Competence Effects for Choices involving Gains and Losses*

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Abstract

We investigate how choices for uncertain gain and loss prospects are affected by the decision maker's perceived level of knowledge about the underlying domain of uncertainty. Specifically, we test whether Heath and Tversky's (1991) competence hypothesis extends from gains to losses. We employ an empirical setup in which participants make choices between hypothetical gain or loss prospects in which the outcome depends on whether a high knowledge or a low knowledge event occurs. We infer the decision weighting functions for high and low knowledge events from choices using a representative agent preference model. For decisions involving gains, we replicate the results of Kilka and Weber (2001), finding that decision makers are more attracted to choices that they feel more knowledgeable about. However, for decisions involving losses, we find a small but insignificant competence effect, INDICATING a small but NEGLIGIBLE preference to bet on choices involving low knowledge events over choices involving high knowledge events.

Keywords: Uncertainty; Decision Weighting Function; Ambiguity; Knowledge; Competence Effect

JEL classification: C91, D81

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1 Introduction

Decision makers often express a preference for betting on a particular source of uncertainty over another. Ellsberg (1961) provided the first and most famous demonstration of such a source preference. Ellsberg's simple setup involved two urns: a "clear" urn with 50 red balls and 50 black balls, and a "vague" urn with an unknown proportion of red and black balls (see also Keynes, 1921). Most individuals prefer to bet on the clear urn over the vague urn, even when they believe that the probability of drawing a red or black ball from either urn is identical (Becker and Brownson, 1964). Under the classical model of decision under uncertainty, subjective expected utility (SEU) (Savage, 1954), subjective probabilities are inferred from preferences over bets. Thus, the typical Ellsberg preferences are inconsistent with the Savage axioms, as these choices reveal that the subjective probabilities of both red and black are higher for the clear urn than the vague urn.

A large body of subsequent empirical research has explored numerous variants of this demonstration (for a review, see Camerer and Weber, 1992). The general conclusion of these studies, that individuals are ambiguity averse or reluctant to bet on vague probabilities, has been qualified by several recent studies. Heath and Tversky (1991) proposed and provided empirical support for the *competence hypothesis*: decision makers prefer to bet on ambiguous events over chance events when they consider themselves to be knowledgeable about the underlying domain of uncertainty (see also Frisch and Baron, 1988). In one study, Heath and Tversky recruited subjects who were either experts in football or politics and non-expert in the other domain. Subjects provided subjective probability assessments of a number of future events involving both political events and football games. They then indicated their preference for a chance lottery, a lottery based on the outcome of a football game, and a lottery based on the outcome of a political event. The lotteries were matched so that the participant's subjective likelihood judgments were identical in all cases. The results showed a source preference consistent with the competence hypothesis. Football experts ranked the lotteries in order: football, then chance, and finally politics. In contrast, political experts preferred politics to chance, and chance to football. Thus, Heath and Tversky argued that choices reflect a source preference, in which individuals are ambiguity seeking when they view themselves to be competent or knowledgeable about the underlying domain of uncertainty and ambiguity averse if the opposite is true.

A number of more recent studies have refined the competence hypothesis. Fox and Tversky (1995) suggested that the feeling of competence or incompetence arises from a comparison of one's knowledge about an event with either one's knowledge about another event or another person's knowledge of the same event. Thus, the feeling of knowledge reflects an inherently comparative process. One implication of their *comparative ignorance hypothesis* is that the classic Ellsberg preferences for the clear urn over the vague urn should be significantly diminished if subjects evaluated the vague and clear urns in isolation. Consistent with this prediction, Tversky and Fox replicated the classic Ellsberg preferences when subjects priced the vague and clear bets in a between-subject design but found no ambiguity aversion when the two bets were presented in a within-subject study (see, however, Chow and Sarin, 2001). In another study, Fox and Tversky documented how an interpersonal comparison might influence the feeling of competence. Stanford undergrads were much less willing to choose an uncertain financial prospect when they were told that the same prospect was being evaluated by more knowledgeable individuals, graduate students in economics and professional stock analysts (see also, Fox and Weber, 2002). Taylor (1995) and Trautman, Vieider, and Wakker (2008) report other psychological accounts of ambiguity aversion.

A number of theoretical models have been proposed to accommodate ambiguity aversion (see Camerer and Weber, 1992). A particularly useful formulation for modeling source preference was proposed by Gilboa (1987) and Schmeidler (1989). Gilboa and Schmeidler's model, Choquet expected utility, relaxes the Savage axioms to permit nonadditivity of subjective probabilities. Savage's Sure Thing Principle no longer applies to all acts, but only to the subset of acts that are "comonotonic," i.e., that share the same weak ranking of states. Choquet expected utility permits nonadditive probability measures, replacing the standard subjective expected utility calculus with a scheme that involves Choquet integration (Choquet, 1954)[1].

Tversky and Kahneman's (1992) cumulative prospect theory (CPT) extended this scheme to permit sign-dependence. Under cumulative prospect theory, the value of a mixed prospect involving the possibility of gains as well as the possibility of losses is the sum of Choquet integrals of the gain and loss portions of the prospect. Cumulative prospect theory extended the scope of Kahneman and Tversky's (1979) original prospect theory from prospects with at most two non-zero outcomes to prospects with multiple outcomes, and from decision under risk (prospects with objective probabilities) to decision under uncertainty (prospects defined on events). The representation for decision under risk uses a rank-dependent expected utility form for both gains and losses (Quiggin, 1982)[2]. In rank-dependent models, the weight attached to an outcome depends on the rank of the outcome relative to other outcomes.

Tversky and Kahneman (1992) also scaled prospect theory for decision under risk, assuming parametric forms for the value function and probability weighting function. Tversky and Fox (1995) extended the measurement of prospect theory to decision under uncertainty and proposed a two-stage model. Consider a lottery in which the decision maker wins x if event E occurs. The two-stage model posits that individuals first judge the probability of event E, then transform this subjective probability by the probability weighting function for risk (see also Fox and See, 2003; Fox and Tversky, 1998; Wu and Gonzalez, 1999). The two-stage model proposed by Tversky and Fox, however, does not permit source preference, and thus cannot accommodate the Ellsberg Paradox. To deal with this shortcoming, Kilka and Weber (2001) extended the two-stage model, allowing the transformation of subjective probabilities to depend on the source of uncertainty. They elicited cash equivalents for un-

[1]Machina (2008) presents a four-color generalization of the Ellsberg Paradox that violates expected utility, as well as Choquet expected utility. However, the two-stage model with source preference discussed below encompasses the behavior displayed in Machinas experiment.

[2]See Wakker (1990) [NOT IN THE REFERENCES] for the relationship between rank-dependent utility and Choquet expected utility.

certain prospects involving two different sources of uncertainty, a more and a less familiar source. The cash equivalents were consistent with Heath and Tversky's competence hypothesis, with the source preference reflected in significantly different estimates of the probability weighting function for the two sources, in particular a more elevated weighting function when the source was more familiar.

