The Behavioral and Neural Mechanisms of

Social and Non-Social Risky Decision-Making

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ABSTRACT

Decisions made under risk have been primarily studied within economic contexts (Platt & Huettel, 2008). This has led to the development of sound methods and models for studying risky choice behavior (Rangel, Camerer & Montague, 2008). In particular, these models are helpful for estimating how much risk an individual is willing to tolerate. However, there may be a limit in the extent to which we can generalize these estimations, in that economic models do not take into account the underlying social preferences that often guide decision makers (Fehr & Camerer, 2007; Fehr & Schmidt, 2004). This suggests that an individual's propensity for risk may be different depending on social or non-social information present within the environment (Bohnet, Greig, Herrmann & Zeckhauser, 2008). The present study aimed to: (i) assess how risk preferences may differ across social and non-social contexts; (ii) identify common and distinct neural correlates of social and non-social risk; and (iii) determine neural characteristics associated with individual sensitivities to social and non-social risk. Subjects (N=30) played an adaptation of the Trust Game while their blood-oxygen-level-dependent response was monitored using functional magnetic resonance imaging. Differences in risk preferences across social and non-social conditions as well as neuroimaging correlates of social and non-social risk will be discussed.

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Introduction

Smoking, drinking alcohol, drug use, and poor diet have been classified as the leading *preventable* causes of death worldwide (WHO, 2013). These risky behaviors often occur within social contexts (Link & Phelan, 1995; Poland, Frohlich, Haines, Mykhalovskiy, & Rock, 2006; Wells & Graham, 2002), thereby highlighting the importance of understanding the mechanisms underlying social and non-social risk is essential. Identifying the extent to which risky behaviors differ across social and non-social conditions may better inform potential methods to predict and regulate cognitions and behaviors that lead to risky decision-making.

Decisions made under risk have been primarily studied within economic contexts (Platt & Huettel, 2008), which has led to the development of sound methods and models for studying risky choice behavior (Rangel, Camerer & Montague, 2008). In particular, these models are helpful for estimating how much risk an individual is willing to tolerate. However, there may be a limit in the extent to which we can generalize these estimations, in that economic models do not take into account the underlying social preferences that often guide decision makers (Fehr & Camerer, 2007; Fehr & Schmidt, 2004). In other words, an individual's propensity for risk may be different depending on social or non-social information.

The present study investigates the extent to which risk preferences vary across social and non-social contexts. Additionally, in order to gain a deeper understanding of this variability in risk preferences, functional magnetic resonance imaging methods were used to identify common and distinct neural correlates of social and non-social risk. Lastly, the current study aims to identify neural correlates of an individual's sensitivity to social risk, over and above non-social risk.

Background

Definition of Uncertainty

Uncertainty can be described as a state of having limited knowledge where the decision maker cannot exactly describe the existing state or make predictions of future outcomes (Knight, 1921). Uncertain situations can vary and be described in terms of the degree of uncertainty associated with a particular set of options. The degree of uncertainty can vary from risky to ambiguous, in which the probabilities of possible outcomes are known or unknown to the decision maker, respectively. Risky choices are defined as situations where the decision maker knows with certainty the probabilities of outcomes (Camerer & Weber, 1992; Hsu, Bhatt, Adolphs, Tranel & Camerer, 2005; Huettel, Stowe, Gordon, Warner & Platt, 2006). Examples of such situations may include choosing to bet on the spin of a roulette wheel or the flip of a fair coin.

Objective Measurement of Risk

Risk is objectively measured by the variation in the probabilities of a situation's outcomes. To increase risk, probabilities and payoffs of high and low outcomes can be manipulated while maintaining the mean preserving spread (Rothschild & Stiglitz, 1970). The extent of variability in relation to the mean of the population can be represented as unitized risk, which is the ratio of the standard deviation to the mean. Therefore, more risky decisions are those where there is large variability within the distribution of possible outcomes, and less risky decisions indicate small variability within the distribution of possible outcomes.

Economic Models of Risky Decision-Making

Expected utility theory (EUT). Expected Utility Theory is the predominant framework used by economists and psychologists to study how risk is incorporated into valuations of

uncertain outcomes (Bernoulli, 1954; Glimcher, 2004). The prevalence of EUT can be attributed to its simple yet powerful framework and interpretability. Before defining and explaining the expected utility function, it is essential to first introduce the concept of expected value. Pascal proposed that choices are a function of each option's objective value (x) multiplied by the likelihood of receiving the outcome (i.e., probability, p): $EV(x) = \Sigma p(x)x$ (Glimcher, 2004; Knutson, Taylor, Kaufman, Peterson & Glover, 2005). In other words, expected value represents the weighted average payoff for a given option. After performing this calculation for each option, a rational decision maker should choose the option with the highest expected value.

To improve the predictive power of expected value, Bernoulli (1954) proposed a new decision criterion based on the idea that decision makers are maximizers of expected utility rather than expected value. This decision criterion, utility, incorporates not only the option's objective value, as in expected value theory, but also an individual's subjective hidden preference for a particular outcome given a variety of factors including wealth level and aversion to risk. Mathematically, expected utility is represented by the following functional form, $EU(x) = \Sigma p(x)u(x)$, where the expected utility of a monetary outcome (x) is equal to the sum of the probability of outcome $p(x)$ multiplied by the utility of outcome $u(x)$. In practice, the decision maker who maximizes expected utility would calculate and compare the utilities for all options in order to find the option with the highest value. Thus, EUT allows for the incorporation of both objective values of options and the individual's subjective preferences for a particular outcome given factors such as wealth level and tolerance for risk. By expanding the expected value model to incorporate these subjective preferences, studies have shown that predictive ability of EUT has significantly improved (Glimcher, 2004).

Axioms of expected utility. According to Von Neumann and Morgenstern (1947), predictions based on EUT must meet the following decision rules (axioms): (i) completeness; (ii) transitivity; (iii) continuity; and, (iv) independence. The first axiom of completeness states that for any outcome A and outcome B, the following must be satisfied: $A > B, A = B, or\ B > A$. It is assumed that the decision maker has a defined preference for either outcome $A\ (A > B)$ or outcome $B\ (B > A)$ or that there is no preference for either outcome $(A = B)$. The transitivity axiom states that if $A > B$ and $B > C$, then it must follow that $A > C$. This maintains that the decision maker's preferences are consistent. Given the lotteries $A, B,$ and C, the continuity axiom states that if preferences are as follows $A > B$ and $B > C$, then some combination of preferences A and C should be equivalent to the decision maker's preference for option B. The last axiom of independence assumes that given preferences of outcomes $A > B$, then this relationship should not change even if another outcome C is added to the outcomes of A and B, respectively. Fulfillment of all the above axioms allows the use of EUT to explain an individual's preferences such that utility values can be assigned to each possible outcome where the rational choice is the one with the highest expected utility.

Risk preferences. EUT allows for the integration of a variety of factors, including individual preferences for risk, to enter into the utility function. Although there is a propensity for risk aversion in uncertain situations, there are individual differences in the uncertainty one is willing to tolerate (Weber, 2009). This inter-individual dimension can be referred to as an individual's risk attitude. The three types of risk attitudes are as follows: risk averse, risk neutral and risk seeking. These attitudes are reflected by the fit of the utility function to the decision maker's set of choices. For instance, if given the choice between a certain payoff of $50 or a 50% chance of receiving $100 or nothing, risk aversion can be described as the reluctance to

accept the uncertain option over the uncertain option. When expected value of the options are equivalent, like in the above example, a risk averse individual would always prefer to choose the certain payoff of $50 over the possibility of earning $100. A concave shape represents the utility function of a risk averse individual where the marginal utility of money diminishes at increasing objective amounts of wealth (see Figure 1). For instance, at lower levels of wealth, increases in wealth are met with higher increases in utility, and as units of wealth are added there is less of an increase in utility. This effect is called diminishing marginal utility. In other words, an individual whose wealth has increased from zero to one million will have greater utility for this change in wealth compared to an individual whose wealth increases from one to two million, two to three million, etc. In contrast, a convex shape of the utility function represents the preferences of a risk seeker such that the marginal utility of money increases as the amount of money increases. In the above example, a risk seeking individual would prefer the uncertain option of earning $100 or nothing as the payoff of $100 is greater than the certain payoff of earning $50. In other words, a risk seeker would have greater utility for increases in the amount of wealth at higher levels of wealth. Lastly, a risk neutral individual is indifferent to both the certain and uncertain payoffs where the utility can be represented by a straight line. Another way to understand how a risk neutral individual views both options is that maximizing utility is equal to maximizing expected value since there is no preference for either the certain or uncertain payoff.

