000 approved Human Intelligence Tasks. Due to random sampling from eligible participants, our sample is not strongly balanced across genders (690 women and 794 men). Moreover, 71% of our sample participants took the survey only once, so there is not a sufficient number of repeaters in our sample to investigate individual changes over time. We therefore combine the three waves, and in our regression analyses we include controls for wave-specific effects. There are some differences in survey responses across genders on factors such as age, political orientation, and education (see Table 4.S*2*). Similar to other studies analyzing survey responses (Dohmen et al., 2011; Falk et al., 2018), we control for these differences statistically using individual level characteristics to establish the robustness of our findings: age, age-squared, indicator for race (Caucasian) or origin (Hispanic), self-reported high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. In addition, we control for occupation adapting a categorization from the Census classification as outlined in the supplementary material (*2010 Census Occupational Classification*, 2016). Our regression analysis also controls for the US state in which the participant resided, in which of the 3 survey waves they participated, and the local (county) death rate of COVID-19 (Bu et al., 2020).

4.3. Hypotheses

Building on previous findings of women reporting higher frequency of negative emotions (Brebner, 2003; A. H. Fischer et al., 2004), we hypothesized that women would report higher fear levels of COVID-19 in the early weeks of the pandemic (question 60 in our survey; see supplementary material). Confirming this hypothesis would bolster the credibility of recent findings that are reported in surveys in the United States and Cuba (Fitzpatrick et al., 2020; Broche-Pérez et al., 2020).

H1: Women, compared to men, report higher fear of the COVID-19 pandemic.

Since emotional experiences are widely believed to affect behavior (Barrett, 2006; Baumeister et al., 2007; Forgas, 1995; Loewenstein et al., 2001; Van Kleef, 2009) and the pandemic evoked emotional responses in many ways (Alsharawy et al., 2020; S. Taylor et al., 2020a, 2020b), we were interested in whether gender differences in adherence to the disease's prevention measures were mediated by fear of COVID-19. In particular, we hypothesized that controlling for self-reported fear of the pandemic would weaken the relationship between gender and adherence to preventative measures (measured in question 54 in our survey; see supplementary material).

H2: Controlling for fear of COVID-19 weakens observed gender differences in adherence to prevention measures.

Worries about the health-related dangers of the COVID-19 have been strongly linked to distress (S. Taylor et al., 2020a), so we explored gender differences in expectations about COVID-19's related outcomes. In particular, we elicited participants' beliefs of experiencing both health and financial hardships as a result of the pandemic. Since women tend to report greater affective intensity (Fujita et al., 1991) and consistent with the affect heuristic (Finucane et al., 2000; Loewenstein et al., 2001; Slovic et al., 2007; Slovic & Peters, 2006), we hypothesized that women have more negative perceptions about the COVID-19 risks (measured in questions 56-59 in our survey; see supplementary material). Moreover, we explore whether gender differences extend to expectations about experiencing negative emotions when decisions made by other people, the government, the media or autonomous devices make matters worse during a crisis (measured in questions 43-46). We hypothesized that women expect to experience stronger negative emotions in such cases.

H3A: Women, compared to men, report higher expectations of negative health and financial-related consequences of the COVID-19 pandemic.
H3B: Women, compared to men, report higher expectations of experiencing negative emotions in a crisis when decisions made by other people, institutions or autonomous devices make matters worse.

4.4. Results

First, we investigate whether emotional responses to the pandemic, in particular fear, differed across self-reported gender. Confirming our first hypothesis, women reported higher fear of the COVID-19 pandemic compared to men in our pooled sample ($\mu_{difference} = 0.939$, Wilcoxon rank-sum test: P<0.001; see Figure 4.*1*). In addition to reporting the results of the widely used non-parametric Wilcoxon rank-sum test that probe for differences in central tendency, we report in Supplementary Table 4.S*1* the results of two additional statistical analyses: two-sided t-tests (parametric: central tendency) and Epps-Singleton tests (non-parametric: distributional characteristics). Importantly, this gender difference in fear of the pandemic is robust across statistical tests. When we examine the distribution of the Likert scale responses, we find that women were more than twice as likely to report extreme levels of fear than men. Nearly 20.0% of women chose the highest available value for fear of the pandemic, compared to around 9.3% of men. This finding of increased fear of the pandemic among women is also robust in multiple regression analysis controlling for state and survey-wave fixed effects (β=0.963, P=0.001) and to individual-specific controls including age, ethnicity, occupation, employment status, political orientation, smoking behavior, self and parent's education, self-reported income, and a self-reported measure of cognitive ability (β=0.654, P=0.014; see Supplementary *Table 4.S3*). As reported in our companion paper, we use the local death rate as a proxy for the intensity of individual experience of the pandemic. The local death rate was positively and significantly associated with fear of COVID-19 (Alsharawy et al., 2020). These results also hold when we standardize (z-score) the Likert response for each individual to account for differences in response styles (R. Fischer & Milfont, 2010) (results available upon request). Moreover, when we include the interaction between the gender and each of the two waves, we find that the rate by which self-reported fear declined over time was similar across genders (P>0.100; result available upon request).

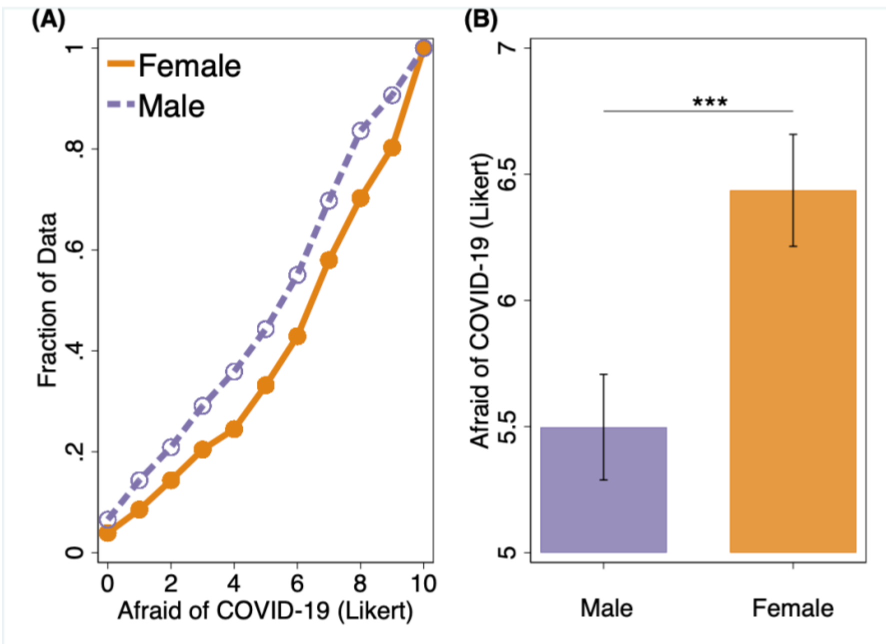

Figure 4.1 Fear of COVID-19 pandemic by gender. (A) Empirical cumulative distribution function for fear of COVID-19 by gender (11-point Likert question with response alternatives ranging from "Not at all afraid" at 0 to "Very afraid" at 11) (B) Average fear of COVID-19 by gender. (Error bars represent 95% confidence intervals). Wilcoxon rank-sum tests: *** p<.001.

Second, we turn to self-reports of whether respondents adopted recommended preventative health behaviors in response to the COVID-19 pandemic. We examine: 1) hand washing, 2) using hand sanitizer, 3) avoiding touching one's face, 4) cleaning and disinfecting surfaces in the home, 5) wearing a face mask, and 6) practicing physical distancing. Using an Ordered Logit regression where the dependent variable is the number of preventative measures taken (see *Table 4.1*), we find that women adopted significantly more preventative measures than men (OR=1.355, P=0.003). This result is robust to including individual-level controls (OR=1.314, P=0.010). Holding all other variables constant, this model suggests that the odds of following all six preventative measures is 1.314 greater for women than men. Interestingly, when we include self-reported fear of the COVID-19 pandemic as a predictor, the gender difference result no longer holds (OR=1.104, P>0.100). Instead, the coefficient for fear of the COVID-19 pandemic is positive and statistically significant (OR=1.255, P<0.001). With a one (Likert) unit increase in self-reported fear of the pandemic while holding other variables constant, the odds of adhering to all six health behaviors versus the combined other categories are greater by a factor of 1.255. Again, these results are robust to the inclusion of individual level controls (see *Table 4.1*). Our findings suggest that gender differences in behavioral responses, both in our and in other studies (e.g., Galasso et al., 2020) are driven by emotional responses to the COVID-19 pandemic. There is recent evidence suggesting that social preferences, in particular pro-sociality, increases adherence to prevention measures (Campos-Mercade et al., 2021). Moreover, in our companion paper, we report that fear of COVID-19 and altruism are positively and significantly associated (Alsharawy et al., 2020). In our survey, we capture an experimentally validated measure of altruism (question 26 in our survey; see supplementary material) (Falk et al., 2016, 2018), and we also find that pro-sociality is positively and significantly associated with compliance to preventative measures (OR=1.173, P<0.001; see *Table 4.1*) (Campos-Mercade et al., 2021). Importantly, however, the positive statistical significance between fear of COVID-19 and compliance to preventative measure remains robust despite controlling for altruism (OR=1.236, P<0.001). In addition, we find a similar result for local COVID-19 infection rates. In particular, the positive relationship between local death rate and the number of prevention measure taken (OR=1.009, P=0.004) is weakened when we control for fear of COVID-19 (OR=1.006, P=0.044). These results confirm the importance of affective responses, namely fear, in behavioral responses during a crisis like the COVID-19 pandemic.

Table 4.1 Fear of COVID-19 pandemic and adherence to prevention measures. Number of preventative measures taken in response to COVID-19 (Ordered Logit Regression). The six measures are: 1) washing hands more frequently, 2) using hand sanitizers more frequently, 3) make more effort to avoid touching face, 4) cleaning and disinfecting surfaces in home more than usual, 5) wearing a face mask, and 6) engaging in physical distancing.

Dependent variable:	(a) Preventative Measures Taken	(b) Preventative Measures Taken	(c) Preventative Measures Taken	(d) Preventative Measures Taken	(5) Preventative Measures Taken
Female	1.3546***	1.1043	1.3141***	1.1419	.992
	(.1397)	(.1249)	(.1392)	(.1451)	(.1433)
Afraid of COVID-19	-	1.2549***	-	1.245***	1.2357***
		(.0262)		(.0262)	(.0269)
Wave 2	2.0753***	2.4407***	2.0755***	2.4736***	2.5451***
	(.1826)	(.2338)	(.1789)	(.2531)	(.2716)
Wave 3	3.193***	4.1211***	2.9551***	3.761***	3.8504***
	(.4561)	(.5525)	(.4651)	(.5781)	(.6041)
Altruism	-	-	-	-	1.1731***
					(.0278)
Local Death Rate	-	-	1.0089***	1.0062**	1.0063**
			(.0031)	(.003)	(.0032)
Cognitive Ability	-	-	.9779	.9975	.9946
			(.0239)	(.0243)	(.024)
Liberal	-	-	1.1104***	1.0572***	1.0475***
			(.0228)	(.0197)	(.0188)
Additional Controls	No	No	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	1484	1484	1484	1484	1484

Odds ratios reported. Standard errors (clustered at the state level) in parentheses. Additional controls included age, age-squared, and indicators for race (Caucasian) and origin (Hispanic), occupation (8 categories), self-reported same or high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. ****p<.010, **p<.05, *p<.1 (*Table was created using asdoc, a Stata program written by Shah (2020)).

We run alternative specifications investigating each of the six prevention measures separately, using a series of Logit regressions that control for state and survey-wave fixed effects and individual-level characteristics (see Table 4.S*4* and Table 4.S*5*). We find that women, compared to men, were significantly more likely to report making an effort to avoid touching one's face (OR=1.483, P=0.030), to clean and disinfect surfaces (OR=1.553, P=0.003) and to engage in physical distancing (OR=1.661, P=0.036). These associations become weaker when we control for fear of COVID-19. Though women are still significantly more likely to report cleaning and disinfecting surfaces (OR=1.409, P=0.025) after controlling for fear, gender differences in making an effort to avoid touching one's face or engaging in physical distancing shrunk when including fear as a covariate (OR=1.311, P=0.172; OR=1.431, P=0.216, respectively). Importantly, however, we find that fear of COVID-19 is strongly associated with adherence to each of our six preventative measures (OR>1.189, P<0.001 for all tests). This result holds even after controlling for altruism, which was positively and significantly associated with compliance to all preventative measures except washing hands more frequently (OR>1.079, P<0.010; results available upon request). Again, these findings provide evidence in favor of our second hypothesis and demonstrate the importance of fear of COVID-19 in predicting preventative behavior (Harper et al., 2020).

Next, we explore whether there were gender differences in self-reported probabilistic beliefs about the likelihood of experiencing health and financial hardships due to the COVID-19 pandemic. We find that beliefs about the likelihood of health consequences of COVID-19 differed between men and women. Contrary to the empirical observation that men are more likely to experience severe illness or die as a result of COVID-19 (Bhopal & Bhopal, 2020; Gebhard et al., 2020; Jin et al., 2020; Peckham et al., 2020), men reported systematically lower expectations of negative health-related consequences of the pandemic. Women, on average, reported a 5.2% higher chance that they or someone close would develop COVID-19 compared to men and 3.4% higher chance of oneself or someone close dying from COVID-19 (see Figure 4.*2*). The distribution of beliefs about the likelihood of experiencing health hardships indeed differed significantly for both contracting COVID-19 and dying from COVID-19 (Wilcoxon rank-sum test: P<0.001 and P<0.001, respectively). Men were more likely to indicate a low likelihood of contracting COVID-19, with 35.0% of men indicating a 10% or less chance, compared to 27.7% of women. This difference holds when we look at beliefs about the likelihood of dying from COVID-19, with 73.5% of women indicating a 10% or less chance of that scenario relative to 80.6% for men. Taken together, this means that we find that women report higher fear of the COVID-19 pandemic and stronger negative beliefs about health consequences. The finding that women believe there are significantly higher chances of developing or dying from COVID-19 is robust to the inclusion of state and survey-wave fixed effects and individual-level controls ($\beta = 3.341$, P=0.009; $\beta = 2.425$, P=0.022, respectively; see Supplementary Table 4.S*6*).

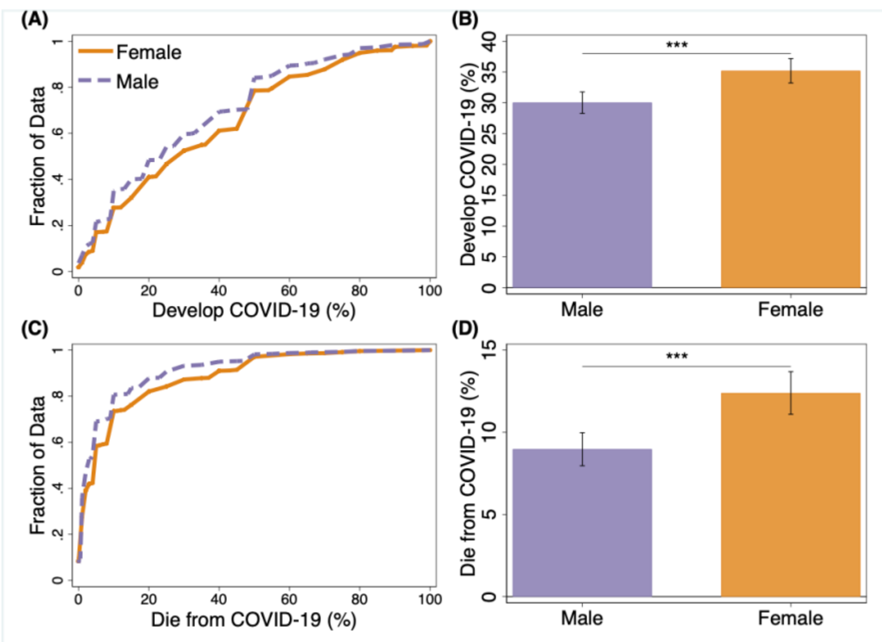

Figure 4.2 Beliefs about the pandemic's health consequences by gender (A) Empirical cumulative distribution function (eCDF) for self-reported beliefs about the likelihood of oneself or someone close developing COVID-19 (develop COVID-19). (B) Average self-reported beliefs of developing COVID-19. (C) eCDF for the self-reported beliefs about the likelihood of oneself or someone close dying from COVID-19 (Die from COVID-19). (D) Average self-reported beliefs of dying from COVID-19. Data is split by gender (Error bars represent 95% confidence Interval). Wilcoxon rank-sum tests: *** p<.001.

