Neuroeconomics

Source preference and ambiguity aversion: models and evidence from behavioral and neuroimaging experiments

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SOURCE PREFERENCE AND AMBIGUITY AVERSION: MODELS AND EVIDENCE FROM BEHAVIORAL AND NEUROIMAGING EXPERIMENTS

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ABSTRACT

Purpose – *This experimental economics study using brain imaging techniques investigates the risk-ambiguity distinction in relation to the source preference hypothesis (Fox & Tversky, 1995) in which identically distributed risks arising from different sources of uncertainty may engender distinct preferences for the same decision maker, contrary to classical economic thinking. The use of brain imaging enables sharper testing of the implications of different models of decision-making including Chew and Sagi's (2008) axiomatization of source preference.*

Methodology/approach – *Using fMRI, brain activations were observed when subjects make 48 sequential binary choices among even-chance lotteries based on whether the trailing digits of a number of stock prices at*

Neuroeconomics
Advances in Health Economics and Health Services Research, Volume 20, 179–201

ISSN: 0731-2199/doi:10.1016/S0731-2199(08)20008-7

market closing would be odd or even. Subsequently, subjects rate familiarity of the stock symbols.

Findings – *When contrasting brain activation from more familiar sources with those from less familiar ones, regions appearing to be more active include the putamen, medial frontal cortex, and superior temporal gyrus. ROI analysis showed that the activation patterns in the familiar–unfamiliar and unfamiliar–familiar contrasts are similar to those in the risk–ambiguity and ambiguity–risk contrasts reported by Hsu et al. (2005). This supports the conjecture that the risk-ambiguity distinction can be subsumed by the source preference hypothesis.*

Research limitations/implications – *Our odd–even design has the advantage of inducing the same "unambiguous" probability of half for each subject in each binary comparison. Our finding supports the implications of the Chew–Sagi model and rejects models based on global probabilistic sophistication, including rank-dependent models derived from non-additive probabilities, e.g., Choquet expected utility and cumulative prospect theory, as well as those based on multiple priors, e.g., α-maxmin. The finding in Hsu et al. (2005) that orbitofrontal cortex lesion patients display neither ambiguity aversion nor risk aversion offers further support to the Chew–Sagi model. Our finding also supports the Levy et al. (2007) contention of a single valuation system encompassing risk and ambiguity aversion.*

Originality/value of chapter – *This is the first neuroimaging study of the source preference hypothesis using a design which can discriminate among decision models ranging from risk-based ones to those relying on multiple priors.*

1. INTRODUCTION

Risks figure prominently in decision-making today as well as in the distant past, when exposure to danger was commonplace. From then to now, a willingness to take risk remains essential to the human condition. Ipso facto, risk has been the focus of much research in economics. Inspired by Ramsey (1931) and De Finetti (1937), Savage (1954) developed the subjective expected utility (SEU) model, which hypothesized that individuals make decisions among options by choosing the one that provides the highest expected utility. Savage showed that both probabilities and utilities can be inferred from choices made among gambles. This model has provided the workhorse for much of the modeling of decision-making under risk in economics and related areas.

Earlier on, Knight (1921) made the distinction between measurable uncertainty or risk, which can be represented by precise probabilities, and unmeasurable uncertainty which cannot. In the same year, Keynes (1921) discussed the following: ''In the first case we know that the urn contains black and white in equal proportions; in the second case the proportion of each colour is unknown, and each ball is as likely to be black as white. It is evident that in either case the probability of drawing a white ball is half, but that the weight of the argument in favor of this conclusion is greater in the first case.'' He argued that ''If two probabilities are equal in degree, ought we, in choosing our course of action, to prefer that one which is based on a greater body of knowledge?''

Keynes' observation found its way into the celebrated paper by Ellsberg (1961) who observed that people prefer to bet on a ball drawn from the known urn rather than betting on the unknown urn. In other words, decision makers have different risk attitudes towards events with known probabilities (risk) and unknown probabilities (uncertainty). Such choice behavior (see, e.g., Camerer & Weber, 1992) is commonly referred to as ambiguity aversion and is incompatible with the SEU model of Savage (1954) or the more general definition of global probabilistic sophistication (Machina & Schmeidler, 1992; Chew & Sagi, 2006). A number of theoretical models have also been proposed to account for ambiguity aversion, including Choquet expected utility (Schmeidler, 1989), maxmin expected utility (MEU) with multiple priors (Gilboa & Schmeidler, 1989), α-maxmin (Ghirardato, Maccheroni, & Marinacci, 2004), and cumulative prospect theory (CPT) (Tversky & Kahneman, 1992).

More recently, Fox and Tversky (1995) coined the term source preference, which refers to the observation that choices between prospects depend not only on the degree of uncertainty but also on the source of uncertainty. The authors interpreted ambiguity aversion as a special case of source preference. This identification of source preference, encompassing the risk-ambiguity distinction, motivated Chew and Sagi (2008) to develop an axiomatic model of source preference, by foregoing global probabilistic sophistication while seeking smaller systems of compatible events, called *small worlds*, within which the decision maker could behave probabilistically. Their axiomatization delivers the theoretical possibility of the decision maker having different attitudes towards risks arising from distinct sources of uncertainty.

The neuroimaging experiment reported in this chapter seeks to test the implications of a number of decision models in the literature relating to source preference and ambiguity aversion. The remainder of the chapter is organized as follows. Section 2 reviews the theoretical models on ambiguity aversion and source preference alongside behavioral evidence. Section 3 discusses neuroimaging evidence on ambiguity aversion while Section 4 presents new neuroimaging results testing the source preference hypothesis. We conclude in Section 5.

