Risk attitude & Economics

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Toulouse, April 15th, 2014
Gilles Motet, Foncsi

This document

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Preamble

THIS DOCUMENT is an introduction, for non-economists, to standard and behavioral economic theories of risk and uncertainty. It describes some broadly-accepted results in economics that are determinant in decision-making under risk or uncertainty and in situations where we have to deal with losses and gains. To illustrate our point, we will present a selection of theoretical results, punctuated with examples taken from everyday life, and research studies in economics and psychology on the perception of risk.

Risk and uncertainty are constantly present in everyday life both on the small and large scale (*e.g.* domestic accidents and major industrial accidents). Economics has a long tradition of analyzing risk as an important and fundamental element of decision-making: most economic decisions cannot be fully addressed if we ignore risk. For example, in the financial literature the analysis of portfolio models is based on strategies to differentiate risk according to investor attitude. In macroeconomics, unemployment levels, exchange and interest rates, political stability, imports and exports are only some of the unstable economic variables that influence the overall economy.

Key issue

This document

Decisions involving risky environments are constantly being studied by researchers in the field of economics. This document aims to explain standard economic theory and some well-known economic results to those members of the public working in risk management, or interested in that topic. Its objective is to help people understand, from the economic point of view, the tradeoffs that are made by individuals facing risks[1].

How do individuals make choices when facing risks? Assuming that the decisions they make are rational, this risk attitude can be modeled. This is the basis of the standard rational model developed by economists that this "Regard" first aims at describing. But little by little throughout the text, we find numerous deviations from the model, mainly linked to psychological biases. How do economics cope with parameters influencing our attitude to risk, leading us to make decisions that are not the rational expected ones? That is what this "Regard" attempts to describe in an accessible fashion.

In this respect, we begin with a brief introduction showing that far from being the business of economists alone, economics and what we will define as economic choices are everywhere in our day to day life. We describe some **basic notions of economics**, starting with a broad definition of the topics covered in this document. In particular, we will see that the definition of risk, from an economic point of view, can be quite different from more classical ones. Next, in chapter 1, we draw the lines of the standard model that explains the rational attitude to risk. We therefore introduce **von Neumann and Morgenstern's expected utility theory** (EUT), which is the standard theoretical model used by most economists. In addition, we describe the **standard risk attitude model** and some of the approaches that are used to evaluate individual attitudes to risk. In the last section of this chapter, we examine some criticisms of the EUT model. For example, we discuss situations where the model gives incorrect predictions. In chapter 2, we examine a more recent line of research in economics that focuses on the psychological aspects of individual choices and the experimental evidence. We show through examples that reality does not always reflect what we would expect from people actually acting rationally when facing risk. An alternative theory, called **prospect theory**, is introduced. Chapter 3 presents some other **examples that contrast with the standard economic literature or rational assumptions**. We examine the experimental and empirical evidence for these deviations in behavior. In particular, we discuss how the perception of risk, probabilities and uncertainty may lead individuals to make mistakes when facing risky choices.

[1] The choice of the topics is neither exhaustive nor representative of the entire literature on issues related to risk. The purpose is to give a flavor of existing lines of research.

Clearly, our discussion is not exhaustive and it is the result of a deliberate choice by the author: the aim is to present and disseminate some basic economic theories and psychological evidence for human behavior in conditions of risk and uncertainty.

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Introduction: what is economics?

A standard, conservative definition of economics is,

> *economics is the social science that analyzes the production, distribution, and consumption of goods and services*[2]*.*

However, a less conventional and more modern definition also takes into account topics that depart from the usual, such as fiscal policy, production, monetary policy, *etc.* Modern economics has focused on issues related to human behavior and become a broad discipline that interacts with many other branches of science (*e.g.* sociology, psychology, biology, and neurology).

Another definition suggests that economics develops theories based on economic phenomena: namely phenomena that

> *relate to any aspect of human behavior that involves the allocation of scarce resources; thus it is very wide-ranging in its subject area. For example all of the following can be described as economic phenomena, although they may also of course involve other disciplines of study: searching for a sexual partner on the Internet, watching a documentary on television, making a charitable donation, giving a lift to one's neighbor in order to make it easier to ask them for a favor later, deciding to take a nap rather than mow the lawn, teaching one's child to play tennis, and going to the church [Wilkinson 2007].*

Key issue

Economic choices

Seen in this way, the main issue for economics is scarcity. Resources (*e.g.* goods, services, land, time) are finite and people must continuously make tradeoffs between a few (or many) possibilities. It is clear from the above examples that economic phenomena concern not only monetary/financial choices *stricto sensu*, but also situations where the options do not have a pecuniary value. In other words, **economic choices**.

The above sections give examples of economic phenomena; next we introduce the "subject" that has to decide between the available alternatives. We call this subject the **decision-maker**, the **economic agent** or the **agent**. It can be a single individual, a group of people, a firm, *etc.* Whether it is an individual or a group, we have to make some assumptions about how this agent makes their decision when faced with an economic choice.

Economic theory has conventionally revolved around the assumption of *homo economicus*. This is a hypothetical representative agent who makes rational decisions based on self-interest. In the standard neoclassical economic model these decision-makers have always been thought of as:

1. purely selfish and not governed by others' concerns;
2. acting rationally to maximize their own profit given the information available at the time; and
3. able to correctly predict how the environment will be affected by their (and others) choices.

