



Decision Analysis Framing and Motivation Application in Business and Tourism

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Abstract

This article rigorously examines the profound implications of framing within decision analysis and proposes a novel analytical tool under the assumption of rationality that systematically incorporates the core attributes of behavioral economic models. The proposed approach suggests that decision agents do not choose in a vacuum; instead, they make a comprehensive, holistic assessment of their state-conditional alternatives in direct association with exogenous environmental and social factors. This evaluative process results in an overall score of urgency, which can be theoretically conceptualized as a decision maker's resource pool of motivation. Mathematically, this behavioral process is formally formulated as a state-contingent input-requirement set, providing a robust microeconomic framework that is uniquely capable of explaining well-documented behavioral biases—such as the certainty and pseudo-certainty effects—alongside issues of Knightian uncertainty, risk management, and corporate innovation. To operationalize this theoretical contribution, a non-parametric Data Envelopment Analysis (DEA) formulation is presented, establishing an empirical methodology to measure decision-making efficiency under different framed scenarios. Finally, the practical utility and managerial relevance of this model are demonstrated through a targeted case analysis applied to real-world scenarios within the business management and international tourism sectors, offering researchers a structured approach to bridge the gap between neoclassical rationality and behavioral reality.

Keywords: decision, analysis, framing, motivation, application, business, tourism

Introduction

Rationality is an idea that one could hardly separate from mainstream economics and it has been crucial in the establishment of an orthodox approach compared to which all other schools of economic thought would be discussed. More than a supportive concept, rationality has been the philosophical benchmark upon which the ideology of Homo Economicus has been developed and affected the way people are viewed as decision makers. Regardless of the uniqueness and complexity of human behavior, an average individual is considered to make rational decisions, always being able to balance between personal preferences and resource restrictions with reason, coherence and consistency, achieving the ultimate goal of optimization. Any discrepancies between theoretical and observed human behavior was initially attributed to the entanglement of uncertainty in an otherwise robust decision framework, with Expected Utility models providing an apparently analogous stable framework for decisions under imperfect information.

However, as analysis grows deeper into the secrets of decision making and contemporary life becomes more complex, repeatable observed anomalies have challenged many of the classical hypotheses and led to the development of important alternatives. Behavioral Economics stand as the study of psychology over economic decision processes, and they have been called to support or even substitute orthodox approaches in many cases. Daniel Kahneman and Amos Tversky challenged mainstream economic ideas through a series of papers that proposed intuitive and testable behavioral assumptions, most notably with the development of Prospect Theory (Kahneman and Tversky 1979) and later on with Cumulative Prospect Theory (CPT, Kahneman and Tversky 1992), a work awarded with the Nobel Prize of Economics in 2002. This set of theories focused on decision processes under risk, acknowledging that risk preferences are influenced by the context of questioning, a type of decision bias and possibly manipulation that is called framing (Kahneman and Tversky 1981). On the other hand, alternatives have also been proposed in support of the orthodox point of view, extending the classical assumptions into inclusive frameworks. Utilizing an idea of Arrow (1953) and Debreu (1952) about "Nature's states", Chambers and Quiggin (2000) have developed the "State-Contingent (SC) approach" to decisions under uncertainty.

This article is incorporating elements from both of the approaches above, in an effort to bring new insight in the analysis of the framing bias, develop a decision structure for motivation and bring together classical and behavioral aspects to an inclusive framework. A primary benefit of this method is the incorporation of behavioral analysis results into a rational decision framework, providing robust explanation for the observed evaluation imbalance of losses over gains and the witnessed empirical patterns of certainty and pseudocertainty. Moreover, this method makes a clear distinction between risk management and Knightian uncertainty, providing a particularly useful framework of analysis for issues of unquantifiable risks, as in the

process of innovation and entrepreneurship, the social impact of A.I. development, and optimal reaction decisions of societies and communities towards prevention or adjustment to climate change. The model is applied in the sectors of business and tourism, producing valuable results about innovation and risk management in these areas.