This paper investigates how choices for gain and loss prospects are affected by the level of knowledge one has about the decision being made. Numerous studies have shown differences in choices for gains and losses. Kahneman and Tversky (1979) documented a reflection effect for decision under risk. Most subjects preferred \$3000 for sure to an 80% chance at \$4000, but preferred an 80% chance at losing \$4000 to losing \$3000 for sure. Consistent with this reflection effect, Tversky and Kahneman (1992) estimated nearly identical value and weighting functions for gains and losses (see, however, Abdellaoui, 2000; Etchart-Vincent, 2004). Several studies have extended the Ellsberg Paradox from gains to losses. These studies have produced mixed results, with some studies showing ambiguity seeking for losses, particularly for high probability losses (Cohen, Jaffray and Said, 1985; Einhorn and Hogarth, 1986; Hogarth and Einhorn, 1990; Kahn and Sarin, 1988). Most recently, Abdellaoui, Vossman, and Weber (2005) elicited decision weights for gains and losses under uncertainty and found that the weighting function for losses was significantly more elevated than the weighting function for gains.

The present investigation tests if source preference reflects from gains to losses, as posited by Tversky and Wakker (1995). The competence hypothesis requires that subjects prefer high to low knowledge bets for gains. Tversky and Wakker (1995) suggested that, in the domain of losses, subjects prefer betting on the low knowledge source over the high knowledge source. The intuition for this reversal and hence the source preference hypothesis we make in the next section is that people shy away from gambles when they feel more confident about the loss they will face. [NEW/REWRITTEN: Basili, Chateauneuf, and Fontini (2005) extend the CPT model letting individuals divide outcomes in familiar and unfamiliar ones, where these individuals display preferences that reflect pessimism for gains and optimism for losses, when outcomes are unfamiliar.]

We test this generalization of the competence hypothesis using a variant of one of Heath and Tversky's studies. Subjects are asked to make a series of choices between pairs of gambles that differ on knowledge (high or low) and domain (gain or loss). Subjects also choose between the complements of these gambles. We fit four probability weighting functions to these data, for high knowledge gains, low knowledge gains, high knowledge losses, and low knowledge losses. For choices involving gains, we replicate Kilka and Weber's results, finding that decision makers prefer high knowledge gambles to low knowledge gambles. For choices involving losses, we find weak support for our hypothesis. We find a small but insignificant reflection in the attractiveness of choices with two different levels of knowledge, such that low knowledge losses are modestly preferred to high knowledge losses. Therefore, the reflection of the competence effect in the loss domain is less strong than the effect of competence in the gains domain, and the result is not significant. We conclude that the competence effect for choices involving losses appears to be less reliable than the competence effect for gains.

Our paper makes one additional contribution. Our empirical study uses direct choices rather than certainty equivalents, as used by Tversky and Fox (1995) and Kilka and Weber (2001). Certainty equivalents are traditionally used when utility and weighting functions are estimated because they provide considerably more information than binary choices. However, subjects find providing direct certainty equivalents extremely difficult, and choice-based elicitation of certainty equivalents is tedious (see, e.g., Fischer, Carmon, Ariely, and Zauberman, 1999). Our study uses binary choices and thus investigates the robustness of Kilka and Weber's findings to alternative choice procedures.

The remainder of the paper is organized as follows. Section 2 reviews cumulative prospect theory, Fox and Tversky's (1995) two-stage model, and also describes the hypothesis we test.

Section 3 presents the experimental study. Section 4 discusses the results. We conclude in Section 5.

2 Preliminaries

We use cumulative prospect theory (CPT) as our theoretical framework, since it allows for a different treatment of gains and losses. Under CPT, preferences for uncertain prospects are represented by a *value function* $v : R \to R$ defined for changes in wealth, and by a *decision weighting function* or *capacity* $W : 2^S \to [0, 1]$ defined on the events under consideration, where S represents the (finite) state space and 2^S is the collection of all events. Let A^c, as well as $S - A$, denote the complement of event A, i.e., A and A^c are disjoint and $A \cup A^c = S$. Let $\mathcal{A}$ and $\mathcal{B}$ represent two distinct families of events that are closed under union and complementation. Each family represent a distinct source of uncertainty.

Let (A, x) denote a prospect that provides x if event A happens and 0 otherwise. (A, x) is a *positive prospect* if the prospect involves a gain (i.e., $x > 0$) and is a *negative prospect* if a loss is possible (i.e., $x < 0$). Under CPT,

$$(A, x) \succeq (B, y) \Longleftrightarrow W^i(A)v(x) \geq W^i(B)v(y),$$

where i is equal to "+" if (A, x) is a positive prospect and "−"if (A, x) is a negative prospect. Thus, the decision weighting function is sign-dependent.

The value function v is defined on changes of wealth, in contrast to expected utility and subjective expected utility, which are most commonly defined on wealth levels directly. It is normalized such that $v(0) = 0$. Empirical studies have found that v is concave for gains, convex for losses and is steeper for losses than for gains (i.e., v exhibits loss aversion) (Abdellaoui, Bleichrodt, and Paraschiv, 2007; Tversky and Kahneman, 1992).

The decision weighting function satisfies two properties: i) $W^i(\emptyset) = 0$ and $W^i(S) = 1$, where $\emptyset$ denotes the empty set, and S denotes the state space; and ii) $W^i(A) \leq W^i(B), \forall A \subset B$. Therefore, W^i does not need to be additive, as is the case with subjective expected utility. Moreover, studies of decision under uncertainty have shown that the decision weighting function is typically a non-additive function (e.g., Kilka and Weber, 2001; Tversky and Fox, 1995; Wu and Gonzalez, 1999).

We now present some of the properties of the decision weighting function that have been documented in previous empirical studies.

Definition 1: A decision maker's decision weighting function W^i displays *bounded subadditivity* (SA) for the source $\mathcal{A}$ if the two conditions below are satisfied for all $A, A' \in \mathcal{A}$:
i) *Lower subadditivity* (LSA): $W^i(A) \geq W^i(A \cup A') - W^i(A')$, when $W^i(A \cup A')$ is bounded away from 1.
ii) *Upper subadditivity* (USA): $1 - W^i(S - A) \geq W^i(A \cup A') - W^i(A')$, when $W^i(A')$ is bounded away from 0.

Intuitively, these conditions mean that the decision maker uses impossibility and certainty as reference points when choosing. Lower subadditivity (LSA) implies that the impact of an event A is higher when added to the null event ($\emptyset$) than when it is added to another event A', provided the two events, $A \cup A'$ are bounded away from one. Upper subadditivity (USA) implies that the impact of an event A is higher when subtracted from the certain event S than when it is subtracted from another event $A \cup A'$, provided that event A' is bounded away from zero. Preference conditions are provided by Tversky and Wakker (1995), and the basic properties have been documented empirically by Kilka and Weber (2001) and Tversky and Fox (1995) for gains and Abdellaoui, Vossman, and Weber (2005) for losses[3].

We compare decision weighting functions for different sources in order to analyze how knowledge affect choices. Let $\mathcal{A}$ and $\mathcal{B}$ be two distinct families of events that correspond to

[3]Wu and Gonzalez (1999) showed that the weighting function satisfies a stronger property, concavity for low probability events and convexity for high probability events.

different sources of uncertainty. For our purposes, we can think of $\mathcal{A}$ as a high knowledge source, that is, composed of events where the decision maker feels more knowledgeable about, and $\mathcal{B}$ as a low knowledge source, that is, composed of events where the decision maker feels less knowledgeable about. We represent general events in $\mathcal{A}$ by A, A', etc. and general events in $\mathcal{B}$ by B, B', etc. We also assume that events A, A' (also for B, B') are disjoint.