However, models based on these assumptions do not always correctly predict human behavior in some contexts. Specifically, they do not take into account various parameters and biases that may interfere, such as others' preferences, limited rationality[3], limited computational skills, failure to predict future events, inadequate statistical capabilities or an agent's inability to understand complex problems.

Classical and neoclassical economists have based their work on theory and empirical evidence. They have tested their theoretical results with econometric tools and, when theoretical and econometric results were not consistent, adjusted their theories according to their data analysis.

[2] Source: http://en.wikipedia.org/wiki/Economics

[3] Limited rationality, also referred to as *bounded rationality*, is defined below.

Econometrics

Definition

Econometrics is the study of the application of statistical methods to economic data. It includes all mathematical and statistical techniques that are developed in order to address economic problems, analyze data, test theories and models.

For a long time, there was a widespread idea that economics could not be an experimental discipline. For decades, the main way to test the power of theories has been to **empirically study observable data** derived from the natural environment. The natural environment is the result of uncontrolled processes and contains many factors, which may not be observable and may affect the statistical analysis. Economic data is affected by a multitude of variables (and the interactions between them); consequently, although econometric techniques made it possible to manipulate the data, some questions could not be answered. The longstanding idea that important economic factors cannot be controlled meant that it became widely accepted that data collection was the only way to verify economic theory.

behavioral economics

More recently, many of these practices have changed and new approaches have been developed. On the one hand, the **behavioral approach** has challenged the assumption of the *homo economicus*, in favor of more flexible and adaptable data models. Behavioral models are able to include various biases that cannot be taken into account in standard theory, for example:

- They account for **limitations in human cognition**[4]. In the decision-making process, humans may not be able to process all the information necessary in order to take the "right" decision (namely, the one that gives the best possible outcome for the individual), and the assumption of fully rational economic agents may not be correct in many settings.
- **Recursive biased behavior**. Individuals can make mistakes in certain situations, and they may not be able to modify their behavior. Even teaching or explaining complex situations may fail to improve their reasoning, and some models account for these wrong behaviors.

Bounded rationality

Definition

The idea of bounded (limited) rationality was introduced "*to focus attention upon the discrepancy between the perfect human rationality that is assumed in classical and neoclassical economic theory and the reality of human behaviour as it is observed in economic life. The point was not that people are consciously and deliberately irrational, although they sometimes are, but that neither their knowledge nor their powers of calculation allow them to achieve the high level of optimal adaptation of means to ends that is posited in economics*" [Simon et al. 1992].

experimental economics

On the other hand, another revolution appeared with the **collection of experimental data** related to economic phenomena. Experimental data is data

> *which are deliberately created for scientific (or other) purposes under controlled conditions [Friedman and Sunder 1994, p. 3].*

This new approach involves an **interaction between economics and other fields of research, in particular psychology**. An indication of the importance of merging these two fields was the award of the Nobel Prize in Economics for work in the emergent fields of experimental and behavioral economics [Kahneman and Smith 2002; Roth and Shapley 2012]. The 2002 Nobel Prize in Economic Sciences went to a psychologist, Daniel Kahneman, and some of his work and its application to economics is discussed later in this report [Kahneman and Smith 2002].

Economics and psychology overlap with respect to many aspects of individual and group behavior. Although initially psychological critiques of the standard rational model were not welcomed by most economists, insights from psychology have inspired not only improvements to economic theories, but also the development of new methods (such as gathering economic data via experimentation).

The integration of psychology and economics is now widely accepted; the two social sciences share many common interests and both benefit from the interaction. However, their different backgrounds, approaches and research questions mean that it is important to clearly distinguish between the aims and methodologies that are typical of each discipline.

[4] A first step in this direction was taken by Herbert A. Simon in the 1950's.

Economics experimentation reflects the interest that economists have in markets, institutions, aggregate behavior and interactions between economic agents – with a focus on outcomes. The typical experiment tests the predictions of a theoretical model under different conditions by looking at the final result. Economists are unlikely to question the motives and procedures leading to these outcomes. On the other hand, psychologists are more interested in individual characteristics and center their attention on processes, in particular, real-world contexts.

Key issue

Research question

The typical research question asked by an economist is *"What do people do?"*, whereas psychologists would prefer to know *"Why do people do it?"*

There are also significant differences between the two human sciences in the way experiments are conducted. Economists maintain a strong belief that people react to **monetary incentives**, and this attitude is reflected in the way experiments are carried out. One basic assumption is that people who have no incentive to tell the truth may lie.

Example

Donation to a charity

For example, if someone is asked how much they would donate to a charity, the amount that they usually state is higher than the amount that they would give, if they were actually asked to pay.

In general, in order to avoid this type of problem, experimental economists pay decision-makers who participate in trials, in an effort to represent real-life incentives. On the other hand, psychologists are interested in hypothetical choices and, in some cases, pay participants a flat fee that is independent of their answers.

Over time, interactions between the two social sciences have blurred the distinction and increased the overlap in methodologies, and experiments and research questions have become increasingly similar. Sometimes, different words are used to address the same problem. For example, economics uses the idea of public good and bargaining, while psychology uses the terms social dilemma and negotiation. For a more detailed article see [Rabin 1996].

The core of economic theory concerns **decision-making under uncertainty**; therefore we begin by describing the basic features of expected utility theory. Next, we introduce some of the characteristics of experimental and behavioral economics through a focus on risk, uncertainty, perception of losses and gains, and the perception of probabilities. We discuss some well-established results and their implications that are generally accepted by the academic community.