2. UTILITY MODELS AND BEHAVIORAL EVIDENCE

Since the advent of probability in the 17th century, the use of mean value to assess the worth of a lottery has been commonplace. In the so-called St. Petersburg paradox, Bernoulli (1738/1954) showed that valuing lotteries strictly according to their mean values can lead one to assign an infinite value to a lottery that pays a finite amount for sure. This observation led him to hypothesize that people have diminishing marginal utility for money. He posited specifically a logarithmic utility function for money. Rather than its expected value, the utility of a lottery would be the expectation of the utilities of its outcomes with respect to the underlying probability distribution. In this case, the decision maker will be averse to risks, i.e., valuing lotteries less than their expected values.

The mean-variance model, introduced by Markowitz (1952), is an alternative approach to model the behavior of a risk-averse investor in modern financial economics. Here, variance acts as a proxy for "risk" which is considered "bad." In other words, the decision maker's "indifference curves" on a two-dimensional mean-variance space always slope upwards. For any two lotteries to be indifferent, it is necessary that the one with a lower mean must have lower variance. Yet, as shown by Borch (1969), the high-mean-high-variance lottery can be constructed in such a way that it always pays more than the low-mean-low-variance lottery, which is preferred. This casts doubt on the normative appeal of the mean-variance preference specification and to some extent also its empirical validity.

There has been a number of works, including the pioneering contribution of von Neumann and Morgenstern (1947), on the axiomatic characterization of the Bernoulli model generally known as the expected utility hypothesis. A significant advance in this strand of thinking came from the seminal work of Savage (1954) who axiomatized the so-called SEU model of choice under uncertainty in which probabilities, being inferred from revealed preference, are purely subjective. In Savage's setting, lotteries or bets are in the form of $f = (x_1, E_1; \cdots; x_n, E_n)$ for some mutually exclusive and exhaustive partition $\{E_1, \cdots, E_n\}$ of the state space Ω and (not necessarily distinct) outcomes $\{x_1, \cdots, x_n\}$ from a consequence set X. Savage's axioms imply the existence of a cardinal *utility* function u over outcomes and a subjective probability measure p over events, such that the individual evaluates such bets according to an ordinal preference specification of the form

$$\mathrm{SEU}(x_1, E_1; \cdots; x_n, E_n) = \sum_{i=1}^{n} u(x_i)p(E_i)$$

A key characteristic of this model, which follows from the additive structure of SEU, is known as the sure-thing principle: *For all f, g, h, h' and event E, $fEh \succcurlyeq gEh$ if and only if $fEh' \succcurlyeq gEh'$, where fEg refers to the act which pays $f(s)$ if s belongs to E and pays $g(s)$ otherwise.* We use $\succ$ to denote the strict preference relation.

Despite the appeal and wide success of the SEU model in economics, finance, and other areas of the behavioral and social sciences, questions about its empirical validity have arisen especially in the work of Ellsberg (1961). In the well-known Ellsberg Paradox, there are two urns. The first contains 50 black balls and 50 red balls. The second contains 100 balls of either black or red color, with no additional information. One ball is picked at random from each urn. There are four events, denoted by R_1, B_1, R_2, B_2, where R_1 denotes the event, for instance, the event that the color of the ball chosen from urn 1 is red. On each of the events a bet is offered: \$100 if the event occurs and zero otherwise. People would generally be indifferent between betting on R_1 or B_1 (urn 1), and similarly between betting on R_2 or B_2 (urn 2). Yet, decision makers tend to prefer betting on either B_1 or R_1 to betting on either B_2 or R_2. Under SEU, indifference between betting on R_1 and B_1 and between betting on R_2 and B_2 implies that $p(B_1) = p(R_1) = 1/2 = p(B_2) = p(R_2)$. Taken together, the decision maker would be indifferent among all four bets, which does not accord well with empirical observations (Camerer & Weber, 1992).

In a 1995 paper, Fox and Tversky argued that Ellsbergian behavior may be subsumed under the more general phenomenon of source preference, in which the appeal of a prospect depends not only on the degree of uncertainty but also on the source of uncertainty. In their experiment, they assessed subject's willingness to pay (WP) for a gamble on whether the temperature of San Francisco (T_{S}) (or Istanbul (T_{I})) is at least or less than 60° F. Should his guess be correct, the subject would win \$100. They found that

$$\mathrm{WP}(T_{\mathrm{S}} \geq 60) > \mathrm{WP}(T_{\mathrm{S}} < 60) > \mathrm{WP}(T_{\mathrm{I}} \geq 60) > \mathrm{WP}(T_{\mathrm{I}} < 60)$$

In other words, subjects are more willing to pay more to bet on the temperature of the more familiar San Francisco than the unfamiliar Istanbul. They labeled this as source preference and concluded that people may prefer to bet on a source of uncertainty where they are more familiar or knowledgeable.

A number of models have been proposed to accommodate Ellsberg-type behavior, including the Choquet expected utility model (Schmeidler, 1989), CPT (Tversky & Kahneman, 1992), MEU model (Gilboa & Schmeidler, 1989), and α-maxmin model (Ghirardato et al., 2004). More recently, Chew and Sagi (2008) offered a *small worlds* axtiomatization of source preference which encompasses the risk-ambiguity distinction.