We now turn to the property that is the central focus of our paper, *source preference* (Tversky and Wakker, 1995):

Definition 2: In the domain of gains, a decision maker displays *source preference* for source $\mathcal{A}$ over source $\mathcal{B}$ if $W^+(A) = W^+(B)$ implies $W^+(A^c) \geq W^+(B^c)$, for all $A \in \mathcal{A}$ and $B \in \mathcal{B}$. In the domain of losses, a decision maker displays *source preference* for source $\mathcal{A}$ over source $\mathcal{B}$ if $W^-(A) = W^-(B)$ implies $W^-(A^c) \leq W^-(B^c)$, for all $A \in \mathcal{A}$ and $B \in \mathcal{B}$[4].

For gains, a decision maker shows a preference for a given source of uncertainty if the sum of the decision weights for an event and its complement is higher than the sum of decision weights for the complements of a second source. The inequality, however, reverses for losses. Therefore, source preference enhances the weighting function for gains and reduces the weighting function for losses. The Ellsberg two-urns experiment described in Section 1 indicates that people usually display a source preference for risk over ambiguity when gains are involved. If we denote by E the event of a red ball in the certain urn and by A the event of a red ball in the ambiguous urn, the standard Ellsberg demonstration shows that $(E, x) \succeq (A, x)$ and $(E^c, x) \succeq (A^c, x)$.

Next we state our hypothesis about the generalization of the competence effect from gains to losses.

Hypothesis: Decision makers prefer betting on high knowledge domains over low knowledge domains for gains. However, they prefer betting on low knowledge domains over high

[4]For both gains and losses, source preference can be written in preference terms, $(A, x) \sim (B, x)$ implies $(A^c, x) \succeq (B^c, x)$, for gains, and $(A, x) \sim (B, x)$ implies $(A^c, x) \preceq (B^c, x)$, for losses. See Tversky and Wakker (1995, pp. 1270-1271).

knowledge domains for losses.

The gain part of the hypothesis is in accord with the findings of Heath and Tversky (1991) and Kilka and Weber (2001), with the loss portion previously untested.

Tversky and Wakker proposed a second property of $W^i(A)$, termed *source sensitivity*:

Definition 3: A decision maker displays *less sensitivity* to source $\mathcal{A}$ than to source $\mathcal{B}$ in the domain $i = +, -$ if the two conditions below are satisfied:
i) If $W^i(A) = W^i(B)$ and $W^i(A \cup A') = W^i(B \cup B')$ then $W^i(A') \geq W^i(B')$, $W^i(A \cup A')$ and $W^i(B \cup B')$ are bounded away from 1.
ii) If $W^i(S - A) = W^i(S - B)$ and $W^i(S - A') = W^i(S - B')$ then $W^i(S - A - A') \leq W^i(S - B - B')$, $W^i(S - A - A')$ and $W^i(S - B - B')$ are bounded away from 0.

Tversky and Fox (1995) studied source sensitivity by comparing decision weights inferred from choices involving risk (objective probabilities) and choices involving five domains of uncertainty. They found that individuals were more sensitive to risk than uncertainty.

We quantify our main hypothesis by using the two-stage process originally proposed by Tversky and Fox (1998) and extended by Kilka and Weber (2001). Tversky and Fox proposed that decision makers evaluate an uncertain prospect, (A, x), by first judging the probability of the event A and then transforming this judged probability using a risky weighting function:

$$W(A) = w_R(P(A)),$$

where W is the weighting function for uncertainty, $P(A)$ is the judged probability for event A, and w_R is the risky weighting function, i.e., the weighting function applied to prospects with objective probabilities. Tversky and Fox (1995) and Fox and Tversky (1998) provided support for this two-stage model, and Wakker (2004) offered a formal justification for this approach. However, this account is clearly incompatible with the Ellsberg Paradox. Thus, Kilka and Weber (2001) extended the two-stage model to account for source preference:

$$W(A) = w_{\mathcal{S}}(P(A)),$$

where $w_{\mathcal{S}}$ is the weighting function for source $\mathcal{S}$ of uncertainty. Source preference and source sensitivity can be captured with the functional specification originally proposed by Goldstein and Einhorn (1987) for risk:

$$w(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}. \tag{2.1}$$

Gonzalez and Wu (1999) used risky choice data to estimate this weighting function[5]. All of their subjects exhibited an inverse S-shaped probability weighting function, such that low probabilities were overweighted and high probabilities were underweighted. However, there was considerable heterogeneity across subjects, and Gonzalez and Wu showed that this two-parameter function was better able to capture the heterogeneity than standard one-parameter weighting functions. This weighting function estimates for the median data in Gonzalez and Wu (1999) are plotted in Figure 1.

Each parameter, δ and γ, in Eqn. (2.1) captures a different psychological characteristic of the subject[6]. The parameter γ measures the curvature of the weighting function, capturing the way the decision maker discriminates between probabilities. As γ approaches 0, the function approaches a step function. The parameter δ measures the elevation of the weighting function, capturing how attractive gambling is to the decision maker. (Of course, $\gamma = 1$ and $\delta = 1$ yield the identity line, $w(p) = p$, and then return the expected utility model). Therefore, the curvature parameter γ is a measure of source sensitivity and the elevation parameter δ is a measure of source preference. If the weighting function for source $\mathcal{A}$ has a higher γ than the weighting function for source $\mathcal{B}$, then source $\mathcal{A}$ displays more source

[5]This function, called linear-in-log-odds, was used by Tversky and Fox (1995), Birnbaum and McIntosh (1996), and Kilka and Weber (2001). Lattimore et al (1992) estimated a similar two-parameter function for risky choices.

[6]For a more through discussion about the psychological interpretation of these two parameters, see Gonzalez and Wu (1999).

sensitivity than source $\mathcal{B}$ (see Definition 3). For source preference, the relation is different for gains and losses. In accord with Definition 2, for gains, larger δ indicates more source preference; for losses, a smaller δ indicates more source preference.

Thus, we extend Eqn. (2.1) to accommodate source dependence, following Kilka and Weber (2001):

$$w_k^i(p) = \frac{\delta_k^i p^{\gamma_k^i}}{\delta_k^i p^{\gamma_k^i} + (1-p)^{\gamma_k^i}}.$$

where i = "+" or "-" (corresponding to gains and losses, respectively) and $k = H$ or L (corresponding to high and low knowledge, respectively). Estimating the values of γ and δ for different sources thus allows us to test for source preference. In particular, we can test whether our hypotheses holds, by comparing δ_H^+ and δ_L^+, and δ_H^- and δ_L^-. Our hypothesis requires that $\delta_H^+ > \delta_L^+$ and $\delta_H^- < \delta_L^-$.

Finally, following Fox and Tversky (1998), who showed that judged probabilities satisfy support theory (Tversky and Koehler, 1994), we also test whether judged probabilities satisfy binary complementarity, i.e., probabilities of complementary events sum to one[7]:

Definition 4: Judged probabilities satisfy *binary complementarity* for a given source (A) if $P(A) + P(A^c) = 1$ for all $A \in \mathcal{A}$.

Empirical support for binary complementarity is provided by Tversky and Koehler (1994) and Tversky and Fox (1995). Violations of binary complementarity, however, have been documented by Brenner and Rottenstreich (1999) and Macchi, Osherson, and Krantz (1999).

[7]Support theory allows nonadditive probability judgments, $P(A \cup A') \leq P(A) + P(A')$. There are other hypothesis besides binary complementarity that follow from support theory, such as proportionality, product rule, and unpacking principle. However, binary complementarity is the only one that our design permits us to test.