1

Rational attitude to risk

This chapter deals with the main insights provided by the standard economic model of expected utility that are relevant to the attitude of individuals to risk. We assume that decision-makers (individuals who must make an economic choice) are rational in the sense that they always perfectly choose what is in their best interest. We start with the definition of risk in economics, and then discuss assumptions and theories.

1.1 Risk and expected value

Two definitions offer an idea of how risk is generally perceived:

- ***Risk*** *noun*
  1. *The possibility of incurring misfortune or loss.*
  2. *Hazard (insurance): a. chance of a loss or other event on which a claim may be filed; b. the type of such an event, such as fire or theft; c. the amount of the claim should such an event occur; d. person or thing considered with respect to the characteristics that may cause an insured event to occur*[1].
- ***Risk***
  "Risk is the potential that a chosen action or activity (including the choice of inaction) will lead to a loss (an undesirable outcome). The notion implies that a choice having an influence on the outcome exists (or existed). Potential losses themselves may also be called 'risks'. Almost any human endeavor carries some risk, but some are much more risky than others[2]*."*

The definition of risk in economics is different to those given above. Although in general, risk is perceived as negative, in economics it can be associated with both negative effects (such as potential accidents) and benefits (such as research-driven innovation). **From an economic point of view, risk is more linked to uncertainty than to negative effects**.

To clarify the terminology, we will use the notion of economic risk, and define **expected value**, **events** and **outcomes**.

Definition

Expected value

The expected value of a random variable is the weighted average of the all possible values that the variable can take.

Assume that an entrepreneur undertakes an activity from which they obtain an annual profit. However, the amount of the profit is not certain:

- in good years it is high (X) with probability (p);
- in bad years it is low (Y) with complementary probability (1-p).

[1] Source: http://www.collinsdictionary.com/dictionary/english/risk.
[2] Source: http://en.wikipedia.org/wiki/Risk.

These occurrences are referred to as events, and their associated profits as outcomes. The entrepreneur does not know in advance if it will be a good or a bad year, and relies on the probabilities p and 1-p to anticipate profits. Note that we assume only two possible events: a good year or a bad year. It is clear that in real life there are many possible situations and the profit variable may take many different values. However, in this simple example we do not discuss continuous variables, which means that we do not need to make assumptions about the distribution of profits (namely, whether the probability distribution is uniform, normal or takes another form).

To evaluate their activity, the entrepreneur must calculate future gains from the probabilities that the possible gains occur. In economics, this is termed the **expected value** (EV) of the activity, and it is calculated as follows:

$$EV = pX + (1 - p)Y$$

Example

Expected profit of an activity

If, for example, the profit in a good year is 100 000€ and in a bad year it is 60 000€ and the probability that these two events occur is the same (*i.e.* p = 50%), the expected profit is 80 000€.

Expected value (EV) is a hypothetical measure of the future value of the activity. **It does not reflect a real situation**; instead it is the weighted mean of all possible real situations. The activity may never provide a future profit of 80 000€; this is simply what we can expect at the present time[3].

It is often the case that when making choices, we focus our attention on the future by choosing options that influence it. For the sake of clarity, next we define what we mean by **event** and **outcome**.

Definition

Event & outcome

An **event** is any circumstance that can occur, independent of its importance. In our example, a "good year" is one event; a "bad year" is another event. Although in real life, events may have important consequences (*e.g.* a birth, a nuclear accident, a G8 summit meeting), in the following discussion events are considered to be independent of their influence or importance.

The **outcome** of an event is its realization (*i.e.* the good year or the bad year). Each event brings consequences that can affect the decision-maker. For example, in a good year sales are high, taxation is low, labor productivity is stable, *etc.* It is assumed that these characteristics are implicit in the outcome of the event, and can be expressed in monetary terms (*e.g.* net profit).

To return to the example, we can define the activity described above as "risky" because it involves events and outcomes that are **not certain**: in other words, the actual outcome may be higher or lower than the expected outcome. On the other hand, an activity that reliably generates 80 000€ each year is "safe". This activity has no risk (certainty *versus* uncertainty), as its outcome is always the same; namely, the probability that it will generate a "safe" profit of 80 000€ is equal to one.

Clearly, the economic definition of a risky activity is much broader than that commonly used. In the latter case risk is associated with loss, damage, a missed opportunity, or a lack of gain. The main difference between the economic definition of risk, and those more commonly used lies in the negative connotations[4] of the latter. In economics, the notion of risk concerns an event that occurs with known or estimable probability, while an event that occurs with a probability of one or zero is said to be safe (or certain).

Key issue

Risk in economics

To summarize, a risky activity means that events and their outcomes are not certain: their occurrence is more or less probable. On the other hand, a safe activity means that the outcome is certain. In economics, risk is associated with uncertainty, regardless of whether the effects are positive or negative.

[3] EV is not a real value but the weighted average of real values, as the average number of children per woman, for example 1.5 children, does not correspond to a real number of children per woman.

[4] This definition is important to keep in mind in the discussion that follows because there are psychological aspects that distinguish risk in the domain of losses and risk in the domain of gains.