The expected utility model provides us with a quantitative framework to describe and estimate not only an individual's attitude toward risky situations, but it also gives us a language to discuss how people make decisions under risk. Two key terms that are used within this framework to describe how individuals make choices are *certainty equivalent* and *risk premium*. Certainty equivalent refers to the guaranteed amount of money that an individual is willing to

accept that is equivalent to the risky gamble (Weber, 2009). Risk premium refers to the amount of money an individual is willing to give up in order to avoid the risk (Weber, 2009). This can be represented by the difference between the expected value or average payoff of an option and the certainty equivalent. For instance, if given the choice between $45 for certain and 50% chance of earning $100 and a 50% chance of earning 0, the certainty equivalent would be equal to $45 while the risk premium is equal to the difference between the expected value of the gamble ($50) and the certainty equivalent ($45) which is $5.

Measures of degrees of risk aversion. Arrow (1965) and Pratt (1964) proposed two measures that model how a decision maker's willingness to take the risky gamble would change as an individual's wealth level changes. The first measure of constant absolute risk aversion (CARA) is defined as $ARA(x) = -u''(x)/u'(x)$, where u' and u'' are equal to the first and second derivative of the utility function u. Under this functional form, the risk premium that a decision maker would pay to avoid the risk is the same across all wealth levels. This function implies that an individual at lower levels of wealth will be willing to bear the same amount of risk as an individual at higher levels of wealth. To address the commonly held assumption that individuals at higher wealth levels can bear more risk than those at lower wealth levels, Arrow (1965) and Pratt (1964) proposed another slightly different but related measure, constant relative risk aversion (CRRA). CRRA is defined $RRA(x) = -x \bullet u''(x)/u'(x)$, where x represents the monetary value that the agent will receive and where u' and u'' are equal to the first and second derivative of the utility function u. This measure reflects the property in which risk aversion is always relative to an individual's current wealth. Specifically, a decision maker becomes more willing to make risky choices proportional to his or her wealth at increasing levels of wealth.

Risk Behavior in Social Contexts

The majority of previous work on risky decision-making has focused on how individuals make decisions within non-social economic environments where one is asked to make a choice between monetary gambles. However, navigating social environments involves interacting with others and may result in making challenging and complex decisions that involve evaluating uncertain outcomes determined by a social partner (King-Casas, Tomlin, Anen, Camerer, Quartz, & Montague, 2005). Under standard economic models of risk described above, the utilities of risky options are independent of the source of the risk (e.g., spin of a roulette wheel or a social partner) (Bernoulli, 1954). In other words, if given the choice between accepting $45 with certainty or 50/50 gamble of earning $100 or nothing, an individual should make the same selection regardless of the mechanism that generated the outcome. However, the source of uncertainty, either social or non-social, may potentially influence decision-making behavior in different ways.

There are inherent differences between social and non-social environments. Social decision-making situations involve interactions with other individuals that increase the complexity of the decision problem such that decision outcomes not only affect the individual but can also affect others as well. However, non-social contexts do not include this additional element and do not require the individual to consider how decisions will affect another. Thus, it follows that we may also expect to see differences in risky choice behavior between risks generated by non-social versus social sources. For instance, in social contexts, it may be that the likelihood of receiving the outcome of a specific option is dependent on a social partner, where beliefs and expectations about this partner influence the perceived likelihood of receiving the outcome (Fehr & Camerer, 2007; Rilling, King-Casas, & Sanfey, 2008).

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A prime example of making risky decisions within social contexts is deciding whether or not to trust a social partner. Trust implies investing valued resources (i.e., money, time, emotions) in another person with the hope that the investment will be reciprocated in the future. The use of economic exchange games derived from game theory models has demonstrated success in understanding how individuals' preferences and motives guide social interactions (Fehr & Camerer, 2007; Rilling, King-Casas, & Sanfey, 2008). One such example is the Trust Game, which is particularly useful for studying risk aversion in reciprocal exchanges of trust between social partners.

In the Trust Game, an investor is given an initial endowment and must decide how much of this endowment should be given to a partner, known as a trustee. If the investor does entrust the trustee with all or some of the endowment, this action is usually performed in the hopes that at least part of the endowment will be returned. The amount given by the investor to the trustee is tripled and the trustee then has the opportunity to decide how much of the invested amount to keep and send back to the investor. If the trustee reciprocates trust and returns at least the amount of money invested back to the investor, both players will end up with a larger payoff relative to the initial endowment. On the other hand, if the trustee does not reciprocate trust and decides to keep the transferred endowment, then the investor would lose the amount that was invested.

In order to gain a better understanding of the relationship between trust behaviors and risk attitudes, it is important to discuss how willingness to trust (i.e., willingness to take a social risk) is influenced by other parameters that are specific to social contexts. An example of this can be seen in violations of game theory predictions in the traditional Trust Game. Under these predictions, a rational investor assumes that the trustee will always keep the invested endowment and thus should always make the decision to keep the endowment rather than invest in the

trustee. However, in a one-shot Trust Game, investors typically entrust at least a portion of their endowment to the trustee and the trustee generally reciprocates trust by sending some or all of the invested amount back to the investor (Camerer, 2003). This behavior provides evidence that individuals may not exclusively act in self-interest, but may also gain or lose utility based on social preferences such as altruism, fairness, inequity aversion, and betrayal aversion (Fehr & Camerer, 2007).

Various behavioral studies have demonstrated that the addition of a social element to traditional economic paradigms influences risky decision making behaviors (Aimone & Houser, 2008; Bohnet & Zeckhauser, 2004; Bohnet, Greig, Herrmann & Zeckhauser, 2008; Fehr & Schmidt, 2002). For instance, Bohnet et al. (2008) found that participants in six countries had different risk acceptance frequencies for gambles determined by a non-social versus social source. A growing body of evidence indicates that individuals have social preferences where decisions are based on a positive or negative concern for the welfare of others and indicative of what they want others to believe about them (Fehr & Camerer, 2007). These social preferences may impact the utility an individual has for a gamble, such that one might send over part of an endowment to a social partner without expectation of repayment simply due to the increased utility that an individual derives from being altruistic. In this case, it would be expected that in situations where the source that generates outcomes is a human partner, the individual would experience decreased risk aversion due to the gain in utility that one receives due to social preferences for another's well being.

On the other hand, an individual may be less willing to trust (i.e., take a social risk) when a social partner relative to a non-social probabilistic mechanism determines the source of risk. This social preference is known as betrayal aversion (Aimone & Houser, 2008; Bohnet et al.,

2008). In this case, it is expected that betrayal by a social partner creates additional disutility above the monetary loss that is incurred, which ultimately results in increased risk aversion when the source generating outcomes is determined by a social partner.

A number of studies have used the Trust Game to further elucidate the relationship between attitudes toward risk and trusting decisions (Houser, Schunk, & Winter, 2010; Karlan, 2005; Schechter, 2007). However, how the role of risk attitudes affects trust behavior remains unclear. For instance, Schechter (2007) conducted two experiments in which subjects from fifteen villages in Paraguay played two games: (i) a game designed to measure risk attitudes and (ii) the traditional Trust Game, where both games had a similar payoff structure. Schechter (2007) found that non-social risk attitudes strongly predicted participant's willingness to trust (i.e., take a social risk) in the Trust Game. Conversely, Houser et al. (2010) conducted experiments where participants played an investment game and the only difference in treatment conditions was whether return decisions were made by a human partner or a computer. Findings from Houser et al. (2010) demonstrated no systematic relationship between attitudes toward risk and willingness to trust where risk attitudes did not predict trust decisions as previously demonstrated by Schechter (2007).

Taken together, there is evidence (Bohnet et al., 2008) to suggest that decisions made in social compared to non-social contexts may result in different risk taking behavior. However, these findings also make apparent the lack of clarity within the literature in distinguishing how risk preferences and behavioral choices may differ between social and non-social types of risks. The conflicting results between Schechter (2007) and Houser et al. (2010) may be due to the fact that social risk was measured by trust behavior in the Trust Game. Although trust can be thought of as a form of social risk, it is not analogous to a risky situation in that the probabilities of

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outcomes generated by social partners are not explicitly known. Rather, the context of the Trust Game more closely resembles an ambiguous situation where probabilities of outcomes are not known.

In order to directly compare risky decision making behavior between socially generated and non-socially generated risk, the present study uses an adaptation of the Trust Game where probabilities of outcomes in the social condition are known. In addition, the current study seeks to deepen our understanding of how social preferences are incorporated into our risk valuations by studying the neural correlates of social and non-social risk using functional magnetic resonance imaging methods.