Framing, heuristics and bounded rationality

Framing and heuristics are two prevalent themes in behavioral economics, arising as deficiencies of the orthodox approach that produce several decision biases. Framing is the process of decisions being affected by the context they are presented in, as decision agents may lack the cognitive resources to analyze the implications of their assumptions in detail. Kahneman (2003a, 2003b) explains that framing effects in his work with Tversky (Kahneman and Tversky 1981) are defined as "discrepancies between choice problems that decision makers, upon reflection, consider effectively identical". Hence, framing is essentially perceived as a negative process that may lead to suboptimal solutions and it should therefore be avoided by decision agents. Heuristics on the other side are decision rules of thumb that find applications in cognitive psychology and artificial intelligence, as shown in Groner et al. (1983) and Dixon (2001). Heuristics act as mental shortcuts leading to faster and often preferred results to those of thorough decision analysis, thus retaining a positive aspect despite its interference as a bias in rational decision making.

Herbert A. Simon in *Models of Man* (1957) attributed these biases to problems of tractability, time restrictions and cognitive limitations, defined with the term of *bounded rationality* (BR) that was later used extensively in literature, including the work of Kahneman and Tversky. On one hand, BR can be viewed as the result of introducing decision analysis costs into the classic framework, which makes agents proceed to decision under imperfect information based on inferences, if the expected results are close to optimum and further costs of analysis would not pay-off. Dixon (2001) considers this approach of approximate optimization as a positive generalization to strict optimization that retains simplicity and coherence without the need of behavioral formulations. On the other hand, suboptimal behavior can generate critical discrepancies from optima that cannot be explained as an intentional risk-preference result. For example, an individual could indeed benefit from a heuristic habit of dressing behavior that saves time and resources from daily decision making, even in exchange for an imperfect appearance, but a heuristic of negligent driving behavior that leads to a potentially fatal road accident could not be reasonably compensated by any small everyday benefits.

The main proposition of this article is that decision agents follow an initial path of low or merely spontaneous analytical process, that can then be decided to be further analyzed for potential decision change, or be left to proceed to straightforward results avoiding further analytical costs. We can rank potential results by preference and depict the possible alternatives of this process in graph 1. We see that the decision

process results in a range of available options, that can be altered by the inclusion of an additional analytical step. The final range of options is now expressing the decision frame that can focus, widen or shift to represent the effects of psychological framing, heuristics and biases. This two-step process of "decision before the decision" is very similar to the BR process, however it is based in a different set of relaxed assumptions:

The inference procedure is not divided into heuristics (positive) and framing (negative) alternatives. Instead, a single neutral framing procedure is assumed, where agents decide on further analyzing their decisions based on conditions, needs and expectations.

The decision process is adjusted to the classical framework and it does not bear any behavioral assumptions.

This process incorporates the analysis of biases and uncertainty decisions under a unified framework, including aspects of Knightian uncertainty.

In order to achieve this strengthening of analytical power together with the relaxation of behavioral assumptions, we need to substitute the latter with a tool that explains how the framing process works. This is achieved with the introduction of a motivation process that was much needed in the decision analysis and it can be based in basic classical assumptions.

Motivation and urgency

Behavioral economics most often covers deficiencies of the classic approach, using input from psychology and other social sciences as axiomatic assumptions. Most popular theories in economic decisions analysis are the axiomatic response to incentives, with empirical support in literature (Gibbons (1997), Lazear (2000)), or alternatively a differentiation of intrinsic and extrinsic motivation supported by advances in psychology and sociology since the 1970s (Ryan and Deci 2000). These approaches are usually in contradiction, but there has been effort for reconciliation of these views (Bénabou and Tirole 2003). In order to produce results for decision analysis avoiding the use of axiomatic assumptions, we need to create a tool describing motivation in classical terms of rationality.