3 Experimental Design

We examined source preference for gains and losses by asking subjects to make a series of hypothetical choices between two uncertain prospects, a "high knowledge" (HK) prospect and a "low knowledge" (LK) prospect. We selected events for the prospects such that most participants would feel more knowledgeable about the high knowledge prospect than the low knowledge prospect. To illustrate, we expected most of our University of Chicago student subjects to be more familiar and hence more knowledgeable about Chicago weather than Bucharest weather. Thus, to test for source preference, subjects were given a choice between a "high knowledge" prospect for which they would win \$160 if the high temperature in Chicago was greater than 85° Fahrenheit on July 15, 2005 (and \$0 otherwise) and a "low knowledge" prospect for which they would win \$160 if the high temperature in Bucharest was greater than 85° Fahrenheit on July 15, 2005 (and \$0 otherwise). Note that most features of the prospects are identical so as to heighten the comparative ignorance. The only difference is whether subjects preferred to "bet on Chicago" or "bet on Bucharest." Subjects were also given a choice between prospects that paid the same \$160 on the complementary events (e.g., the high temperature in Chicago was less than 85° on July 15, 2005), and loss prospects in which they would either win or lose \$160 if the relevant event obtained.

We used hypothetical gambles throughout. The primary reason is pragmatic: It is difficult to run studies that might expose participants to real losses (see Thaler and Johnson, 1990). The second reason is empirical. Camerer and Hogarth (1999) reviewed 74 studies in which subjects were the performance-based incentives were zero, low, or high. Although higher incentives seem to improve performance on some tasks (e.g., memory tasks), they harm performance on other tasks (e.g., difficult tasks for which simple and intuitive heuristics can perform well). Most critically, Camerer and Hogarth conclude that "(t)here is no replicated study in which a theory of rational choice was rejected at low stakes in favor of a well-specified behavioral alternative, and accepted at high stakes." (p. 33).

3.1 Detailed Methods

We recruited 107 University of Chicago undergraduate students in May 2005 to participate in our study. Participation was voluntary, and subjects received $3 for participating.

The experiment was entirely computer-based[8]. Participants first saw an opening page that provided an overview of the study. The opening page was followed by an instruction page that explained the subsequent trials. After the instruction page, subjects were given three practice trials, aimed to familiarize subjects with the structure of choices and the procedure involved for making these choices. The trials appeared on their own page, with one choice involving gains, one choice involving losses, and one page involving a probability assessment.

The bulk of the experiment consisted of three sections. In the first section, subjects chose between pairs of similar ambiguous gambles like the ones described above. The gambles are listed in Table 1. In all cases, the choice involved one gamble for which we expected subjects to be knowledgable about (e.g., `ChiTemp`) and one gamble which we expected subjects to be less knowledge about (e.g., `BuchTemp`). Subjects also chose between the complements of the same gambles (e.g., $\texttt{ChiTemp}^c$ vs $\texttt{BuchTemp}^c$). The events were repeated for both the gains and losses domains, with the outcomes being winning either $160 or $0 for the gain prospects, or losing either $160 or $0 for the loss prospects. Each subject made a total of 24 choices, 12 for gains and 12 for losses. Figure 2 contains a screenshot of a typical choice window.

We chose events that were similar to ones used in Fox and Tversky (1995) and Kilka and Weber (2001). In particular, events were paired in choices to heighten a subject's feeling of comparative ignorance. For example, the Chicago temperature gamble was paired with the Bucharest temperature gamble. Both gambles involved the same fixed high temperature and the same date in the future. Finally, both cities were chosen to have similar weather

[8]Full instructions and program code are available upon request.

ChiTemp	High temperature in Chicago is AT LEAST 85F on July 15, 2005
BuchTemp	High temperature in Bucharest is AT LEAST 85F on July 15, 2005
ChiTemp^c	High temperature in Chicago is AT MOST 85F on July 15, 2005
BuchTemp^c	High temperature in Bucharest is AT MOST 85F on July 15, 2005
MH	Miami Heat wins next year's NBA championship
Juve	Juventus wins next year's Italian series A soccer championship
MH^c	Miami Heat loses next year's NBA championship
Juve^c	Juventus loses next year's Italian series A soccer championship
DJIA	The Dow Jones Industrial Average closes BELOW 11,000 points[9] on Dec 31, 2005
DJNeth	The DJ Netherlands Stock index closes BELOW 250 points on Dec 31th, 2005
DJIA^c	The Dow Jones Industrial Average closes ON OR ABOVE 11,000 points on Dec 31, 2005
DJNeth^c	The DJ Netherlands Stock index closes ON OR ABOVE 250 points on Dec 31th, 2005
USInf	The United States inflation rate is BELOW 4% for the 2006 year
SwInf	The Swedish inflation rate is BELOW 4% for the 2006 year
USInf^c	The United States inflation rate is ON OR ABOVE 4% for the 2006 year
SwInf^c	The Swedish inflation rate is ON OR ABOVE 4% for the 2006 year
USOly	The United States wins more than 100 medals in the Olympic Games in Beijing 2008
PolOly	Poland wins more than 10 medals in the Olympic Games in Beijing 2008
USOly^c	The United States wins less than 100 medals in the Olympic Games in Beijing 2008
PolOly^c	Poland wins less than 10 medals in the Olympic Games in Beijing 2008
ChiSnow	Snows more than 1 inch in Chicago on January 10, 2006
OsloSnow	Snows more than 1 inch in Oslo on January 10, 2006
ChiSnow^c	Snows 1 inch or less in Chicago on January 10, 2006
OsloSnow^c	Snows 1 inch or less in Oslo on January 10, 2006

Table 1: Uncertain events used for gambles. Gambles were constructed from these uncertain events such that for gains, subjects won $160 if the event obtained, and for losses, subjects lost $160 is the event obtained.

conditions for the date specified. Although we expected `ChiTemp` to be the high knowledge gamble and `BuchTemp` to be the low knowledge gamble since our study took place on Chicago, subjects provided their own self-rating of knowledge for each domain. We used these ratings as both a manipulation check and an independent variable in our analyses below.

One critical difference between our study and that of Fox and Tversky (1995) and Kilka and Weber (2001) is that our study involved direct choices, whereas their experiment required subjects to assign cash equivalents to various prospects. We used direct choices because trying to elicit certainty equivalents would increase enormously the number of choices a typical participant would have to make.

The order of the questions were randomized within section. We also randomized the position of the gamble in the choice window, left or right (see Figure 2). Finally, to minimize confusion, all the gain prospects and all the loss prospects were kept together, although we randomized the domain subjects saw first.

In the second section, subjects provided probability assessments for the 24 events listed in Table 2. The order of the assessments was randomized within this section. In the third section, subjects reported their knowledge ratings for the events underlying the prospects in Table 1. For the `ChiTemp` question, subjects were asked to rate their knowledge about "Chicago weather" in the following way: "Using the scale below, check the option you think that best describes your knowledge about the weather in Chicago." Knowledge ratings were assessed using a 1 ("no knowledge at all") to 7 ("expert knowledge") scale.

4 Results

4.1 Summary Statistics

We first present summary statistics for the knowledge ratings and probability assessments and then summarize the choice data.

Knowledge ratings are summarized in Table 2. The ratings served as a manipulation check to validate our selection of high and low knowledge events. The vast majority of subjects gave higher knowledge ratings for the source we designated to be high knowledge than for the source we designated to be low knowledge. For example, 98% of subjects reported higher knowledge for Chicago weather than Bucharest weather (last row, Table 2). In addition, the knowledge rating question for Chicago weather was repeated and thus provided a measure of the reliability of knowledge ratings: 95 out of 107 subjects provided identical knowledge ratings for the two questions, with the ratings for the remaining 12 subjects differing by only one rating point. Note also that the largest discrepancy in reported knowledge across the 6 domains was found for the weather questions where subjects tended to feel the most knowledgeable about the high knowledge event.