Similarly, the ISO 31000 definition of risk includes economic notions [Motet 2009]. It defines risk as *"the effect of uncertainty on [the achievement of] objectives"*. Three important issues are included in this definition:

- ▷ Risk depends on the indeterminacy or uncertainty of events, in the sense that they may or they may not happen.
- ▷ Risk has to be managed because it has future effects (changes with respect to the initial status) that affect decision-makers.
- ▷ Risk is only relevant when compared to the decision-maker's current objectives in the context of decisions that will have an effect in the future.

The question that naturally follows is:

> "*How do people react to uncertain events compared to those that are risk-free?*"

Everyday life shows there is heterogeneity in people's perceptions and reactions to risk and, in economics, individuals are classified according to their attitude to risk.

1.2 Risk attitude

To continue with the previous example: imagine that you own a risky activity R that generates an income of either 60 000€ with a probability of 0.5 or 100 000€ with a probability of 0.5. In this case the expected value of R is EV(R) and it equals 80 000€ (EV(R) = 80 000). Now assume a safe activity S that generates 80 000€ with a probability of one (EV(S) = 80 000). Although both activities have the same expected value, we can only be sure about the second activity. If we were to choose one of these activities, some people would be indifferent; some would prefer the risky activity R; and others would choose the safe activity S. In other words, some individuals enjoy risk and choose R, some clearly favor safe choices and are attracted to S, and others don't really care if the activity is safe or risky, as long as the expected values are equal. From this, emerges the notion of **attitude to risk** (lover/seeker, averse and neutral).

Now we look in more detail at the risky activity R and classify people according to the price they would be prepared to sell it at, using EV as a "cursor". People have preferences about the level of risk they are happy with, their preferences are heterogeneous. We now consider the risky activity R. If a group of people are asked,

> "*Assuming you owned the activity, how much would you ask someone to pay to take it over for one year?*"

most people ask for an amount that is less than 80 000€.

Example

Ann, Luc and Ned

Assume that Ann asks 75 000€ to sell the activity. If she does not sell it, she might make a low gain (60 000€) or a high gain (100 000€); however, if she sells the activity she is certain to gain 75 000€. This would be perceived as a good deal by many individuals, although the selling price is lower than the expected value. It can be seen as the price that is paid to avoid the risk of only earning 60 000€. Although there are many factors that determine human reactions to risky activities (psychological, personal, *etc.*) in economic terms, an individual can be classified as risk averse, risk neutral or a risk lover (seeker) independent of the cause of their attitude. In this example, Ann would be classified as risk averse because 75 000€ is less than the expected value of the activity. Suppose now that Luc and Ned ask, respectively, 82 000€ and 80 000€. Luc is said to be a risk lover because he asks more than the expected value; Ned is risk neutral because the amount he asks is the same as the EV.

The fact that the decision-maker can give the risky activity a value that differs from its expected value introduces the concept of the **certainty equivalent**.

Definition

Certainty equivalent

The certainty equivalent (CE) of a risky activity is the amount that is thought to be equal to the value of the activity. The CE can also be called the **selling price**. It is the definite price at which the activity would be sold.

In other words, the certainty equivalent is the amount of money needed to make the individual indifferent about whether they continue to hold the risky activity or sell it.

Obviously, the selling price (certainty equivalent) is given by the answer to the previous question:

- ▷ Ann's certainty equivalent is 75 000€;
- ▷ Ned's is 80 000€;
- ▷ and Luc's is 82 000€.

This leads to a simple definition of risk attitude through a comparison of the individual agent's CE and the objective EV:

Definition

Risk aversion and risk premium

Risk aversion implies that the certainty equivalent for a risky activity is lower than its expected value (CE < EV), because a risk averse person will try to get rid of the risk, even if they may give up an (expected) possible gain. The difference between the expected value and the certainty equivalent is called the **risk premium** (RP = EV - CE). The risk premium is positive in the context of risk averse behavior; it is the maximum amount of money that an individual accepts they might lose in order to avoid risk.

Given this definition, Ann is risk averse because her CE (75 000€) is lower than the EV (80 000€). She prefers to give up a part of her expected outcome (a risk premium of 5 000€) to avoid risking the outcome of a bad year. Note that if Ann could sell for more than her certainty equivalent of 75 000€, the outcome would be even better than expected.

Definition

Risk loving

Risk loving goes in the opposite direction: the certainty equivalent of a risk lover is always higher than the expected value. Thus, the risk premium is negative and represents the maximum amount of money that the person is willing to give up in order to maintain the risky activity. For risk lovers, the absolute value of the risk premium represents the maximum amount that they are ready to lose when choosing between a risky activity and its expected value. They prefer to maintain the risky activity rather than accept its expected value: risk is a positive characteristic.

Luc is ready to accept the risk and his CE (82 000€) is higher than the EV. His RP is -2 000€. Luc would refuse any amount below 82 000€; on the other hand, offers above 82 000€ will be accepted.

To conclude, individuals such as Ned, for whom the risk premium is null (the certainty equivalent is equal to the expected value) are said to be **risk neutral**. Ned is risk neutral because his CE is equal to the EV of the risky activity. He is indifferent about accepting a known amount of 80 000€ or bearing the risk of an activity that has the same expected value.

Another way to measure attitude to risk is to simply ask an individual if they prefer one risky activity to another risky activity with the same expected value but lower variability. For example we can ask Ann, Luc and Ned to choose between two activities:

- ▷ the one given in the previous example (expected to yield either 100 000€ or 60 000€ with the same probability: expected value 80 000€);
- ▷ or another activity that can earn either 70 000€ or 90 000€ with the same probability (expected value also 80 000€).

