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Beware of black swans but do not ignore white ones ?

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Beware of black swans and do not ignore white ones?

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Abstract

Uncertainty pervades most aspects of life. From selecting a new technology to choosing a career, decision makers often ignore the outcomes of their decisions. In the last decade a new paradigm has emerged in behavioral decision research in which decisions are “experienced” rather than “described”, as in standard decision theory. The dominant finding from studies using the experience-based paradigm is that decisions from experience exhibit "black swan effect", i.e. the tendency to neglect rare events. Under prospect theory, this results in an experience-description gap. We show that several tentative conclusions can be drawn from our interdisciplinary examination of the putative experience-description gap in decision under uncertainty. Several insights are discussed. First, while the major source of under-weighting of rare events may be sampling error, it is argued that a robust experience-description gap remains when these factors are not at play. Second, the residual experience-description gap is not only about experience *per se*, but also about the way in which information concerning the probability distribution over possible outcomes is learned.

Additional econometric and empirical work might be required to fully flech out these tentative conclusions. However, there was a consensus that an initially polemical literature turns out to be constructive in drawing researcher towards greater rapprochements.

Key words: Black swans, risk, ambiguity, four-fold pattern, (non)-expected utility, probabilistic choices, experience-based decision making, description-based decision making.

1 Introduction

The standard paradigm for studying decision under uncertainty entails presenting participants with choices between prospects that are described as event-contingent outcomes (e.g. lose $50 with probability .5, and nothing otherwise; gain $100 if the home team wins and nothing otherwise). The decision maker is either provided with objective probabilities from the outset (risk), or has to assign subjective likelihoods to events (ambiguity). Most of the accumulated empirical findings observed a robust tendency for people to overweight small probabilities, and to underweight moderate to high probabilities under risk (e.g. Tversky and Kahneman 1992). Similarly, under ambiguity people tend to overweight events that they perceive to be unlikely, and underweight events that they perceive to be likely (Tversky and Fox, 1995; Fox and Tversky, 1998; Wakker 2010).

In the last decade a new paradigm has emerged in behavioral decision research in which decision are "experienced" rather than "described". Both probabilities *and* outcomes must be learned through sampling, i.e. repeated draws with replacement from a probability distribution unknown to the decision maker (Hertwig et al. 2004). The dominant finding from studies using this paradigm is that decisions from experience are characterized by diminished impact of rare events (see Barron and Erev 2003; Hertwig et al. 2004). Taleb (2007) refers to a related under-sensitivity to rare events as the Black Swan effect. The contrast between decisions from experience and decisions under risk is usually referred to as the "experience-description gap."

In this paper we take a critical look at the experience-description gap. First, we take stock of prior contributions to this literature. Second, we propose to investigate ways to enrich the study of the experience-description gap using advanced econometric tools that explicitly account for errors and heterogeneity. Third, we attempt to reconcile the literature on decisions from experience with recent empirical literature on (description based) decision under ambiguity (Attanasi, Gollier, Montesano and Pace, 2013).

2 Risk and Ambiguity in Prospect Theory

In standard decision making under uncertainty paradigm, an alternative, or a *prospect*, is described by a list of event-contingent outcomes. To illustrate, let $x_{\mathrm{E}}y$ denote the prospect that pays $\$x$ if event E obtains, and $\$y$ otherwise. For instance, setting $x = 10$, $y = 1$, and R = "rain tomorrow," the prospect $10_{\mathrm{R}}1$ denotes a prospect yielding \$10 if there is rain tomorrow and \$1 otherwise. The evaluation of such alternatives requires an assessment not only of the desirability of outcomes (utilities), but also of the likelihoods of the corresponding events (probabilities or their generalizations). Under risk, standard decision theory recommends evaluating an alternative using *expected utility* (EU), i.e. the probability-weighted average utility of the outcomes. Thus, the EU of $10_{\mathrm{R}}1$ is $P(\mathrm{R})u(10) + (1-P(\mathrm{R}))u(1)$ (P: probability; u: utility). *Risk aversion,* the preference of a sure outcome over a risky prospect with equal or higher expected value, is commonly assumed to hold. For risk, with $p = P(\mathrm{E})$, we often write x_py instead of $x_{\mathrm{E}}y$. EU explains risk aversion using a concave utility function over states of wealth—for example if gaining \$200 adds less than twice the utility of gaining \$100, then a decision maker should prefer \$100 for sure to a prospect that offers a 50-50 chance of \$200 or nothing.