Despite the absence of central tendency gender differences in the expectation of experiencing financial hardships such as job loss or decline in income ($\mu_{difference} = 0.793$ and $\mu_{difference} = -1.912$; Wilcoxon rank-sum test: P=0.354 and P=0.137, respectively; see Supplementary Figure 4.S*1*, Table 4.S*1*, and Table 4.S*6*), tests that probe more broadly to distributional characteristics (Epps & Singleton, 1986; Goerg & Kaiser, 2009) reveal some variations in the spread of expectations in the probabilistic beliefs about the likelihood of job loss and income loss across genders (see Supplementary Table 4.S*1*). These differences can be attributed to lower expectations of experiencing financial hardship among women than among men. For example, 48.0% of women indicated a 10% or less chance of job loss compared to only 42.8% of the men. Furthermore, 32.3% of women indicated a 10% or less chance of experiencing income loss compared to only 27.1% of men. Thus, we find significant gender differences in expectations regarding health, but not financial consequences of the COVID-19 pandemic, partially confirming hypothesis 3A. Moreover, both women and men predicted a lower chance of job loss due to the COVID-19 pandemic than of income loss ($\mu_{difference_{women}} = 13.465$; $\mu_{difference_{men}} = 16.171$, Wilcoxon signed-rank test: P <0.001). Overall, survey responders anticipated a 26.6% chance of job loss and a 41.5% chance of a decline in household income.

We also elicited the extent to which survey responders experience negative emotions such as sadness or anger when decisions made by other people, the government, the media or autonomous devices might make matters worse during a crisis. Across all these measures, we find that women anticipated experiencing significantly more intense negative emotions than men ($\mu_{difference_{people}} = 0.517$, $\mu_{difference_{government}} = 0.594$, $\mu_{difference_{media}} = 0.528$ and $\mu_{difference_{autonomous}} = 0.488$, Wilcoxon rank-sum test: P<0.001 for all four measures; see *Figure 4.3*). We find that women not only reported higher fear of the COVID-19 pandemic but also a higher tendency to experience negative emotions during crises in general, in particular as a result of unfavorable actions taken by people, institutions and devices. This confirms hypothesis 3B. After including state and survey-wave fixed effects and individual-level controls in multiple regression analysis, the intensity of negative emotions that women report experiencing during crises was significantly greater than that of men (People: β= 0.356, P=0.007; Government: β= 0.463, P=0.002; Media: β= 0.385, P=0.016; Autonomous: β= 0.315 P=0.016; see Supplementary *Table 4.S7*).

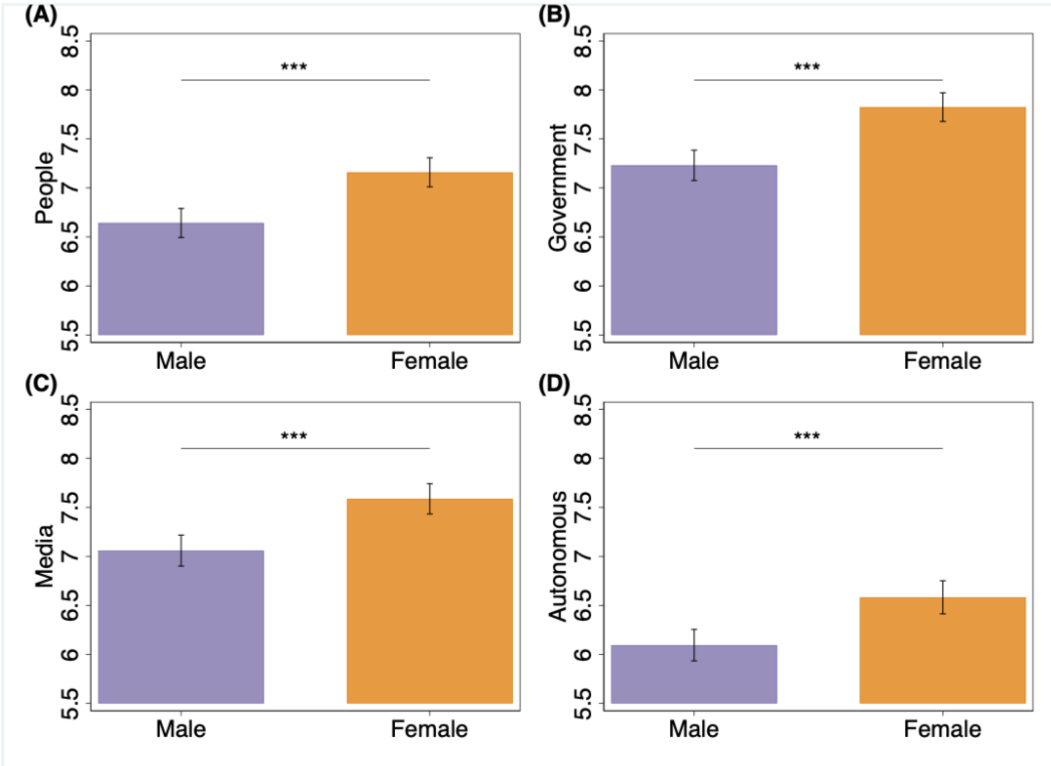

Figure 4.3 Expected negative emotional responses during crises by gender. Expected negative emotional experience (e.g. sadness or anger) in a hypothetical scenario where (A) other people, (B) the government, (C) the media or (D) an autonomous system take actions that make matters worse in a crisis (11-point Likert question with response alternatives ranging from "Not at all" at 0 to "A great deal" at 11). Data is split by gender. (Error bars represent 95% confidence Interval). Wilcoxon rank-sum test: *** $p<.001$.

4.5. Discussion

We investigated gender differences in the intensity of experiencing negative emotions, namely fear, in response to the COVID-19 outbreak. In our study, women report higher fear of the COVID-19 pandemic compared to men. Gender differences in preventative health behaviors disappeared once we controlled for emotional experiences, suggesting that fear of the COVID-19 pandemic, and not gender per se, drives behavioral differences. Women report more negative perceptions about the pandemic's health, but not economic, risks. Thus, our findings on health risks are consistent with the affect heuristic: the notion that emotional experience shapes the perception of risk (Finucane et al., 2000; Loewenstein et al., 2001; Skagerlund et al., 2020; Slovic et al., 2007; Slovic & Peters, 2006). Maladaptation in face of threats has been linked to overconfidence and positive illusion (Johnson & Levin, 2009). Our results may thus be related to domain specific overconfidence/underconfidence (Johnson & Fowler, 2011; Klayman et al., 1999), with men being more overconfident and women being more underconfident (Barber & Odean, 2001; Bengtsson et al., 2005; Johnson et al., 2006). Gender stereotypes are manifested in women's emphasis on care compared to men's emphasis on agency (Ellemers, 2018) while social concerns have been argued to modulate overconfidence (Burks et al., 2013). Our results may suggest that gender stereotyping may play a role in the existence of a gap between negative perception of health but not financial risks. In addition, structural labor market concerns, such as the gender wage gap, as well as workplace- and occupation-specific factors (Blau &

Kahn, 2017; Wiswall & Zafar, 2018), may also contribute to the observed differences in perceptions of health and financial risks. While we account for occupation in our analyses, the broad classifications utilized (see methods section) are somewhat limited. For example, our observation that women have less extreme views of the financial consequences of the pandemic could result from their self-selection into jobs with greater work flexibility and job stability (Wiswall & Zafar, 2018). Nonetheless, we find that women report stronger negative emotions resulting from crises in general, as a result of unfavorable actions taken by, for example, other people and the government. Our results contribute to the literature on gender differences in economic preferences, which finds that women are typically more risk averse (Charness & Gneezy, 2012; Dohmen et al., 2011; Eckel & Grossman, 2002) and less likely to prefer competition (Buser et al., 2014; Niederle & Vesterlund, 2007). As in our study, these gender differences may reflect state dependent variation, rather than stable traits (Frey et al., 2017; Mata et al., 2018; Pedroni et al., 2017).

One limitation of our study is the reliance on questionnaire responses. This seemed a reasonable compromise between our desire to obtain data at the beginning of the COVID-19 event in the United States and the need to keep both participants and experimenters safe. In fact, recent empirical work on preference elicitation suggests that self-reported preferences are generalizable and may be more stable across time compared to incentivized behavioral measures (Frey et al., 2017; Mata et al., 2018; Pedroni et al., 2017). Our questionnaire was designed in the early days of the pandemic and prior to the development of the multiple-scale measures of fear of COVID-19 (Ahorsu et al., 2020; Feng et al., 2020; Mejia et al., 2020). Nonetheless, our survey question that captures fear of the pandemic matches one of the items with a strong factor loading in the commonly used fear of COVID-19 scale (Ahorsu et al., 2020). The finding of gender differences in fear of the pandemic is not unique to the early days of the pandemic (Alsharawy et al., 2021). In addition, though our study relies on correlations between survey measures, and therefore our results cannot be interpreted as causal, we demonstrate that our findings are robust.

Our study suggests avenues for future study for researchers interested in effective crisis management. To mitigate the severity of a crisis, for example, policy makers sometimes employ fear messaging, or scare tactics, to promote adherence to prevention measures. Our results suggest that this approach may have differential impact depending on gender, since women report higher fear. Furthermore, scare tactics may also have unintended consequences, such as increasing message avoidance (Kok et al., 2014) or exacerbating existing stressors (Stolow et al., 2020). Messaging strategies that emphasize the pro-social implications of preventative measures, that focus on evidence-based health communications, or that “nudge” behavior in a contextually appropriate manner (Campos-Mercade et al., 2021; Heffner et al., 2021; Kreuter & Wray, 2003; Milkman, Patel, Gandhi, Graci, Gromet, Ho, Kay, Lee, Akinola, et al., 2021; Milkman, Patel, Gandhi, Graci, Gromet, Ho, Kay, Lee, Bogard, et al., 2021) without increasing psychological distress may be preferred during health crises.

4.6. Supplementary material

4.6.1. Occupation classification

We categorized each of the free form self-reported occupations into one of 22 broad occupation categories, based upon the 2010 census occupational classification. To have adequate number of observations within each category, we then assign occupations into broader categories, again adapted from the 2010 census occupational classification, while creating a separate category for health care workers (technical practitioners and support staff). This method assigned participants to one of eight occupation categories: 1) Healthcare, 2) Management, business, and financial operations, 3) Natural resources, construction, and maintenance 4) Production, transportation, and material moving, 5) Professional and related -not healthcare, 6) Sales and office, 7) Service -not healthcare, and 8) Other. Our last category includes responders whose occupations could not be matched to one of the other categories, such as students, homemakers, unemployed/retired, or participants indicating that their occupation is being an MTurk worker.

4.6.2. Statistical tests for gender differences in survey responses

In this section, to further investigate the robustness of our findings, we compare the results of the Wilcoxon rank-sum tests (non-parametric: central tendency) from the main manuscript to two-sided t-tests (parametric: central tendency) and Epps-Singleton tests (non-parametric: distributional characteristics).

4.6.3. Supplementary figures

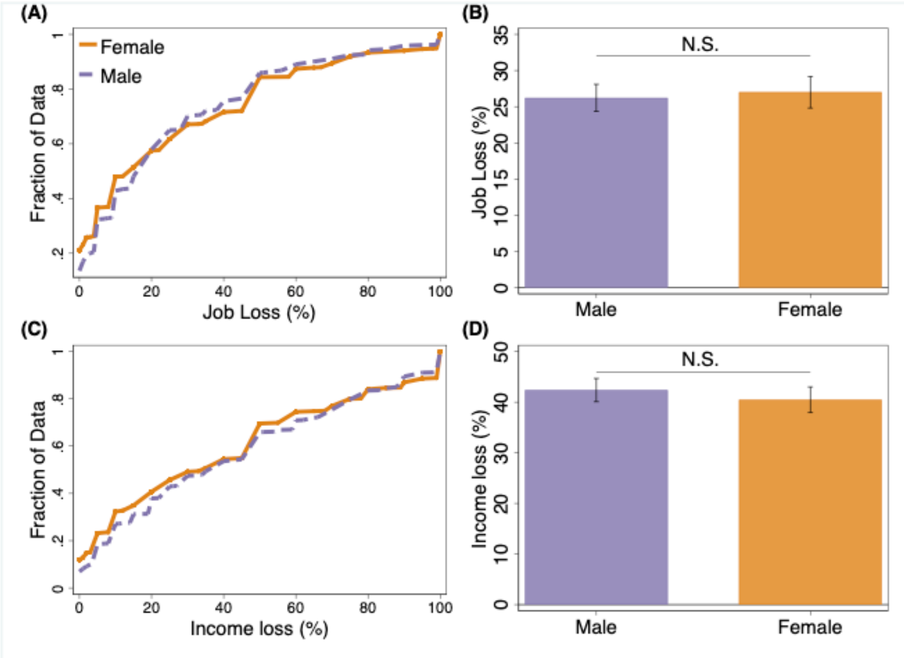

Figure 4.S1 Beliefs about the pandemic's health consequences by gender. (A) Empirical cumulative distribution function (eCDF) for self-reported beliefs about the likelihood of oneself or another member of one's household losing a job or a business in the next 12 months (job loss). (B) Average self-reported beliefs of job loss. (C) eCDF for the self-reported beliefs about the likelihood of one's total household income to decline in the next 12 months (income loss). (D) Average self-reported beliefs of income loss. Data is split by gender (Error bars represent confidence Interval). Wilcoxon rank-sum test: N.S. Non-significant.

4.6.4. Supplementary tables

Table 4.S1 Statistical tests for gender differences in survey responses

Test for gender differences in		Mean difference (Women− Men):	Wilcoxon Rank-sum test	Two-sided t-test P-value	Epps-Singleton distribution test P-value
Fear of the COVID-19 pandemic		0.939	P<0.001	P<0.001	P<0.001
Chance that they or someone close would…	develop COVID-19	5.167	P<0.001	P<0.001	P=0.003
	die from COVID-19	3.422	P<0.001	P<0.001	P<0.001
Chance that…	oneself or another member of one's household losing a job	0.793	0.354	0.588	P<0.001
	one's total household income will decline	-1.912	0.137	0.274	P<0.001
Anticipation of experiencing significantly more intense negative emotion when matters are made worse during a crisis by…	other people	0.517	P<0.001	P<0.001	P<0.001
	the government	0.594	P<0.001	P<0.001	P<0.001
	the media	0.528	P<0.001	P<0.001	P<0.001
	autonomous devices	0.488	P<0.001	P<0.001	P<0.001

Table 4.S2 Descriptive Statistics for control variables

	All	Women	Men	Women vs Men
Variables	Mean (sd)			p-values: ttests for difference
Age	40.8	42.9	38.9	<0.001
	(11.4)	(11.9)	(10.6)	
Number of years in college	3.3	3.2	3.3	0.869
	(1.9)	(1.967)	(1.9)	
Political views: liberal	6.1	6.3	5.9	0.019
	(3.025)	(3.1)	(2.9)	
Self-reported cognitive (math) ability	5.8	5.0	6.4	<0.001
	(2.9)	(3.0)	(2.6)	
US Citizen, %	99.3	99.1	99.5	0.391
Race: Caucasian, %	84.4	86.8	82.4	0.019
Hispanic, %	5.8	3.5	7.8	<0.001
Attend Religious services, %	17.8	20.1	15.7	0.027
Relative Household Income:				
Significantly lower, %	10.4	10.6	10.2	0.812

Somewhat lower, %	28.2	29.9	26.7	0.178
About the same, %	43.7	42.9	44.3	0.579
Somewhat higher, %	16.9	15.7	18	0.227
Significantly higher, %	0.9	1.0	0.8	0.594
Smoker, %	17.6	18.3	17.0	0.526
Do not have a job, %	12.5	13.8	11.3	0.157
Work full time, %	75.3	67.7	82	<0.001
Work part time, %	12.2	18.6	6.7	<0.001
Occupation:				
Healthcare, %	4.9	7.8	2.4	<0.001
Management, business, and financial operations occupations, %	22.3	18.8	25.3	0.003
Natural resources, construction, and maintenance occupations, %	4.4	2.2	6.3	<0.001
Production, transportation, and material moving occupations, %	3.8	2.9	4.5	0.099
Professional and related occupations -not healthcare, %	27.6	25.5	29.3	0.099
Sales and office occupations, %	21.8	25.5	18.5	0.001
Service occupations -not healthcare, %	4.6	3.9	5.2	0.251
Other, %	10.7	13.3	8.4	0.002
Education:				
High school, %	12.5	12.6	12.3	0.877
Some college, %	29.8	33.6	26.4	<0.001
Bachelor's/equivalent, %	45.2	40.7	49.1	<0.001
Masters or above, %	12.5	13.0	12.1	0.581
Mother Education:				
Some high school/less, %	6.6	6.1	7.1	0.455
High School, %	36.9	40.0	34.3	0.022
Some college, %	22.2	23.6	21.0	0.232
Bachelor's/equivalent, %	24.1	20.7	27.1	0.004
Masters or above, %	10.0	9.4	10.6	0.459
Do not know, %	0.1	0.1	0.0	0.284
Father Education:				
Some high school/less, %	9.4	10.3	8.6	0.255
High School, %	33.3	35.1	31.7	0.174
Some college, %	19.4	20.0	18.9	0.591
Bachelor's/equivalent, %	23.7	21.0	26.1	0.022
Masters or above, %	13.0	12.6	13.4	0.672
Do not know, %	1.2	1.0	1.4	0.515
ZIP code:				
NY, %	6.9	6.8	6.9	0.930
CA, %	9.1	7.7	10.3	0.077
Sample used in Analysis	1484	690	794	0.007
Wave 1: April 2nd	488	238	250	0.588

Wave 2: April 16th	499	240	259	0.396
Wave 3: April 30th	497	212	285	0.001
Exclusions				
Unmatched ZIP code	4	0	4	
>=2 wrong check questions	3	1	2	
Total number of responses	1491	691	800	

Table 4.S3 Fixed effect linear regression: fear of COVID-19 (11-point Likert question).