Choquet Expected Utility, Rank-Dependent Expected Utility, and Cumulative Prospect Theory

Choquet expected utility model and its extension to CPT both satisfy a comonotonic sure-thing principle (Chew & Wakker, 1996): *For all comonotonic f, g, h, h' and event E, $fEh \succcurlyeq gEh$ if and only if $fEh' \succcurlyeq gEh'$.* (Two acts f and g are *comonotonic* if it never happens that $f(s) \succ f(t)$ and $g(t) \succ g(s)$ for some states s and t.) For $f = (x_1, E_1; \cdots; x_n, E_n)$ with $x_1 \succ x_2 \succ \cdots \succ x_n$, its *Choquet expected utility* is given by

$$\mathrm{CEU}(f) = \sum_{i=1}^{n} \left[\pi(\cup_{j=1}^{i} E_j) - \pi(\cup_{j=1}^{i-1} E_j)\right] u(x_i)$$

where π is a unique non-additive probability (or capacity) which is monotone by set inclusion and assigns zero to the empty set, and 1 to Ω. It is straightforward to see that the empirically observed choice pattern in Ellsberg's 2-urn paradox could be consistent with CEU. Specifically, $\pi(R_1) = \pi(B_1) > \pi(B_2) = \pi(R_2)$.

Rank-dependent expected utility (RDEU), axiomatized in Quiggin (1982) and Quiggin and Wakker (1994), can be viewed as a special case of the Choquet expected utility in the presence of a known underlying probability distribution p, in conjunction with an auxiliary hypothesis that relates closely to stochastic dominance: $\pi(E) = \pi(E')$ if and only if $p(E) = p(E')$ (see Chew & Wakker, 1996). The RDEU specification is defined by a non-decreasing function g: [0,1] → [0,1] with $g(0) = 0$ and $g(1) = 1$ such that $\pi(E) = g(p(E))$, for any event E. For $f = (x_1, E_1; \cdots; x_n, E_n)$ $(x_1 \preccurlyeq x_2 \preccurlyeq \cdots \preccurlyeq x_n)$ where $q_j = p(E_j)$, its RDEU is given by:

$$\sum_{i=1}^{n}\left[g\left(\sum\nolimits_{j=1}^{i} q_j\right) - g\left(\sum\nolimits_{j=1}^{i-1} q_j\right)\right]u(x_i)$$

For the case of a 2-outcome lottery which delivers a positive outcome x with probability p and zero otherwise, its RDEU has a simple expression:

$$g(1-p)u(0) + [1 - g(1-p)]u(x)$$

which can be further simplified into $\pi(p)u(x)$ with $\pi(p) = [1-g(1-p)]$ and $u(0) = 0$. Subsequently, Chew, Karni, and Safra (1987) showed that a sufficient condition for risk aversion (risk affinity) in terms of mean-preserving increase in risk (Rothschild & Stiglitz, 1970) is for both u and g functions to be concave (π convex).

CPT incorporates a status quo or reference point e and a capacity π^+ for gain-oriented uncertainties and a possibly different capacity π^- for loss-oriented uncertainties. For $f = \{x_1, E_1; \cdots; x_n, E_n\}$ where $x_1 \succ \cdots \succ x_k \succ e \succcurlyeq x_{k+1} \succ \cdots \succ x_n$, its CPT utility is given by:

$$\sum_{i=1}^{n}\left[\pi^+(\cup_{j=1}^{i} E_j) - \pi^+(\cup_{j=1}^{i-1} E_j)\right]u(x_i) + \sum_{i=k+1}^{n}\left[\pi^-(\cup_{j=i}^{n} E_j) - \pi^-(\cup_{j=i+1}^{n} E_j)\right]u(x_i)$$

As demonstrated in Chew and Wakker (1996), CPT also reduces to a globally probabilistically sophisticated counterpart, called *rank-linear utility* (Green & Jullien, 1988), under consistency with stochastic dominance.

Maxmin Expected Utility and α-Maxmin Expected Utility

Gilboa and Schmeidler (1989) introduced Maxmin Expected Utility (MEU) as

$$\mathrm{MEU}(f) = \min_{\pi \in C}\left[\sum_{i=1}^{n} u(f_i)\pi(s_i)\right]$$

where C is a set of possible probability measures. The decision maker under MEU is extremely pessimistic in the sense that he behaves as if the worst among the possible probability distributions will take place. This model accords with Ellsberg-type behavior in the following sense. For urn 1, the probability of R_1 and B_1 are well-defined and equal half while for urn 2, the worst possible probability of drawing R_2 (resp: B_2) is zero. Consequently, the observed choice pattern – preferring to bet on urn 1 can be rationalized. However, MEU has the implausible implication that the certainty equivalent of betting on either color in urn 2 is zero.

The MEU model was further generalized by Ghirardato et al. (2004) to the α-MEU model in which decision makers evaluate each act by forming a convex combination of the best and worst expected utilities by placing a decision weight $\alpha(\in[0, 1])$ and $1-\alpha$ for the worst and the best expected utilities respectively:

$$\alpha\text{-MEU}(f) = \alpha\min_{\pi\in C}\left[\sum_{i=1}^{n} u(f_i)\pi(s_i)\right] + (1-\alpha)\max_{\pi\in C}\left[\sum_{i=1}^{n} u(f_i)\pi(s_i)\right]$$

Like MEU, α-MEU is compatible with Ellsbergian behavior and enjoys the additional advantage that the certainty equivalent of betting on R_2 or B_2 would be bounded away from zero as long as $\alpha<1$.

Source-Dependent Expected Utility (SDEU)

Chew and Sagi (2008) offered an axiomatic approach to model source preference in terms of possibly distinct attitudes towards risks arising from within each source of uncertainty. In the 2-urn Ellsberg paradox, indifference between betting on B_1 and on R_1 reveals that the decision maker has the same subjective likelihood between these two complementary events. This is similarly the case for B_2 and R_2. Yet, a strict preference in favor of betting on either B_1 or R_1 over B_2 or R_2 tells us that the decision maker exhibits greater aversion (often called ambiguity aversion) towards urn 2 bets. In other words, an individual is ambiguity averse for one source of uncertainty over another if she is more averse to risks from that source than for risks arising from another source of uncertainty. The simplest source preference model corresponds to having possibly distinct SEU preferences, with different von Neumann-Morgenstern (vNM) utility functions, for risks arising from different sources of uncertainty, e.g., u_1 for urn 1 and u_2 for urn 2. The certainty equivalents c_1 and c_2 for the bets on the two urns are given by $u_1(c_1) = 1/2u_1(100)$ and $u_2(c_2) = 1/2u_2(100)$. It follows that c_1 is greater than

c_2 if u_2 is more concave than u_1. A similar reasoning could apply to the source preference examples in Fox and Tversky (1995).