Several empirical results challenge the descriptive validity of EU. Allais' (1953) famous example for risk challenged the descriptive validity of EU. It suggests that people do not weight the utilities by their probabilities. More generally, the assumption of risk aversion is violated by the commonly observed *fourfold pattern* of risk preferences: risk aversion for moderate to high probability gains and low probability losses, coupled with risk seeking for low probability gains and moderate to high probability losses (Tversky and Kahneman, 1992).

Rabin (2000) showed that moderate risk aversion for small-stakes mixed (gain-loss) gambles at all levels of wealth (assuming a strictly increasing and concave utility function) implies an implausible level of risk aversion for large-stakes gambles.

These empirical and theoretical violations of EU are accommodated by *prospect theory* (PT), the leading descriptive model of decision under uncertainty (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). Under PT, outcomes are evaluated with respect to a *reference point*, normalized to 0. Utility u is strictly increasing and $u(0)=0$. It exhibits diminishing sensitivity: marginal utility diminishes with the distance from the reference point, leading to concavity for gains but convexity for losses. Diminishing sensitivity contributes to risk aversion for gains and risk seeking for losses. The latter goes against conventional wisdom, but has been confirmed empirically. Furthermore, utility u is characterized by *loss aversion* in which the function is steeper for losses than gain—typically this is modeled by multiplying utility for losses by a coefficient $\lambda > 1$ (Figure 1). Loss aversion accommodates risk-aversion for modest stakes gambles that scales up reasonably proportionally. Probabilities are transformed by a weighting function w^+ for gains and by w^- for losses, both normalized so that $w(0)=0$ and $w(1)=1$, and strictly increasing (Figure 2). Hence; $x_p y$ is evaluated by: $w^+(p)u(x) + [1-w^+(p)]u(y)$ if $x \geq y \geq 0$; $w^-(p)\lambda u(x) + [1-w^-(p)]\lambda u(y)$ if $x \leq y \leq 0$; $w^+(p)u(x) + w^-(1\text{-}p)\lambda u(y)$ if $x > 0 > y$.

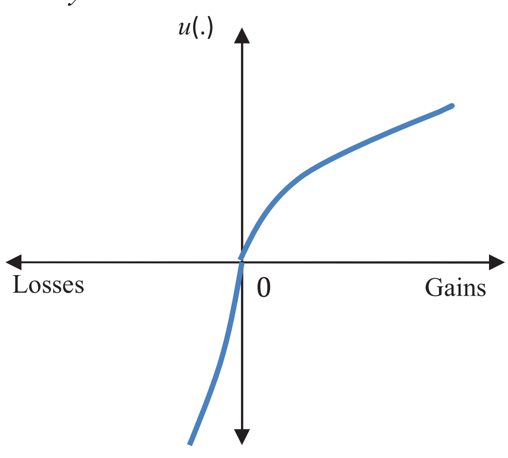

Figure 1: Prospect theory utility function

Figure 2 illustrates an S-shaped probability weighting function. It shows that the lower probability interval [0,q] has more impact than the middle interval [p, p+q], which is bounded away from the lower and upper endpoints. Similarly, the upper interval [1-q, 1] has more impact than the middle interval [p, p+q]. The underweighting of moderate to large probabilities reinforces the tendency implied by the S-shaped utility function toward risk averse for gains and risk seeking for losses, but reverses this pattern for very low probabilities, which are overweighted.