Functional Magnetic Resonance Imaging

Functional magnetic resonance imaging (fMRI) is a tool used to measure functional activity in the brain for both clinical and research purposes (Huettel, 2004). Expanding on MRI technology, fMRI allows for the indirect measurement of cognitive processing associated with the reaction to a given stimulus, thereby enabling researchers to correlate activity in specific brain structures with responses to a wide range of stimuli. The idea behind this technology lies in the assumption that cognitive processing is related to increasing firing rates of neurons, which tends to require increased delivery of metabolic resources via the blood stream. Dilation of blood vessels allows for a surge of oxygenated blood to supply energy to areas with increased neural activity in the brain. As the name implies, fMRI takes advantage of the magnetic property, iron, which is found in hemoglobin in order to measure blood flow. Hemoglobin is responsible for transporting oxygen in red blood cells. When oxygen is not bound to these iron atoms (i.e., deoxygenated hemoglobin), these atoms cause small distortions to the surrounding magnetic field. Thus, when blood flows to sites of increased activity, there are several reactions that

follow. First, the hemodynamic response or blood flow in the brain as well as cerebral blood volume increases, in which an increased amount of oxygenated blood enters areas of the brain that are active in response to the intended stimuli. This then causes a reduced amount of deoxygenated blood producing small changes to the magnetic field. These changes in the magnetic field are captured by the MRI signal. When these field changes start to decrease, the MRI signal increases and generates what is known as the blood-oxygen-level-dependent (BOLD) response (Huettel, 2004). Thus, using properties of physics and multivariate statistics, researchers are able to measure this BOLD response to various stimuli and tasks.

Risky Decision-Making and the Brain

Due to the utilization of economic models in conjunction with neuroimaging methods, researchers have been particularly successful in identifying various neural substrates of non-social risk in the brain. Under standard models of expected utility, it is assumed that agents will choose the option with the highest utility. These decisions typically are based on two parameters: (i) the expected value associated with the outcomes and (ii) the risk or statistical variance of the outcomes (Stephen & Krebs, 1986). Tobler, O'Doherty, Dolan & Schultz (2007) found that when participants were asked to discriminate between stimuli associated with varying levels of expected value and variance, these two parameters were correlated with neural responses in two distinct regions. Specifically, stimuli that were associated with higher levels of expected value were related to increasing activation in the ventral striatum, while stimuli related to higher levels of variance were significantly correlated with increasing activation in the lateral orbitofrontal cortex (lOFC). High expected value of an option increases the likelihood that it will be chosen by all individuals. However, individual differences in risk preferences may also have the potential to increase or decrease the utility of a given option. In the same study, Tobler et al. (2007) found

that individual risk attitudes may involve different areas of the prefrontal cortex such that risk aversion may be related to lOFC and risk seeking with medial (OFC) responses. Consistent with these findings, lesion studies provide evidence that the OFC is involved in the processing of uncertainty due to differences in participants' sensitivity to risk pre- and post-injury (Bechara, Damasio, Damasio & Anderson, 1994; Hsu et al., 2005; Sanfey, Hastie, Colvan & Grafman, 2003).

Another region frequently identified to be involved in risk processing is the insula (Kuhnen & Knutson, 2005; Huettel et al., 2006; Paulus, Rogalsky, Simmons, Feinstein & Stein, 2003; Platt & Huettel, 2008; Preuschoff, Quartz, & Bossaerts, 2008). A common result found across multiple studies is the increased neural response of the insular cortex when risky relative to safe outcomes are chosen (Kuhnen & Knutson, 2005; Paulus et al., 2003; Platt & Huettel, 2008; Preuschoff et al., 2008). However, Preuschoff et al. (2008) conducted a study that provides evidence that the insula may be the primary region involved in a risk prediction system that functions analogous to the well documented reward prediction system (Schultz, Dayan & Montague, 1997). Particularly, risk prediction as well as risk prediction errors were related to increases in bilateral insula activation (Preuschoff et al., 2008).

Other regions such as the prefrontal cortex (Tobler, Christopoulos, O'Doherty, Dolan & Schultz, 2009), anterior cingulate (Kuhnen & Knutson, 2005), and posterior parietal cortex (Huettel et al., 2006) have also been associated with risk. For example, BOLD responses in the prefrontal cortex (PFC) changed as a function of the subject's risk preference such that risk-seekers exhibited increased hemodynamic activity in the PFC while risk-averse subjects exhibited decreased activity (Tobler et al., 2009). Consistent with this finding, Huettel et al. (2006) also found that risk preference was significantly correlated with neural responses in the

lateral PFC. In addition, Kuhnen & Knutson (2005) found increases in the anterior cingulate (ACC) reflected conflict during financial risk taking decisions. In a study examining the neural correlates of risk and ambiguity, Huettel et al. (2006) provided evidence showing that posterior parietal cortex activation was modulated by individuals' preferences for risk.

As evidenced by previous literature, it is apparent that the processing of risk is related to activation in multiple regions and that individual risk preferences are also represented in the brain (Platt & Huettel, 2008). The majority of literature has focused on examining risk in monetary decision-making contexts where outcomes are generated by non-social probabilistic mechanisms. However, the research investigating behavioral and neural differences in social and non-social risk is limited. Although there are few studies directly comparing how the brain encodes socially generated and non-socially generated risks, there is a growing body of literature examining the underlying neural substrates of trust, a form of social risk.

One method researchers have utilized to study risk in the brain is the Trust Game in which participants make decisions involving a social partner. There are a number of studies that compare differences in decision-related neural activity between interactions involving a social versus a non-social (computer) partner. These studies highlight patterns of responses specific to social compared to non-social stimuli. For instance, in a study examining cooperation within the Trust Game, an increased BOLD response of the PFC was found when subjects were playing the game with a human partner over a computer partner that had a fixed and known probabilistic strategy (McCabe, Houser, Ryan, Smith & Trouard, 2001). Similarly, another study identified increased levels of BOLD response in the dorsolateral prefrontal cortex (dlPFC), posterior cingulate and temporal-parietal junction (TPJ) when subjects played the Trust Game with a human compared to a computer partner (Rilling, Sanfey, Aronson, Nystrom & Cohen, 2004). In

a later study, researchers showed that increased dlPFC activity was associated with the building up of trust and that this activity declines after trust has been established within an interaction which suggests that this region may be involved in learning the trustworthiness of a social partner (Krueger, McCabe, Moll, Kriegeskorte, Strenziok & Graftman, 2007; Rilling & Sanfey, 2011). These findings provide evidence that there are differences in neural responses to social relative to non-social stimuli. Thus, it is clear that the introduction of social elements to the decision environment influences individuals to make different choices. Since choices are reflections of an individual's preferences, then it follows that they may also exhibit different risk preferences in response to social or non-social risk.

The level of risk involved in decisions to trust incorporates an agent's assessment of a partner's trustworthiness (Rilling & Sanfey, 2011). This assessment can be influenced by a myriad of potential factors. The willingness to take a social risk by trusting a social partner is significantly associated with facial judgments of trustworthiness (Van't Wout & Sanfey, 2008). Several research studies provide evidence that neural responses in the amygdala changed as a function of facial trustworthiness such that amygdala response increased when viewing untrustworthy faces (Todorov, Baron & Oosterhof, 2008; Winston, Strange, O'Doherty, & Dolan, 2002). Interestingly, exposure to increased levels of oxytocin, a neuropeptide that is linked to trusting behavior, decreases amygdala activity in males (Baumgartner, Heinrichs, Vonlanthen, Fischbacher, & Fehr, 2008).

Another potential factor that could potentially influence trust behavior is perceptions of another's moral character. Delgado, Frank, & Phelps (2005) conducted a study where participants played a modified version of the Trust Game, where participants played three fictional partners whose descriptions revealed their overall moral character as being "bad",

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"neutral", or "good." Although the three fictional partners were designed to have the same probability of repayment and after completing multiple trials where participants indicated that the three fictional partners had similar repayment rates, participants still continued to invest in partners of "good" moral character and invest less in those of "bad" moral character. Activity in the cingulate and insular cortex regions, regions associated with cognitive control and conflict judgments, were correlated with making decisions to invest in partners of "good" moral character over partners of "bad" moral character. In line with previous studies, increased activation of the caudate nucleus, a region associated with trial and error learning with feedback, was found for positive relative to negative feedback for neutral partners. These findings demonstrate that the addition of social partners to risky choice decisions adds a layer of complexity that differentially affects economic decisions and the underlying substrates of those decisions in comparison to situations void of social elements.