Although the two activities have the same EV (80 000€), the variance is higher for the first (800; standard deviation: 28.28) than the second (variance: 200; standard deviation: 14.14).

Definition

Variance

Variance measures the distribution of values and is obtained by subtracting the mean of the squared deviation of the observed values from their mean in a frequency distribution.

When the expected value is the same, a risk averse individual always prefers a safer activity to a risky one (*i.e.* the activity with less variability). A risk lover, on the contrary, always prefers the risky activity (the one with higher variability). Finally, a risk neutral individual does not have a clear preference: they consider the two to be equivalent and are indifferent. As Ann is risk averse, she would prefer the second activity (with less variability), risk neutral Ned would be indifferent, and Luc, the risk lover, would prefer the first activity (with more variability).

Therefore, we can ask how individuals make choices in the presence of uncertainty and, in particular, according to their personal risk attitude. In the next section, we briefly describe the most common approaches used by economists in the last sixty years to study **decision-making under risk**, namely the **expected utility theory (EUT)**. This theory was developed by von Neumann and Morgenstern in 1944 [Von Neumann and Morgenstern 1953] and expanded by Savage [Savage 1954].

Key issue

Hypothesis

Expected utility theory (EUT) has its roots in the hypothesis that an agent who must make a decision in uncertain conditions weighs the benefits derived from different events with the probability that these particular events will occur.

1.3 Preferences and utility

Some further examples and definitions are necessary in order to illustrate the theory and to better understand the discussion that follows.

Example

Lottery

We begin with a lottery; for simplicity let us call this particular lottery L1. Each individual can choose between two alternatives: to buy or not buy a lottery ticket. The ticket offers you the opportunity to win 100€ with probability of 0.1. The expected value of lottery L1 is therefore 10€ (100€ x 0.10). If the price of the ticket is equal to the EV of L1 (*i.e.* 10€) a risk averse (lover) person would not (would) buy the ticket. Now assume that there is another lottery L2; in this case, a ticket costs 1 Euro and you can win 100€ with a probability of 0.05. Clearly, as the expected value of L2 is higher than the cost of the ticket (100€ x 0.05 > 1€), everyone who is not highly risk averse is likely to take the chance of winning 100€.

If we assume that each individual can only buy one ticket, there are now three alternatives:

- buy a ticket from L1,
- buy a ticket from L2,
- or do not buy a ticket.

Using the definition given earlier, each lottery is an event, because it is an occurrence that happens at a future time independent of the individual. The realization of the future event will determine the outcome for the individual; for example a loss of 10€ if they bought a L1 ticket and lost, or winnings of 99€ if they bought a L2 ticket and won. So we have three alternative events A = {no ticket, L1 ticket, L2 ticket} and five possible outcomes O = {no ticket, buy L1-win, buy L1-lose, buy L2-win, buy L2-lose}[5].

Like the lottery example, we constantly face situations in which we have to choose between alternatives. A set of possible alternatives is, for example, the multitude of goods and services that a decision-maker can afford. Whenever an individual consumes a good or a service, or has an experience, they derive some sort of satisfaction or pleasure from the good, service or experience and, in general, can rank which one they prefer. Thus, it is assumed that individuals have preferences; namely they can draw up a list of alternatives from the most preferred to the least.

Example

Ann, Luc, Ned and the lottery

For example, as Ann is risk averse, her preferences for lottery tickets are: an L2 ticket is preferred to no ticket, because L2 has a higher expected value with respect to the price of the ticket; however, she prefers no ticket to an L1 ticket, because the price of the L1 ticket price is equal to its expected value; and, clearly, an L2 ticket is preferred to an L1 ticket. So Ann's lottery preferences can be summarized as follows: L2 ticket > no ticket > L1 ticket. On the other hand, risk lover Luc would always prefer to buy one of the two tickets than avoid risk.

[5] These are the outcomes in which we have an interest. As we only aim to give a flavor of economic theory, we have simplified the list.

In general, economics assumes that each individual has a clear idea of which alternatives they prefer, namely they have a **system of preferences**. A **rational decision-maker** is an individual who, given their system of preferences, **can choose which alternatives they prefer from a set of possible alternatives**.

As this document does not aim to give a complete analytic description of economic theory, what follows is a simple outline of the **rational preference relation**. We assume a decision-maker who is able to rank their preferences in order to take correct decisions. On the one hand, they are always able to describe their preferences: if presented with two alternatives X and Y, they can always say whether: (i) X is preferred to Y, (ii) Y is preferred to X; or (iii) they are indifferent; in economics, this is known as **the axiom of completeness**. On the other hand, preferences can be sorted in an orderly manner (this is the core of the rational assumption): they can say whether they prefer alternative A to B and alternative B to C. Rational, in this context, means that they will prefer alternative A to alternative C (given the opportunity to choose between the two). In economic terminology, this is **the axiom of transitivity**.

However, to put the system of preferences into mathematical form, we need to introduce a function that measures the individual's level of satisfaction, namely the "pleasure" derived from the consumption of the good, service or experience. The rational preference relation can be represented by a **utility function** u(.). The utility function assigns a numerical value (representing the level of satisfaction) to each alternative, in order to rank it with respect to others. The higher the number associated with the alternative, the higher the preference given to it. The comparison of utilities makes it clear whether the individual prefers one alternative to another. Preferences can vary from individual to individual, thus utility is a subjective measure that reflects "taste". However, some characteristics of the utility function are assumed to be common to everyone, such as the **principle of non-satiation** for the utility of money. This principle can be summarized as "more is better" and "less is not better". In the case of money, it seems reasonable to assume that individuals always prefer to have more money than less. This is reflected in the **monotonically increasing utility function** for money.