More recently, Chew, Li, Chark, and Zhong (2008) conducted a number of experiments using a Japanese ascending price clock auction design to discriminate between the Chew–Sagi approach and models based on global probabilistic sophistication or having multiple priors. To elicit subject's valuations towards different source of uncertainties, subjects bid for even-chance lotteries whose payoffs depended on whether the trailing digit of the closing price of a specific stock the following day would be odd or even. The authors used questionnaires to assess each subject's degree of familiarity with the various stocks. They tested the hypothesis, discussed earlier, that subjects would be willing to pay more for bets based on the price of a more familiar stock. Subjects' risk premia for different sources of uncertainty are found to be negatively correlated with their self-reported degrees of familiarity, a result compatible with the source preference approach. At the same time, their finding is incompatible with the implications of the α-maxmin model or any model that coincides with global probabilistic sophistication.

In the Chew–Sagi formulation, ambiguity aversion towards one source of uncertainty relative to another source arises from the decision maker having distinct attitudes towards risks from multiple sources of uncertainty. In this sense, one may expect a decision maker who is more risk averse than another decision maker in one source to also be comparatively more averse to risks arising from another source. This implication is supported by Halevy (2007) who finds positive correlation between the risk premium and ambiguity premium in the Ellsberg urns. This implication is further corroborated by the findings in Bossaerts, Ghirardato, Guarneschelli, and Zame (2007) in the setting of an experimental asset market.

3. NEUROIMAGING EVIDENCE

Identifying the brain regions that encode reward and risk has been the theme of a number of papers. Knutson, Taylor, Kaufman, Peterson, and Glover (2005) conduct an fMRI experiment to investigate the neural mechanisms that compute expected value. They find that nucleus accumbens is activated in proportion to anticipated gain magnitude while the cortical mesial prefrontal cortex is activated according to the probability of anticipated gain. In another study, activation of anterior insular and posterior inferior frontal gyrus and intraparietal sulcus correlate positively with the degree of 'uncertainty' (Huettel, Song, & McCarthy, 2005). More recently, Preuschoff, Bossaerts, and Quartz (2006) find that activation of putamen and ventral striatum are positively correlated with the expected reward value of the gamble. On the other hand, activation of anterior insula correlates positively with the reward variance (as a proxy for risk). Anterior insula is implicated in negative somatic states (Bechara, 2001). On the other hand, Chua, Krams, Toni, Passingham, and Dolan (1999) report that the anterior insula is activated during anticipation of physical pain, which correlates with self-reported anxiety. Kuhnen and Knutson (2005) investigate the relationship between the anterior insula and risk attitude. Subjects with greater insula activation, tend to be risk neutral or risk averse in an experiment involving financial risk taking.

Smith, Dickhaut, McCabe, and Pardo (2002)

Using PET, Smith et al. (2002) conducts the first neuroimaging study on the distinction between risk and ambiguity. Subjects make binary choices between gambles involving known probabilities (risk) and gambles with unknown probabilities (ambiguity). The authors investigate how risk and ambiguity interact with gambles in the domain of gain and loss. Their design includes four conditions: risk with gains (RG), risk with losses (RL), ambiguity with gains (AG), and ambiguity with losses (AL). They find that subjects display different risk attitudes in gain and loss conditions. Subjects avoid riskier gambles in the gain domain and less so in the loss domain. Subjects also avoid ambiguity gambles in both gain and loss conditions. There is significant interaction between the gain and loss domains and the risk and ambiguity conditions. Subjects' ambiguity aversion is significantly stronger in the gain condition than it is in the loss condition.

The authors present two difference-on-difference contrasts [(RG–RL)–(AG–AL)] and [(RL–RG)–(AL–AG)] as major results. The former shows that the ventromedial network is more activated, while the latter contrast shows the dorsomedial network is more involved.

Rustichini, Dickhaut, Ghirardato, Smith, and Pardo (2005)

A more recent study by Rustichini et al. (2005) introduces gambles involving partial ambiguity. Subjects in this study make binary choices between two gambles. These gambles are classified as certain (C), risky (R), ambiguous (A), and partially ambiguous (PA). In the PA gambles treatment, experimenter tells the subjects that there are at least 10 balls of each color without the exact number of balls for each type. These four types of gambles constitute six conditions (or pairs of gambles) of which three have a R gamble as the reference gamble (RR, PAR, and AR) and the other three have a certainty amount (a C gamble) as the reference gamble (RC, PAC, and AC). According to the ''choice-theoretic point of view'' discussed in Rustichini et al. (2005), the partially ambiguous gambles should be in an intermediate position between risky and ambiguous gambles in terms of reaction time (RT), subject's valuation, and brain activation. Yet, the experimental result suggests otherwise.

For the completely ambiguous case, if a subject possesses α-maxmin preference, she would consider that all balls would lead to the high payoff under the best possible scenario. At the same time, she would consider that all balls would lead to the low payoff in the worst scenario. Unlike complete ambiguity, for the partially ambiguous case, neither the best scenario nor the worst scenario would be viewed as being certain. For a α-maxmin decision maker, it appears that partial ambiguity would be more involved than the complete ambiguity. It seems most straightforward for a α-maxmin decision maker to assess gambles involving pure risks (and she would behave as if she has SEU preference) and she can skip the phase of evaluating the best and worst scenarios.