Dependent variable:	(a) Afraid of COVID-19	(b) Afraid of COVID-19
Female	.9625***	.6542**
	(.2627)	(.2564)
Wave 2	-.5552***	-.6466***
	(.1313)	(.1433)
Wave 3	-.7139***	-.7745***
	(.1996)	(.2131)
Local Death Rate	-	.0079***
		(.0023)
Cognitive Ability	-	-.0996**
		(.0378)
Liberal	-	.2662***
		(.0361)
Additional controls	No	Yes
State fixed effects	Yes	Yes
Observations	1484	1484
R-squared	.0366	.1316

Standard errors (clustered at the state level) in parentheses. Additional controls included age, age-squared, and indicators for race (Caucasian) and origin (Hispanic), occupation (8 categories), self-reported same or high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. *** *p<.01, ** p<.05, * p<.1*

Table 4.S4 Separate analyses for preventative measures taken in response to COVID-19 (A): 1) washing hands more frequently, 2) using hand sanitizers or disinfection wipes more frequently, 3) make more effort to avoid touching face (Logit regression)

Dependent variable:	(a) Washed hands	(b) Washed hands	(c) Used hand sanitizers	(d) Used hand sanitizers	(e) Avoid touching face	(f) Avoid touching face
Female	1.3151	1.1294	1.2438	1.1079	1.4831**	1.3105
	(.322)	(.2885)	(.2065)	(.1992)	(.2686)	(.2597)
Afraid of COVID-19	-	1.4115***	-	1.2129***	-	1.2205***
		(.0784)		(.0404)		(.0336)
Wave 2	.9958	1.1830	1.1614	1.3226**	1.2672*	1.4797***
	(.2341)	(.3229)	(.1355)	(.1814)	(.1537)	(.204)
Wave 3	.8408	.9735	1.3923	1.6311**	1.1666	1.3815
	(.2888)	(.3528)	(.3071)	(.3621)	(.2332)	(.2748)
Local Death Rate	1.0104***	1.0069*	1.0028	1.0007	1.0093**	1.0067*
	(.0033)	(.0042)	(.0031)	(.0031)	(.0038)	(.004)
Cognitive Ability	.9027**	.9387	.9429	.9615	1.0427	1.0697**
	(.04)	(.0468)	(.036)	(.0362)	(.0319)	(.0348)
Liberal	1.0700	.9562	1.0709***	1.0156	1.1425***	1.0836***
	(.0552)	(.0592)	(.0279)	(.0282)	(.0319)	(.0299)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1242	1242	1461	1461	1442	1442

Odds ratios reported. Standard errors (clustered at the state level) in parentheses. Additional controls included age, age-squared, and indicators for race (Caucasian) and origin (Hispanic), occupation (8 categories), self-reported same or high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. ****p<.01, **p<.05, *p<.1*

Table 4.S5 Separate analyses for preventative measures taken in response to COVID-19 (B): 1) Cleaning and disinfecting surfaces in home more than usual, 2) Wearing a face mask, 3) Engaging in physical distancing (PD) (Logit regression)

Dependent variable:	(a) Cleaned more	(b) Cleaned more	(c) Worn a facemask	(d) Worn a facemask	(e) Engaged in PD	(f) Engaged in PD
Female	1.5525***	1.4091**	1.0538	.9413	1.6608**	1.4306
	(.2284)	(.215)	(.1281)	(.1285)	(.4028)	(.4138)
Afraid of COVID-19	-	1.2135***	-	1.1888***	-	1.3293***
		(.0227)		(.0245)		(.0894)
Wave 2	.8953	1.0027	7.3309***	9.0008***	.9080	1.1124
	(.1283)	(.1608)	(1.1878)	(1.5596)	(.2626)	(.3291)
Wave 3	1.075	1.2283	12.7076***	16.1669***	.9501	1.1974
	(.1749)	(.2087)	(3.0383)	(3.9878)	(.3139)	(.4177)
Local Death Rate	1.0012	.9992	1.0102*	1.0082	1.0026	.9984
	(.0029)	(.003)	(.0058)	(.0055)	(.0067)	(.0072)
Cognitive Ability	.9807	.9995	.9820	.9982	1.0264	1.0618
	(.0287)	(.0297)	(.0248)	(.0268)	(.0515)	(.0599)
Liberal	1.0733***	1.0167	1.1026***	1.0566**	1.1811***	1.1051**
	(.0235)	(.0225)	(.0265)	(.0256)	(.0386)	(.0441)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1478	1478	1476	1476	1170	1170

Odds ratios reported. Standard errors (clustered at the state level) in parentheses. Additional controls included age, age-squared, and indicators for race (Caucasian) and origin (Hispanic), occupation (8 categories), self-reported same or high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. ****p<.01, **p<.05, *p<.1*

Table 4.S6 Fixed effect linear regression: beliefs of financial and health hardships

Dependent variable:	(a) % Job Loss	(b) % Income Loss	(c) % Develop COVID-19	(d) % Die COVID-19
Female	.6182	-2.6648	3.3407***	2.4245**
	(1.2807)	(1.8464)	(1.2238)	(1.0241)
Wave 2	-5.1791***	-7.3799***	-6.1417***	-2.6616***
	(1.4053)	(1.927)	(1.3933)	(.811)
Wave 3	-4.9088***	-6.4673***	-6.1561***	-2.4501***
	(1.8276)	(2.1922)	(1.7764)	(.9032)
Local Death Rate	.0231	.0391	.0329*	.0244
	(.0354)	(.0573)	(.0189)	(.0174)
Cognitive Ability	-.4742	-.5207	-.687***	-.8268***
	(.3271)	(.4628)	(.2482)	(.1394)
Liberal	.3471	.7254	1.4148***	.2491
	(.3695)	(.4429)	(.2697)	(.1903)
Additional controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	1484	1484	1484	1484
R-squared	.0602	.0833	.0984	.0556

Standard errors (clustered at the state level) in parentheses. Additional controls included age, age-squared, and indicators for race (Caucasian) and origin (Hispanic), occupation (8 categories), self-reported same or high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. ****p<.01, **p<.05, *p<.1*

Table 4.S7 Fixed effect linear regression: expected negative emotional responses during crises. Expected negative emotional experience (e.g. sadness or anger) in a hypothetical scenario where (a) other people, (b) the government, (c) the media or (d) an autonomous system take actions that make matters worse in a crisis.

	(a) People	(b) Government	(c) Media	(d) Autonomous
Female	.3555***	.4630***	.3846**	.3148**
	(.1263)	(.1426)	(.1546)	(.1256)
Wave 2	-.3385***	-.2408***	-.2832**	-.2000
	(.1195)	(.0897)	(.1101)	(.1524)
Wave 3	-.1623	-.2449	-.2120	-.1320
	(.1627)	(.1732)	(.1789)	(.1931)
Local Death Rate	.0021	.0012	.0018	.0017
	(.002)	(.0024)	(.0021)	(.0019)
Cognitive Ability	-.0109	.0132	-.0078	-.0275
	(.0211)	(.0192)	(.021)	(.0234)
Liberal	.0624***	.1056***	-.0456**	.0291
	(.0208)	(.0252)	(.0203)	(.0181)
Additional controls	Yes	Yes	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
Observations	1484	1484	1484	1484
R-squared	.0674	.0999	.0719	.0732

Standard errors (clustered at the state level) in parentheses. Additional controls included age, age-squared, and indicators for race (Caucasian) and origin (Hispanic), occupation (8 categories), self-reported same or high household income relative to others in one's community, working full time, education level, parents receiving a bachelor's degree, smoking behavior and frequency of attending religious services. ****p<.01, **p<.05, *p<.1*

4.6.5. Administered survey

The following questions will be completed on the computer, and will not be handed out physically.

Section 1:

Section 1.1 (block1)

1. Gender:
    a. Male
    b. Female
2. Age (numeric field)
3. What is your current zip code?
4. Are you
    a. American citizen
    b. Non-American citizen: please specify country
5. Are you Hispanic or Latino?
    a. Yes
    b. No
6. How would you describe yourself?
    a. American Indian or Alaska Native
    b. Asian
    c. Black or African American
    d. Native Hawaiian or Other Pacific Islander
    e. White
    f. Other
7. Do you regularly attend religious services?
    a. Yes
    b. No
8. What is your household income relative to others in your county/city?
    a. Significantly higher
    b. Somewhat higher
    c. About the same
    d. Somewhat lower
    e. Significantly lower
9. What is your height? (numeric field)
10. Are you a smoker?
    a. Yes
    b. No

Section 1.2 (block 2)

11. Do you:
    a. Work at a full-time job
    b. Work at a part-time job?
    c. Do not have a job

12. If you are in (went to) college, how many years of formal education had you completed?
    a. Not applicable
    b. 1 year of college (or equivalent)

c. 2 years of college (or equivalent)
d. 3 years of college (or equivalent)
e. 4 years of college (or equivalent)
f. 5 years of college (or equivalent)
g. 6 years of college (or equivalent)
h. More than 6

13. If you are (were) in college, what is (was) your Major/College? (if more than one pick what you consider to be your primary Major or College).
    a. Economics
    b. Architecture and Urban Studies
    c. Agriculture and Life Science
    d. Business other than Economics
    e. Engineering
    f. Liberal Arts and Human Sciences
    g. Natural Resources and Environment
    h. Science other than Economics
    i. Other major/college
    j. Not applicable
14. How many Economics classes have you taken at the university level?
    a. None
    b. One
    c. Two
    d. Three
    e. Four or more
15. Please indicate the highest level of education YOU completed:
    a. Some high school
    b. High school diploma or equivalent
    c. Some college or associate degree
    d. B.A.
    e. M.A./M.S./M.B.A.
    f. M.D./J.D./PhD
    g. Other
16. What is YOUR current occupation? If you are retired, please list your most recent occupation. (text field)
17. Please indicate the highest level of education your MOTHER completed:
    a. Some high school
    b. High school diploma or equivalent
    c. Some college or associate degree
    d. B.A.
    e. M.A./M.S./M.B.A.
    f. M.D./J.D./PhD
    g. Other
18. What is your MOTHER's current occupation? If she is retired or deceased, please list her most recent occupation. (text field)
19. Please indicate the highest level of education your FATHER completed:
    a. Some high school
    b. High school diploma or equivalent
    c. Some college or associate degree

   d. B.A.
   e. M.A./M.S./M.B.A.
   f. M.D./J.D./PhD
   g. Other

20. What is your FATHER's current occupation? If he is retired or deceased, please list his most recent occupation. (text field)

Section 2:
Section 2.1 (block3)

21. Please describe your political orientation in general, using a scale from 0 to 10, where 0 means you are "complete conservative" and 10 means you are "complete liberal."
22. How willing or unwilling you are to take risks, using a scale from 0 to 10, where 0 means you are "completely unwilling" and 10 means you are "very willing."
23. How willing or unwilling are you to give up something that is beneficial for you today in order to benefit more from that in the future, using a scale from 0 to 10, where 0 means you are "completely unwilling" and 10 means you are "very willing."
24. How willing or unwilling are you to punish someone who treats YOU unfairly, even if there may be costs for you, using a scale from 0 to 10, where 0 means you are "completely unwilling" and 10 means you are "very willing."
25. How willing or unwilling are you to punish someone who treats OTHERS unfairly, even if there may be costs for you, using a scale from 0 to 10, where 0 means you are "completely unwilling" and 10 means you are "very willing."
26. How willing or unwilling are you to give to good causes without expecting anything in return, using a scale from 0 to 10, where 0 means you are "completely unwilling" and 10 means you are "very willing."

How well do the following statements describe you as a person, using a scale from 0 to 10, where 0 means "does not describe me at all," and 10 means "describes me perfectly."

27. When someone does me a favor, I am willing to return it.
28. If I am treated very unjustly, I will take revenge at the first occasion, even if there is a cost to do so.
29. I assume that people have only the best intentions.
30. I am good at math.
31. I tend to postpone tasks even if I know it would be better to do them right away.

Section 2.2 (block 4)

32. For the gambles on each line of the following table, think about the chance of getting each prize being determined by the flip of a coin, for example, for Gamble 3 you would get 32 if the coin comes up "heads" and 8 if it comes up "tails."

    Please choose your favorite gamble below.

Gamble Choice	Probability	Payoff	Probability	Payoff
1	50%	16	50%	16
2	50%	24	50%	12
3	50%	32	50%	8
4	50%	40	50%	4
5	50%	48	50%	0

33. Imagine the following situation: Today you unexpectedly received 1,600 U.S. dollars. How much of this amount would you donate to a good cause? (Values between 0 and 1,600 are allowed)
34. Please think about what you would do in the following situation. You are in an area you are not familiar with, and you realize that you lost your way. You ask a stranger for directions. The stranger offers to take you to your destination.
    Helping you costs the stranger about 40 U.S. dollars in total. However, the stranger says he or she does not want any money from you. You have six presents with you. The cheapest present costs 10 U.S. dollars, the most expensive one costs 60 U.S. dollars. Do you give one of the presents to the stranger as a "thank you" gift?
    Which present do you give to the stranger?
    a. No, would not give a present
    b. The present worth 10 U.S. dollars
    c. The present worth 20 U.S. dollars
    d. The present worth 30 U.S. dollars
    e. The present worth 40 U.S. dollars
    f. The present worth 50 U.S. dollars
    g. The present worth 60 U.S. dollars

Section 3:

Section 3.1 (block 5)

How much do you agree with each of the following statements, using a scale from 0 to 10, where 0 means "do not agree at all," and 10 means "totally agree"?

35. People can generally be trusted
36. Nowadays one can't rely on anyone
37. If one is dealing with strangers, it is better to be careful before trusting them
38. Would you say that people usually…
    a. Try to be helpful
    b. only pursue their own interests
39. Do you believe that most people…
    a. Would exploit you if they had the opportunity
    b. Would try to be fair to you

Section 3.2 (block 6)

How much do you agree with each of the following statements?
Use a scale from 0 to 10, where 0 means "do not agree at all," and 10 means "totally agree"

40. Government can generally be trusted
41. Media can generally be trusted
42. Autonomous systems, for example, artificial intelligence devices can generally be trusted
43. Suppose there is a crisis and other people make a decision or provide information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? Use a scale from 0 to 10, where 0 means "Not at all," and 10 means "A great deal."
44. Suppose there is a crisis and the Government makes a decision or provides information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? Use a scale from 0 to 10, where 0 means "Not at all," and 10 means "A great deal."

45. Suppose there is a crisis and the Media makes a decision or provides information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? Use a scale from 0 to 10, where 0 means "Not at all," and 10 means "A great deal."
46. Suppose there is a crisis and an autonomous system, for example, an artificial intelligence device, makes a decision or provides information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? Use a scale from 0 to 10, where 0 means "Not at all," and 10 means "A great deal."