Although the majority of subjects rated their *relative* knowledge as hypothesized, we coded subjects according to their knowledge ratings in the analysis that follows. Thus, if a non-modal subject reported higher knowledge for Italian soccer than U.S. basketball, then we coded `Juve` as the high knowledge event and `MH` as the low knowledge event for that subject.

Table 2: Knowledge Ratings

	Weather	International Sports	Economic Indicators	Financial Markets	International Sports	Weather
			High Knowledge			
	Chicago	US BBall	US	US	US	Chicago
Average	4.85	3.34	3.20	3.15	3.59	4.83
Std Dev	1.14	1.63	1.47	1.38	1.43	1.14
			Low Knowledge			
	Bucharest	Ital Soccer	Sweden	Netherlands	Poland	Oslo
Average	1.90	2.36	1.74	1.53	1.75	2.21
Std Dev	1.08	1.66	0.96	0.88	0.97	1.31
HK Ratings > LK Ratings	98%	84%	98%	95%	95%	100%

Probability assessments are summarized in Table 3. The majority of probability assessments (64%) fell between .30 and .70, with 23% of assessments being .50. Probabilities of .50 were more common for low knowledge events such as `DJNeth` (28.8%) than high knowledge events such as `ChiTemp` (18.0%), consistent with the rule of thumb documented by de Bruin et al. (2000). We also tested for binary complementarity of probability judgments using a t-test. Binary complementarity is not rejected for any of the 12 events, using the standard 5% significance level (p-values are shown in Table 3).

Table 3: Probability Assessments

	Weather	International Sports	Economic Indicators	Financial Markets	International Sports	Weather
	`ChiTemp`	`MH`	`DJIA`	`USInf`	`USOly`	`ChiSnow`
Average	0.631	0.372	0.482	0.449	0.513	0.545
Std Dev	0.206	0.217	0.209	0.244	0.295	0.215
	$\texttt{ChiTemp}^c$	$\texttt{MH}^c$	$\texttt{DJIA}^c$	$\texttt{USInf}^c$	$\texttt{USOly}^c$	$\texttt{ChiSnow}^c$
Average	0.493	0.609	0.423	0.488	0.502	0.458
Std Dev	0.225	0.234	0.200	0.230	0.274	0.219
p-value for t-test for Binary Complementarity	0.66	0.94	0.73	0.82	0.95	0.99
	`BuchTemp`	`Juve`	`DJNeth`	`SwInf`	`PolOly`	`OsloSnow`
Average	0.545	0.500	0.463	0.525	0.427	0.557
Std Dev	0.219	0.205	0.191	0.214	0.216	0.255
	$\texttt{BuchTemp}^c$	$\texttt{Juve}^c$	$\texttt{DJNeth}^c$	$\texttt{SwInf}^c$	$\texttt{PolOly}^c$	$\texttt{OsloSnow}^c$
Average	0.478	0.489	0.417	0.430	0.536	0.423
Std Dev	0.185	0.187	0.181	0.207	0.218	0.231
p-value for t-test for Binary Complementarity	0.93	0.96	0.67	0.87	0.86	0.94

Table 4 provides an initial summary of the choice data. We consider choices of subjects who report a knowledge difference of 2 or more (e.g., if a subject gave a rating of 5 for Chicago weather and 3 for Oslo weather)[10]. Consider the choice between the `ChiTemp` and `BuchTemp` gambles, and the $\texttt{ChiTemp}^c$ and $\texttt{BuchTemp}^c$ gambles. Under SEU for gains, a subject who prefers `ChiTemp` over `BuchTemp` must judge $P(\texttt{ChiTemp}) > P(\texttt{BuchTemp})$, and thus must prefer $\texttt{BuchTemp}^c$ over $\texttt{ChiTemp}^c$. To test for source preference, we count the number of

[10]The same basic findings discussed below hold if we use different criteria to distinguish between low and high knowledge domains.

subjects who chose the high knowledge gamble over its low knowledge counterpart gamble (denoted, $\texttt{HK} \succ \texttt{LK}$) and also chose the complement of the high knowledge gamble over the complement of the low knowledge gamble (denoted, $\texttt{HK}^c \succ \texttt{LK}^c$). We also count the number of subjects with the opposite pattern. For example, for the Chicago-Bucharest temperature gambles for gains, 20 subjects chose $\texttt{HK}$ over $\texttt{LK}$ and $\texttt{HK}^c$ over $\texttt{LK}^c$ compared to 15 subjects who chose $\texttt{LK}$ over $\texttt{HK}$ and $\texttt{LK}^c$ over $\texttt{HK}^c$. Recall that we scored knowledge according to a subject's reported knowledge, not our initial designations.

If subjects satisfied SEU strictly, then all entries should be in the "Other" row. However, since subjects make choices with error (e.g., Ballinger and Wilcox, 1997; Blavatskky, 2007; Harless and Camerer, 1994; Hey, 1995; Loomes and Sugden, 1998), we used a sign test to determine whether choices exhibited a systematic bias. All 6 of the gain choices are directionally consistent with our hypothesis, with the patterns significant at the .05 level for 3 of the 6 gain questions. In contrast, 4 of the 6 loss choices are directionally consistent with our hypothesis, with only 1 of the 6 loss questions significant (with another marginally significant). Thus, the competence effect is stronger for gains than for losses: the discrepancy between $\texttt{HK}$ and $\texttt{LK}$ choices for gains is higher than the discrepancy between $\texttt{LK}$ choices and $\texttt{HK}$ choices for losses. Recall that the competence hypothesis for losses implies a preference towards the low knowledge domain, since subjects are more comfortable in choosing a less knowledgeable event in the hope that will turn out more favorably.

We next examine whether there is a significant difference in choices for gains and losses, using a Stuart-Maxwell chi-square test (Maxwell, 1970; Stuart, 1955) to determine if the marginal frequency of responses for gains is similar to the one for losses. This test is a version of the Pearson chi-square test that is valid for dependent data[11]. For example, for the temperature gambles, we tested whether the responses for gains (20, 15, and 58) are similar to the responses for losses (18, 30, 45). Since the competence effect for losses implies

[11] We also computed Pearson statistics and found similar results.

Table 4: Choices, Knowledge Difference at least 2

	Gains					
	ChiTemp - BuchTemp	MH - Juve	DJIA - DJNeth	USInf - SwInf	USOly - PolOly	ChiSnow - OsloSnow
$\texttt{HK} \succ \texttt{LK}$, $\texttt{HK}^c \succ \texttt{LK}^c$	20	15	20	8	11	27
$\texttt{LK} \succ \texttt{HK}$, $\texttt{LK}^c \succ \texttt{HK}^c$	15	3	5	5	5	5
Other	58	36	27	34	47	49
Total	93	54	52	47	63	81
Sign Test (p-value)	0.25	< 0.01	< 0.01	0.29	0.10	< 0.01
	Losses					
	ChiTemp - BuchTemp	MH - Juve	DJIA - DJNeth	USInf - SwInf	USOly - PolOly	ChiSnow - OsloSnow
$\texttt{HK} \succ \texttt{LK}$, $\texttt{HK}^c \succ \texttt{LK}^c$	18	14	11	10	8	23
$\texttt{LK} \succ \texttt{HK}$, $\texttt{LK}^c \succ \texttt{HK}^c$	30	10	15	12	18	18
Other	45	30	26	25	37	40
Total	93	54	52	47	63	81
Sign Test (p-value)	0.06	0.85	0.28	0.42	0.04	0.73

a preference for the low knowledge source for losses, we also ran an inverted Stuart-Maxwell chi-square test, i.e., we tested whether the responses for gains (20, 15, and 58) are different from the inverse of the responses for losses (30, 18, and 45). The Stuart-Maxwell tests show that the marginal distribution for gains is statistically different from the one for losses, for all six types of gambles. The inverted Stuart-Maxwell test shows that the competence hypothesis does not reflect strictly, except perhaps for the DJ, Olympics, and Inflation gambles. Table 5 reports these tests statistics.