This article proposes that individuals at any given time of decision making, possess a bounded set of cognitive ability that they can focus or distribute among decision problems at hand. We can call this cognitive resource *urgency*, that is translated through the decision process into motivation about specified choices. Urgency expresses a general concept of how prompt and eager a person is to deal with an issue and it is associated with the amount of cognitive resource consumption. A first important result from this relaxed formulation is that it allows for customized analysis, since different individuals can bear a personalized potential of urgency depending on their specified attributes. It is also compatible with both intrinsic and extrinsic approaches, as it allows for interpretation of the sources of this cognitive

resource. In order to produce useful results with this tool, one should prefer to view urgency in terms of percentages instead of absolute values. Hence, even if we are not aware of detailed characteristics of an agents urgency, we can produce an estimation of the percentage of cognitive resource dedicated to the decision problem. In a simplified rational framework urgency and motivation coincide, because the classic framework axiomatically accepts as straightforward the connection between preference and action. Even in this case the proposed tool is useful for measures of motivation and efficiency, while in the distinct urgency-motivation form it allows for more complicated formulations, where individuals are not always able to perform their full potential, even when they are adequately motivated. A useful application could be the performance distinction between trained and untrained employees, with the second group presenting low performance rates even in the case of provided incentives.

In figure 2 we observe a concave function of marginal motivation that responds to total motivation function of s-shape. We see that we can measure the percentage of motivation produced or a maximum percentage lower than 100% in case of maximum motivation not met. More types of functions are applicable, following the orthodox formulations, or behavioral types as well. In CPT the s-shaped value function is similar to the one above, but it is asymmetrical. Hence, such a formulation can also be used for purposes of decisions under uncertainty. In cases of symmetrical functions, the middle area is characterized by a critical point, where dedication of urgency results in increasing levels of motivation. The latter can be then transformed into productivity using a linear function of performance, or diminishing returns in the case of accumulated fatigue. Then, a decision agent who is highly motivated could be underperforming because of exhaustion.

State-Contingent and DEA formulation

For a mathematical formulation we can follow the State-Contingent approach of Chambers and Quiggin (2000) which transforms non-stochastic inputs through states of conditions into stochastic outputs. First we define a state space Ω , that is a finite set of S conditions that are mutually exclusive and affect the transformation from urgency to motivation.

$$\Omega = \{1, 2, \dots, S\} \quad (1)$$

Decision makers are motivated according to which of the states occurs or the one they expect to occur. In the second case, expectations are also entered into the analysis. The set of states theoretically includes all possible states of our environment, but since this can be infinite we use Ω to index only the exogenous factors that may have an effect in our decisions. Decisions are made over a set of N non-stochastic inputs $x \in \mathbb{R}_+^N$ and produces a set of M results $y \in \mathbb{R}_+^M$, which combined with the set of states, it produces $M \times S$ state-contingent results $y \in \mathbb{R}_+^{M \times S}$. Then, the SC transformation can

be modeled by either an input requirement set of the resources needed to produce the desired results:

$$X(y) = \{x \in \mathbb{R}_+^N : x \text{ can produce } y \in \mathbb{R}_+^{M \times S}\} \quad (2)$$

This representation of technology is free from behavioral assumptions and it can be adapted to all the aforementioned frameworks. Moreover, with the help of distance functions it can be treated in a formulation of Data Envelopment Analysis that produces measures of efficiency and productivity.

We can use either an input oriented:

$$I(y, x) = \sup \left\{ \theta > 0 : \frac{x}{\theta} \in X(y) \right\} \quad (3)$$

or an output oriented distance function:

$$O(y, x) = \sup \{ \theta > 0 : \theta \cdot y \in Y(x) \} \quad (4)$$

Let $D(y, x)$ represent the distance of a bundle (y, x) from its potential frontier, without any specification of input or output orientation. Following the state-contingent approach we can include factors of imperfect information, that transform a bundle of certainty into a state-contingent bundle of uncertainty. Then, $D(y, x; s)$ can be used for the distance function of a bundle z under a vector of exogenous conditions s , while $D(y, x; \varepsilon)$ can be used to include factors of uncertainty ε , on which the decision maker has imperfect information or control. Using this representation we can produce Malmquist productivity measures:

$$P_{s_0, s_1}(y_0, x_0; y_1, x_1) = \left[\frac{D(y_1, x_1; s_1)}{D(y_0, x_0; s_1)} \frac{D(y_1, x_1; s_0)}{D(y_0, x_0; s_0)} \right] \quad (5)$$

that can be decomposed into efficiency and heterogeneity components, with the latter being the effect of different exogenous conditions:

$$P_{s_0, s_1}(y_0, x_0; y_1, x_1) = E_{s_0, s_1}(y_0, x_0; y_1, x_1) \times H_{s_0, s_1}(y_0, x_0; y_1, x_1) \quad (6)$$

$$E_{s_0, s_1}(y_0, x_0; y_1, x_1) = \frac{D(y_1, x_1; s_1)}{D(y_0, x_0; s_0)} \quad (7)$$

$$H_{s_0, s_1}(y_0, x_0; y_1, x_1) = \left[\frac{D(y_0, x_0; s_0)}{D(y_0, x_0; s_1)} \frac{D(y_1, x_1; s_0)}{D(y_1, x_1; s_1)} \right] \quad (8)$$