Section 4:

Section 4.1 (block 7)
For the following questions, physical distancing refers to limiting physical contact with people outside household as much as possible.
How much do you agree with each of the following statements, using a scale from 0 to 10, where 0 means "do not agree at all," and 10 means "totally agree"

47. Right now, people in my area engage in physical distancing
48. Right now, people in my area expect me to engage in physical distancing
49. Right now, people in my area expect others to engage in physical distancing
50. Right now, people in my area should engage in physical distancing
51. Physical distancing will slow the spread of a highly infectious disease.
52. I am willing to make personal sacrifices to prevent the spread of coronavirus disease (COVID-19)
53. The COVID-19 outbreak is causing financial stress to me and my family.
54. I have taken the following steps in response to the coronavirus disease (COVID-19). Check all that apply
    - Washed my hands more frequently than usual
    - Used hand sanitizer or disinfecting wipes more frequently than usual
    - Made more of an effort to avoid touching my eyes, nose, mouth
    - Cleaned and disinfected surfaces in my home more than usual
    - Worn a face mask
    - Started working from home
    - Engaged in physical distancing

Section 4.2 (block 8)

55. In the past week, I have purchased more household items and food than usual.
    a. Yes
    b. No

Now, we will ask you some questions about future, uncertain outcomes. In each case, try to think about the whole range of possible outcomes and think about how likely they are to occur during the next 12 months. In some of the questions, I will ask you about the PERCENT CHANCE of something happening. The percent chance must be a number between zero and one hundred. Numbers like 2 or 5 percent may be "almost no chance," 20 percent or so may mean "not much chance," a 45 or 55 percent chance may be a "pretty even chance," 80 percent or so may mean a "very good chance," and a 95 or 98 percent chance may be "almost certain." The percent chance can also be thought of as the NUMBER OF CHANCES OUT OF 100.

56. What do you think is the percent chance that you or another member of your household will lose a job or business due to COVID-19? (numeric field from 0 to 100)
57. What do you think is the percent chance that your total household income will decrease over the next 12 months? (numeric field from 0 to 100)
58. What do think is the percent chance that you, or someone you are close to, will develop COVID-19? (numeric field from 0 to 100)
59. What do think is the percent chance that you, or someone you are close to, will die from COVID-19? (numeric field from 0 to 100)
60. Are you afraid of the COVID-19 pandemic? Please indicate your answer using a scale from 0 to 10, where 0 means "not at all afraid," and 10 means "very afraid."

The following check questions added in between some of the survey questions:

1. There are 12 days in a week (True/False)
2. There are two L's in the word "Log" (True/False)
3. Dogs have wings (True/False)
4. Would you rather have $50 or $75?
5. Fish live in water (True/False)

4.6.6. Summary table for all survey responses

Table 4.S8 Summary statistics for all survey responses

Measure	Question no.	Mean	Median	Standard Deviation	Minimum	Maximum
Section 1						
Female, %	1	46.50				
Age	2	40.76	38.00	11.37	20	77
Zip code	3					
New York, %		6.87				
California, %		9.10				
American citizen, %	4	99.33				
Hispanic, %	5	5.80				
Race	6					
American Indian or Alaska Native, %		0.74				
Asian, %		7.28				
Black or African American, %		5.32				
White, %		84.43				

Other, %		2.22				
religious, %	7	17.79				
Income	8					
Significantly lower, %		10.38				
Somewhat lower, %		28.17				
About the same, %		43.67				
Somewhat higher, %		16.91				
Significantly higher, %		0.88				
height (inches)	9	67.88	68.00	3.91	48	79
smoker, %	10	17.59				
Work status	11					
Do not have a job, %		12.47				
Work at a full-time job, %		75.34				
Work at a part-time job, %		12.20				
Years in college	12	3.26	4.00	1.91	0	7
Primary major studied	13					
Agriculture and Life Science, %		0.81				
Architecture and Urban Studies, %		0.54				
Business other than Economics, %		19.00				
Economics , %		2.90				
Engineering, %		7.88				
Liberal Arts and Human Sciences, %		26.62				
Natural Resources and Environment, %		1.42				
Science other than Economics, %		14.22				
Not applicable, %		14.96				
Other, %		11.66				
Number of economics classes taken	14					
None, %		42.25				

One course, %		26.35				
Two courses, %		20.49				
Three courses, %		3.84				
Four course or more, %		7.08				
Education	15					
High school , %		12.47				
Some college or associate degree, %		29.78				
Bachelor degree, %		45.22				
Masters/above, %		12.53				
Occupation (coded from free response)	16					
Healthcare, %		4.92				
Management, business, and financial operations occupations, %		22.30				
Natural resources, construction, and maintenance occupations, %		4.38				
Production, transportation, and material moving occupations, %		3.77				
Professional and related occupations -not healthcare, %		27.56				
Sales and office occupations, %		21.77				
Service occupations -not healthcare, %		4.58				
Other, %		10.71				
Mother education	17					
Some high school or less , %		6.60				
High school , %		36.93				
Some college or associate degree, %		22.24				
Bachelor degree, %		24.12				
Masters/above, %		10.04				
Other, %		0.07				
Mother occupation (free response)	18					

Father education	19					
Some high school or less , %		9.37				
High school , %		33.29				
Some college or associate degree, %		19.41				
Bachelor degree, %		23.72				
Masters/above, %		13.01				
Other, %		1.21				
Father occupation (free response)	20					
Section 2						
Political orientation (10 is complete liberal)	21	6.07	7.00	3.02	0	10
Willingness to take risks (10 is very willing)	22	4.07	4.00	2.45	0	10
Willingness to delay rewards (10 is very willing)	23	7.08	7.00	1.98	0	10
Willingness to punish someone who treats you unfairly (10 is very willing)	24	3.98	4.00	2.71	0	10
Willingness to punish someone who treats others unfairly (10 is very willing)	25	4.62	5.00	2.63	0	10
Willingness to give to good causes (10 is very willing)	26	7.33	8.00	2.40	0	10
Willing to return favor (10 is describes me perfectly)	27	8.75	9.00	1.55	0	10
Will take revenge (10 is describes me perfectly)	28	2.66	2.00	2.68	0	10
Assume that people have only the best intentions (10 is describe me perfectly)	29	5.16	6.00	2.77	0	10
Good at math (10 is describes me perfectly)	30	5.77	6.00	2.85	0	10
Tend to postpone tasks (10 is describes me perfectly)	31	3.80	3.00	2.80	0	10
Unincentivized lottery task	32	2.53	2.00	1.35	1	5
Unincentivized dictator game	33	108.33	50.00	184.34	0	2500
Gift in exchange for help	34	3.27	4.00	1.94	1	6
Section 3						
People can generally be trusted, (10 is totally agree)	35	5.61	6.00	2.61	0	10
One can't rely on anyone, (10 is totally agree)	36	3.94	3.00	2.95	0	10

Its better to be careful before trusting strangers, (10 is totally agree)	37	6.50	7.00	2.59	0	10
People usually try to be helpful (base: only persue their own interests), %	38	64.02				
People would try to be fair (base: exploit you if they had the opportunity), %	39	64.76				
Government can generally be trusted, (10 is totally agree)	40	3.84	4.00	2.57	0	10
Media can generally be trusted, (10 is totally agree)	41	4.03	4.00	2.80	0	10
Autonomous systems can generally be trusted, (10 is totally agree)	42	5.39	5.00	2.42	0	10
Expected negative emotions when other people make matters worse in a crisis (10 is a great deal)	43	6.88	7.00	2.08	0	10
Expected negative emotions when government make matters worse in a crisis (10 is a great deal)	44	7.51	8.00	2.12	0	10
Expected negative emotions when media make matters worse in a crisis (10 is a great deal)	45	7.30	8.00	2.20	0	10
Expected negative emotions when autonomous systems make matters worse in a crisis (10 is a great deal)	46	6.32	6.00	2.30	0	10
Section 4						
People in my area engage in physical distancing (10 is totally agree)	47	8.01	8.00	1.92	0	10
People in my area engage expect me to engage in physical distancing (10 is totally agree)	48	8.34	9.00	1.98	0	10
People in my area engage expect others to engage in physical distancing (10 is totally agree)	49	8.37	9.00	1.83	0	10
People in my area engage should engage in physical distancing (10 is totally agree)	50	9.09	10.00	1.73	0	10
Physical distancing will slow the spread of a highly infectious disease (10 is totally agree)	51	8.77	10.00	1.89	0	10
Willing to make personal sacrifices to prevent the spread of COVID-19 (10 is totally agree)	52	8.75	10.00	2.02	0	10
COVID-19 outbreak is causing financial stress to me and my family (10 is totally agree)	53	5.29	6.00	3.39	0	10
Measures taken in response to COVID-19	54					
Washed my hands more frequently than usual, %		94.20				

Used hand sanitizer or disinfecting wipes more frequently than usual, %		78.23				
Made more of an effort to avoid touching my eyes, nose, mouth, %		82.75				
Cleaned and disinfected surfaces in my home more than usual, %		72.51				
Worn a face mask , %		51.75				
Started working from home, %		54.65				
Engaged in physical distancing, %		93.80				
Purchased more household items and food than usual in the past week, %	55	37.47				
Probabilistic beliefs about the likelihood of job loss	56	26.58	20.00	28.13	0	100
Probabilistic beliefs about the likelihood of income loss	57	41.49	37.50	33.57	0	100
Probabilistic beliefs about the likelihood of oneself or someone close developing COVID-19	58	32.43	25.00	25.78	0	100
Probabilistic beliefs about the likelihood of oneself or someone close dying from COVID-19	59	10.56	5.00	15.95	0	100
Afraid of COVID-19 (10 is very afraid)	60	5.93	7.00	3.02	0	10

Chapter 5

5. Vaccine hesitancy and betrayal aversion

Abdelaziz Alsharawy, Esha Dwibedi, Jason Aimone, and Sheryl Ball

Abstract

While vaccinations are important in protecting public health, many individuals are vaccine hesitant, delaying or refusing available vaccines. Betrayal aversion occurs when people avoid situations involving trust in order to avoid betrayal. In this pre-registered vignette experiment, we find that over a third of participants have betrayal averse preferences, resulting in an 8-26% decline in vaccine acceptance. People are significantly less willing to get vaccinated when the risk of dying involved the vaccine actively contributing to the cause of death. We also find that betrayal aversion is amplified in situations where the betrayal risk can be attributed to scientists or government. However, aligning with the political party of the government developing the vaccine is associated with reduced sensitivity to betrayal. Moreover, we find there is little correlation between betrayal aversion and current measures of vaccine hesitancy. We explore an exogenous message intervention and show that messages can significantly increase vaccine willingness. Successful message content may act through narrow channels like other-regarding preferences without, however, reducing vaccine hesitancy barriers like betrayal aversion. Message-based interventions to increase vaccine up-take should consider accounting for betrayal aversion, particularly when the risk of betrayal is salient.

5.1. Introduction

While vaccinations are important in protecting public health, many individuals are vaccine hesitant, delaying or refusing available vaccines. The prevalence of vaccine hesitancy has been typically attributed to three factors: confidence (trust in safety and effectiveness), convenience (physical and psychological constraints,) and complacency (perceived risks of disease are low). This is often referred to as the 3C model (Larson et al., 2014; MacDonald, 2015). Recently, individual differences in information processing and in social preferences have been proposed as additional factors influencing hesitancy (Betsch et al., 2018). Nonetheless, the determinants of vaccine hesitancy remain complex and context specific (MacDonald, 2015).

Betrayal aversion is a decision-making preference that occurs when people avoid situations involving trust in order to avoid disutility associated with being betrayed (Aimone et al., 2015; Aimone & Houser, 2012; Bohnet et al., 2008; Koehler & Gershoff, 2003). When choosing between safety products like vaccines, betrayal averse individuals may accept lower levels of protection from the primary risk in order to avoid a relatively small secondary risk of being harmed by the safety product itself. Thus, the disutility of betrayal may inhibit trust independent of risk or regret aversion (Bohnet et al., 2008; Lauharatanahirun et al., 2012). People were significantly more likely to choose to purchase airbags and smoke alarms, and marginally more likely to choose vaccines, when the potential risks of the products involved no betrayal (Koehler & Gershoff, 2003). Levels of betrayal aversion also decline in contexts that dampen emotional responses (Gershoff & Koehler, 2011).

Current measures of vaccine hesitancy capture overall beliefs about the safety of vaccines without disassociating the source of the assumed risks (Larson et al., 2016; Opel et al., 2013; Opel, Mangione-Smith, et al., 2011; Opel, Taylor, et al., 2011), and hence, are unable to determine whether betrayal aversion represents an additional, currently unmeasured, source of hesitancy. In this work, we seek to establish the importance of betrayal aversion as a preference construct in the decision to vaccinate. We developed a pre-registered vignette experiment involving a highly infectious hypothetical disease to measure willingness to get the vaccine across different betrayal scenarios while holding the overall risk level constant. We hypothesized that willingness to get the vaccine is lower when there is an additional risk of betrayal (death due to side effects) compared to a non-betrayal risk. We found evidence confirming this hypothesis.

During pandemics, information about the disease and available vaccines develops rapidly. The nature of communication and spread of information may have significant influences on vaccine hesitancy (Quinn et al., 2013; Nyhan et al., 2014; Odone et al., 2015; Opel et al., 2015; Ozawa et al., 2016; Trueblood et al., 2020; Loomba et al., 2021; Milkman, Patel, Gandhi, Graci, Gromet, Ho, Kay, Lee, Akinola, et al., 2021; Milkman, Patel, Gandhi, Graci, Gromet, Ho, Kay, Lee, Bogard, et al., 2021; Romaniuc et al., 2021; Bokemper et al., 2021) (for a review, see Romaniuc et al., 2021). Learning that President Obama had his daughters vaccinated, for example, was positively associated with willingness to get vaccinated against H1N1 influenza (Quinn et al., 2013). Recent studies on COVID-19 vaccination approval report a positive impact of messaging that stresses the importance of herd immunity (Trueblood et al., 2020) as well as endorsement statements by the director of the National Institute of Allergy and Infectious Diseases (Bokemper et al., 2021). On the other hand, misinformation around COVID-19 caused a decline in vaccination intent (Loomba et al., 2021). In this study, we investigate whether a message that primes regret for not getting the vaccine increases willingness to vaccinate and, separately, whether it decreases betrayal aversion. We find that willingness to get the vaccine increased among responders exposed to our messaging intervention. Contrary to our pre-registered hypothesis, the prevalence of betrayal aversion did not significantly decline after message exposure. To identify the channels by which the messaging treatment operates on vaccination intent, we administered another pre-registered survey to another group of responders that reported the motives for getting the vaccine and found that exposure to the message treatment increased the intent to protect others.

The COVID-19 pandemic has served as an illustration that there are many potential factors connecting betrayal aversion and vaccine hesitancy. To explore some of these factors, in addition to our two pre-registered studies, we designed an exploratory study (not pre-registered) to investigate betrayal aversion and vaccine hesitancy when the risk of betrayal is brought about by 1) a chance of the vaccine weakening the immune system, 2) a partisan government approving the vaccine rapidly, overlooking certain safety measures, or 3) scientists approving the vaccine rapidly, overlooking certain safety measures. We find that betrayal aversion was higher when a partisan government or scientists actively contribute to the associated risk. However, betrayal sensitivity is dampened when the political party of the government developing the vaccine was aligned with an individual's own preferences. This result demonstrates that political polarization is an important determinant of vaccine-related betrayal aversion, which can yield and/or amplify differences in vaccination intent (Bokemper et al., 2021; Hamel et al., 2020; Kreps et al., 2020; Weisel, 2021; Betsch et al., 2021).

5.2. Overview of experimental procedures

We administered an online survey via Amazon Mechanical Turk (MTurk). We have a final sample of 595 participants to test our pre-registered hypotheses (https://osf.io/4peuy) (from registered studies 1 and 2) and additional 293 participants to test exploratory hypotheses on variant betrayal sources (study 3). This study was approved by the Institutional Review Board of a large public university in the United States, where the principal investigator is affiliated. Participants provided informed consent and received $2 compensation for the task, which took an average of 19 minutes to complete. Our survey included two parts: a vignette experiment followed by questions that capture real world experiences, including those related to COVID-19, as well as demographic characteristics.

Upon completing the vignette experiment that elicits betrayal aversion (explained in detail in the study specific sections below and in *Table 5.1*), all participants answered several groups of survey questions. The first group of surveys asked about participants' general attitudes toward vaccination (5 questions) and toward COVID-19 in particular (3 questions). Note that data was collected in the United States during the COVID-19 pandemic between March 30th, 2021 and April 8th, 2021. In the United States, by March 30th, the cumulative number of reported COVID-19 cases surpassed 29 million and the number of the associated deaths was 543,003 (*COVID-19 Weekly Epidemiological Update, March 30 2021*, 2021). By this time more than 130 million COVID-19 vaccines had been administered (*COVID Data Tracker Weekly Review for March 26, 2021*, 2021).