The reaction time (RT) data, however, do not support the implication of the α-maxmin model. For the C reference type, AC takes subjects the least time to decide, followed by the PAC, with RC taking the most time. By contrast, for the R reference type, AR takes subjects the most time to decide, followed by the PAR, with RR taking the least time. The R gambles seem to trigger more deliberation as evident by the fact that the R-based comparisons, on average, always yield higher RT than C-based comparisons.

In the analysis of the cutoff data – that is, the threshold above which subjects will switch to C – the cutoff value is similar for AC and PAC, but strikingly different for RC. In addition, different brain regions are activated under the PAC condition relative to the AC condition. Contrasting the PAC with AC shows significant activations in the regions of middle frontal gyrus, parietal lobe, lingual gyrus, and superior frontal gyrus. The frontal lobe, occipital lobe and precuneus are more activated in the contrast of PAC–RC. The medial frontal gyrus is more activated in the RR–PAR.

In sum, these results reveal that subjects have distinct attitudes towards ambiguity, risk, and partial ambiguity, and hence reject the implications of the α-maxmin utility model, and is compatible with the implications of the source preference model.

Hsu, Bhatt, Adolphs, Tranel, and Camerer (2005)

Hsu et al. (2005) conducts a fMRI study on ambiguity aversion incorporating additionally Fox and Tversky's suggestion of source preference which encompasses the risk-ambiguity distinction. In each of the three treatments, subjects make 48 choices between certain amounts of money and bets on card decks or events. The *card-deck* treatment is similar to the urn treatment in previous studies. Researchers present subjects with a choice to bet on the color of a card drawn from two decks of cards in which the proportion of blue and red cards is known (i.e., risky) in one deck and is not known (i.e., ambiguous) in the other. In the *knowledge* treatment (adapted from Fox & Tversky, 1995), the experimenters classify events into the familiar (whether the high temperature in New York City on a particular day was above a certain level) and the unfamiliar (the high temperature in Dushanbe, Tajikistan). "Risky" bets are those placed on familiar events; "ambiguous" bets are those placed on unfamiliar events. In the third (*informed opponent*) treatment, subjects decide whether to bet against an opponent. Should their choices of color match, both receive the certainty payoff. Otherwise, the subject wins only if his or her choice of color is realized. Here, the "ambiguous" case corresponds to being disadvantaged by betting against an opponent who can see a sample of up to nine cards (with replacement) before choosing his or her color. The "risky" case corresponds to betting against an uninformed opponent who cannot view a sample of cards before choosing a color.

Under all three treatments, for risky tasks, subjects are assumed to have SEU preference with vNM utility, $u(x,\rho) = x^{\rho}$, where $\rho >$ ($=$, $<$) 1 corresponds to the case of risk affinity (neutrality, aversion). For ambiguous tasks, subjects are assumed to have RDEU preference (exposited in Section 2) with probability weighting function $\pi(p,\gamma) = p^{\gamma}$. In particular, $\rho < 1$ and $\gamma > 1$ ($\rho > 1$ and $\gamma < 1$) implies risk aversion (risk affinity) in terms of mean-preserving increase in risk. Hsu et al. (2005) interprets γ as a measure of ambiguity aversion with $\gamma <$ ($=$, $>$) 1 corresponding to ambiguity affinity (neutrality, aversion). For a lottery which yields x with probability p, we have $\mathrm{RDEU}(x, p; 0, 1-p) = p^{\gamma} x^{\rho}$, where subjects' subjective probability of winning p is assumed to be half in the unknown deck in the card-deck treatment and for all questions in both the knowledge and the informed opponent treatments.

In this analysis, the authors employ a theoretical framework which can be cast in terms of the Chew–Sagi source preference model in which subjects have distinct risk attitudes for risky and ambiguous gambles. Specifically, for ambiguous gambles, subjects have probability weighting function p^{γ} in addition to utility function x^{ρ}. For risky gambles, they have EU preference with the same utility function. In this connection, as a special case, the Chew–Sagi approach delivers a simple and tractable SDEU model with x^{ρ} as utility function for risky gambles and x^{θ} ($\theta < \rho$) for the modeling of attitude towards ambiguous risks.

In the estimated behavioral results, reported in Table S6 of the supporting online materials in Hsu et al. (2005), they find that, on average, subjects are risk averse in the card-deck treatment while risk seeking in the knowledge treatment. In addition, they find that subjects are, on average, ambiguity seeking in the card-deck treatment while more ambiguity averse in the knowledge treatment. These observations contravene the usual findings in the literature, and suggest the need for an empirically successful model accommodate multiple levels of ambiguity aversion.

At the perception epoch, orbitofrontal cortex (OFC), amygdala, and the dorsomedial prefrontal cortex (DMPFC) are found to be more activated under the ambiguity condition than under the risk condition. The reverse contrast shows the dorsal striatum as having greater activation in response to the risk condition than to the ambiguity condition. It is noteworthy that under all treatments, the certainty payoffs for risky tasks are, on average, higher than those for the ambiguous tasks. This factor could contribute to the observed stronger striatum activation in risky–ambiguity contrast. At the decision epoch (Table S9–S10 in Hsu et al., 2005), they observe significant bilateral insula and left ventral striatum activation in the contrast of choosing to gamble over choosing certainty payoffs. Interestingly, these regions do not exhibit significant interaction with risk and ambiguity.

Since the bilateral OFC is more activated under "ambiguity" than under "risk," the authors conduct a separate behavioral experiment involving subjects with OFC lesion versus control subjects with temporal lobe lesion. The control group displays both risk aversion and ambiguity aversion while the target group displays neutrality towards risk as well as ambiguity. The authors interpret this finding as validating the necessity of the OFC in distinguishing between risk aversion and ambiguity aversion.