We can empirically implement this formulation with the help of DEA, calculating input or output distance functions directly from a dataset. If decision makers were considered as producers of state-contingent decision outputs, for K number of agents, N number of inputs and M number of outputs, the input distance of agent i from the technology frontier is computed as follows:

$$I(y_i, x_i) = \min \left\{ \theta: \theta x_{ni} \geq \sum_{k=1}^K \lambda_k x_{nk}, y_{mi} \geq \sum_{k=1}^K \lambda_k y_{mk}, \right. \\ \left. \lambda_k \geq 0, k = 1, \dots, K, n = 1, \dots, N, m = 1, \dots, M \right\} \quad (9)$$

The above represents a CRS technology that can easily be extended to a VRS technology.

Model implications

Competition between classical and behavioral economics has leaned towards two extreme approaches, that judges individuals making suboptimal decisions as either rational but unlucky optimizers, or as feckless carriers of naturalistic impulses. Considering two biases explained by CPT, certainty effect is the extreme valuation of small changes in probability when this is subtracted from absolute certainty, and pseudo-certainty is the same behavior expressed against illusive apparitions of certainty. CPT is able to identify this preference for absolute certainty, however it attributes both effects to psychological tendencies without making any distinction between efficient and inefficient behaviors. On the same problems, classical approaches can neither identify these effects, nor explain the reasons for deviations from optimum.

The new approach proposed in this article incorporates elements from CPT into a classical structure, thus being able to identify the certainty and pseudo-certainty effects, while also making a distinction between efficient and inefficient behavior through the urgency information requirement set. The preference for certainty is established through the incorporation of an s-shaped valuation function as in the CPT. However, when an individual receives an illusive certainty offer, he would either be deceived if the cost-to-benefit ratio is too high to further explore the problem, or if the urgency pool is depleted to other problems demanding attention. Finally, in the case of complete focus on this problem and inadequacy of solving, external factors like education or cognitive support can expand the existent urgency pool to meet the requirements.

Furthermore, the proposed model is able to provide insight to problems on Knightian uncertainty, as it does not need probability information, especially for marginal cases. For example, a patient deciding on participating in a trial over a new untested medicine is more probable to participate if he hopes to cure a serious disease than a minor one. The reason is that patients facing serious health issues are situated very low on the valuation function with much to gain from risk and almost nothing to lose, while urgency for results is immediate. Similar results can prove useful in the analysis of innovation, as it is usually characterized by significant levels of Knightian uncertainty. An established company holding a high market share would reasonably

avoid investing in groundbreaking innovation plans that would put the established success in risk, while many revolutionary ideas are produced by small pioneering businesses. However, even an established firm would consider significant and risky investment decisions, if potential innovation of competitors could challenge their position and put in prospect the lower levels of their valuation function.

Case analysis on business and tourism

Heuristics and framing are based on acquired experience, since they need collected information to produce inferences that may assist or bias decisions respectively. Therefore, decision inferences should be related to areas of interest, affected by their environment and experiences as they form their information basis. In business, diversification of decision analysis can be made by several inter-sector and intra-sector factors. Kumar and Van Dissel (1996) examined how IT affected the transition from inter-firm competition to cooperation, pointing that IT-enabled cooperation should be nurtured in order not to degenerate into conflict. This results come in support of the proposed analysis, as factors transform the decision environment, but agents also bear the potential of responding to these changes. Nevertheless, Carr (2003) proposed that the effect of IT as it becomes more widespread and easily available, it would turn from gaining a strategic advantage to an investment that gives firms a cost disadvantage. This result reflects the different way an innovation enters the urgency set at its early adoption stages, compared to late adoption.