The second group of surveys included two widely used vaccine hesitancy surveys adopted from the Parental Attitudes About Childhood Vaccines questionnaire (Opel, Taylor, et al., 2011; Opel et al., 2013) (the 5-question PACV-short version (Oladejo et al., 2016)) and the Vaccine Confidence Index questionnaire (H. J. Larson et al., 2015) (the 4-question VCI core survey (Larson et al., 2018; Larson et al., 2016)). To compute the PACV score that we use in our regression analysis, a hesitant response was assigned a value of 2, a don't know response was assigned a value of 1 and a non-hesitant response was assigned a value of 0 (Opel et al., 2013). We also take the average across the four VCI survey responses before we multiply it by -1 such that a higher number denotes higher hesitancy.

In the third group of surveys, we measured the individual and socioeconomic characteristics. Interestingly, women and democrats, for example, reported significantly higher fear of the COVID-19 pandemic ($M_{difference_{men-women}}$ = -0.600: Two-sided t-test: $P < 0.0001$; $M_{difference_{Republican-Democrat}}$ = -1.057: Two-sided t-test: $P < 0.0001$). Thus, in our regression analysis, we control for individual and socioeconomic characteristics to confirm the robustness of our findings. Almost all survey responses were provided on a 7-point Likert scale, with the exception of the PACV (5-point Likert scale) and binary questions. To identify the responder's geographic location, participants provide their ZIP code numbers that were matched to counties and states using a publicly available ZIP code database (www.unitedstateszipcodes.org/zip-code-database). We then use the Bureau of Economic Analysis (BEA) region classification that is widely used by economists to group states into one of 8 regions: New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountain, and Far West (*Metropolitan Statistical Areas (MSAs), Micropolitan Statistical Areas, Metropolitan Divisions, Combined Statistical Areas (CSAs), and BEA Regions*, n.d.).

Our inclusion criteria for the MTurk responders were to be a United States resident with 97% and higher approval rating and at least 5000 HITs (Human Intelligence Tasks) approved. We provide summary statistics for sample characteristics in supplementary material (*Table 5.S1*). The full list of the vignette conditions and the subsequent questionnaire is available in the supplementary material (section 5.7.2). Data were collected using Qualtrics, and Stata (version 15.1) was used for statistical analyses.

5.3. Study 1: betrayal aversion related vaccine hesitancy

5.3.1. Methods

In the vignette experiment, participants were presented with a hypothetical scenario about a novel future disease that is described as both highly infectious and deadly (see *Table 5.1*). In the scenario there is a free and easy-to-take vaccine that has been developed to prevent the spread of the disease. To investigate betrayal aversion, we adapt the scenarios used by Koehler and Gershoff on safety products to our vignette (Gershoff & Koehler, 2011; Koehler & Gershoff, 2003). Here, participants were told that there is a 2% risk of dying from the virus if they are not treated with the vaccine. Those who are vaccinated have a lower 1.01% risk of death, where 1% was due to the virus and the explanation for the remaining 0.01% risk is varied across treatments (see *Table 5.1*). By measuring changes in willingness to get the vaccine across treatments while holding the probability of death constant, we were able to explore how the causes of betrayal aversion affect its severity.

Table 5.1 List of treatment conditions.

	Treatments (Explanations for the 1.01% chance of Death after Vaccine)		
	Treatments with Undivided Probability		
Treatment	**1.01%**		**Observations**
Risk-Only	"a 1.01% chance that people treated with the vaccine will contract the virus and die as a result."		103
Risk-Only w/ Message			97
	Treatments with Divided Probabilities		
Treatment	**1.00%**	**0.01%**	**Observations**
	"a 1% chance that people treated with the vaccine will contract the virus and die as a result."	"an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die *due to…*	
Non-Betrayal (Benchmark)		… *problems unrelated to the vaccine.*"	This treatment is run counterbalanced with all other treatments below
Side-Effects		…*vaccine-induced complications (side effects).*"	198
Side-Effects w/ Message		…*vaccine-induced complications (side effects).*"	197 (The message was also displayed in the Non-Betrayal benchmark)
Counter-Productivity		…*the vaccine lowering the recipient's immunity making them more prone to catching the virus.*"	97
Government		…*a [XYZ} government in charge that approved the vaccine too rapidly, overlooking certain safety concerns.*"	102 ("XYZ" read "Democrat" or "Republican", order counterbalanced)
Scientists		…*scientists who work for [XYZ} developing the vaccine too rapidly, overlooking certain safety concerns.*"	94 ("XYZ" read "the government" or "pharmaceutical companies", order counterbalanced)

In our benchmark *Non-Betrayal* treatment, the cause of the 0.01% chance of death faced by those who get the vaccine was described as "problems unrelated to the vaccine." The cause of the 0.01% chance of death in our *Side-Effects* treatments involved active betrayal and was described as "vaccine-induced complications (side effects)." We asked participants (N=395) to indicate their willingness to get the vaccine (single 7-point Likert question with response alternatives ranging from "Definitely reject" at 1 to "Definitely accept" at 7) under both scenarios, with the order of scenarios presented counterbalanced across participants. By subtracting an individual's willingness to get the vaccine in the *Side-Effects* treatments (where there is a risk of active betrayal) from their willingness in the *Non-Betrayal* treatment (where there is no risk of active betrayal), we get an individual level measurement of betrayal aversion.

5.3.2. Results

We first explore whether betrayal aversion substantially influenced the decision to vaccinate. To do so, we compare willingness to get the vaccine when the 0.01% additional risk associated with vaccination was due to vaccine-induced complications (*Side-Effects* treatments) instead of unrelated problems (*Non-Betrayal* treatment). Participants reported a significantly lower willingness to vaccinate when the risk associated with vaccination was due to the vaccine actively contributing to the cause of death via side effects ($M_{difference}$= 0.453; Two-sided paired t-test, $P < 0.0001$; Wilcoxon signed-rank test, $P < 0.0001$) (*Figure 5.1*A-B). This implies betrayal aversion is playing a significant role in the decision to vaccinate. Next, we compute a binary measure of vaccine hesitancy by collapsing the Likert responses for each treatment into two categories: vaccine hesitant (a score lower than 5) or vaccine non-hesitant (a score that was at least 5). When the additional risk was caused by side-effects, 8.4% more people were identified as vaccine hesitant (McNemar test, P<0.0001). These results support our pre-registered hypothesis.

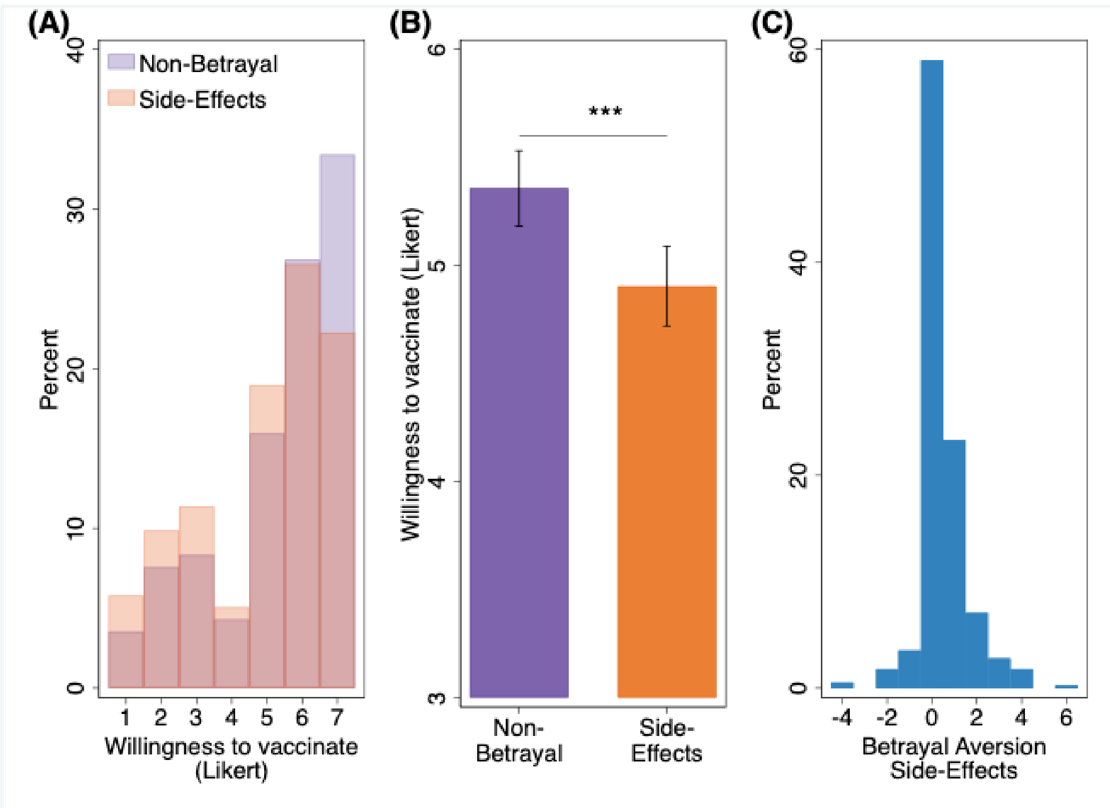

Figure 5.1 Willingness to vaccinate and betrayal aversion (A) Distribution of willingness to vaccinate responses across Non-Betrayal and Side-Effects treatments. (B) Average willingness to vaccinate across betrayal treatments. (C) Betrayal aversion distribution (Difference in willingness to vaccinate across treatments). $N_{Side-Effects_{pooled}}$=395 (Side-Effects + Side-Effects w/ Message) Errors bars denote 95% confidence intervals. Two-sided paired t-tests: *** P<.01, ** P<.05, * P<.1, N.S. Not significant.

To derive an individual-level measure of betrayal aversion, we calculate the difference between willingness to get the vaccine in the *Non-Betrayal* treatment and that in the *Side-Effects* treatment. As shown in *Figure 5.1*C, the distribution of betrayal aversion is skewed to the right with more than 30% of responders classified as betrayal averse (having a positive level of betrayal aversion). Taken together these results indicate that, in keeping with previous studies (Koehler & Gershoff, 2003; Bohnet et al., 2008; Aimone & Houser, 2012; Aimone et al., 2015), a substantial portion of the population is betrayal averse, and that betrayal aversion is likely influencing the willingness of individuals to vaccinate.

5.4. Study 2: Messaging, vaccine hesitancy and betrayal aversion

5.4.1. Methods

Our next set of treatments allows us to investigate the role of messaging on willingness to get the vaccine (see *Table 5.1*). We first explore the influence of messaging on willingness to get the vaccine without betrayal concerns and then explore the influence of messaging when vaccine betrayal is possible as well. We test Dan's Ariely's message suggestion for convincing vaccine skeptics to get vaccinated (Ferreri, 2020):

"There is no chance you will regret getting the vaccine, but, if you don't get it then you may either get sick and might die or may get other people sick meaning that they might die, and you could regret it. Imagine how you would feel if you passed the virus to someone else. Just try to imagine how that would feel. Now tell us that you should not do a lot to prevent that terrible feeling of regret that you didn't get the vaccination earlier."

We use this messaging to prime regret caused by a decision to not get the vaccine. The *Risk-Only* treatment (N=103) involves the presentation of the simple probabilities associated with the risk of getting the vaccine with no betrayal risk associated with either option (1.01% chance of death upon vaccination compared to the 2% chance of death without the vaccine). In the *Risk-Only w/ Message* treatment (N=97), we presented the message prior to participants making decisions in the *Risk-Only* treatment framework. By comparing the responses to five vaccine uptake questions in both treatments, we get a detailed identification of the causal role of the regret message on vaccine hesitancy. This allows us to delve into more detailed motives behind vaccination intent and hesitancy compared to the first study (Loomba et al., 2021). Participants reported their benchmark willingness to accept a vaccine, their willingness to get the vaccine in order to protect oneself, and separately their willingness to get the vaccine to protect others (family, friends, and at-risk groups). In addition, responders indicated their willingness to wait and see how the vaccine is working before getting vaccinated and their willingness to only get the vaccine if it was required by their work or school (7-point Likert questions; see supplementary material section 5.7.2).

5.4.2. Results

Similar to other studies that have explored vaccine hesitancy and communication (Quinn et al., 2013; Nyhan et al., 2014; Odone et al., 2015; Opel et al., 2015; Ozawa et al., 2016; Trueblood et al., 2020; Loomba et al., 2021; Milkman, Patel, Gandhi, Graci, Gromet, Ho, Kay, Lee, Akinola, et al., 2021; Milkman, Patel, Gandhi, Graci, Gromet, Ho, Kay, Lee, Bogard, et al., 2021), we find that participants exposed to the message treatment in the *Risk Only w/ Message* condition reported higher willingness to get the vaccine relative to the group that did not receive the message ($M_{difference}$= 0.668; Two-sided t-test, $P = 0.011$; Two-sample Wilcoxon rank-sum test, $P = 0.009$) (*Figure 5.2*A). We further find that the channel through which the message appears to work is social – our regret messaging increased willingness to get the vaccine to protect others ($M_{difference}$= 0.522; Two-sided t-test, $P = 0.031$; Two-sample Wilcoxon rank-sum test, $P = 0.022$; *Figure 5.2*A) rather than protecting oneself. After collapsing the Likert responses into a binary measure of vaccine hesitancy as before, we find that exposure to the message reduced vaccine hesitancy by about 11.7% (One-sided Fisher's exact test, P=0.032). Confirming the social channel of the message, the likelihood of accepting the vaccine to protect others (family, friends, and at-risk groups) was 14.8% higher among participants exposed to the message compared to the control group (One-sided Fisher's exact test, P=0.008).

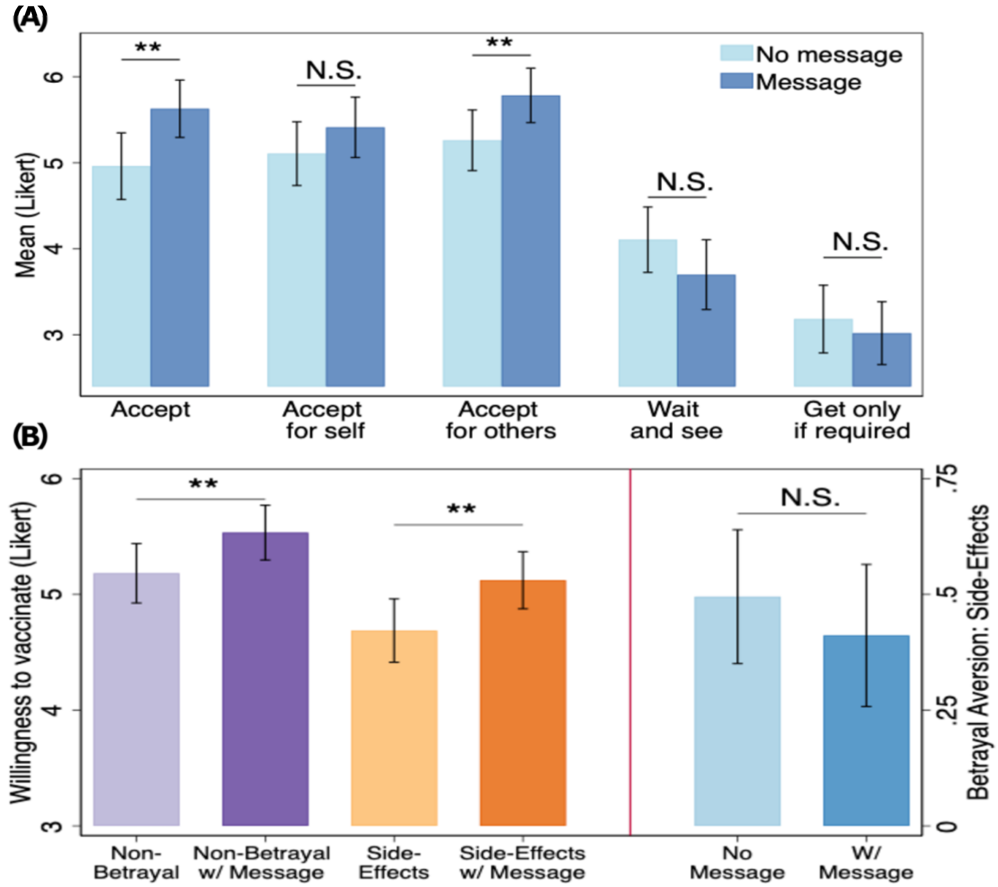

Figure 5.2 Message exposure, willingness to vaccinate, and betrayal aversion. (A) Willingness to get the vaccine, and associated motives with undivided probabilities across message and no message treatments (see Table 5.1; $N_{Risk-Only}$=103; $N_{Risk-Only\ w/\ message}$ =97). (B) Willingness to get the vaccine with divided probabilities across message treatments (see Table 5.1; $N_{Side-Effects}$=198; $N_{Side-Effects\ w/\ message}$=197) and the corresponding average betrayal aversion across message treatments. Errors bars denote 95% confidence intervals. Two-sided t-tests: *** p<.01, ** p<.05, * p<.1, N.S. Non-significant.