In another study investigating the individual variation in motivations for repayment in the Trust Game, activation in the TPJ, bilateral anterior insula and ACC was modulated by individual differences in social value orientation (i.e., pro-social or pro-self) (Van Den Bos, Dijk, Westenberg, Rombouts, & Crone, 2009). In particular, participants who identified as pro-social exhibited increased ventral striatal and insular cortex activity when choosing to reciprocate compared to when choosing to defect, while pro-self individuals exhibited decreased activity in both regions (Van Den Bos et al., 2009). Another study showed that individual differences in social preferences over the allocation of resources have also been shown to scale with activity in the amygdala (Haruno & Frith, 2009). This social preference for inequity aversion, the preference for fairness between oneself and others, was related to increased hemodynamic activity in the amygdala for pro-social individuals (Haruno & Frith, 2009).

In summary, researchers have identified common and distinct neural correlates associated with risk and trust. Common regions affiliated with non-social risk and trust include the amygdala (Van't Wout & Sanfey, 2008; Winston et al., 2002; Haruno & Frith, 2009), insula (Presuchoff et al., 2008; Kuhnen & Knutson, 2005; Paulus et al., 2003), and ACC (Kuhnen & Knutson, 2005; Christopoulos, Tobler, Bossaerts, Dolan, & Schultz, 2009; Van Den Bos et al., 2009). These regions are primarily associated with the processing of emotions, interpersonal experience, conflict monitoring and the processing of rewards. Although processing in non-social risk and trust recruit common regions, researchers have also identified distinct neural substrates of non-social risk and trust. Regions unique to non-social risk include the lOFC (Tobler et al., 2007) and posterior parietal cortex (Huettel et al., 2006), which are involved in several functions such as decision-making and the integration of sensory information. On the other hand, the main region distinguishing trust from non-social risk is the TPJ (Rilling et al., 2004; Van Den Bos et al., 2009). This region is particularly important for social and interpersonal ability as well as the ability to discriminate between the intentions and beliefs of others and one's own.

Decisions made under risk have been primarily studied by assessing the tradeoffs made between economic parameters such as expected value and the variability within a distribution of outcomes. Expected utility theory, a predominant and empirically supported quantitative model, has been influential in the understanding of decision-making under risk (Rangel et al., 2007; Weber, 2009). Under standard models of expected utility, it is assumed that risky choices are not influenced by the source of uncertainty. In other words, these models assume that the decision maker should choose the same option regardless of whether the outcomes are generated by the roll of a die, horse race, or human partner. However, given the inherent differences between non-

social (e.g., roll of a die) and social (e.g., human partner) contexts, this assumption may not represent decision-making in the real world.

Utilizing expected utility models, risk attitudes can be estimated to indicate how much uncertainty a decision maker is willing to tolerate. There is evidence to suggest that an individual's risk attitude during trust exchanges, a form of social risk, is different from that of non-social contexts (Schechter, 2007). The study of the neurobiological substrates associated with non-social and social risk may provide us with a deeper understanding of the mechanisms that underlie behavioral differences in decisions made across these contexts.

The purpose of the present study is to examine the extent to which the source of uncertainty affects behavioral decisions as well as to investigate the neural correlates associated with social risk and non-social risk. Across behavioral and neuroimaging studies, it is suggested that choice behavior differs in social versus non-social contexts (Aimone & Houser, 2008; Bohnet & Zeckhauser, 2004; Eckel & Wilson, 2004; Fehr & Schmidt, 2004). It also has been shown that decisions may differ in response to social compared to non-social stimuli (McCabe et al., 2001; Rilling et al., 2004). This evidence suggests that these behavioral differences may be a reflection of an individual's risk preference, where utilities for socially or non-socially generated risks may not be equivalent.

Specific Aims

1.   To assess differences in risk preferences for socially generated risks compared to non-socially generated risks.

Hypothesis 1: There will be significant variability in risk preferences when risk is generated by a social source (i.e., social partner) compared to when risk is generated

by a non-social source (i.e., non-social probabilistic mechanism) (Bohnet et al., 2008; Bohnet & Zeckhauser, 2004; Fehr & Schmidt, 2004).

2.   To identify the common and distinct neural correlates associated with socially generated risks and non-socially generated risks.

Hypothesis 2: Neural responses to risk across social and non-social conditions will be associated with hemodynamic activity in the insula (Kuhnen & Knutson, 2005; Presuchoff et al., 2008; Paulus et al., 2003). Hemodynamic activity specific to non-socially generated risks relative to socially generated risks will be found in the lateral orbitofrontal cortex (Tobler et al., 2007) and posterior parietal cortex (Huettel et al., 2006) while socially generated risks relative to non-socially generated risks will be found in the TPJ (Rilling et al., 2004; Van Den Bos et al., 2009).

3.   To determine the neural characteristics that distinguish between (i) individuals who are more sensitive to socially (relative to non-socially) generated risks and (ii) individuals who are more sensitive to non-socially (relative to socially) generated risks.

Hypothesis 3: During the decision phase, it is expected that when making risky relative to safe choices, sensitivity to non-socially generated risk will be associated with decreased amygdala activity while sensitivity to socially generated risk will be associated with increased amygdala activity (Haruno & Frith, 2009; Todorov et al., 2008; Van't Wout & Sanfey, 2008; Winston et al., 2004).

Method

Participants

Thirty-eight right-handed participants with a mean age of 26 years (SD=7 yrs.; females= 23) were recruited from the Houston metropolitan area. The methods of recruitment that were used included: word of mouth, posters/flyers, internet ads, newspaper ads, and brochures. All participants were monetarily compensated for their time. Participants were paid a minimum amount of twenty dollars for each hour spent in the MRI scanner and ten dollars per hour for filling out pre- and post-task behavioral questionnaires. In addition to the base compensation, participants had the opportunity to earn additional compensation based on their performance in the task. This strategy was used in order to incentivize participants to make choices in the game as they would in real life (Smith, 1976). In addition, in order to remove possibility of potential wealth effects, compensation was determined in the following way. Three of the 86 trials were randomly selected and subjects were paid based on performance in one of the three trials in addition to the base compensation rate.

Prior to enrollment in the study, subjects answered screening questions to determine whether they met the inclusion and exclusion criteria for the study. Inclusion criteria consisted of men and women ages 18 to 64 of all ethnicities. In addition, in order to be eligible to participate, subjects must have had vision corrected in order to see the computer screen clearly. Participants were excluded if they had contraindications to magnetic resonance imaging (MRI), such as claustrophobia, history of head injury resulting in loss of consciousness for more than 10 minutes, pregnancy, use of a pacemaker, aneurysm clips, neurostimulators, cochlear implants, metal in the eyes, or other implants. All subjects provided verbal consent upon being screened

either on the phone or in-person. All participants provided written informed consent as part of an approved protocol by the Baylor College of Medicine Institutional Review Board.

Data from five participants were excluded prior to individual and group level analysis due to > 3mm of movement across the x, y, and z dimensions (Friston, Williams, Howard, Frackowiak, & Turner, 1996), and three participants with extreme risk aversion parameters were excluded (detailed in RA Results section).

Experimental Paradigm

Subjects played an adaptation of the Trust Game while their BOLD response was monitored using fMRI. The Trust Game is an economic exchange game that has been used to quantify trust and reciprocity in an interpersonal interaction (Berg, Dickhaut, & McCabe, 1995).

The current study used a within-subjects design consisting of two conditions: social risk and non-social risk. Subjects made a total of 86 decisions of which 43 were social risk and 43 were non-social risk. The order of the blocks was balanced across subjects in order to remove possible order effects. On each trial, subjects ("investors") chose between two options: (i) to keep the original endowment that ranged from five to fifteen dollars (certain outcome) or (ii) to gamble their endowment for a chance of a higher payoff (risky outcome).

In one condition ('social risk'), participants chose to gamble their endowment with a social partner ("trustee"), which was represented by a picture of an individual from a previous experiment (see Figure 2). Trustees were depicted using neutral face images of actual trustees from a previous study who had consented for their images to be used as stimuli in future experiments. Neutral face images were used in order to control for bias effects of gender, ethnicity, and facial expression. The faces included both men and women from diverse racial and ethnic backgrounds, and pairings of faces to options were randomized across trials to mitigate

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possible learning effects. If the subjects chose to invest their endowment in the trustee, the trustee then could reciprocate by giving back a larger or smaller amount of the invested endowment back to the investor. The investor was shown the percentage of times the trustee has 'repaid' trust in the past.