4.2 Estimation of the Probability Weighting Function

The preceding analysis of choices did not take into account probability judgments. In this section, we use the judgments of probabilities provided by our subjects to estimate probability weighting functions for high and low knowledge sources of uncertainty. To do so, we assume

Table 5: Tests for Differences in Choices between Gains and Losses

	ChiTemp - BuchTemp	MH - Juve	DJIA - DJNeth	USInf - SwInf	USOly - PolOly	ChiSnow - OsloSnow
Stuart-Maxwell $\chi^2(1)$	31.84	11.00	9.74	21.54	31.81	15.13
p-value	< 0.001	< 0.001	< 0.01	< 0.001	< 0.001	< 0.001
Inverted Stuart-Maxwell $\chi^2(2)$	21.44	10.95	2.51	4.60	2.67	15.16
p-value	< 0.001	< 0.01	0.27	0.10	0.26	< 0.001

a random utility model where all agents have the same underlying preferences and thus estimate an empirical representative agent. Similar procedures have been used in decision under risk by Camerer and Ho (1994), Wu and Gonzalez (1996), and Wu and Markle (2008) (see also Stott, 2006).

As in Camerer and Ho, we assume that all agents have the same preferences (i.e., decision weighting and value function). We also assume that the source of preference affects only the probability weighting function and not the value function. Variation in choices is accounted for by the stochastic part in the utility function and the differences in assessments of assessments of the likelihood of the events. Let A_k represent the ambiguous event, and $G_k^i = (A_k, x)$ the uncertain prospect corresponding to the ambiguous event A_k, where k indexes the source of ambiguity and i="+" if $x > 0$ and i ="-" if $x < 0$. Then, the random utility model is written as:

$$U_j(A_k, x) = W_{j,k}^i(A_k)v^i(x) + \varepsilon_j, \tag{4.1}$$

where U_j denotes the utility of G_k^i to individual j. The weighting function $W_{j,k}^i$ is modelled using Eqn. (2.2):

$$W_{j,k}^i(A_k) = w_k^i(P_j(A_k)) = \frac{\delta_k^i P_j(A_k)^{\gamma_k^i}}{\delta_k^i P_j(A_k)^{\gamma_k^i} + (1 - P_j(A_k))^{\gamma_k^i}}, \tag{4.2}$$

where $P_j(A_k)$ is individual j's subjective probability that event A_k occurs[12]. The parameter δ_k^i measures the elevation of w_k^i and is sign- and source-dependent, with a higher (lower) δ_k^i corresponding to more risk-seeking behavior for gains (losses), and $\delta_k^i = 1$ giving a symmetric weighting function with $W_{j,k}^i(A) = .5$ when $P_j(A) = .5$. The parameter γ_k^i measures the curvature of w_k^i, with a lower γ_k^i yielding a more curved weighting function and $\gamma_k^i = 1$ and $\delta_k^i = 1$ corresponding to the identity function, $W_{j,k}^i(A_k) = P_j(A_k)$ for all A_k.

We model the competence effect through the elevation parameter, δ_k^i, with the main goal to determine if there are any substantial differences between the elevation parameters for the high and low knowledge domains. Therefore, we let $\delta_H^i = \delta_L^i + \Delta^i$, and thus test the null hypothesis that $\Delta^i = 0$, where $i = +, -$. Our hypothesis requires that $\Delta^+ > 0$ and $\Delta^- < 0$.

We use a logit model to account for the randomness in choice:

$$Q_j(G_H^i \succeq G_L^i) = \frac{1}{1 + \exp\left[-\mu^i \left(U_j(G_H^i) - U_j(G_L^i)\right)\right]}, \tag{4.3}$$

where Q_j denotes the likelihood of choosing one option over another, and μ^i is a scaling parameter that reflects the sensitivity of choices to utility differences. When $\mu^i = 0$, the decision maker choices randomly between all options, and as $\mu^i \to \infty$, the decision maker always chooses the option with the highest utility. We rewrite Eqn. (4.3) as follows:

$$Q_j(G_H^i \succeq G_L^i) = \frac{1}{1 + \exp\left[-\lambda^i \left(W_{j,k}^i(A_H) - W_{j,k}^i(A_L)\right)\right]},$$

where $\lambda^+ = (\mu^+)v(160)$ for gains and $\lambda^- = (\mu^-)v(-160)$ for losses. Thus the value function is subsumed in λ^i and drops out of the estimation.

The likelihood function is given by

$$\ln(L) = \sum_{i=1}^{n} [I_j \ln Q_j(G_H^i \succeq G_L^i) + (1 - I_j)\ln(1 - Q_j(G_H^i \succeq G_L^i))], \tag{4.4}$$

[12] We also produced similar results using Prelec's (1998) two-parameter function.

where n is the number of observations and I_j is a characteristic function such that $I_j = 1$ if individual j chose G_H over G_L and $I_i = 0$ otherwise.

Our problem is then to find the values of δ_k^i, Δ^i, γ_k^i, and λ^i that maximize the log-likelihood function above, where Eqn. (4.4) is maximized over the 1284 choices (107 subjects and 12 choices for both gains and losses). The two parameters of the weighting function are highly multicolinear (see Gonzalez and Wu (1999, footnote 11). Thus, because of data restrictions and because our primary concern was estimating Δ^i, we equated the curvature parameters $\gamma_H^i = \gamma_L^i$ and varied the levels between .30 and 1.00 to test the robustness of our results. The maximization problem was implemented in MATLAB. Table 7 shows the results of this estimation procedure for gains and losses.

The gain estimates are consistent with the competence hypothesis. We find a significantly higher elevation parameter for the high knowledge source than for the low knowledge source for all values of $\gamma_H^i = \gamma_L^i$. The parameter estimates generally agree with the result of Kilka and Weber. Their estimates of δ_H^+ ranged from 0.891 to 1.315, while their estimates of δ_L^+ ranged from 0.790 to 1.167. Thus, for gains, we find that individuals are more attracted to high knowledge gambles than low knowledge gambles.

For losses, the competence effect reverses, but not significantly so. Although $\Delta^- < 0$ for all values of $\gamma_H^i = \gamma_L^i$, the values are not significant in any case[13]. Therefore, knowledge is not consistently used to differentiate uncertainty in the domain of losses, and thus there is only directional support for our hypothesis[14].

[13]We also performed an additional estimation, restricting the sample of the observations in which the reported knowledge difference exceeded 3. This left us with 468 of 1284 observation. This analysis produced qualitatively similar results (Gains: $\Delta^i \approx .50, p < .001$, Losses: $\Delta^i \approx -.05$, n.s.).

[14]We also compared expected utility to our more general model. The expected utility restriction was conducted by setting all parameters equal to 1. A likelihood ratio rest strongly rejected the expected utility model for both the gain and loss domains.