With evidence that messaging is effective at reducing overall vaccine hesitancy, we now explore whether the message also decrease betrayal aversion. This is measured by contrasting decisions in the *Side-Effects* treatment (N=198) to that from the *Side-Effects w/ Message* treatment (N=197) that involves displaying the treatment message prior to presenting participants with the *Non-Betrayal* and *Side-Effects* treatment frameworks. As shown in *Figure 5.2*B (right panel), betrayal aversion, on average, was not statistically significantly lower for participants exposed to the message treatment ($M_{difference}$= 0.084; Two-sided t-test, $P = 0.434$). In addition, there were no significant differences in the distributions of betrayal aversion across message treatments (Two-sample Wilcoxon rank-sum test; $P = 0.712$). Failure of the message to decrease betrayal aversion could arise either from similar changes of vaccine hesitancy in both treatments or from a lack of change of vaccine hesitancy in both the *Non-Betrayal* and *Side-Effects* treatments due to the message. *Figure 5.2*B (left panel) shows that relative to the no message comparison treatment groups, participants exposed to the message treatment reported a higher willingness to vaccinate under both *Non-Betrayal* ($M_{difference}$= 0.351; Two-sided t-test: $P = 0.048$; Two-sample Wilcoxon rank-sum test, $P = 0.028$) and *Side-Effects* conditions ($M_{difference}$= 0.435; Two-sided t-test, $P = 0.020$; Two-sample Wilcoxon rank-sum test, $P = 0.034$). These results suggest that while regret messaging is effective at reducing vaccine hesitancy, it is acting orthogonally to betrayal aversion related vaccine hesitancy. Consequently, this result seems to be consistent with the evidence from the *Risk-Only* and *Risk-Only w/ Message* treatments that suggested the messages were acting to increase willingness to get the vaccine to protect others. In particular, the effect of the message operates through an external/other focused channel while betrayal aversion would be expected to be an emotional/internal focused channel (Gershoff & Koehler, 2011).

Our results exploring messaging's effects on vaccine hesitancy using the *Risk-Only* and *Risk-Only w/ Message* treatments are robust to exploring the data with a multiple linear regression analysis with vaccine acceptance as the dependent variable while controlling for individual characteristics, measures of vaccine hesitancy and region fixed effects in fixed effects linear regression models (Effect on benchmark acceptance: $\beta_{message}$>0.661, P<0.050; Effect on acceptance to protect others: $\beta_{message}$>0.279, P<0.050; see *Table 5.S2* and *Table 5.S3*). For the regression analyses reported in *Table 5.S2* and *Table 5.S3*, and subsequent tables in supplementary material (section 5.7.1), we standardize all 7-Likert scale measures at the responder level, prior to calculating betrayal aversion, and use the z-scores in model estimation. All participants completed two vaccine hesitancy surveys adopted from the Parental Attitudes About Childhood Vaccines questionnaire (Opel, Taylor, et al., 2011; Opel et al., 2013) (PACV) and the Vaccine Confidence Index questionnaire (Larson et al., 2015) (VCI) (see Overview on experimental procedures section). Importantly, when betrayal aversion is modeled as the dependent variable while controlling for individual characteristics, vaccine hesitancy as well as region fixed effects, the null effect of the message treatment on betrayal aversion persisted ($\beta_{message} = -0.059 \text{ in (a)}, \beta_{message} = -0.063 \text{ in (b)}; P > 0.100$) (see supplementary *Table 5.S4*). Note that the coefficients for these commonly used vaccine hesitancy measures are not significantly associated with betrayal aversion ($\beta_{PACV} = -0.023, P > 0.100; \beta_{\text{VIC}} = -0.154, P > 0.100$) and seem to move in the opposite direction. We obtain an identical result when we include each of the four measures in the VCI separately in the regression (Larson et al., 2016) (available upon request). Moreover, the finding that the message increased willingness to get the vaccine in both treatments (*Non-Betrayal* and *Side-Effects*) holds in our regression analysis ($\beta_{message}$>0.251, P<0.050; see supplementary Table 5.S5). Even though the null result of the effect of the message on betrayal aversion related vaccine hesitancy is in conflict with our pre-registered hypothesis that vaccine hesitancy reducing messages would mitigate betrayal aversion, our findings suggest that the current measures of vaccine hesitancy, and potentially messaging interventions, seem to fall short in accounting for an important preference construct that influences the vaccination decision.

5.5. Study 3: Source of betrayal and vaccine hesitancy

5.5.1. Methods

We next turn to our exploratory treatments, where we exogenously manipulated the source of betrayal to examine whether these sources differentially impact vaccine hesitancy related betrayal aversion (see *Table 5.1*). In all of the three conditions with varied sources of betrayal, participants also made decisions in a *Non-Betrayal* condition as well (order counter-balanced across subjects). In the *Counter-Productivity* treatment (N=97), we elicited willingness to get the vaccine in an active betrayal condition where the 0.01% risk was caused by the vaccine lowering the recipient's general immunity making them more prone to catching the virus. Concerns about the vaccine overloading the immune system has been one of the most stated reasons behind vaccine hesitancy (Salmon et al., 2005). In the *Government* treatment (N=102), we elicited willingness to get the vaccine when the 0.01% risk of active betrayal is caused by having either a Democrat or a Republican government overseeing an accelerated vaccine approval process that overlooks potential safety concerns. Note that in this condition, participants were presented with three different conditions: *Non-Betrayal*, Democrat Government, and Republican Government. The order of the presented scenarios was counter-balanced across participants with half of participants completing the *Non-Betrayal* condition first followed by the two *Government* active betrayal scenarios and the other half undergoing the opposite order. In addition, we counter-balanced the order presentation of the Democrat versus Republican scenarios across participants. Last, in the *Scientists* treatment (N=94), we investigate betrayal aversion when the active betrayal is attributed to the behavior of scientists. In this condition, we elicit willingness to get the vaccine when the 0.01% risk of active betrayal is caused by scientists developing the vaccine too rapidly while overlooking certain safety concerns in the process. The scientists were described as either working for pharmaceutical companies or for the government. We again counter-balanced the order of *Non-Betrayal* and active betrayal conditions with pharmaceutical and government scientists' scenarios in a similar fashion as before.

5.5.2. Results

We investigated whether the explanation for possible vaccine harm differentially influences betrayal aversion. First, we compared whether the level of betrayal aversion differs when active betrayal comes from side effects (*Side-Effects* treatment) or when due to the vaccine causing an individual to suffer weakened immunity that makes them more prone to catching the virus (*Counter-Productivity* treatment.) As seen in *Figure 5.3*A, there was no discernable difference in betrayal aversion between these two types of active betrayals ($M_{difference}$= 0.135; Two-sided t-test, $P = 0.308$; Two-sample Wilcoxon rank-sum test, $P = 0.715$).

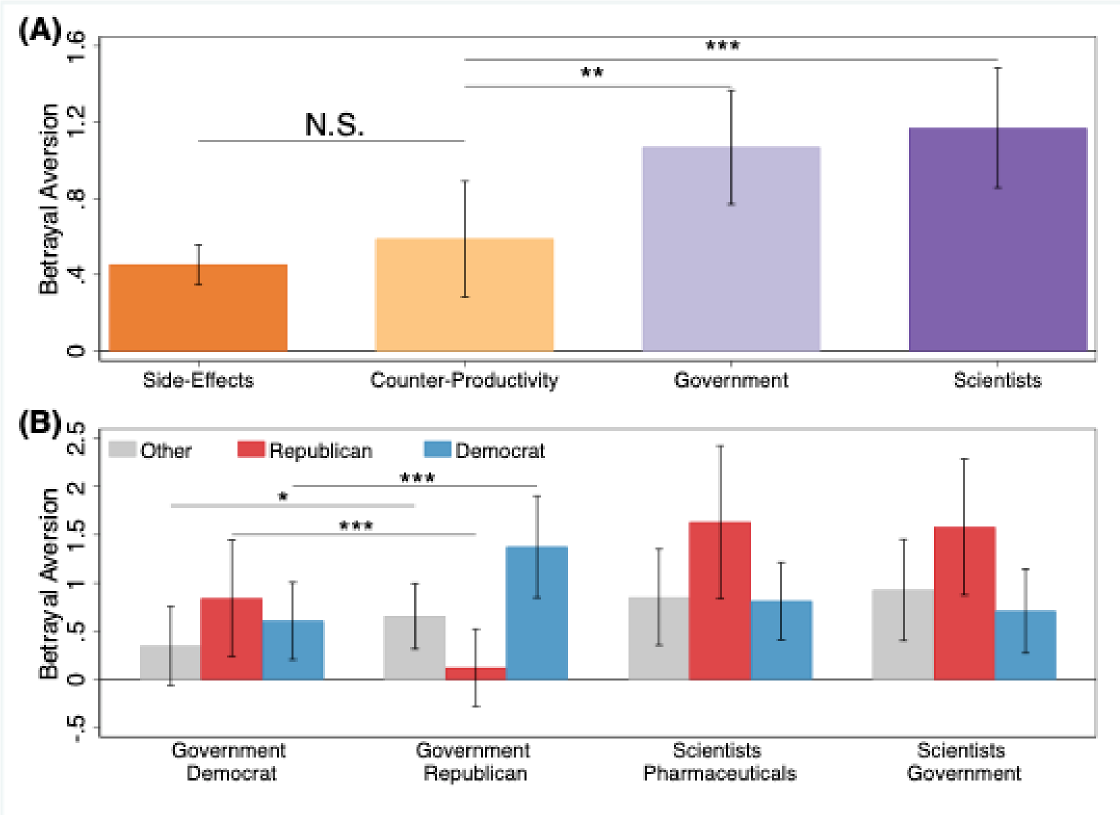

Figure 5.3 Betrayal aversion across betrayal sources. *(A) Betrayal aversion across betrayal source conditions ($N_{Side-Effects(pooled)}$=395; $N_{Counter-Productivitiy}$=97; $N_{Government}$=102; $N_{Scientists}$=94). For Government (Scientists), the lowest willingness to get the vaccine between Democrat or Republican governments (Pharmaceutical or Government scientists) is used to calculate betrayal aversion. (B) Betrayal aversion by political orientation for the two betrayal treatments: Government (N_{Other}=29; $N_{Republican}$=25; $N_{Democrat}$=48) and Scientists (N_{Other}=27; $N_{Republican}$=19; $N_{Democrat}$=48). Errors bars denote 95% confidence intervals. Two-sided t-tests (paired tests in (B) only): *** p<.01, ** p<.05, * p<.1, N.S. Non-significant.*

On the other hand, we find that betrayal aversion was higher in conditions involving either politicians or scientists actively contributing to the betrayal risk. For the *Government* (*Scientists*) treatment, the lowest willingness to get the vaccine between Democrat or Republican government (Pharmaceutical or Government scientists) was used to derive betrayal aversion. Relative to the active betrayal treatment (*Counter-Productivity)*, betrayal aversion to vaccination was significantly higher when betrayal was channeled through the government ($M_{difference}$= 0.481; Two-sided t-test, $P = 0.026$; Two-sample Wilcoxon rank-sum test, $P = 0.020$) or scientists ($M_{difference}$= 0.583; Two-sided t-test, $P = 0.009$; Two-sample Wilcoxon rank-sum test, $P = 0.006$; *Figure 5.3*A). Similar results are found when comparing against betrayal aversion in the *Side-Effects* treatment (*Government* $M_{difference}$ = 0.615; *Scientists* $M_{difference}$ = 0.717; Two-sided t-tests: $P < 0.0001$, Two-sample Wilcoxon rank-sum tests, $P < 0.001$). Again, we confirm these results using regression analysis that controls for individual characteristics, measures of vaccine hesitancy and region fixed effects ($\beta_{Government} > 0.346, P < 0.010$; $\beta_{Scientists} > 0.388$, $P < 0.010$; see supplementary *Table 5.S6*). When the additional risk of betrayal was caused by *Counter-Productivity*, vaccine acceptance was reduced by about 12.4% (McNemar test, P=0.008). This decline is again comparable to the 8.4% decline in vaccine acceptance reported in *Study 1* for betrayal caused by *Side-Effects*. On the other hand, vaccine acceptance was reduced more steeply by 20.6% and 25.6% when the additional risk of betrayal was caused by the government or the scientists (McNemar tests, P<0.0001), respectively.

Participants reported lower willingness to vaccinate when the betrayal source was a Republican led government compared to a Democrat led government ($M_{difference}$ = 0.275; Two-sided paired t-test, $P = 0.041$; Wilcoxon signed-rank test, $P = 0.017$). Interestingly, we find that betrayal aversion to a vaccine developed by a Democrat or Republican led government is modulated by political orientation. Here, responders who self-identified as Democrats were more betrayal averse to a vaccine from a Republican led government compared to a Democrat led government ($M_{difference}$ = 0.771; Two-sided paired t-test, $P = 0.0002$; Wilcoxon signed-rank test, $P < 0.0001$) (*Figure 5.3*B). Analogously, Republicans were more sensitive to betrayal when the vaccine risk was brought about by a Democrat led government instead of a Republican led government ($M_{difference}$ = 0.720; Two-sided paired t-test, $P = 0.008$; Wilcoxon signed-rank test, $P = 0.014$). Willingness to get the vaccine for self-identified Republicans in the *Non-Betrayal* scenario was not significantly different from that in the scenario involving the Republican government as a proxy cause of betrayal ($M_{difference} = 0.120$; Two-sided paired t-test, $P = 0.543$; Wilcoxon signed-rank test, $P = 0.420$). On the other hand, betrayal aversion persisted for self-identified Democrats who reported higher willingness to get the vaccine in the *Non-Betrayal* scenario relative to that involving the Democrat government as a proxy cause of betrayal ($M_{difference}$ = 0.604; Two-sided paired t-test, $P = 0.004$; Wilcoxon signed-rank test, $P = 0.009$). Responders who self-identified as neither Republicans nor Democrats were marginally more betrayal averse when the source of betrayal involved a Republican led government instead of a Democrat led government ($M_{difference}$ = 0.310; Two-sided paired t-test, $P = 0.071$; Wilcoxon signed-rank test, $P = 0.056$).

Conversely, willingness to vaccinate did not differ significantly when the betrayal source involved either pharmaceutical company scientists or government employed scientists ($M_{difference}$ = 0.043; Two-sided paired t-test, $P = 0.661$; Wilcoxon signed-rank test, $P = 0.461$). Moreover, betrayal aversion to vaccines developed rapidly by pharmaceutical company or government employed scientists were not differentiated by political affiliation ($M_{difference}$ < 0.104; Two-sided paired t-tests, $P > 0.521$; Wilcoxon signed-rank tests, $P > 0.206$). Interestingly, however, we find that Republican responders were significantly more betrayal averse to vaccines from government employed scientists than Democrat responders ($M_{difference}$ = 0.871; Two-sided t-test, $P = 0.035$; Two-sample Wilcoxon rank-sum test, $P = 0.015$) and marginally more averse to betrayal from vaccines developed by pharmaceutical company employed scientists ($M_{difference}$ = 0.819; Two-sided t-test, $P = 0.042$; Two-sample Wilcoxon rank-sum test, $P = 0.058$).

5.6. Discussion

Betrayal aversion is an important economic preference that influences decision-making in situations where trust can be broken. Despite their potential to reduce the overall risk of harm, safety products with small chances of causing the very same harm they are expected to prevent are often less preferred (Aimone et al., 2015; Gershoff & Koehler, 2011; Koehler & Gershoff, 2003). In this study, we demonstrate that betrayal aversion is an important preference construct in the decision to vaccinate and is one not accounted for by widely used vaccine hesitancy measures.