In a second condition ('non-social risk'), the investor similarly chose to either keep their endowment that ranged between five and fifteen dollars or give up their endowment in order to accept a risky gamble (see Figure 2). The game mechanics in addition to the probabilities and amounts of repayment were identical between conditions. In this condition, players made choices that would affect only their own earnings and there were no social elements involved.

The outcome probabilities and values associated with risky outcomes in the social condition were determined based on behavior of a group of trustees making decisions in a previous study, and the distribution of outcomes in the non-social risk condition were matched to have the same mean (10.5), variance (36.7), and skewness (-139.2). The probabilities and amounts attached to each outcome varied across trials. By explicitly revealing the probabilities associated with outcomes in both social and non-social conditions, this design removes a common confound of comparisons of risk and trust. That is, trust often involves outcomes for which probabilities are at least partly unknown, while decisions involving risk do not.

Neural Measure

Images were acquired using 3.0T Siemens Trio MR scanners at Baylor College of Medicine. Functional images were acquired using an interleaved T2* weighted EPI sequences with a TR of 2 seconds, TE of 30 ms, flip angle of 90°, 64 x 64 matrix size with resolution of 3 x 3 mm^2. Thirty-four 4 mm axial slices with a voxel size of 3.4mm x 3.4mm x 4mm were used to cover the cerebral cortex and subcortical structures. The slices were tilted 30° clockwise from the

anterior and posterior commissure in order to improve signal detection in the orbitofrontal cortex as well as decrease potential signal distortion in the temporal cortices from eye movements and sinus cavity. The structural scan was obtained using a high-resolution magnetization prepared rapid acquisition gradient echo (MPRAGE) sequence (TR= 1200 ms, TE 2.66 ms, FoV 245 mm, 1mm slice thickness, 192 slices with spatial resolution of 1 x 1 x 1 mm^3).

Procedure

After participants provided written informed consent, the experimenter reviewed the participant's initial screening form to ensure the accuracy of the responses. Next, the experimenter took a neutral face picture (above shoulders only) of the participant that was used in the upcoming task. Participants were instructed that they would be making decisions to keep an endowment or invest their endowment in a risky option, either in another person (social condition) or in a gamble (non-social condition). In addition, participants were instructed that, in the social condition, a pie chart would indicate the average values and frequencies of actual repayments made by trustees in a previous session, and that repayments in the current session would be determined based on draws from that distribution. Participants were similarly instructed that in the non-social condition, a pie chart would indicate the values and probabilities of potential outcomes. Lastly, the participants were informed that they would be compensated based on the outcomes of three randomly chosen trials from the experiment. Following instructions, the experimenter answered any questions the participants had regarding participation in the experiment. Prior to scanning, the subject played five practice rounds of the task in order to ensure full comprehension of the task. In preparation for the scanning portion of the study, the participants were asked to remove all metal items from their bodies, and were given an MRI safety talk by the experimenter. The participants were informed that participation

was voluntary and that participation in the study could be stopped at any time. As part of the safety talk, participants were made aware of the emergency squeeze bulb that could be used to signal to the experimenter in the control room to discontinue participation. The experimental task took approximately 35 to 40 minutes to complete depending on the variance in the subject's response time. Once finished with the scan, participants were asked to fill out a demographics questionnaire. Subjects were then debriefed and compensated for their time.

Data Analysis

Risk Attitude (RA) Estimation

Risk aversion, as expressed by decisions made in both social and non-social conditions, was modeled using a constant relative risk aversion utility function (Pratt, 1964; Arrow, 1965; Holt and Laury, 2002), in which the utility of money x, for $x > 0$ is described by,

$U(x) = \frac{x^{(1-r)}}{1-r}$, where x represented the monetary value that the agent will receive and where r represented a risk attitude parameter such that $r < 0$ implied risk preference, $r = 0$ implied risk neutrality, and $r > 0$ implied risk aversion. When $r = 1$, we used $U(x) = log(x)$ (Pratt, 1964; Arrow, 1965; Holt & Laury, 2002). A probabilistic choice function was used to model the probability of choosing the certain or risky option $(A \ or \ B)$ given the utility of each option,

$P(choose \ A) = Ua^{1/\mu} + Ub^{1/\mu}$, where μ varies between 0 and 1 and reflected the sensitivity of choices to the utilities associated with each option (Luce, 1959).

MATLAB 10.6 was used to fit parameters of the model to actual choices made in the task. Specifically, the 'nlinfit' function was used. For each subject, the model was estimated 100 times for choices made in each condition (social and non-social).

Preprocessing

Preprocessing of images and statistical analysis were carried out using SPM (Statistical Parametric Mapping) version 8.0 and MATLAB 10.6. Functional images were corrected for head motion and acquisition time of TR. Images were normalized to the standard Montreal Neurological Institute (MNI) space. Images were realigned and normalized using parameters derived from a segmented anatomical image coregistered to the mean EPI, and were smoothed (6 x 6 x 6 mm). Data from five participants were excluded prior to individual and group level analysis due to > 3mm of movement across the x, y, and z dimensions (Friston et al., 1996).

RA Results

Three participants for whom estimates of r were outliers (mean greater than 1.5 standard deviations of the cohort) were excluded. These participants chose the risky option over 80% of the trials, while the remaining sample chose the risky option approximately half the time $(M_{non-social} = 48.09\%, SD_{non-social} = 21.64; M_{social} = 47.31\%, SD_{social} = 19.24)$. Among the 30 remaining participants, the average r for each subject in each condition were used as metrics of risk preference. Furthermore, a correlation analysis confirmed convergent validity between estimated RA parameters and decisions (keep or invest) during the task, such that a greater number of decisions to invest were negatively associated with greater risk aversion $(r = -.88, p < .001)$.

<div align="center">

Results

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Aim 1 Results

In order to test whether participants' exhibited differences in risk preferences between social and non-social conditions, a Wilcoxon signed-rank test was conducted. Results revealed no significant differences between risk preferences in the social and non-social conditions, $(Wilcoxon\ Z = .54,\ p = .59)$. In both conditions, participants as a whole were risk averse,

$(RA_{non-social} = .54, SD = .38; RA_{social} = .59, SD = .32)$. Correlation analysis results revealed that estimates of RA in the social condition were strongly related to estimates of RA in the non-social condition across subjects $(Spearman\ \partial = .60, p < .001)$.

Although there was no significant difference found between risk preferences for social and non-social risk, further analyses were conducted to assess the variability in risk preferences between social and non-social conditions across the sample. Specifically, a difference score for each subject was computed in which the subject's risk preference in the social condition was subtracted from risk preference in the non-social condition. Absolute values of difference scores were calculated in order to assess the magnitude of the difference irrespective of direction. Results revealed that the difference between social and non-social risk preferences was not likely due to chance, $(Wilcoxon\ Z = 4.78,\ p < .001)$. Given this prior finding, it is expected that the magnitude of difference in investment decisions between conditions should also be significant, as risk preferences are reflections of decisions made in the task, $(Wilcoxon\ Z = 4.63,\ p < .001)$.

Based on the above analysis, an index of social risk sensitivity (SRS) was calculated for each subject $(SRS = RA_{social} - RA_{non-social})$. Positive values of SRS (+SRS) signify that the participant exhibits higher risk aversion when a social partner determined the outcome of a risky choice compared to when the outcome was determined by a non-social gamble process. Similarly, negative values of SRS (-SRS) indicate greater risk aversion when the outcome was determined by a non-social versus social process. Figure 3 illustrates mean SRS coefficients for –SRS and +SRS groups.

To confirm that these subgroups indeed differed in risk aversion preference across social and non-social conditions, a two-way, repeated measures analysis of variance with group (+SRS,

-SRS) and condition (social, nonsocial) was performed. While no significant effects of group or condition were identified, a significant group x condition interaction

($F_{(1,28)} = 17.51, p < .001$) confirmed that risk aversion preferences for social and non-social options differed between the two subgroups. Within the +SRS group, RA_{social} was greater than $RA_{non-social}$ ($Wilcoxon\ Z = 3.5, p < .001$), and within the –SRS group, $RA_{non-social}$ was greater than RA_{social} ($Wilcoxon\ Z = -3.3, p < .001$).