Sector differentiation also plays a role in the decision making process and overall management of risk. For example, the tourism sector presents unique characteristics associated with the nature and purpose of traveling, developing a related decision and risk management. Lepp and Gibson (2003) examined tourists' risk aversion over several sources of risk, detecting that the purpose of traveling, seeking familiarity over novelty, is the primary factor of risk aversion. Using the methodology of this article, familiarity seekers focus their decision frame on narrow options avoiding risk, since the purpose of vacation tourism demands lower rates of urgency. Following this reasoning, literature detects a significant effect on tourism from the risk factors of terrorism (Sönmez and Graefe 1998, Sönmez et al. 1999) and climate change. The proposed model offers extended analytical power over risk preferences, with distinct features over Knightian uncertainty. Analysis of cases in business and tourism validates initial results through the existent literature.

Conclusions

This article examines the role of framing in decision analysis and proposes a new tool that introduces framing and heuristics results into a classic framework. Relaxing the behavioral assumptions of Cumulative Prospect Theory and using the mathematic formulas of State-Contingent analysis we get intuitive results under rationality, supported by contemporary literature, and a formulation of efficiency and productivity measures that can be used with Data Envelopment Analysis. The

mechanism of urgency as a step towards decision making provides an explanatory process of motivation that was missing from classical economics and incorporates behavioral economic results.

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Figures

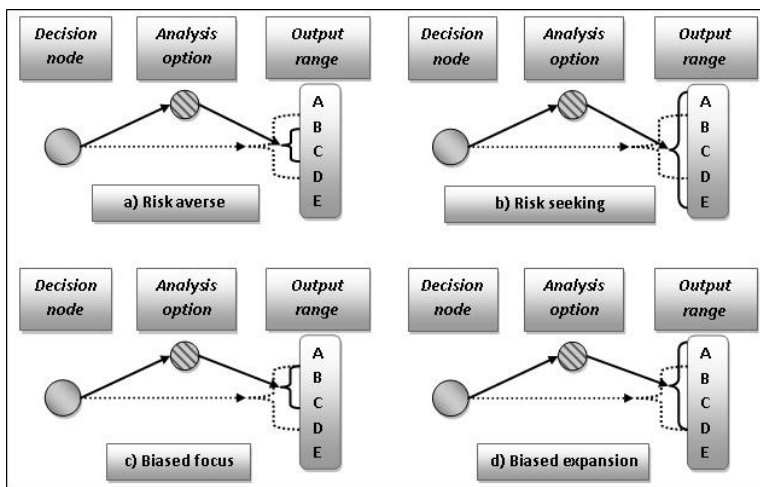


Figure 1: Comparative results of adding an analytical step in the decision process.

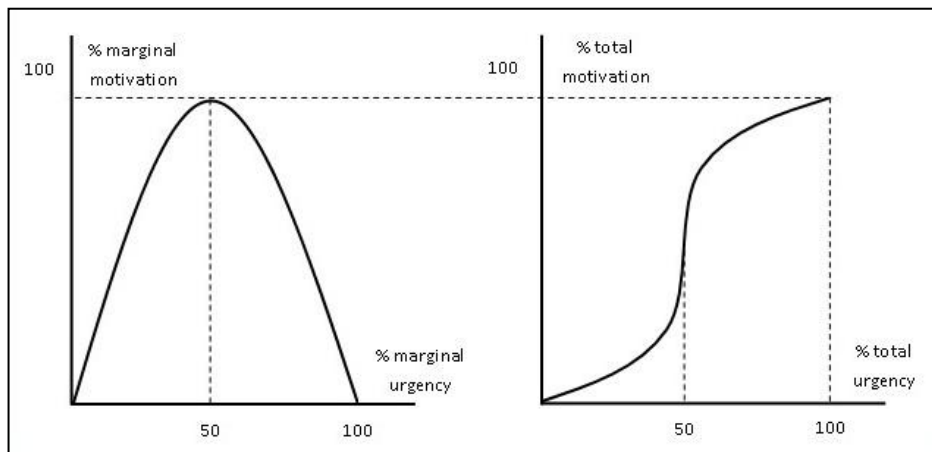


Figure 2: Percentage marginal and total motivation associated with analogous percentage of urgency.