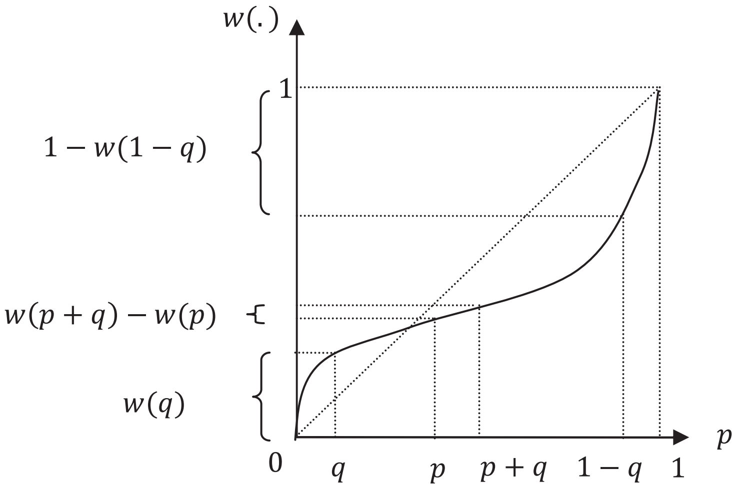

Figure 2: Probability weighting function

Numerous studies surveyed by Wakker (2010) have confirmed the above qualitative empirical properties using choices among simple risky prospects.

3 The Description-Experience Gap

Research on "decisions from experience" (DFE) employ paradigms in which individuals learn outcomes and their likelihoods through the sequential sampling of outcomes. Three experimental paradigms (see Hertwig and Erev 2009) and variants thereof have been used. All involve a choice between two or more payoff distributions. In the most popular *sampling* *paradigm*, people first sample from the distributions as long as they wish without costs. Once search is terminated, they decide from which distribution to make a single incentivized draw. In the *full-feedback paradigm*, each draw adds to a person's income, and she receives draw-by-draw feedback about the actual and forgone payoffs. Finally, the *partial-feedback paradigm* restricts feedback to the actual payoffs. Comparisons of DFE with decisions from descriptions (DFD; made on described distributions as in the studies of decision-making under risk; Section 2) reveal a large experience-description gap (Hertwig and Erev 2009). Figure 3 illustrates this gap using six representative decision problems. In DFE, people behave as if the rare events have less impact than they deserve according to their objective probabilities, whereas in DFD people behave as if the rare events have more impact than they deserve (consistent with PT).

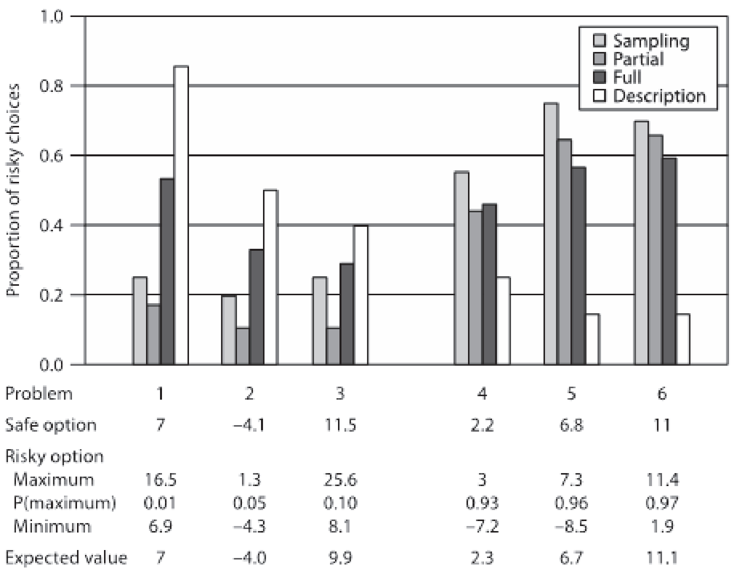

Figure 3: The experience–description gap

Choice patterns in all three experience-based paradigms are surprisingly similar with the tendency to "underweight" rare events particularly robust in the full-feedback paradigm. It should be noted that when all possible payoffs are identified explicitly, this eliminates underweighting of rare events in the sampling paradigm (see Abdellaoui et al. 2011b, Hadar and Fox 2009) though this does not appear to occur in the full-feedback paradigm (see Yechiam et al. 2005).

What causes the description–experience gap?

Five broad contributors to the gap have been advance in prior research—the first two relate to DFE and choices consistent with underweighting and neglect of rare events; the next two relate to DFD, and choices consistent with overweighting of rare events; the final relates to both.