Aim 2 Results

 fMRI Model Specification. On the first level of the general linear model, an event representing the 4 s decision phase of the task was modeled within each trial and convolved with a hemodynamic response function (HRF). The first subject-specific design matrix was created using a multiple-regression model that consisted of four regressors of interest (plus six motion-parameter regressors): two regressors modeled the type of condition (social or non-social) and an additional two regressors in each condition in the form of parametric modulators reflective of the variance of the gamble outcomes. The second subject-specific design matrix was similar to the first, but contained four regressors representing the following trial types: social invest, social keep, non-social invest, and non-social keep.

 Group level fMRI analysis. Group level one-sample t tests were conducted at each voxel across the entire brain volume. In order to identify common regions across social and non-social conditions, a contrast representing social and non-social conditions parametrically modulated by the variance of gamble outcomes was computed at the individual level. As predicted, common risk-related neural activation across conditions was observed in the right insula during the decision phase and was small volume corrected using a sphere of 6mm ($t_{(29)}$=4.11; p (FWE, small volume correction) $< .05$; x=39, y=2, z=-2; see Figure 4).

To identify differential activity between the social and non-social conditions during the decision phase, a 'social – non-social' contrast and 'non-social – social' contrast were computed at the individual level and pooled for group level analysis. As predicted, significant differential neural responses in the mPFC ($t_{(29)}$=5.77; p (FDR, whole brain correction) < .05; x=3, y=56, z=19; see Figure 6), vmPFC ($t_{(29)}$=6.30; p (FDR, whole brain correction) < .05; x=-3, y=38, z=-20; see Figure 5), bilateral amygdala ($t_{(29)}$=7.58; p (FDR, whole brain correction) < .05; x=-18, y=-4, z=-11; see Figure 5), and TPJ ($t_{(29)}$=7.51; p (FDR, whole brain correction) < .05; x=-51, y=-61, z=-25; see Figure 6) for social relative to non-social risk were observed. Conversely, greater neural responses in the posterior parietal cortex ($t_{(29)}$=5.64; p (FDR, whole brain correction) < .05; x=-30, y=-46, z=-34) and lateral OFC ($t_{(29)}$=3.93; p (FDR, whole brain correction) < .05; x=-33, y=44, z=-16) were observed for non-social compared to social risk during the decision phase of the task.

Aim 3 Results

To identify neural correlates of social risk sensitivity during the decision-making phase of the task, hemodynamic activity was examined using a 2 (+SRS group, -SRS group) x 2 (social, non-social) x 2 (keep, invest) ANOVA analysis was conducted. Analysis was restricted to a region-of-interest (ROI) analysis that included the left amygdala as previous reports have implicated this region in both social and risky decision-making processes (Coricelli et al., 2005; Hsu et al., 2005; De Martino, Kumaran, Seymour, & Dolan, 2006; Seymour & Dolan, 2008; Weber & Huettel, 2008). The WFU_Pickatlas (Lancaster, Rainey, Summerlin, Freitas, Fox, Evans, Toga & Mazziotta, 1997) was used to generate the anatomical ROI of the left amygdala.

Based on this anatomical ROI, eighty-six voxels were included. A significant effect of group (+SRS, -SRS) x condition (social, non-social) x choice (keep, invest) on hemodynamic activity was identified in left amygdala ($F_{(1,28)}$=23.14; p (FWE, small volume correction) < .05; x=-24; y=-

2, z=-29; see Figure 7). In three of four conditions, amygdala activity is consistent with the SRS bias, despite no overall effects of condition (social vs. non-social). For instance, among the subgroup that preferred social over non-social risk (-SRS), greater amygdala activity was observed when choosing the certain versus risky option in the social condition, and the risky versus certain option in the non-social condition. This pattern also holds true for the preference congruent condition among subjects preferring non-social risk: greater amygdala activity was observed in the certain relative to risky option in the non-social condition among subjects in the +SRS group. The only exception to this pattern is for the preference incongruent condition in the +SRS group.

Discussion

The present study provides both behavioral and neural evidence that improves our understanding of how risky decisions may be differentially influenced within social and non-social contexts. Specifically, the findings of this research make three main contributions.

First, to our knowledge, this is one of the first studies to use a within-subjects design to directly compare how social and non-social sources of risk influence decision-making behavior within a risk elicitation paradigm. The majority of previous work has focused on understanding choice behavior in non-social environments, largely leaving social risk unexplored. Some studies focus on understanding how risk preferences, as typically assessed via a lottery choice task, are related to trust behavior, measured through decisions made within the Trust Game. Results from these studies have been used to make inferences regarding how non-social and social risk preferences may or may not be related (Eckel & Wilson, 2004; Houser et al., 2010; Schechter, 2007). However, trust measures how one makes decisions in situations of social ambiguity and not social risk. Risky decisions are defined as situations in which the decision-maker is explicitly

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aware of the likelihoods associated with outcomes (Camerer & Weber, 1992; Hsu et al., 2005; Huettel et al., 2006). Since in the Trust Game, investors do not know with certainty what the probabilities are of receiving the invested amount back from the trustee, this situation is more descriptive of an ambiguous situation rather than one of risk. In previous studies, risk preferences were estimated for non-social contexts and then correlated with trust behavior. The present study computes unique RA estimates for social and non-social conditions, allowing for the comparison of behavioral differences, which then can be used to examine distinct hemodynamic responses in the brain.

Secondly, results of the first aim indicate that responses to risk in social and non-social contexts were not significantly different across the sample and were strongly correlated. This is consistent with the notion that social risk preferences are partially accounted for by baseline preferences for risk. While some studies (Eckel & Wilson, 2004; Houser et al., 2010) have suggested that there is no relation between risk and trust behavior, other studies provide support to show that risk and trust behavior are related (Schechter, 2007). This behavioral result may help resolve this debated issue within previous literature by providing evidence to support that decisions to trust another may be influenced by non-social risk preferences.

However, there is a large portion of variance that can be explained by distinct preferences for social or non-social risks. The heterogeneity of within-subject differences in risk preferences between social and non-social conditions suggests that individuals may vary in their sensitivity to social and non-social sources of risk. Specifically, SRS differences signify that regardless of baseline risk preference, there are some participants whose risk-seeking preferences are facilitated by social sources, while others exhibit risk-averse preferences toward social sources. Taken together, these behavioral findings suggest that due to the lack of consideration of context

within standard utility models, an additional parameter could be included within the expected utility framework in order to take into account possible effects of context in predicting individual RA.

As predicted, ROI results indicate that differences in SRS depend on differential functional amygdala response to risk in social and non-social risk. During the decision phase, it appears that the amygdala biases behavioral choices consistent with underlying social preferences. In particular, participants who were socially risk averse exhibited reduced amygdala activity preceding risky non-social choices, but not risky social choices. In contrast, social risk-preferring participants show reduced amygdala activity before risky social choices, but not risky non-social choices. This pattern of results extends our understanding of the functional role that the amygdala may play in value-based decision-making. For example, De Martino et al. (2006) found that the amygdala may be particularly responsive to the sensitivity of framing effects, suggesting that this region may be functional in processing contextual information. Within the present study, although social and non-social conditions were distinct, the amygdala might play a role in recognizing underlying social preferences and associated emotional factors. In a recent study, differences in social value orientation over the distribution of resources have also been shown to scale with amygdala activation, implying that activation in the amygdala is related to other-regarding preferences (Haruno & Frith, 2009). This evidence suggests that social preferences over and above non-social risk preferences may contribute to the additional utility or disutility reflected by the behavioral differences in SRS. Furthermore, findings of the current study in combination with results from previous literature demonstrate the amygdala's functional role in synthesizing contextual and emotional information in order to mediate cognitive biases.

Lastly, a number of neuroimaging studies investigating the neural correlates of decision-making under uncertainty have identified several regions specifically involved in the encoding of risk. However, these studies do not address how the brain may deal with different types of risk. The present study fills this gap in the literature by examining the common and distinct neural correlates of social and non-social risk. As predicted, during the decision phase, neural responses to risk (i.e., variance in the distribution of outcomes) across both conditions were significantly correlated with heightened activation in the insula. This suggests that the insula plays a prominent role in the processing of risk prediction (i.e., anticipated risk) and the tracking of risk via risk prediction errors regardless of the context in which risk occurs (Bossaerts, 2010; Preuschoff et al., 2008). This neural result is consistent with the behavioral finding for Aim 1 that social risk preferences were strongly related to non-social risk preferences. Since the insula has been identified as an important region involved in interpreting social signals in decision-making environments (Rilling & Sanfey, 2011), this may indicate that both social and non-social factors are jointly incorporated into underlying valuations of risk.