Huettel, Stowe, Gordon, Warner, and Platt (2006)

Using fMRI, Huettel et al. (2006) demonstrate a correlation between activations in specific brain regions and subjects' attitudes towards risk and ambiguity. They introduce gambles with certainty outcomes which enable the calibration of subjects' degrees of both risk aversion and ambiguity aversion. In each trial, subjects face one of four pair types: ambiguous gamble versus sure amount (AC), ambiguous gamble versus risky gamble (AR), risky gamble versus sure amount (RC), and risky gamble versus another risky gamble (RR). All gambles are resolved during scanning and subjects receive feedback at the end of each trial.

Huettel et al. (2006) assumes that subjects possess α-MEU with power utility function, $u(x, \rho) = x^{\rho}$. To assess risk attitudes, they calibrate this power function for each subject by finding a value of ρ that maximizes the number of correct predictions in the RC and RR trials. To assess attitude towards ambiguity, they make use of ρ estimated before in conjunction with the α-MEU function to find a value of α that maximizes the number of correct predictions in the AC and AR trials. As observed earlier, SDEU offers an alternative model for estimating subjects' source preference from choice behavior during the risky and the ambiguous trials.

The pIFS, anterior insular cortex (aINS), and posterior parietal cortex (pPAR) are significantly more activated during choices involving ambiguous gambles than those involving risky gambles. The authors also show positive correlation between subjects' degrees of ambiguity preference and the difference in pIFS activation between the average of the AC and AR trials and average of the RC and RR trials. In other words, subjects with greater increase in pIFS activation during the ambiguous trials (average of the AC and AR trials) relative to the risky trials (average of RC and RR trials) display less ambiguity aversion in their choices. At the same time, there is positive correlation between subjects' risk preferences and increases in their pPAR activation (relative to the AC and AR trials) during the RC and RR trials. The observed activation of pIFS in the ambiguous related trials is distinct from the activation in the parietal cortex in Smith et al. (2002) and Rustichini et al. (2005). The pIFS finding also agrees with findings in the neuroeconomics literature (Huettel et al., 2005) in which pIFS has been implicated in risky decision-making.

Levy, Rustichini, and Glimcher (2007); Preuschoff and Bossaerts (2008)

In two more recent studies (Levy et al., 2007; Preuschoff & Bossaerts, 2008), the researchers investigate how decision makers would respond to different degrees of ambiguity. Levy et al. (2007) focus on the question of whether there is a common neural substrate underlying the difference in choice behaviors in the presence of differing degrees of ambiguity or, as most of the previous studies suggest, if there are multiple systems that represent value under different conditions. The authors ask subjects to choose between a reference gamble and either a risky or an ambiguous gamble with different degrees of ambiguity (RR or RA). The authors find that activations in the medial prefrontal cortex, posterior cingulate, and ventral striatum correlate with the subjective risk-adjusted valuations of the risky gambles. They find the same correlation between these activations and the subjective ambiguity-adjusted valuations of ambiguous gambles. Levy et al. (2007) further argue that these results suggest a unitary system for subjective valuation for gambles spanning the whole spectrum of varying degrees of ambiguity.

Summary

On the whole, the neuroimaging evidence surveyed supports the idea of subjects having source preference encompassing the risk-ambiguity distinction. In facing pure risk, pure ambiguity, and partial ambiguity (Rustichini et al., 2005), the reaction times and brain activations data suggest that partial ambiguity is processed differently from pure risk and pure ambiguity. In this connection, the experimental designs in Huettel et al. (2005), Hsu et al. (2005), and Levy et al. (2007) enable observations of neural correlates of decision-making in the presence of multiple levels of ambiguity.

The choice of data under the knowledge treatment in Hsu et al. (2005) reveal that uncertainty associated with familiar events is preferred to those associated with unfamiliar events. Since the event's probability is not known in both cases, subjects appear to have an intrinsic source preference driven by familiarity. Moreover, the OFC-lesion data in Hsu et al. (2005) – OFC-lesion patients are ambiguity and risk neutral – hint at aversion to both risk and ambiguity as having a common root. This is compatible with the suggestion in Levy et al. (2007) of a unitary system responding to the valuations of gambles with different degrees of ambiguity. This also corroborates the Chew–Sagi model which posits that ambiguity aversion and source preference arise from the individual's risk attitude being distinct towards risks from different sources of uncertainty.

4. NEW NEUROIMAGING EXPERIMENT ON SOURCE PREFERENCE

Experiment Design

This experiment involves the participation of 16 subjects recruited from universities in Hong Kong. We report further details of the subjects and fMRI image acquisition procedure in the Appendix. In each trial, we require subjects to choose between two lotteries (see Fig. 1). Each lottery consists of a bet on the trailing digit – odd or even – of the closing price on the following trading day of one of two different stocks listed on the exchange.[1]

We conduct the experiment under both gain and loss trials. In the gain trials, the subjects earn the corresponding amount of money if they win the bet and receive zero otherwise. In the loss trials, subjects earn zero if they win the bet and lose the corresponding amount of money otherwise. The payoff for each gain-oriented lottery ranges from HK\$150 to HK\$200 while the payoff for each loss-oriented lottery ranges from losing HK\$20 to losing HK\$40. The total earnings of each subject consist of adding the outcome of a randomly drawn gain-oriented lottery and a randomly drawn loss-oriented lottery, plus a HK\$100 endowment. To assess subjects' degree of familiarity towards the stocks, subjects are asked to indicate their degree of familiarity from 0 to 9 for each of the 48 stocks.