Sampling error and sheer unawareness of the rare events' existence

A world in which *all* risks and hazards are fully described is unattainable. Therefore, we often cannot help but be unaware of rare events. A close cousin of unawareness is obliviousness due to reliance on the wrong model such as estimating financial risks with tools that assume a normal distribution in non-Gaussian environments (Taleb 2007). Unawareness of rare events can also occur in the sampling paradigm in which people tend to sample little (see Hertwig et al. 2004) and likely contributed to the experience-description gap documented using the original sampling paradigm (cf. Hadar and Fox, 2009). In fact, when one accounts for sampling error in the seminal study of Hertwig et al. (2004) so that decisions are analyzed with respect to *sampled* probability distributions over outcomes (i.e. what participants actually experienced) rather than the "objective" probability distributions from which outcomes were sampled (which was opaque to participants), choices accord well with prospect theory (Fox and Hadar 2006).

Selective reliance on past experiences

Reliance on past experiences contributes to the attenuated impact of rare events in DFE. In many settings people behave as if they rely on small samples drawn from their past experiences (e.g. those more recently experienced; see Hertwig et al., 2004), and tend to choose as if they underweight rare events that they have, in fact, experienced. The impact of this tendency also emerged in two *choice prediction competitions* focusing on the full- and the partial-feedback paradigms (Erev et al. 2010a, 2010b): the winning models in both competitions implied reliance on small set of past experiences.

Tallying

A factor amplifying the gap concerns the way people search in the sampling paradigm. Hills and Hertwig (2010) found that those who frequently switch between the payoff distributions are likely to choose options that win most of the time in round-wise comparisons. Such comparisons ignore the magnitude of the win (defeat), thus giving little weight to rare events. Frequent switchers thus strongly contribute to the description-experience gap, whereas infrequent switchers are more likely to take account of impactful rare events by forming a running mean.

The mere-presentation effect: Analogical vs. propositional representations

Erev, Glozman and Hertwig (2008) have argued that a *mere-presentation effect* may contribute to overweighting in DFD but not DFE. Specifically, DFD involve *propositional* representations – e.g., 32 with probability 0.1; 0 otherwise – thus putting more *equal* emphasis on outcomes than their actual probabilities warrant. If attention translates into decision weights, rare and common events' weights will regress toward the mean. DFE, in contrast, invoke an *analogical* representation: for instance, draws from the aforementioned option could lead to this sequence: {0, 0, 0, 0, 0, 32, 0, 0, 0, 0}. More attention is allocated to the processing of the frequent than the rare events.

Unpacking and Repacking

When participants sample an entire distribution of outcomes without replacement so that there is no sampling error, and therefore no unawareness, there appears to remain a reduced but significant description-experience gap in their choices, and selective reliance on past experiences may not play a role, as judgments are quite accurate (Ungemach et al. 2009).

Fox et al. (2013) validated the robustness of this finding and argued that it was due to the fact that decisions from experience using the sampling paradigm "unpack" occurrence of outcomes (and therefore attention afforded them) in proportion to their objective probabilities (Similar to Erev et al, 2008 cited above). Fox et al. (2013) show that decisions from description can be made to resemble decisions from experience if described outcomes are explicitly unpacked. For example, describing the outcome of a game of chance in a "packed" manner (e.g., "get $150 if a 12-sided die lands 1-2; get $0 otherwise") leads to PT-like preferences. In contrast, "unpacking" the same description using a table of outcomes by die roll (e.g., "$150 if the die rolls 1; $150 if the die rolls 2; $0 if the die rolls 3; $0 if the die rolls 4"; etc.) leads to the opposite pattern of risk preferences, much like decisions from experience. Moreover, Fox et al. (2013) show that prompting decisions makers to mentally "repack" events that are sampled from experience (by postponing identification of outcomes associated with sampled events until after sampling is completed) leads to choices that accord with prospect theory. This result accords with the aforementioned observation of Hills and Hertwig (2010) that participants who sample each distribution separately tend toward more prospect-theory like behavior—one presumes that such sampling facilitates a spontaneous "repacking" of probabilities (i.e. consideration of overall impressions of probability of each outcome). This work is important because it suggests that the putative experience-description gap is not about experience *per se* but rather about the way in which information is presented.