Since all outcomes and preferences can be represented in monetary terms, let us see how individual preferences can be described via utility functions using the example from the previous section. It is straightforward to assume that everyone would prefer to have good year and earn 100 000€ than a bad year and only earn 60 000€. There is no need to develop an explicit form for the utility function; we can simply say that: u(100 000) > u(60 000) for any individual.

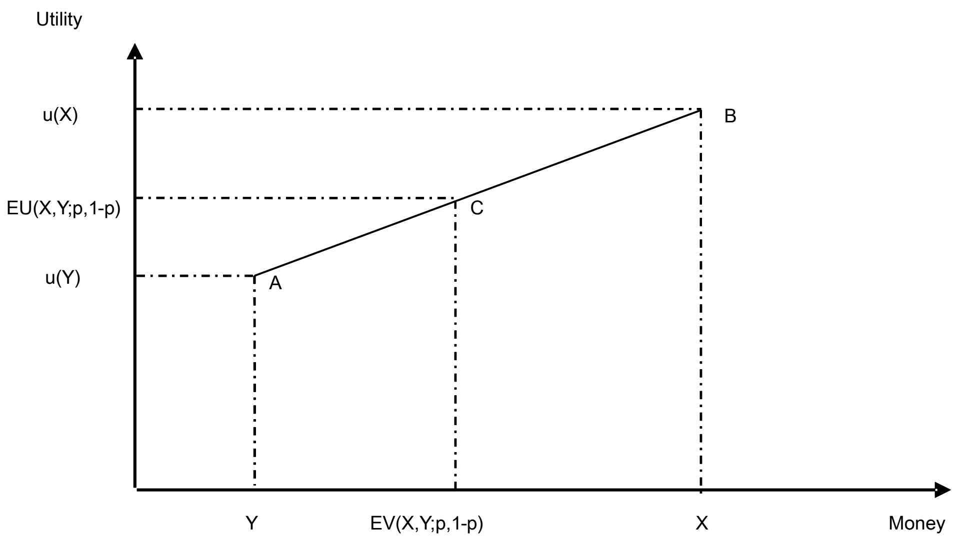

Figure 1.1 – *Example of the relation between utility function and money: the higher the amount of money, the higher the utility u(.) associated with that amount*

In fact, it is not really that important to know by how much u(100 000) is greater than u(60 000): the only thing we are interested in is that the utility of one of the two outcomes is larger than the other (100 000€ compared to 60 000). Utility is said to be ordinal: what matters is the sign of the difference u(100 000) - u(60 000) > 0 and the ranking of alternatives, rather than the actual value of the difference. If the scale changes, for example by expressing values in dollars, the order does not change (*i.e.* with each monotonic transformation). Similarly, the absolute value of the utility is not as important as its relative value, or the ranking between utilities for different outcomes.

So far we have considered the good year and the bad year separately; however we would like to know how to represent a risky event and what is the role of probability in ranking uncertain alternatives. The next section addresses this question and introduces expected utility theory.

1.4 Expected utility theory

A utility function helps to rank alternatives that are certain to happen (a probability of one). However, if the alternatives that we have to rank are uncertain and occur with a probability somewhere between zero and one, we can summarize the utility derived from the risky activity in a single measure through a calculation of the **expected utility**.

In our example, the risky activity has two possible outcomes (a good year and a bad year) for which there are two possible utilities u(100 000) and u(60 000) depending on the outcome of the event in the future. Let us define X as the amount of money earned in the good year that occurs with probability p, and Y as the money earned in a bad year with complementary probability 1-p. In this case, the risky activity can be defined as (X,Y; p, 1-p). The expected value (EV) of the activity has already been defined as the expected outcome before the event takes place:

$$EV\left(X,Y;p,1-p\right) = 0.5 \times 100\,000 + 0.5 \times 60\,000 = 80\,000$$

The expected value can be plotted on the abscissa of the graph in figure 1.1.

However, the decision-maker must take action before the outcome is known and needs to evaluate the risky activity in advance, given the specific probabilities that they either know or have correctly estimated. The **expected utility (EU)** of the risky activity is the average of the utilities derived from the possible outcomes, weighted according to the probability that they will occur. In the previous example, the expected utility of the risky activity is given by:

$$EU(X,Y;p,1-p) = p \times u(X) + (1-p) \times u(Y) = 0.5 \times u(100\,000) + 0.5 \times u(60\,000)$$

This shows that the utilities of the certain outcomes in the two possible years (good or bad) contribute to the expected utility only to the extent that they are likely to occur. In other words, EU is the expectation of the future utility, $E(U(X,Y;p,1-p))$. From a mathematical perspective, expected utility is a linear combination. In fact, in the graph in figure 1.1, the line that connects point A to point B is the expected utility for each possible combination of complementary probabilities (p, 1-p) and outcomes X and Y (if p = 0, the expected utility is exactly u(Y), while if p = 1, the expected utility is u(X)). The ordinate of point C is the expected utility deriving from the risky activity with p = 0.5; and its abscissa is its expected value.