In addition, we find that the observed level of betrayal aversion depends on the source of betrayal. In comparison to the levels observed when the source of betrayal is a vaccine side effect, betrayal aversion is amplified when the government or scientists may be at fault. This finding may be due to stronger emotional responses when potential betrayals involve institutions or personnel that were expected to prevent harm. Thus, the active involvement of the government or scientists in breaking the trust may have compounded betrayal aversion to the safety product itself. Interestingly, we find that Democrats (Republicans) are more sensitive to betrayal by a Republican (Democrat) government. Thus, betrayal aversion seems to further amplify political polarization in vaccination decisions (Betsch et al., 2021; Bokemper et al., 2021; Hamel et al., 2020; Kreps et al., 2020; Weisel, 2021).

We explore a messaging intervention that increased overall willingness to vaccinate but did not ameliorate betrayal aversion. The messaging intervention primes feelings of regret for not getting the vaccine via phrases like "*Imagine how you would feel if you passed the virus to someone else.*" We show that the message operates through other regarding preferences, such as altruism, enhancing receivers' willingness to vaccinate to protect friends, family members and at-risk groups. Since the message was not targeted at reducing concerns about betrayal, we were not surprised that it failed to decrease hesitancy through that channel. In fact, in a sense the message's ineffectiveness in reducing betrayal aversion underscores the importance of treating betrayal aversion as a unique preference construct so that it is not overlooked in health communications and behavioral interventions.

Vignette experiments are a valuable first step in a multi-method research agenda where a lot of data is needed and when circumstances preclude other data collection strategies (e.g. ethical issues are present) (Erfanian et al., 2020). At the same time, we acknowledge that research using survey methods and hypothetical vignettes may have relatively reduced external validity when compared with some other approaches because participants are not actually experiencing the presented circumstances and making consequential decisions. When we test the external validity of our hypothetical vaccine acceptance data, we find that willingness to get COVID-19 vaccination, as hypothesized, was positively and significantly correlated with willingness to accept the vaccination in the vignette experiment ($\beta_{Willingness\ to\ vaccinate\ in\ vignette} > 0.299, P < 0.050$; see Table 5.S7) suggesting that the vignette data connects well to salient real-world preferences.

The results of this study suggest several areas for future study. First, betrayal aversion might be added to measures of vaccine hesitancy to augment their accuracy. Next, research on interventions to increase vaccination rates should address the betrayal aversion channel of vaccine hesitancy, which we show is less malleable to some messaging. Emotion regulation interventions (Gross, 2015), however, may be a potential candidate to mitigate betrayal aversion to vaccination (Gershoff & Koehler, 2011). Finally, we believe that, with additional research and perhaps including a field or randomized controlled study, results from this study may shed light on how to reduce COVID-19-related vaccine hesitancy.

5.7. Supplementary material

5.7.1. Supplementary tables

Table 5.S1 Summary statistics.

Woman, %	42.23
Man, %	57.43
Non-binary, %	0.34
Age, Mean (SD)	40.87 (12.45)
Hispanic, %	6.6
Caucasian, %	76.1
Education:	
High School and Less, %	12.4
Some college, %	25.2
Bachelor, %	48.8
Masters or above, %	13.6
Work full time, %	73.5
Political Orientation:	
Independent, %	28.2
Republican, %	22.9
Democrat, %	49.0
Bureau of Economic Analysis (BEA) Regions:	
Far West, %	16.5
Great Lakes, %	15.2
Mideast, %	16.7
New England, %	5.3
Plains, %	5.7
Rocky Mountain, %	3.3
Southeast, %	24.9
Southwest, %	12.4
Total number of responses	897
Unmatched ZIP code	1
Failed check question criteria	8
Sample used in analysis after exclusions:	888

Table 5.S2 Willingness to get the vaccine disassociated by motivation, controlling for PACV (Fixed effect linear regressions).

Dependent variable: Willingness to vaccinate	(a) Benchmark	(b) To protect oneself	(c) To protect others	(d) Wait and see	(e Only if required
Message	.676**	.304	.283**	-.198	-.033
	(.214)	(.263)	(.082)	(.217)	(.126)
Woman	-.162	-.316	-.192	.267***	.281*
	(.255)	(.224)	(.132)	(.05)	(.139)
Age/100	.867	1.156	.43	-1.889**	-1.246**
	(.713)	(.654)	(.539)	(.582)	(.369)
Hispanic	-.4	-.743*	.171	.246*	.615**
	(.409)	(.343)	(.099)	(.105)	(.231)
Caucasian	.112	-.042	-.068	.057	-.137
	(.294)	(.375)	(.11)	(.217)	(.197)
Education (Base: high school or less)					
Some college	-.288	-.348	.103	-.111	-.032
	(.599)	(.555)	(.153)	(.478)	(.244)
Bachelor	.114	.158	.179	-.283	-.227
	(.266)	(.355)	(.115)	(.325)	(.316)
Masters or above	.67	.459	.349**	-.428	-.587**
	(.357)	(.363)	(.113)	(.275)	(.202)
Work full time	.042	-.078	.046	-.016	-.003
	(.256)	(.211)	(.147)	(.149)	(.055)
Political orientation (Base: Democrat)					
Independent	-.263	-.295	-.072	.357	.255**
	(.353)	(.313)	(.228)	(.199)	(.102)
Republican	.174	.051	.085	-.031	.097
	(.546)	(.438)	(.168)	(.108)	(.188)
PACV	-.394***	-.402**	-.113***	.265***	.248***
	(.108)	(.126)	(.018)	(.036)	(.062)
Constant	6.087***	6.494***	.356*	-.725	-1.431***
	(.449)	(.451)	(.168)	(.551)	(.334)
Region (BEA) fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	199	199	199	199	199
R-squared	.207	.198	.13	.228	.219

Standard errors (clustered at the region level) are in parentheses. Likert-scale (7-point) measures, including dependent variable, are standardized at the individual level (z-score). A more positive score on PACV or VCI denotes higher hesitancy. One responder is dropped from analysis: reported a non-binary gender. (Tables created using asdoc, a Stata program written by Shah (2020)) **** p<.01, ** p<.05, * p<.1*

Table 5.S3 Willingness to get the vaccine disassociated by motivation, controlling for VCI (average of four z-scored measures) (Fixed effect linear regressions)

Dependent variable: Willingness to vaccinate	(a) Benchmark	(b) To protect oneself	© To protect others	(d) Wait and see	(e) Only if required
Message	.661**	.29	.279**	-.193	-.03
	(.21)	(.261)	(.081)	(.218)	(.118)
Woman	-.12	-.273	-.179	.237*	.253
	(.319)	(.303)	(.14)	(.107)	(.201)
Age/100	1.459*	1.758**	.599	-2.268**	-1.596***
	(.633)	(.569)	(.496)	(.686)	(.222)
Hispanic	-.094	-.419*	.262***	-.018	.348
	(.415)	(.191)	(.074)	(.163)	(.317)
Caucasian	.011	-.142	-.097	.114	-.086
	(.24)	(.298)	(.088)	(.238)	(.15)
Education					
(Base: high school or less)					
Some college	-.516**	-.586***	.036	.065	.141
	(.218)	(.163)	(.09)	(.223)	(.104)
Bachelor	-.148	-.115	.102	-.083	-.03
	(.29)	(.347)	(.147)	(.174)	(.225)
Masters or above	.481	.263	.294	-.287	-.45
	(.382)	(.365)	(.159)	(.256)	(.254)
Work full time	.122	.002	.068	-.056	-.036
	(.257)	(.227)	(.153)	(.164)	(.098)
Political orientation					
(Base: Democrat)					
Independent	-.434	-.47	-.121	.47*	.36**
	(.433)	(.454)	(.251)	(.21)	(.127)
Republican	-.043	-.172	.022	.121	.243
	(.496)	(.39)	(.175)	(.107)	(.184)
VCI (average)	-.614*	-.671**	-.188**	.642***	.68***
	(.3)	(.252)	(.055)	(.175)	(.114)
Constant	4.27***	4.622***	-.169	.584	-.172
	(.323)	(.364)	(.162)	(.583)	(.202)
Region (BEA) fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	199	199	199	199	199
R-squared	.098	.084	.085	.152	.16

Standard errors (clustered at the region level) are in parentheses. Likert-scale (7-point) measures, including dependent variable, are standardized at the individual level (z-score). A more positive score on PACV or VCI denotes higher hesitancy. One responder is dropped from analysis: reported a non-binary gender. *** *p<.01, ** p<.05, * p<.1*

Table 5.S4 Betrayal aversion to side effects and message treatment (Fixed effect linear regressions).

Dependent variable:	(a) Betrayal Aversion	(b) Betrayal Aversion
Message	-.059	-.063
	(.091)	(.088)
Non-Betrayal scenario first	.262***	.273***
	(.064)	(.065)
Woman	.146	.143
	(.122)	(.116)
Age/100	-.014	-.012
	(.224)	(.239)
Hispanic	.052	.052
	(.217)	(.21)
Caucasian	.047	.028
	(.138)	(.124)
Education		
(Base: high school or less)		
Some college	-.008	-.021
	(.11)	(.104)
Bachelor	.055	.033
	(.094)	(.087)
Masters or above	.183	.171
	(.126)	(.118)
Work full time	.05	.051
	(.115)	(.111)
Political orientation		
(Base: Democrat)		
Independent	-.008	-.028
	(.091)	(.109)
Republican	-.096	-.109
	(.055)	(.067)
PACV	-.023	-
	(.023)	
VCI (average)	-	-.154
		(.117)
Constant	.144	.008
	(.238)	(.25)
Region (BEA) fixed effects	Yes	Yes
Observations	394	394
R-squared	.048	.052

Standard errors (clustered at the region level) are in parentheses. Likert-scale (7-point) measures are standardized at the individual level (z-score). Dependent variable is constructed by taking the difference between the z-scored willingness to get the vaccine across the non-betrayal and active betrayal conditions. A more positive score on PACV or VCI denotes higher hesitancy. One responder is dropped from analysis: reported a non-binary gender. **** p<.01, ** p<.05, * p<.1*

Table 5.S5 Willingness to get the vaccine and message treatment (Fixed effect linear regressions).

Dependent variable: Willingness to vaccinate	(a) Non Betrayal	(b) Non Betrayal	(c) Active Betrayal (Side effects)	(d) Active Betrayal (Side effects)
Message	.251**	.253***	.31***	.316***
	(.073)	(.07)	(.059)	(.067)
Non-Betrayal scenario first	.073	.116	-.19	-.156
	(.092)	(.09)	(.11)	(.114)
Woman	-.105	-.126	-.251	-.269
	(.056)	(.08)	(.163)	(.178)
Age/100	-.782	-.692	-.769	-.681
	(.481)	(.472)	(.503)	(.479)
Hispanic	.124	.086	.072	.033
	(.166)	(.197)	(.298)	(.333)
Caucasian	.143	.089	.097	.061
	(.079)	(.081)	(.107)	(.136)
Education (Base: high school or less)				
Some college	.173	.149	.181	.17
	(.18)	(.195)	(.106)	(.139)
Bachelor	.267	.246	.213	.213
	(.156)	(.148)	(.118)	(.135)
Masters or above	.259	.256	.076	.085
	(.259)	(.226)	(.221)	(.201)
Work full time	-.062	-.082	-.112	-.132
	(.071)	(.06)	(.108)	(.102)
Political orientation (Base: Democrat)				
Independent	-.021	-.171*	-.014	-.143
	(.073)	(.088)	(.096)	(.112)
Republican	-.137**	-.297***	-.041	-.187**
	(.047)	(.066)	(.072)	(.078)
PACV	-.179***	-	-.156***	-
	(.021)		(.028)	
VCI (average)	-	-.549***	-	-.395***
		(.133)		(.073)
Constant	.868*	-.025	.724**	-.033
	(.393)	(.347)	(.265)	(.255)
Region (BEA) fixed effects	Yes	Yes	Yes	Yes
Observations	394	394	394	394
R-squared	.212	.15	.143	.097

Standard errors (clustered at the region level) are in parentheses. Likert-scale (7-point) measures, including dependent variable, are standardized at the individual level (z-score). A more positive score on PACV or VCI denotes higher hesitancy. One responder is dropped from analysis: reported a non-binary gender. *** *p<.01*, ** *p<.05*, * *p<.1*

Table 5.S6 Betrayal aversion across different source conditions (Fixed effect linear regressions).

Dependent variable:	(a) Betrayal Aversion	(b) Betrayal Aversion
Betrayal condition (Base: Side-Effects)		
Active betrayal (Counter-productivity)	-.003	-.004
	(.072)	(.068)
Government (maximum betrayal)	.346***	.346***
	(.061)	(.057)
Scientists (maximum betrayal)	.395***	.388***
	(.074)	(.074)
Message	-.085	-.093
	(.092)	(.088)
Non-Betrayal scenario first	.247***	.251***
	(.059)	(.059)
Woman	.175	.179*
	(.097)	(.091)
Age/100	-.319	-.32
	(.174)	(.187)
Hispanic	-.162	-.158
	(.176)	(.175)
Caucasian	.056	.041
	(.093)	(.087)
Education (Base: high school or less)		
Some college	.079	.063
	(.149)	(.146)
Bachelor	.053	.025
	(.091)	(.087)
Masters or above	.132	.109
	(.133)	(.135)
Work full time	.023	.024
	(.09)	(.086)
Political orientation (Base: Democrat)		
Independent	-.071	-.067
	(.111)	(.119)
Republican	.029	.038
	(.082)	(.09)
PACV	-.013	-
	(.015)	
VCI (average)	-	-.173***
		(.049)
Constant	.237	.126
	(.203)	(.161)
Region (BEA) fixed effects	Yes	Yes
Observations	684	684
R-squared	.077	.083

Standard errors (clustered at the region level) are in parentheses. Likert-scale (7-point) measures are standardized at the individual level (z-score). Dependent variable is constructed by taking the difference between the z-scored willingness to get the vaccine across the non-betrayal and active betrayal conditions. A more positive score on PACV or VCI denotes higher hesitancy. Four responders are dropped from analysis: two reported a non-binary gender, and one provided a non-existent Zip code, and another indicated an age above 150. **** p<.01, ** p<.05, * p<.1*

Table 5.S7 Willingness to get COVID-19 vaccination (Fixed effect linear regressions).

	(a)	(b)	(c)	(d)
Dependent variable:	Willingness to accept COVID-19 vaccine	Willingness to accept COVID-19 vaccine	Willingness to accept COVID-19 vaccine	Willingness to accept COVID-19 vaccine
Willingness to vaccinate				
Non-betrayal (benchmark)	.384***	.439***	-	-
	(.056)	(.046)		
Risk-only (benchmark)	-	-	.299**	.393**
			(.119)	(.126)
Non-Betrayal scenario first	-.039	-.015	-	-
	(.053)	(.051)		
Message	-.064	-.081	-.036	-.065
	(.095)	(.087)	(.13)	(.13)
Woman	-.126	-.122	.102	.071
	(.073)	(.067)	(.12)	(.105)
Age/100	1.14***	1.255***	.835**	1.234***
	(.114)	(.113)	(.261)	(.289)
Hispanic	-.097	-.1	-.129	.11
	(.143)	(.139)	(.28)	(.328)
Caucasian	-.073	-.097	.273	.254*
	(.056)	(.071)	(.183)	(.115)
Education				
(Base: high school or less)				
Some college	.244***	.206***	-.112	-.208
	(.042)	(.053)	(.359)	(.218)
Bachelor	.26***	.193**	.159	.06
	(.048)	(.062)	(.339)	(.245)
Masters or above	.328***	.279**	.23	.145
	(.069)	(.097)	(.36)	(.268)
Work full time	.168***	.153**	.199	.191
	(.043)	(.047)	(.255)	(.27)
Political orientation				
(Base: Democrat)				
Independent	-.287**	-.354***	-.124	-.219
	(.092)	(.096)	(.194)	(.208)
Republican	-.311***	-.385***	-.523**	-.708***
	(.08)	(.087)	(.159)	(.141)
PACV	-.135***	-	-.198***	-
	(.02)		(.043)	
VCI (average)	-	-.514***	-	-.602***
		(.121)		(.172)
Constant	.426***	-.321**	.472	-.603*
	(.119)	(.101)	(.342)	(.287)
Region (BEA) fixed effects	Yes	Yes	Yes	Yes
Observations	684	684	199	199
R-squared	.382	.37	.379	.356

Standard errors (clustered at the region level) are in parentheses. Likert-scale (7-point) measures are standardized at the individual level (z-score). Responses for participants who indicated being fully or partially vaccinated (N=269) were coded as definitely willing to get COVID-19 vaccination. A more positive score on PACV or VCI denotes higher hesitancy. Five responders are dropped from analysis: three reported a non-binary gender, and one provided a non-existent Zip code, and another indicated an age above 150. ****p<.01, **p<.05, *p<.1*

5.7.2. Administered survey

[everything that is underlined and/or in square brackets is not shown to participants]
Please answer the following questions about the following hypothetical scenario.