Nevertheless, distinct patterns of activation were identified for social and non-social risk conditions. In particular, during the decision phase, greater hemodynamic activity was found in the mPFC, TPJ, bilateral amygdala, and vmPFC regions in response to social risk contexts. These findings indicate that even in basic social contexts, regions in social (Van Den Bos et al., 2009) and affective processing (Haruno & Frith, 2009; Seymour & Dolan, 2008; Winston et al., 2004) networks are recruited. These results may also be related to the activation of underlying social preferences within social contexts that could potentially influence risky choice behavior. On the other hand, neural responses during the decision phase distinct to non-social risk were identified in the lOFC and posterior parietal cortex. This was consistent with study predictions as

these regions have been previously associated with the processing of risks in non-social contexts (Huettel et al., 2006; Tobler et al., 2007). Moreover, Tobler et al. (2007) found that lOFC activity scaled with an individual's non-social risk preferences. These neural results provide a deeper understanding of the neural substrates related to behavioral differences observed between social and non-social risk.

In summary, these findings provide greater understanding of behavioral and neural mechanisms underlying risky decision-making within social and non-social environments. More specifically, these data suggest that the evaluation of decision-making under risk should take into consideration individual's risk preference sensitivities to social risk and non-social risk. Since these data show that there may be some who prefer to make risky choices in social environments while others may not, these results may have potential implications for understanding how risky behaviors may lead to either positive or negative outcomes depending on the environmental influences on an individual's risk sensitivity.

Limitations

Although these results offer insight into how social preferences can potentially lead to differential risky choice behavior, there are some potential limitations to consider. First, it may be possible that behavioral differences in RA between social and non-social conditions could be attributed to differences in the physical features of social and non-social stimuli. Second, within the social condition, 43 distinct facial stimuli were displayed for each trial. In contrast, only one stimulus was used to represent the non-social probabilistic mechanism. It is possible that the behavioral differences in RA may be driven by a potential novelty or familiarity effect. Future studies should modify the experimental task to include multiple stimuli for the non-social risk

condition. Nevertheless, the three-way interaction observed in the amygdala further distinguishes the social versus non-social results in that it reflects a differentiation of sensitivity to social risks.

Future Directions

Assessing the extent to which individual differences in risk preferences is related to traits such as impulsivity, neuroticism, and interpersonal functioning may help us identify individuals who are more likely to have negative outcomes given risky opportunities. During the decision phase, both emotion and social information processing regions were identified when contrasting social versus non-social choice. Future work should explore the interaction between emotional and social information processing in social decision-making contexts.

Social environments call for decision-makers to evaluate and make choices involving varying degrees of uncertainty, namely risk and ambiguity. The present study focuses on risk, but future studies should also investigate the extent to which social preferences affect behavioral and neural responses to ambiguity. Finally, understanding individual sensitivity for risk and ambiguity in social decision-making contexts across the lifespan may be useful for identifying potential individuals who may be at risk for negative outcomes. In addition, the study of risk in social contexts may be applicable for understanding abnormal social biases present in those who suffer from interpersonal dysfunction such as borderline personality disorder. Future work in this area could identify possible neurobehavioral markers for social dysfunction that may inform the diagnosis and treatment of those suffering from marked interpersonal dysfunction.

Conclusions

In conclusion, these findings provide evidence to show that decision-makers are influenced by the source of risk even in basic social contexts. This suggests that when social elements are introduced into the decision environment, individual biases are an important factor

in influencing how one will respond to risk. Individuals appear to have differential sensitivities

to social risk, which seems to be captured by activation in the amygdala.

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Figure 1. Expected utility function.
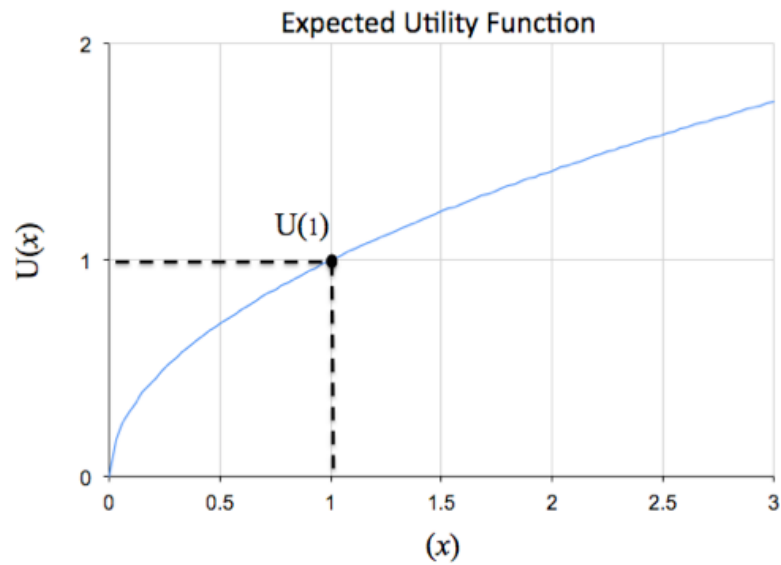
Note: The expected utility function translates monetary units of (*x*) into units of utility, U(*x*) and describes an individual's attitude toward risk (RA). The concave shape of this utility function describes an individual who exhibits risk aversion.

Figure 2. Experimental paradigm and timeline of task.
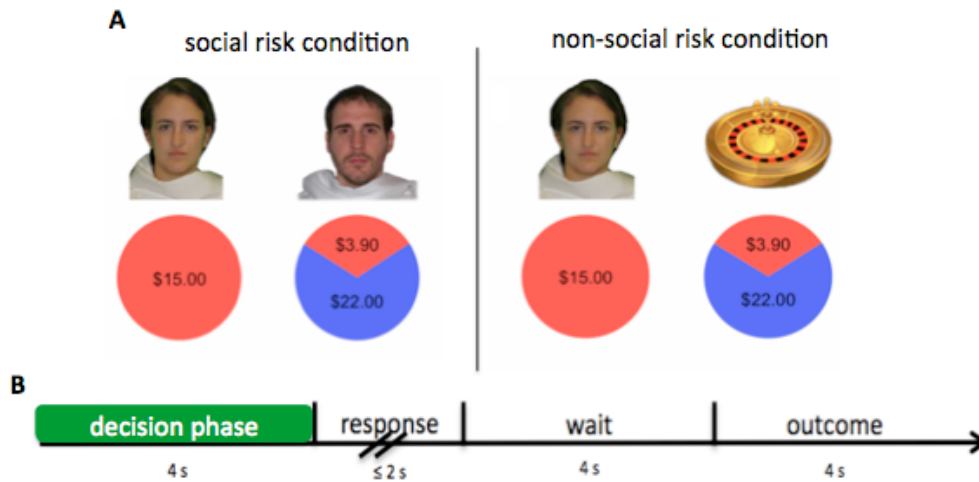
Note: A) Examples of a single trial in the 'social risk' and 'non-social risk' conditions. In the 'social risk' condition, subjects chose between keeping the original endowment or investing their endowment in a social partner. In the 'non-social risk' condition, subjects chose between keeping the original endowment or taking a gamble in which their payoff was determined by a non-social probabilistic mechanism. The amounts represent the possible outcomes and the size of the pie represents the likelihood of receiving those outcomes. B) Decision phase activity was modeled across 4 s prior to the selection of an option.