We now have a single measure to describe the level of satisfaction of maintaining the activity. Therefore we can compare the level of satisfaction of safe and risky activities, and have a single theoretical background for the different attitudes to risk that we introduced in the previous section.

We have defined the certainty equivalent as the amount of money that the individual thinks has the same utility as the risky activity (*i.e.* the one that has the same amount of utility):

$$u\left(CE(X,Y;p,1-p)\right) = EU(X,Y;p,1-p)$$

thus,

$$u\left(CE(X,Y;p,1-p)\right) = 0.5 \times u(100\,000) + 0.5 \times u(60\,000)$$

The relation between the certainty equivalent and expected utility depends on the attitude to risk of the individual in question.

1.5 Risk aversion

As we have discussed, a risk averse individual always prefers safe activities to risky ones. In other words, their utility function for a risky activity is always lower than the utility derived from an activity with the same expected value but without risk. This implies that the following relationship can be applied to every risk averse agent and every risky activity:

$$u\left(EV(X, Y; p, 1-p)\right) > EU(X, Y; p, 1-p)$$

This is the exact mathematical definition of a concave function, namely

> *A real-valued function f on an interval (or, more generally, a convex set in vector space) is said to be concave if, for any x and y in the interval and for any t in [0, 1], $f\left(tx + (1-t)y\right) > tf(x) + (1-t)f(y)$ for any t in (0, 1) and $x \neq y$.*

We can conclude that the utility function for a risk averse individual can always be represented by a concave function.

Let us go back to our previous example. For Ann, the following inequality is always valid:

$$u(0.5 \times 100\,000 + 0.5 \times 60\,000) > 0.5 \times u(100\,000) + 0.5 \times u(60\,000)$$

Moreover, since $u\left(CE(X, Y; p, 1-p)\right) = 0.5 \times u(100\,000) + 0.5 \times u(60\,000)$, we can also say that u(80 000) > u(CE). As the expected value of the activity is always higher than the expected utility of the activity, we see a difference in the ordinates of points C and D in the graph shown in figure 1.2 below. Moreover, we can easily find the certainty equivalent using a graphical analysis. Knowing how much the individual would pay for the same utility, we can find the certainty equivalent by finding the amount that corresponds to the expected utility of the two uncertain events (*i.e.* u(100 000, 0.5; 60 000, 0.5) = 50% × u(100 000) + 50% × u(60 000) = u(CE)). In this specific example, Ann's certainty equivalent was $CE\left(X, Y; p, 1-p\right)$ = 75 000€ and, in fact, the utility of 80 000€ is always higher than the utility of 75 000€.

As we explained earlier, the risk premium is the difference between the expected value and the certainty equivalent (thus 5 000€ for Ann). We note that risk premium is a valid measure of risk aversion: the higher the risk premium, the higher the amount the agent is willing to give up in order to avoid risk and move to the safe option. Furthermore, this measurement is reflected in the concavity of the utility function, *i.e.* the more concave the function, the more risk averse the agent.

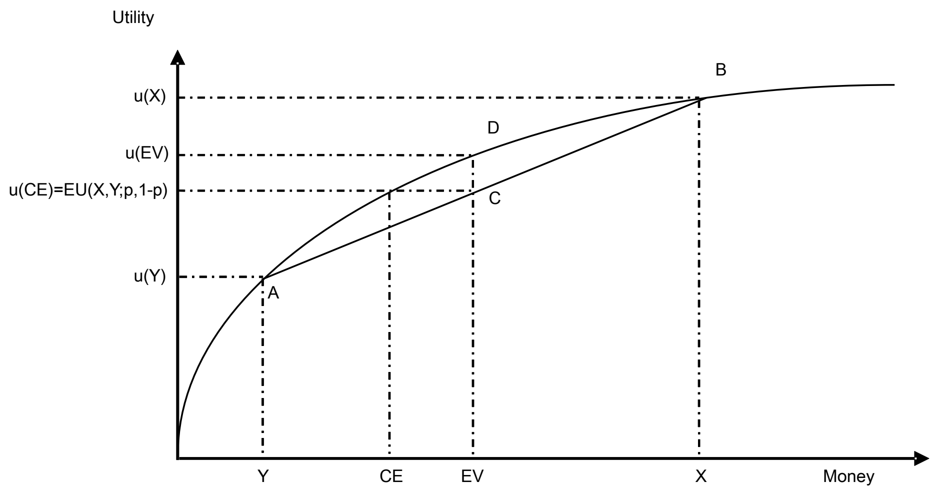

Figure 1.2 – *Utility function for a risk averse agent*

Similarly, the preferences of a risk lover can be represented by a convex function, as for them the utility of the certainty equivalent is always higher than the utility of the expected value. Risk neutral preferences can be described by linear utility functions: as defined above, the expected utility is a linear combination of utilities weighted by their probabilities; thus, clearly, the only function for which the certainty equivalent is equal to the expected utility is the linear function.

Key issue

EUT

We can summarize expected utility theory as follows:

1. it is possible to measure utility for known amounts of money; the higher the amount of money, the higher the measured utility;
2. it is possible to measure the expected utility of a risky activity by weighting the utility derived from known values with the probability of occurrence;
3. risk averse (lover) individuals always prefer safe amounts to uncertain equivalent amounts and this can be graphically represented by a concave (convex) utility function.