[For treatments *Side Effects, Side Effects', Side Effects w/ Message* and *Side Effects w/ Message'*]
In today's study, you will be asked to complete two tasks involving hypothetical scenarios. After you complete both tasks, you will be asked to answer survey questions about real world experiences and demographic characteristics.

Please proceed to the next page to begin the first task. Note the highlighted bold text in each hypothetical scenario, which reflects some differences between the two scenarios. Please make sure to read each scenario carefully before selecting your choices.

[next page – *Non-betrayal*; order randomized between *Side Effects, Side Effects'*]

Please answer the question based on the following hypothetical scenario:

In the future, a new deadly, highly infectious disease has been spreading across the world. In response, a vaccine has been developed by the scientific community to prevent the spread of the disease.

Suppose you are given the opportunity to get the free vaccine for the highly infectious deadly virus (via an easy-to-take pill) at a convenient location.

[message condition -shown only in message treatments]
The following statement has been circulated to the public: "There is no chance you will regret getting the vaccine, but, if you don't get it then you may either get sick and might die or may get other people sick meaning that they might die, and you could regret it. Imagine how you would feel if you passed the virus to someone else. Just try to imagine how that would feel. Now tell us that you should not do a lot to prevent that terrible feeling of regret that you didn't get the vaccination earlier."

You are also informed that scientific tests indicate that there is a 2% chance that people like you, who are not treated with the vaccine, will contract the virus and die as a result. Scientific tests also indicate that there is a 1% chance that people treated with the vaccine will contract the virus and die as a result. However, some people who are treated with the vaccine, and who would not have died if they did not get the vaccine, may die in another way.

Specifically, some people that get the vaccine may die due to problems unrelated to the vaccine. Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to problems unrelated to the vaccine.**

1. Would you accept or reject getting the vaccine?
    a. Definitely reject (1)
    b. Reject (2)
    c. Unsure, but leaning towards reject (3)
    d. Indifferent between accepting and rejecting (4)
    e. Unsure, but leaning towards accept (5)

f. Accept (6)
g. Definitely accept (7)

[next page – *Side Effects*; order randomized between *Side Effects* and *Side Effects'*]

Please answer the question based on the following hypothetical scenario:

In the future, a new deadly, highly infectious disease has been spreading across the world. In response, a vaccine has been developed by the scientific community to prevent the spread of the disease.

Suppose you are given the opportunity to get the free vaccine for the highly infectious deadly virus (via an easy-to-take pill) at a convenient location.

[message condition -shown only in message treatments]
The following statement has been circulated to the public: **"There is no chance you will regret getting the vaccine, but, if you don't get it then you may either get sick and might die or may get other people sick meaning that they might die, and you could regret it. Imagine how you would feel if you passed the virus to someone else. Just try to imagine how that would feel. Now tell us that you should not do a lot to prevent that terrible feeling of regret that you didn't get the vaccination earlier."**

You are also informed that scientific tests indicate that there is a 2% chance that people like you, who are not treated with the vaccine, will contract the virus and die as a result. Scientific tests also indicate that there is a 1% chance that people treated with the vaccine will contract the virus and die as a result. However, some people who are treated with the vaccine, and who would not have died if they did not get the vaccine, may die in another way.

Specifically, some people that get the vaccine may die due to vaccine-induced complications (side effects). Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to vaccine-induced complications (side effects).**

2. Would you accept or reject getting the vaccine?
   a. Definitely reject (1)
   b. Reject (2)
   c. Unsure, but leaning towards reject (3)
   d. Indifferent between accepting and rejecting (4)
   e. Unsure, but leaning towards accept (5)
   f. Accept (6)
   g. Definitely accept (7)

[For treatments *Risk-Only* and *Risk-Only w/ Message*]

Instructions
In today's study, you will be asked to complete one task involving a hypothetical scenario. After you complete the task, you will be asked to answer survey questions about real world experiences and demographic characteristics.

Please proceed to the next page to begin the task. Please make sure to read the scenario carefully before selecting your choices.

[next page – no risk; get either *Risk-Only* and *Risk-Only w/ Message*]

In the future, a new deadly, highly infectious disease has been spreading across the world. In response, a vaccine has been developed by the scientific community to prevent the spread of the disease.

Suppose you are given the opportunity to get the free vaccine for the highly infectious deadly virus (via an easy-to-take pill) at a convenient location.

[message condition -shown only in message treatment]
The following statement has been circulated to the public: **"There is no chance you will regret getting the vaccine, but, if you don't get it then you may either get sick and might die or may get other people sick meaning that they might die, and you could regret it. Imagine how you would feel if you passed the virus to someone else. Just try to imagine how that would feel. Now tell us that you should not do a lot to prevent that terrible feeling of regret that you didn't get the vaccination earlier."**

You are also informed that scientific tests indicate that there is a 2% chance that people like you, who are not treated with the vaccine, will contract the virus and die as a result. Scientific tests also indicate that there is a 1.01% chance that people treated with the vaccine will contract the virus and die as a result.

1. Would you accept or reject getting the vaccine?
    a. Definitely reject (1)
    b. Reject (2)
    c. Unsure, but leaning towards reject (3)
    d. Indifferent between accepting and rejecting (4)
    e. Unsure, but leaning towards accept (5)
    f. Accept (6)
    g. Definitely accept (7)

[DR/R/UR/ID/UA/A/DA]

Please indicate the extent by which you agree or disagree with the following statements.

2. I will accept getting the vaccine to protect myself
3. I will accept getting the vaccine to protect friends, family, and at-risk groups.
4. I will wait and see how the vaccine is working before getting it.
5. I will only get the vaccine if it was required by my work or school.
    a. Strongly disagree (1)
    b. Disagree (2)
    c. Mildly disagree (3)
    d. Neither agree nor disagree (4)
    e. Mildly agree (5)
    f. Agree (6)
    g. Strongly agree (7)

[SD/D/MD/NAD/MA/A/SA]

[follow-up treatments: not pre-registered]

[Non-betrayal: benchmark as before]
Specifically, some people that get the vaccine may die *due to problems unrelated to the vaccine.* Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to problems unrelated to the vaccine.**

[participants were randomly assigned to one of three treatments: Counter-Productivity, Government or Scientists (consult treatments Table in main text)]

[Active betrayal 2: by safety device's counter-productivity]
Specifically, some people that get the vaccine may die *due to the vaccine lowering the recipient's immunity making them more prone to catching the virus.* Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to the vaccine lowering the recipient's immunity making them more prone to catching the virus.**

[Government: Democrat led]
Specifically, some people that get the vaccine may die *due to a Democrat government in charge that approved the vaccine too rapidly, overlooking certain safety concerns.* Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to a Democrat government in charge that approved the vaccine too rapidly, overlooking certain safety concerns.**

[Government: Republican led]
Specifically, some people that get the vaccine may die *due to a Republican government in charge that approved the vaccine too rapidly, overlooking certain safety concerns.* Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to a Republican government in charge that approved the vaccine too rapidly, overlooking certain safety concerns.**

[Scientists: pharmaceutical companies]
Specifically, some people that get the vaccine may die *due to scientists working for pharmaceutical companies developing the vaccine too rapidly, overlooking certain safety concerns.* Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to *scientists working for pharmaceutical* companies developing the vaccine too rapidly, overlooking certain safety concerns.**

[Scientists: government]
Specifically, some people that get the vaccine may die *due to scientists working for the government developing the vaccine too rapidly, overlooking certain safety concerns.* Medical tests indicate that there is an additional one chance in 10,000 (0.01%) that someone who is treated with the vaccine will die **due to *scientists working for the government* developing the vaccine too rapidly, overlooking certain safety concerns.**

Indicate your preference below:
Would you accept or reject getting the vaccine? [DR/R/UR/ID/UA/A/DA]

[next page – real world experiences and demographic characteristics]

Next, you will be asked to answer non-hypothetical survey questions about real world experiences and demographic characteristics.

Please proceed to the next page to begin the survey.

Part 3: Vaccination History [U.S. specific]

Please answer the following survey questions on your own experiences:

6. Are you up to date on vaccines? [Y/N]
7. Have you gotten a flu vaccine during the current flu season? [yes/no]
8. In the last 5 years (not including the current flu season), how many times have you got the seasonal flu vaccine? [numeric]
9. As new effective vaccines come out in the future, do you plan on remaining up to date with vaccinations? [Y/N]
10. If you were travelling to a country and your doctor says that its recommended but not mandatory to get a vaccine while traveling (such as for Malaria or for Yellow Fever), would you get the vaccine? [Y/N]

Vaccine Confidence Index (VCI)

Please evaluate how much you agree or disagree with the following statements: [SD/D/MD/NAD/MA/A/SA]

11. It is important for individuals to get vaccinated
12. Overall, I think the vaccines currently available are safe
13. Overall, I think the vaccines currently available are effective
14. Vaccines are compatible with my religious belief

PACV [5-POINT Likert]

15. I trust the information I receive about vaccines. [SA/A/NS/D/SD]
16. It is better for my child to develop immunity by getting sick than to get a vaccine (if you do not have children, consider children in general). [SA/A/NS/D/SD]
17. It is better for children to get fewer vaccines at the same time. [SA/A/NS/D/SD]
18. Children get more vaccines than are good for them. [SA/A/NS/D/SD]
19. Overall, how hesitant about childhood vaccines would you consider yourself to be? [NAH/NTH/NS/SH/VH]

Part 4: COVID Vaccine history questions

20. Have you been vaccinated for COVID-19? [yes, partially, no]
    a. If yes or partially, under what category you got it?
        i. 65 years and older
        ii. Healthcare personnel
        iii. Educational sector personnel
        iv. Essential worker (other than health and education: e.g., police, firefighter)
        v. People aged 16-64 years with underlying medical conditions
        vi. Other [text field]

21. [If No in 1] If a COVID-19 vaccine became available to you, would you accept or reject getting the vaccine? [DR/R/UR/ID/UA/A/DA]

22. If you have been (or plan to be) vaccinated, why did (or will) you get the vaccine? [check all that apply]
    a. Self-protection
    b. Protecting more vulnerable family members
    c. Protecting more vulnerable peers/social circle
    d. Pressure from family members
    e. Pressure from peers/social circle
    f. To feel more comfortable outside home
    g. To participate in voluntary activities that require being vaccinated
    h. Required by work/school
    i. For travel purposes
    j. To set an example for others
    k. Other [please explain]
    l. Do not plan to get vaccinated

<u>Part 5: Demographic questions</u>

23. What is your current zip code?
24. Gender:
    a. Man
    b. Non-binary
    c. Woman
    d. Prefer to self-describe [text field]
25. Age (numeric field)
26. Are you
    a. American citizen
    b. Non-American citizen: please specify country of citizenship
27. Are you Hispanic or Latino?
    a. Yes
    b. no
28. How would you describe yourself?
    c. American Indian or Alaska Native
    d. Asian
    a. Black or African American
    b. Native Hawaiian or Other Pacific Islander
    c. White
    d. Other
29. How many children do you have (include stepchildren or any children whom you are/were a primary caregiver)? [Numeric field]
30. What is your total household income?
    a. Less than $10,000
    b. $10,000 to $19,999
    c. $20,000 to $29,999
    d. $30,000 to $39,999
    e. $40,000 to $49,999
    f. $50,000 to $59,999

   g. $60,000 to $69,999
   h. $70,000 to $79,999
   i. $80,000 to $89,999
   j. $90,000 to $99,999
   k. $100,000 to $149,999
   l. $150,000 or more
31. Are you a smoker?
   a. yes
   b. no
32. Do you:
   a. Work at a full-time job
   b. Work at a part-time job
   c. Do not have a job
33. Please indicate the highest level of education YOU completed:
   a. Some high school
   b. High school diploma or equivalent
   c. Some college or associate degree
   d. B.A.
   e. M.A./M.S./M.B.A.
   f. M.D./J.D./PhD
   g. Other

34. Generally speaking, what do you usually think of yourself as politically?
   a. Republican
   b. Democrat
   c. Libertarian
   d. Independent
   e. Something else

Part 6: Other supplementary questions (including some (not all) Global Preference Survey measures)

35. How willing or unwilling are you to take risks. [SU/U/SWU/NWU/SWW/W/SW]
   c. Strongly unwilling [SU]
   d. Unwilling [U]
   e. Somewhat unwilling [SWU]
   f. Neither willing nor unwilling [NWU]
   g. Somewhat willing [SWW]
   h. Willing [W]
   i. Strongly willing [SW]
36. How willing or unwilling are you to give up something that is beneficial for you today in order to benefit more from that in the future. [SU/U/SWU/NWU/SWW/W/SW]
37. How willing or unwilling are you to punish someone who treats YOU unfairly, even if there may be costs for you. [SU/U/SWU/NWU/SWW/W/SW]
38. How willing or unwilling are you to punish someone who treats OTHERS unfairly, even if there may be costs for you. [SU/U/SWU/NWU/SWW/W/SW]

39. How willing or unwilling are you to give to good causes without expecting anything in return. [SU/U/SWU/NWU/SWW/W/SW]

How much do you agree with each of the following statements?

40. When someone does me a favor, I am willing to return it. [SD/D/MD/NAD/MA/A/SA]
41. People can generally be trusted. [SD/D/MD/NAD/MA/A/SA]
42. Government can generally be trusted. [SD/D/MD/NAD/MA/A/SA]
43. Media can generally be trusted. [SD/D/MD/NAD/MA/A/SA]
44. Scientists can generally be trusted. [SD/D/MD/NAD/MA/A/SA]

Now, we will ask you some questions about future, uncertain outcomes. In each case, try to think about the whole range of possible outcomes and think about how likely they are to occur during the next 12 months. In some of the questions, we will ask you about the PERCENT CHANCE of something happening. The percent chance must be a number between zero and one hundred. Numbers like 2 or 5 percent may be "almost no chance," 20 percent or so may mean "not much chance," a 45 or 55 percent chance may be a "pretty even chance," 80 percent or so may mean a "very good chance," and a 95 or 98 percent chance may be "almost certain." The percent chance can also be thought of as the NUMBER OF CHANCES OUT OF 100.

45. Estimate the following:
    The percentage of the population you believe are willing to receive at some point, or have already received, a vaccination for COVID-19 [Toggle bar]
46. Estimate the following:
    How do you think an average American resident would answer the previous question? [Toggle bar]

47. To what extent are you afraid of the COVID-19 pandemic?
    j. An extremely small extent [ES]
    k. A small extent [S]
    l. A somewhat small extent [SWS]
    m. A moderate extent [M]
    n. A somewhat large extent [SWL]
    o. A large extent [L]
    p. An extremely large extent [EL]

How much do you agree with each of the following statements?

48. I have regularly practiced social distancing in response to the Covid-19 pandemic.
49. I believe that one should practice social distancing in response to the COVID-19 pandemic. [SD/D/MD/NAD/MA/A/SA]

50. Estimate the following:
    The percentage of the population who are practicing social distancing in response to the COVID-19 pandemic.
51. Estimate the following:
    The percentage of the population who believe that one should practice social distancing in response to the COVID-19 pandemic.

52. Suppose there is a crisis and **other people** make a decision or provide information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? [ES/S/SWS/M/SWL/L/EL]
    q. An extremely small extent [ES]
    r. A small extent [S]
    s. A somewhat small extent [SWS]
    t. A moderate extent [M]
    u. A somewhat large extent [SWL]
    v. A large extent [L]
    w. An extremely large extent [EL]
53. Suppose there is a crisis and **the government** makes a decision or provides information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? [ES/S/SWS/M/SWL/L/EL]
54. Suppose there is a crisis and **the media** makes a decision or provides information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? [ES/S/SWS/M/SWL/L/EL]
55. Suppose there is a crisis and **scientists** make a decision or provides information that makes matters worse. To what extent would you experience negative emotions (e.g. sadness or anger) as a result? [ES/S/SWS/M/SWL/L/EL]

Check questions to be included:

1. There are 12 days in a week (True/False)
2. There are two L's in the word "Log" (True/False)
3. Dogs have wings (True/False)
4. Would you rather have $50 or $75?
5. Fish live in water (True/False)

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