Experimental Results

At the behavioral level, subjects tend to choose the more familiar source of uncertainty in the gain domain ($p<0.021$). We use general linear model

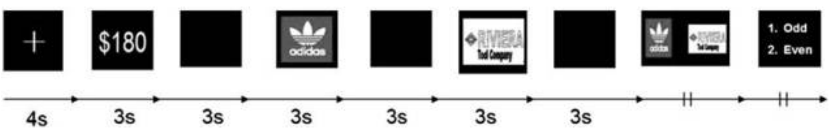

Fig. 1. Experiment Design. At the Beginning of Each Trial, a Fixation Sign is Shown to Indicate the Start of a New Trial and the Amount of the Gamble Would Appear. Then after Three Seconds, the Logos of the Two Lotteries (Stocks) are Presented Sequentially and Then Together. Subjects Indicate Their Preferences on Sources by Pressing a Left or Right Button. Afterwards, They Select the Last Digit of the Closing Price of the Chosen Stock on the Next Trading Day as Either Odd or Even by Pressing a Left or Right Button. There are 48 Trials. Half of the Trials are Gain Trails and the Reminding are Loss Trials.

analysis, with familiarity rating as a regressor, to identify neural correlates for decisions involving the choice of more familiar sources over those of less familiar sources. Regions appearing to be more active when subjects decide to bet on more familiar sources under gain-oriented lotteries included the putamen (part of the striatum; see Fig. 2), medial frontal cortex, and superior temporal gyrus (Table 1). Hsu et al. (2005) finds the striatum, implicated in reward prediction (O'Doherty et al., 2004), to be more active in the risk condition than in the ambiguity condition.[2] Hsu et al. (2005) suggests that ambiguous gambles have lower anticipated reward, thus leading to lower activation in the striatum relative to the risky gambles. The medial frontal cortex is consistently implicated in reward processing and in anticipation of risky gambles (Gehring & Willoughby, 2002). On the other hand, the middle frontal cortex and superior frontal cortex are more activated when subjects decide to bet on more familiar

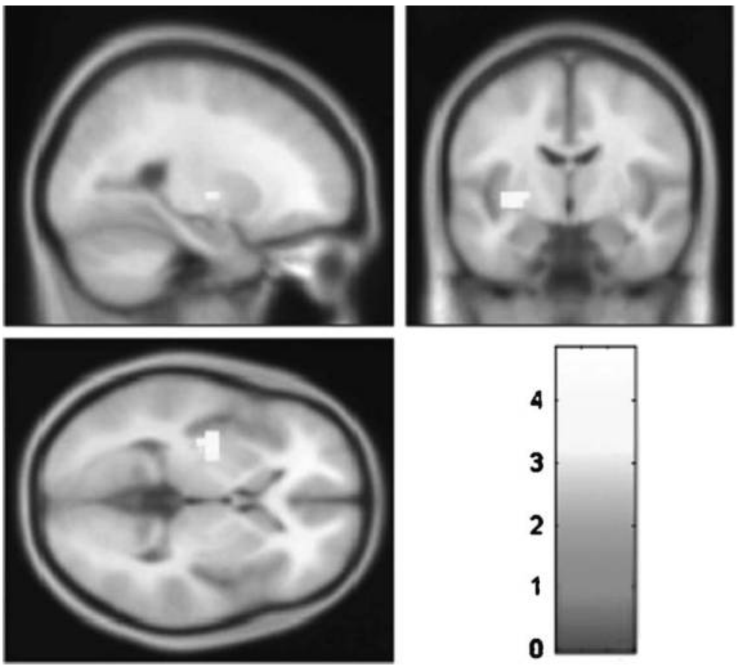

Fig. 2. Putamen Shows Higher Activation when Subjects Choose more Familiar Sources under Gain Oriented Lotteries ($P<0.005$ Uncorrected; Cluster Size $k\geqslant 9$ voxels).

Table 1. Regions Associated with Choosing a more Familiar Source under Gain-Oriented Lotteries.

Region of Activation	*X*	*Y*	*Z*	*T*-Value	*Z*-Value
Superior temporal Gyrus	−56	12	−8	5.23	3.77
Putamen	28	−12	0	4.86	3.6
Medial frontal cortex	12	−4	52	3.67	2.99
Medial frontal cortex	12	−12	60	3.24	2.72

Note: $P<0.005$ uncorrected; cluster size $k \geqslant 9$ voxels. MNI coordinates (mm) presented.

Table 2. ROI Analysis.

Region	*X*	*Y*	*Z*	*P*-Value
Familiar–Unfamiliar				
Striatum	0	−6	−6	0.03*
	9	6	6	0.01*
	−12	6	0	0.03*
Precuneus	−15	−72	51	0.01**
	12	−75	51	0.05*
	21	−84	39	0.07
Unfamiliar–Familiar				
Amygdala	−15	−15	−15	0.08
	−21	−6	−18	0.06
	33	−6	−27	0.02*
Dorsomedial prefrontal cortex	18	54	18	0.01**
	12	54	30	0.03*
	−9	48	39	0.02*
	−12	63	21	0.01**
Lateral orbitofrontal cortex	51	33	−6	0.07
	54	18	−21	0.08
	−54	36	−6	0.06
	54	27	6	0.01*

Note: *significant at the $P<0.05$ level; **significant at the $P<0.01$ level.

sources under loss-oriented lotteries. These regions have also been implicated in reward processing (Nieuwenhuis et al., 2005; Hsu et al., 2005). Intriguingly, this finding supports the hypothesis that choosing a more familiar source is more rewarding.