4 Decision under described ambiguity

It seems a little odd to some of us that evidence for the experience-description gap has relied almost exclusively on comparisons between DFE paradigms involving sampled experience to DFD under *risk*. Because outcome probabilities are generally ambiguous to decision makers in the DFE paradigms, a more apt comparison might be between DFE and DFD under *ambiguity*.

The presence of ambiguity introduces two complications to decision weighting under prospect theory. First, decision makers must judge the likelihood of events for themselves. Several studies suggest that to a first approximation, choices accord with a two-stage model (Tversky and Fox, 1995; Fox and Tversky, 1998; Fox and See, 2003) in which the probability weighting function from prospect theory is applied judged probabilities of events, consistent with support theory (Tversky and Koehler, 1994; Rottenstreich and Tversky, 1997). Generally people tend to overestimate the likelihood of rare events and underestimate the likelihood of very common events, which would tends to amplify the characteristic pattern of over- and underweighting- in prospect theory. That said, with the standard sampling paradigm in which a small number of outcomes is sampled in a very compact period of time, judged probabilities are generally quite accurate (e.g., Fox and Hadar, 2006), perhaps due people's natural facility in counting (e.g. Hasher and Zachs, 1984).

Second, the shape of the weighting function can vary by domain or *source of uncertainty,* which is defined as a group of events that – being generated by the same mechanism of uncertainty – have similar characteristics (see Tversky and Fox 1995, Wakker and Tversky, 1995; Abdellaoui et al., 2011a). There is accumulating experimental evidence that the probability weighting function is systematically affected by specific characteristics of the decision situation, whereas the curvature of the utility function is not (e.g., Fehr-Duda and Epper 2012). For example, departures from linear weighting are more pronounced in affect-laden situations than in comparatively pallid ones (Rottenstreich and Hsee, 2001), and high-stake prospects are evaluated much less optimistically (i.e. lower elevation) than low-stake prospects are (Fehr-Duda et al. 2010). More to the point, people typically exhibit aversion to betting on ambiguous events (Ellsberg, 1961), particularly when they feel relatively ignorant or incompetent assessing those events (Heath and Tversky, 1991; Fox and Tversky, 1995; Fox and Weber, 2002) though ambiguity seeking is occasionally observed, especially for losses (Camerer and Weber, 1991).

If ambiguous probabilities are weighted comparatively more pessimistically than chance (risky) probabilities, it stands to reason that sampled outcomes will also be evaluated more pessimistically (especially when directly contrasted with described risk; cf. Fox and Tversky, 1995). In fact, Abdellaoui et al. (2011b) observe such a difference in elevation of probability weighting functions between DFD and DFE, consistent with this point of view.

5 Calibration and estimation

We assert that the study of the putative experience-description gap can be enriched by applying advanced econometric estimation of decision parameters, first individual, then for (heterogeneous) groups (See Ben-Akiva et. 2012, and Wilcox 2008). We assume observed preferences between J pairs of prospects x_py and x'_qy' The vector δ denotes the subjective parameters determining (w,u,λ). We assume only gains, writing $w = w^+$. The PT value of x_py, $PT_\delta(x_py)$, ,depends on δ. Our general notation facilitates applications of the following techniques to decision models other than PT and can allow us to examine robustness of an experience-description gap.

Deterministic models

One way to estimate δ is by minimizing some distance function. If we can, say, derive certainty equivalents from our data, then we can take δ such that the certainty equivalents predicted by δ are as close as possible to the observations. Another way is to minimize the number of observed choices in J that δ mispredicts. This will usually give a region of optimal δs.

Stochastic models

Thus far we have assumed a deterministic model of choice and specified no error theory. We next consider a number of probabilistic choice models. After describing an error process, *maximum likelihood* (ML) estimation can be used to estimate δ.

Trembling or misreporting

Decision makers can get confused and choose randomly, say with probability π. In this case the probability of a "wrong" choice becomes $\pi/2$. It can be shown that the likelihood is then maximized by maximizing the number of correctly predicted choices, agreeing with the aforementioned second deterministic way. The ML estimate of π is twice the proportion of incorrect prediction choices.