Table 6: Maximum likelihood estimates for gains and losses, assuming different values for γ

	γ values ($\gamma_H^i = \gamma_L^i$)							
	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
				Gains				
δ_L^+	1.10	1.01	0.94	0.89	0.85	0.82	0.79	0.77
Δ^+	0.17	0.20	0.22	0.24	0.25	0.27	0.28	0.30
t-value	3.59	3.49	3.38	3.28	3.18	3.09	3.01	2.93
λ^+	6.98	5.68	4.86	4.29	3.88	3.57	3.32	3.12
$\ln(L)$	−786.11	−781.97	−779.54	-777.93	−776.82	−776.01	−775.41	−774.98
				Losses				
δ_L^-	1.03	1.00	0.99	0.99	0.99	1.01	1.02	1.04
Δ^-	−0.05	−0.06	−0.07	-0.08	−0.09	−0.09	−0.10	−0.11
t-value	−0.88	−0.90	−0.90	-0.89	−0.87	−0.85	−0.82	−0.79
λ^-	4.17	3.48	2.99	2.64	2.37	2.17	2.00	1.87
$\ln(L)$	−846.00	−844.00	−843.23	-843.14	−843.08	−843.28	−843.55	−843.87

5 Conclusion

In this paper, we investigated the effect of knowledge on choices that involve gains and losses. We found that competence effects choices involving gains, thus replicating a common result in the literature (Chow and Sarin, 2001; Fox and Tversky, 1995; Fox and Weber, 2002). Like Kilka and Weber (2001), the competence effect for gains produced a larger elevation parameter for the high knowledge source than the low knowledge source probability weighting function, consistent with the psychological hypothesis that when decision makers feel more competent about the underlying source of uncertainty, they are more likely to be on that source. Our study also extended the results of Kilka and Weber by using direct choices instead of certainty equivalents. Therefore, our study provides an important robustness check of the methods used in most studies, as choices are considerably less involved cognitively than eliciting certainty equivalents.

In the domain of losses, Tversky and Wakker (1995) conjectured that subjects should prefer betting on the low knowledge source over the high knowledge source. The intuition for this reversal and hence the source preference hypothesis we test in this paper is that people shy away from gambles when they feel more confident about the loss they will face. Basili, Chateauneuf, and Fontini (2005) suggest that such preferences reflect pessimism for gains and optimism for losses. Therefore, when confronted with losses, people are optimistic in the sense that they prefer to gamble over a chance of losing nothing and losing a higher amount than losing an intermediate value for sure, where the contrary happens when choices involve gains. The focal point for choice changes from gaining with certainty to the possibility of losing nothing, a crucial psychological distinction between choices in the domain of losses and choices in the domain of gains that has been observed in previous research on decision under risk.

Interestingly, we find that the competence effect does not extend well to losses, as proposed by Tversky and Wakker (1995). Although results are directionally consistent with Tversky and Wakker's conjecture, that individuals would prefer to bet on low knowledge sources over high knowledge sources for losses, the results are not significant. Specifically, the decision weighting function parameters estimated for losses show an elevation parameter for less familiar domains higher than the elevation parameter for more familiar domains, but this difference is not statistically significant.

We suggest several reasons for the absence of a significant competence effect for losses. First, in Section 2, we reviewed studies of ambiguity aversion for losses. Past studies like Cohen, Jaffray and Said (1985, see also Einhorn and Hogarth, 1986; Hogarth and Einhorn, 1990; Kahn and Sarin, 1988) show that results are usually mixed for losses. Second, choices for losses is noisier. This interpretation is supported by the logit parameter λ, which is lower for losses than gains, indicating that choosing among losses is noisier than choosing among gains. Thus, a competence effect may exist for losses, but our empirical test may have lacked the statistical power to detect this diminished effect.

Third, by equating the amount to win for each choice gamble, as well as many of the characteristics of the underlying events, our experimental design provides a stark test of the competence hypothesis. For example, the events `ChiTemp` and `BuchTemp` shared the same target temperature and the target day. As a result, a subject confronted with the choice of whether to select $(\texttt{ChiTemp}, x)$ or $(\texttt{BuchTemp}, x)$ might have simplified the choice to a judgment of whether Chicago or Bucharest was more likely to be 85° on July 15, 2005. Of course, such a simplifying strategy would have produced choices consistent with SEU. Apparently subjects did not resort to such an approach when choosing among gains, but it is possible that they did so when faced with losses. Such a speculation is consistent with two well-documented observations: (i) response times are higher for losses than gains (Dickhaut et al, 2003); and (ii) subjects are more likely to use constructive decision processes as task complexity increases (e.g., Bettman, Luce, and Payne, 1998). If this conjecture is true, then the competence effect for losses may be observed when subjects provide cash equivalents, as in Kilka and Weber (2001), a response mode that is incompatible with the simplifying strategy outlined above.

Finally, competence may simply not be used to differentiate events when choices involve losses. If this is the case, it means that there is a crucial behavioral difference in choices involving gains from choices involving losses. The psychological reasons for this difference in behavior should be investigated, if other studies corroborate this finding.

References

[1] Abdellaoui, Mohammed (2000). "Parameter-free elicitation of utility and probability weighting functions," *Management Science* 46, 1497-1512.

[2] Abdellaoui, Mohammed, Frank Vossmann, and Martin Weber (2005). "Choice-based elicitation and decomposition of decision weights for gains and losses under uncertainty," *Management Science* 51, 1384-1399.

[3] Abdellaoui, Mohammed, Han Bleichrodt, and Corina Paraschiv (2007). "Measuring loss aversion: A parameter-free approach," *Management Science* 53, 1659-1674.

[4] Ballinger, T. Parker and Nathaniel T. Wilcox (1997). "Decisions, error and heterogeneity," *Economic Journal* 106, 1090-1105.

[5] Basili, Marcello, Alain Chateauneuf, and Fulvio Fontini (2005). "Choices under ambiguity with familiar and unfamiliar outcomes," *Theory and Decision* 58, 195-207.

[6] Becker, Selwyn W. and Fred O. Brownson (1964). "What price ambiguity? Or the role of ambiguity in decision-making," *Journal of Political Economy* 72, 62-73.

[7] Bettman, James R., Mary F. Luce, and John W. Payne (1998). "Constructive Consumer Choice Processes." *Journal of Consumer Research* 25, 187-217.

[8] Birnbaum, Michael H. and William R. McIntosh (1996). "Violations of branch independence in choices between gambles," *Organizational Behavior and Human Decision Processes* 67, 91-110.

[9] Blavatskyy, Pavlo (2007). "Stochastic expected utility theory," *Journal of Risk and Uncertainty* 34, 259-286.

[10] Brenner, Lyle A. and Yuval Rottenstreich. (1999). "Focus, repacking, and the judgment of grouped hypotheses," *Journal of Behavioral Decision Making* 12, 141-148.

[11] Camerer, Colin F. and Teck-Hua Ho (1994). "Violations of the betweenness axiom and nonlinearity in probability," *Journal of Risk and Uncertainty* 8, 167-196.

[12] Camerer, Colin F. and Robin Hogarth (1999). "The effects of financial incentives in experiments: A review and capital-labor-production framework," *Journal of Risk and Uncertainty* 3, 7-42.

[13] Camerer, Colin F. and Martin Weber (1992). "Recent developments in modeling preferences: Uncertainty and ambiguity," *Journal of Risk and Uncertainty* 5, 325-370.

[14] Choquet, Gustave (1954). "Theory of capacities," *Annales de l'Institut Fourier* 5, 131-295.