Region-of-Interest Analysis (ROI)

We conduct region-of-interest analysis (ROI) on the regions reported by Hsu et al. (2005), who find that the striatum is associated with risky decisions while the amygdala, dorsomedial prefrontal cortex, and lateral orbitofrontal cortex are associated with ambiguity. In the analysis of these five regions, we define the ROIs by drawing spheres of 10 mm radius centering on the peaks of activation in each of these regions. We further test the activation patterns in the familiar–unfamiliar and unfamiliar–familiar conditions and investigate whether they are similar to those in the risk–ambiguity and ambiguity–risk conditions. Most of the ROIs are significant at the p-value <0.05 level (See Table 2 for results). These findings support the hypothesis that people have distinct attitudes towards risks arising from different sources and brain activation in the familiar–unfamiliar and unfamiliar–familiar contrasts are similar to the brain activation of the risk–ambiguity and ambiguity–risk contrasts.

5. CONCLUSION

This chapter reports the first neuroimaging study of source preference in relation to ambiguity aversion. Our odd–even experimental design offers the advantage of being able to induce the same "unambiguous" probability of half for each lottery. This enables us to discriminate between the source preference approach (Chew & Sagi, 2008) and models based on multiple priors, such as α-maxmin as well as those based on non-additive probabilities, such as Choquet expected utility and cumulative prospect theory.

The behavioral result of our neuroimaging experiment shows that subjects tend to choose the more familiar source of uncertainty despite both lotteries (sources) delivering the same outcomes with equal probability. Regions that are more activated when subjects choose to bet on more familiar sources include the putamen, part of the striatum, which Hsu et al. (2005) finds to be more activated in the risky relative to the ambiguity condition. We confirm this result in a ROI analysis on the finding of Hsu et al. (2005).

It will be valuable to pursue follow up research towards understanding the neural mechanisms of source preference which encompasses a broad range of observed risk taking behavior, such as home market bias in financial markets, brand preference in marketing, the distinction between risk taking and gambling in casinos, and policy making involving social and natural risks. More generally, this study suggests that decision theory can offer a powerful tool for designing neuroeconomics experiments leading to greater understanding of neural mechanisms involved in decision-making. The methodology of neuroeconomics can in turn help discriminate among competing models of decision-making and contribute to their further theoretical development.

NOTES

1. Our odd-even design inducing the same ''unambiguous'' probability of one-half for each subject exemplifies Machina's (2004) ''almost-objective'' events which he showed to induce unanimously agree-upon revealed likelihoods.

2. Hsu et al. (2005) find caudate (part of dorsal striatum) to be more active in the risk condition than in the ambiguity condition. Both caudate (part of dorsal striatum) and putamen, involved in reward processing, are part of the striatum. See O'Doherty et al. (2004) for a discussion on the difference between the two regions in reward processing.

ACKNOWLEDGMENTS

We thank Richard Ebstein, Nicholas Hon, Tanjim Hossain, Hsu Ming, Li Geng, Li Jian, Read Montague, Ngooi Chiu Ai, Ryo Okui, Jacob Sagi, Xu Cui, Edward Yang, Rami Zwick as well as seminar participants at the Asia Pacific Meeting of Economic Science Association in Osaka (February 2007) and in Singapore (February 2008). We gratefully acknowledge Eric Set, Annie Tang, Xue Fei, and Zhu Xingtian for valuable research assistance, and the financial support of the Research Grants Council of Hong Kong.

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APPENDIX

fMRI Acquisition

fMRI was performed on a Philips Achiva 3T whole body MRI at the Jockey Club MRI Engineering Centre, Hong Kong with an 8 channel quadrature birdcage head coil. A sagittal spin echo localizer image was acquired initially. fMRI was performed in the transverse plane, parallel to the anterior–posterior commisura (AC-PC) line. A 35-slice set of fMRI images was acquired with the following scan parameters: TR = 2,000 ms; TE = 30 ms; flip angle = 90°; matrix = 64 × 64; field of view = 22 cm × 22 cm; slice thickness = 4.0 mm, without inter-slice gap. Anatomical whole brain MRI was acquired using a T1-weighted turbo spin echo (TSE) sequence with TR 2,000 ms and TE 10 ms with IR delay 800 ms. Around 700 fMRI volume images, depending on subjects' response time, were collected during each run. The first four fMRI volume images of each run were discarded to insure steady state magnetization.

Data Processing and Analysis

Post-processing of fMRI data was done using Statistical Parametric Map (SPM2) software package (Wellcome Department of Cognitive Neurology, Institute of Neurology, Queen Square, UK), running on Matlab (Version 7.0.0; Math Works Inc., Natick, MA, USA). Each fMRI image volume was automatically realigned to the first image of the time series to correct for head movements during the fMRI acquisition. The time series volumes were then registered to the brain template adopted by the International Consortium for Brain Mapping (ICBM) (Mazziotta, Toga, Evans, Fox, & Lancaster, 1995); spatial normalization into Montreal Neurological Institutes coordinates (resampled 4 mm × 4 mm × 4 mm). The spatially normalized EPI volumes were smoothed by an 8 mm full-width-half-maximum Gaussian kernel. Physiological noise was filtered using a window function that corresponds to a homodynamic impulse response function (HRF). Statistical analysis was conducted at two levels. Individual task-related activation was evaluated. To make inferences at a group level, individual data were summarized and incorporated into a random effects model.

Subjects

Sixteen right-handed undergraduate students were recruited from universities in Hong Kong. Each participant underwent fMRI scanning while performing 48 trials (not including 2 practice trials) of the experimental task illustrated in Fig. 1. Informed consent was obtained using a consent form approved by the human subjects committee at HKUST. Subjects were briefed on the (Chinese) instructions before entering the scanner. It was known that at the end of the experiment, one trial from each of the two treatments would be chosen at random, and the subject's choice on that trial would determine her pay. The earning is the total from the two randomly-chosen choices plus HK$100 endowment.

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