Continuous error

An alternative error process entails that a random and independent, continuously distributed noise term ε is added to each PT value, or that each PT value is multiplied by a random positive factor. It can be seen that we obtain the well-known logit model when ε has an extreme value distribution. In the additive case, the decision maker now chooses x_py over x'_qy' with probability

$$\frac{\exp[\frac{1}{\sigma}PT_\delta(x_py)]}{\exp[\frac{1}{\sigma}PT_\delta(x_py)] + \exp[\frac{1}{\sigma}PT_\delta(x'_qy')]},$$

where σ > 0 denotes the scale parameter of the extreme value distribution. The bigger σ is, the closer we are to random, fifty-fifty, choice. For σ tending to 0, we approximate deterministic choice. ML can again be used to estimate σ and δ.

Random parameters

Some error models assume that in each choice situation a new PT model is chosen according to some probability distribution over δ. For example, the power of the utility function may be determined randomly for each choice. Whereas the above models allow for implausibly frequent violations of stochastic dominance (when the PT value is close between two options, but one stochastically dominates another prospect), these models allow for no such violation. The resulting likelihood functions are more complex and require simulation methods (Train 2009) especially when several individual parameters have to be measured simultaneously (e.g. the power of the utility function, the kink of utility between gains and losses, and the parameter of the probability weighting function, as in de Palma and Picard, 2010).

Error theories for decision from experience

In DFE, probabilities of outcomes are not described to subjects, but subjects have to learn them from sampling. To formulate this learning one could define the decision maker's knowledge about the unknown probabilities p and q as the (prior) probability distribution $f(p,q)$. One can then apply PT using $f(p,q)$ and invoke the above error theories, combined with theories of learning and updating. This may lead to new explanations of the discrepancies between DFE and DFD, such as regarding the weighting for rare events (black swans).

Group models and heterogeneity

While the above models focus on parameters at the individual level, the techniques can also be used to estimate population or group level parameters. Heterogeneity of δ can either systematically vary across the population in the logit equation above (by interacting the parameters with individual characteristics) or randomly vary as in the random parameter model. The random parameter distribution is assumed to be a distribution across a population rather than across decision instances of a single individual. The random distribution can be either continuous or discrete. The discrete case (a latent class choice model) allows one to estimate segments of the population that have distinctly different decision behaviors. The resulting model describes both who is likely to be in the segment as well as the segment-specific behavior (Walker and Ben-Akiva 2011). This could be useful in capturing different probability weighting functions and loss aversion characteristics as influenced by the experimental design.

In one early attempt at econometric estimation, Fox et al. (2013) compared choices in a DFE sampling paradigm to choices in decision under risk by the same participants over a number of studies. They relied on the most successful parameterization of PT from a horse race run by Stott (2006), which included a logit error model. A common utility function parameter and error parameter were assumed to apply to DFE and DFD, but the (single) weighting function parameter was allowed to vary across methods. Estimation was accomplished using simple MLE. Results of this investigation found that data accord well with a stochastic PT model in which decisions from description are characterized by an inverse-S shaped weighting function and decisions from experience are characterized by decision weights that almost exactly linear (i.e., $w(p) = p$).

6 Conclusions

Several tentative conclusions can be drawn from our interdisciplinary examination of the putative experience-description gap in decision under uncertainty.

First, while the major source of under-responsiveness to rare and “Black Swan” events may be sampling error (which can cause sheer unawareness that rare events could occur) and misplaced faith in Gaussian distributions (which can give rise to misplaced confidence that rare events will not occur), a robust experience-description gap remains when these factors are not at play.

Second, the residual experience-description gap is not only about experience *per se* but also about the way in which information concerning the probability distribution over possible outcomes is learned by a decision maker. Thus, methods that draw decision makers’ attention to possible outcomes in proportion to their probabilities of occurrence (in any sort of analogical fashion) may cause decision makers to weight them more linearly.

Third, if one accounts for the fact that DFE paradigms entail ambiguity then one ought to compare DFE to DFD under ambiguity (rather than risk), where decision makers generally tend toward more “pessimistic” decision weights; the presence of ambiguity may therefore account for some of the putative experience-description gap.

Finally, much future empirical and econometric work is required to fully flesh out these tentative conclusions, but we are encouraged to see that an initially polemical literature has spawned so much constructive new empirical work that is drawing researchers toward greater rapprochement.

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