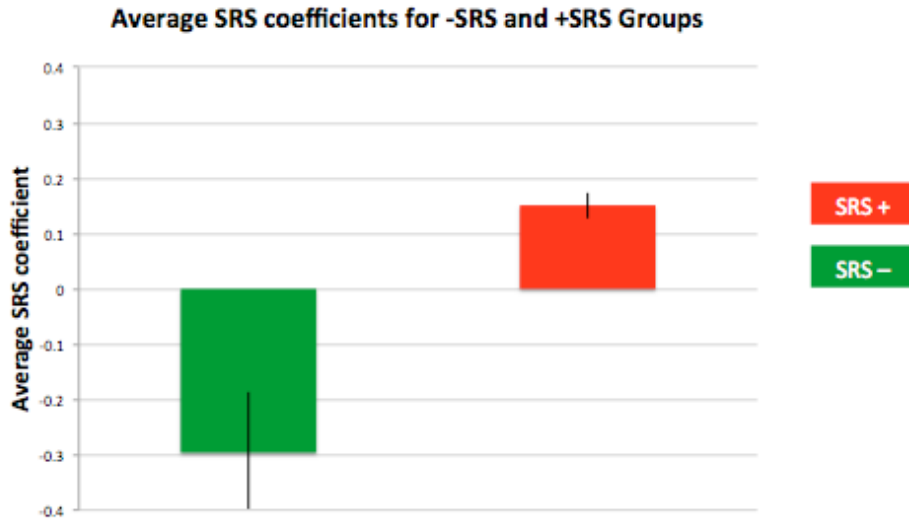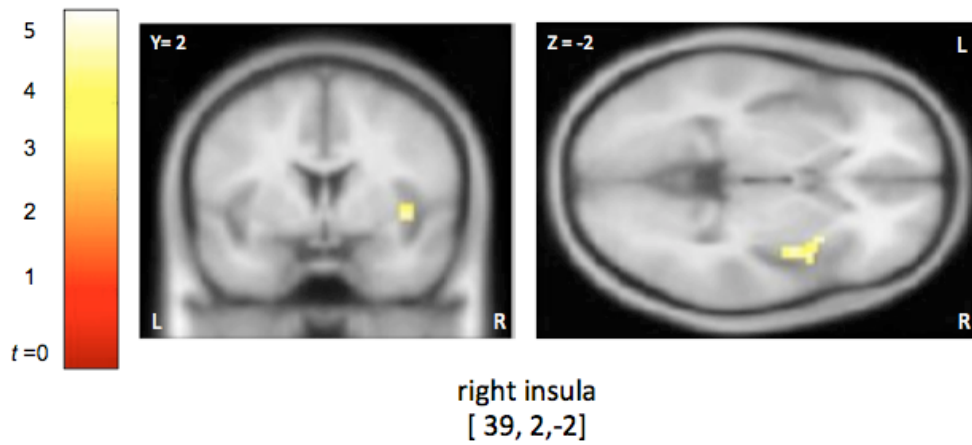*Figure 3*. Average SRS coefficients for SRS + and SRS – groups.

Average SRS coefficients for -SRS and +SRS Groups

Figure 4. Common neural activity for social and non-social risk.

right insula
[39, 2,-2]

Note: Participants exhibited greater activation in the right insula in response to risk regardless of condition during the decision phase of the task, ($t_{(29)}$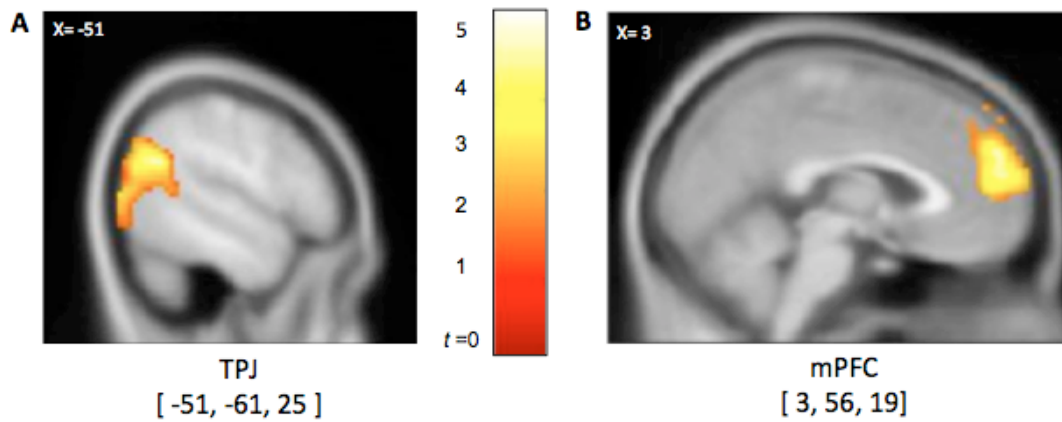=4.11; $p_{(FWE, svc)}$ < .05; x=39, y=2, z=-2). Images were normalized to the MNI coordinate space and coordinates shown were extracted from the peak voxel.

*Figure 5.* Social – Non-social: bilateral amygdala and vmPFC.

bilateral amygdala
[-18,-14,-11]
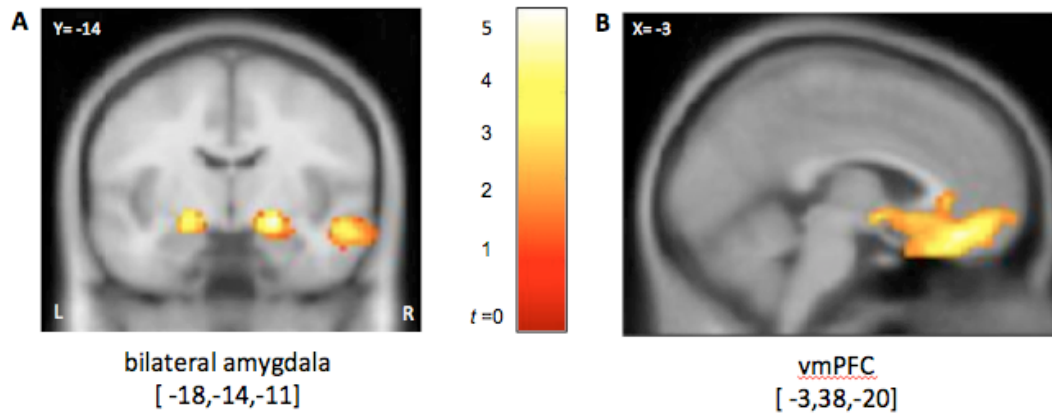
vmPFC
[-3,38,-20]

Note: Participants exhibited greater activation in the (A) bilateral amygdala ($t_{(29)}$=7.58; p (FDR, whole brain correction) < .05) and (B) vmPFC ($t_{(29)}$=6.30; p (FDR, whole brain correction) < .05) in the 'social risk' relative to 'non-social risk' condition during the decision phase of the task. Images were normalized to the MNI coordinate space, and coordinates shown were extracted from the peak voxel.

Figure 6. Social – Non-social: TPJ and mPFC.

Note: Participants exhibited greater activation in the (A) TPJ ($t_{(29)}=7.51$; $p_{(FDR, whole brain correction)} <$ .05) and (B) mPFC ($t_{(29)}=5.77$; $p_{(FDR, whole brain correction)} <$ .05) in the 'social risk' relative to 'non-social risk' condition during the decision phase of the task. Images were normalized to the MNI coordinate space, and coordinates shown were extracted from the peak voxel.

Figure 7. Group X Condition X Choice interaction.
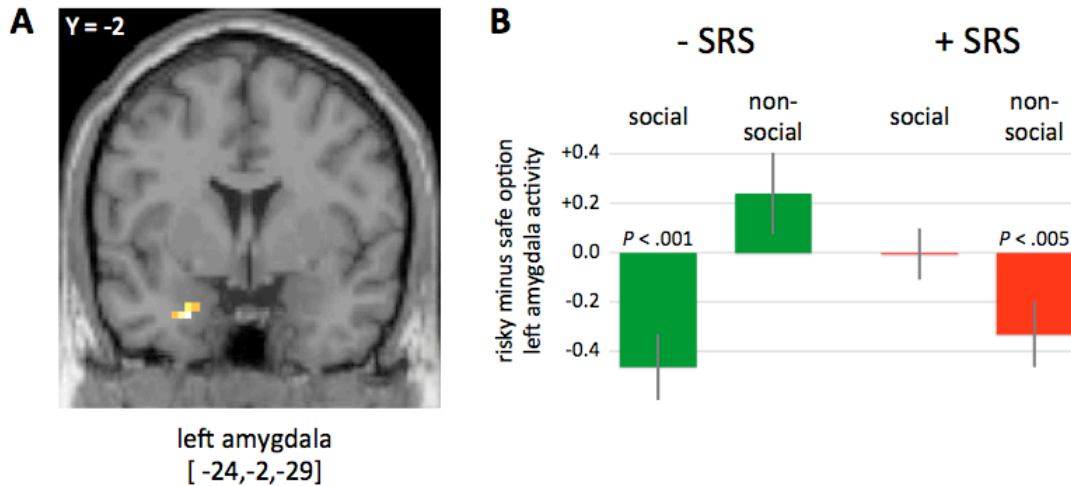
Note: A) A significant effect of the three-way interaction of 'group' (+SRS, −SRS) × 'condition' (social, non-social) × 'choice' (risky, safe) was identified in hemodynamic activity in left amygdala, ($z =4.43$, $p_{(FWE, small volume correction)} < .05$). Image was normalized to the MNI coordinate space, and coordinates shown were extracted from the peak voxel. B) Participants who were more risk averse in the social condition (+SRS) exhibited lower amygdala activity prior to choosing risky relative to certain options in the non-social condition. In contrast, participants who were more risk averse in the non-social condition (−SRS) exhibited lower amygdala activity prior to choosing risky relative to certain options in the social condition.