[15] Chow, Claire Chua and Rakesh K. Sarin (2001). "Comparative ignorance and the Ellsberg paradox," *Journal of Risk and Uncertainty* 2, 129-139.

[16] Cohen, Michelle, Jean-Yves Jaffray, and Tanios Said (1985). "Individual behavior under risk and under uncertainty: An experimental study," *Theory and Decision* 18, 203-228.

[17] de Bruin, Wandi Bruine, Baruch Fischhoff, Susan G. Millstein, and Bonnie L. Halpern-Felsher (2000). "Verbal and numerical expressions of probability: 'It's a fifty-fifty chance'," *Organizational Behavior and Human Decision Processes* 81, 115-131.

[18] Dickhaut, John, Kevin McCabe, Jennifer C. Nagode, Aldo Rustichini, Kip Smith, and Jose V. Pardo (2003). "The impact of the certainty context on the process of choice." *Proceedings of the National Academy of Sciences of the USA* 100, 3536-3541.

[19] Einhorn, Hillel J. and Robin M. Hogarth (1986). "Decision making under ambiguity," *Journal of Business* 59, S225-S250.

[20] Ellsberg, Daniel (1961). "Risk, ambiguity and the Savage axioms," *Quarterly Journal of Economics* 75, 643-669.

[21] Etchart-Vincent, Nathalie (2004). "Is probability weighting sensitive to the magnitude of consequences? An experimental investigation on losses," *Journal of Risk and Uncertainty* 3, 217-235.

[22] Fischer, Gregory W., Ziv Carmon, Dan Ariely, and Gal Zauberman (1999). "Goal-based construction of preferences: Task goals and the prominence effect," *Management Science* 45, 1057-1075.

[23] Fox, Craig R. and Amos Tversky (1995). "Ambiguity aversion and comparative ignorance," *Quarterly Journal of Economics* 110, 585-603.

[24] Fox, Craig R. and Amos Tversky (1998). "A Belief-based account of decision under uncertainty," *Management Science* 44, 879-895.

[25] Fox, Craig R. and Kelly E. See (2003). "Belief and preference in decision under uncertainty," In D. Hardman and L. Macchi (Eds.), *Thinking: Psychological Perspectives on Reasoning, Judgment and Decision Making*, New York: Wiley, pp. 273-314.

[26] Fox, Craig R. and Martin Weber (2002). "Ambiguity aversion, comparative ignorance and decision context," *Organizational Behavior and Human Decision Processes* 88, 476-498.

[27] Frisch, Deborah and Jonathan Baron (1988). "Ambiguity and rationality," *Journal of Behavioral Decision Making* 1, 149-157.

[28] Gilboa, Itzhak (1987). "Expected utility with purely subjective nonadditive probabilities," *Journal of Mathematical Economics* 16, 65-88.

[29] Goldstein, William M. and Hillel J. Einhorn (1987). "Expression theory and the preference reversal phenomena," *Psychological Review* 94, 236-254.

[30] Gonzalez, Richard and George Wu (1999). "On the shape of the probability weighting function," *Cognitive Psychology* 38, 129-166.

[31] Harless, David W. and Colin F. Camerer (1994). "The predictive utility of generalized expected utility theories," *Econometrica* 62, 1251-1290.

[32] Heath, Chip and Amos Tversky (1991). "Preference and belief: Ambiguity and competence in choice under uncertainty," *Journal of Risk and Uncertainty* 4, 5-28.

[33] Hey, John D. (1995). "Experimental investigations of errors in decision-making under risk," *European Economic Review* 39, 633-640.

[34] Hogarth, Robin M. and Hillel J. Einhorn (1990). "Venture theory: A model of decision weights," *Management Science* 36, 780-803.

[35] Kahn, Barbara E. and Rakesh K. Sarin (1988). "Modelling ambiguity in decisions under uncertainty," *Journal of Consumer Research* 15, 265-272.

[36] Kahneman, Daniel and Amos Tversky (1979). "Prospect theory: An analysis of decision under risk," *Econometrica* 47, 263-291.

[37] Keynes, John M. (1921). *A treatise on probability*. London: Macmillan.

[38] Kilka, Michael and Martin Weber (2001). "What determines the shape of the probability weighting function under uncertainty?," *Management Science* 47, 1712-1726.

[39] Lattimore, Pamela K., Joanna K. Baker, and Ann D. Witte (1992). "The influence of probability on risky choice: A parametric examination," *Journal of Economic Behavior and Organization* 17, 377-400.

[40] Loomes, Graham and Robert Sugden (1998). "Testing Different Stochastic Specifications of Risky Choice," *Economica* 65, 581-598.

[41] Macchi, Laura, Daniel Osherson, and David M. Krantz (1999). "A note on superadditive probability judgment," *Psychological Review* 106, 210-214.

[42] Machina, Mark (2008). "Risk, ambiguity, and the rank-dependence axioms," *Departmente of Economics, UCSD.*

[43] Maxwell A (1970) "Comparing the classification of subjects by two independent judges," *British Journal of Psychiatry* 116, 651-655.

[44] Prelec, Drazen (1998). "The probability weighting function," *Econometrica* 66, 497-527.

[45] Quiggin, John (1982). "A theory of anticipated utility," *Journal of Economic Behavior and Organization* 3, 323-343.

[46] Savage, Leonard J. (1954). *The Foundations of Statistics*. Wiley: New York.

[47] Schmeidler, David (1989). "Subjective probability and expected utility without additivity," *Econometrica* 57, 571-587.

[48] Stott, Henry (2006). "Cumulative prospect theory's functional menagerie," *Journal of Risk and Uncertainty* 32, 101-130.

[49] Stuart, Alan (1955). "A test for homogeneity of the marginal distributions in a two-way classification," *Biometrika* 42, 412-416.

[50] Taylor, Kimberly A. (1995). "Testing Credit and Blame Attributions as Explanation for Choices under Ambiguity," *Organizational Behavior & Human Decision Processes* 64, 128-137.

[51] Thaler, Richard and Johnson, Eric (1990). "Gambling with the House Money and Trying to Break Even: The Effects of Prior Outcomes on Risky Choice," *Management Science* 36, 643-660.

[52] Trautmann, Stefan T., Ferdinand M. Vieider, and Peter P. Wakker (2008). "Causes of ambiguity aversion: Known versus unknown preferences," *Journal of Risk and Uncertainty* 36, 225-243.

[53] Tversky, Amos and Craig R. Fox (1995). "Weighing risk and uncertainty," *Psychological Review* 102, 269-283.

[54] Tversky, Amos and Daniel Kahneman (1992). "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and Uncertainty* 5, 297-323.

[55] Tversky, Amos and Derek J. Koehler (1994). "Support theory: A nonexistencial representation of subjective probabilities," *Psychological Review* 101, 547-567.

[56] Tversky, Amos and Peter Wakker (1995). "Risk attitudes and decision weights," *Econometrica* 63, 1255-1280.

[57] Wakker, Peter P. (2004). "On the Composition of Risk Preference and Belief," *Psychological Review* 111, 236-241.

[58] Wu, George and Richard Gonzalez (1996). "Curvature of the probability weighting function," *Management Science* 42, 1676-1690.

[59] Wu, George and Richard Gonzalez (1999). "Nonlinear decision weights in choice under uncertainty," *Management Science* 45, 74-85.

[60] Wu, George and Alex B. Markle (2008). "An empirical test of gain-loss separability in prospect theory," *Management Science* 54, 1322-1335.