So far, we have seen how to represent individual preferences in terms of utility and how expected utility theory can rank events which have an uncertain outcome. Standard economic theory related to choice under risk and uncertainty assumes that any reasonable individual follows the axioms of expected utility theory and that most people behave as the theory predicts in most situations. Similarly, most economists would argue that a good choice in risky circumstances should be coherent with the theory.

1.6 Measures of risk aversion

Economic situations mostly involve risky outcomes. Thus, knowing people's attitude to risk is important for many reasons as they have implications for economics, investment levels, individual insurance choices, and public policy. On the one hand, if we seek to understand human behavior on an individual level, we might be interested in individual levels of risk aversion; on the other hand, understanding aggregate behavior is a useful way to address more general questions and model validity. For example, a market analysis requires having an idea of the general population's risk attitude, and the implementation of national policy means that governments have to take into account the global level of risk aversion rather than that of individuals.

1.6.1 Econometric analysis

Econometric studies that aim to estimate aggregate risk attitudes rely on datasets from particular sectors or activities. For example, it is well-known that workers with similar tasks, but who are exposed to different levels of danger, earn wages that reflect the risk they take. By measuring this difference and the severity of the risk, we can evaluate the level of risk aversion: a very risk averse agent should demand a high wage to work in a risky environment.

Example

Smokers and non-smokers

The work of Hersch and Viscusi provides a good example [Hersch and Viscusi 2001]. They categorized workers into two sets: smokers and non-smokers. They used smoking as a proxy for a more risk-seeking attitude, and studied the wage differential of smokers and non-smokers who held risky jobs. They found that smokers looked for riskier jobs, but were paid less than similar workers who were non-smokers. Although both categories of workers were compensated for the risks they incurred, the level of compensation was lower for smokers. Note that both categories of workers (smokers and non-smokers) were risk averse, as they were both compensated for the risk they incurred.

Given the definition discussed earlier, a risk lover would expect to be paid less than a risk averse individual for the same, risky job. Different preferences (risk attitudes) lead to different job markets and salaries. Using this information, and assuming a general form of the utility function, we can estimate the level of risk aversion from the wage differential of workers with similar characteristics (*e.g.* smokers) in analogous working situations, but where the likelihood of being injured is different. We expect that the higher the difference in the number of injures, the higher the level of risk aversion.

Similar analyses have been carried out in other contexts. For example, Irwin Friend and Marshall E. Blume used "*cross-sectional data on household asset holdings to assess the nature of households' utility* *functions*[6] [Friend and Blume 1975]". Their dataset consisted of the usual socioeconomic-demographic characteristics of households. They also included information on income and assets, such as the quantity and type of assets and liabilities (bank accounts, bonds, life insurance, stocks, equity, *etc.*).

George G. Szpiro used time-series data on property insurance to test different utility functions, and find those that best fit the data [Szpiro 1986]. Many researchers have looked at insurance premiums as a way to evaluate an agent's willingness to pay for insurance, and the number of claims as a proxy for the probability that an accident occurs. Insurance markets (*e.g.* life, car or health) are frequently used as the basis for estimates of risk attitudes [Friedman 1973].

To summarize, the usual way to estimate risk attitude is, first, to assume a generic functional form for the utility function, which can be convex, concave or linear depending on the coefficient, and, second, to estimate the coefficient by means of an econometric analysis of decisions taken under uncertainty. The overall conclusion is that the vast majority of people are risk averse, both in general and in many specific contexts. Equally important in these types of studies is the finding that there are different classes of people for whom the level of risk aversion is different. Important factors are socio-demographic data such as age, gender, job, education, wealth, area, religious affiliation, *etc.* For instance, we can look at differences between males and females, and whether risky behavior is affected by age or if it is stable throughout a person's lifetime.

1.6.2 Experimentation

Another approach is to measure individual levels of risk aversion via experimentation. These studies are usually less ambitious than estimating the overall form of the utility function: they concentrate on local estimates of risk aversion levels (*i.e.* a part of the curve rather than all of it). Other studies investigate risk attitude by testing to see which utility function best fits the experimental data. We now look at some of the methods used to measure risk attitude. These methods examine behavior in risky situations and evaluate participant's responses using questionnaires or experiments.

Charles A. Holt and Susan Laury addressed the issue in an experiment based on lotteries [Holt and Laury 2002]. Participants were presented with a list of 10 lotteries (see Table 1.1), and asked which of the two options (A or B) they preferred.

Option A	Option B	Expected payoff difference
1/10 of \$2.00, 9/10 of \$1.60	1/10 of \$3.85, 9/10 of \$0.10	\$1.17
2/10 of \$2.00, 8/10 of \$1.60	2/10 of \$3.85, 8/10 of \$0.10	\$0.83
3/10 of \$2.00, 7/10 of \$1.60	3/10 of \$3.85, 7/10 of \$0.10	\$0.50
4/10 of \$2.00, 6/10 of \$1.60	4/10 of \$3.85, 6/10 of \$0.10	\$0.16
5/10 of \$2.00, 5/10 of \$1.60	5/10 of \$3.85, 5/10 of \$0.10	−\$0.18
6/10 of \$2.00, 4/10 of \$1.60	6/10 of \$3.85, 4/10 of \$0.10	−\$0.51
7/10 of \$2.00, 3/10 of \$1.60	7/10 of \$3.85, 3/10 of \$0.10	−\$0.85
8/10 of \$2.00, 2/10 of \$1.60	8/10 of \$3.85, 2/10 of \$0.10	−\$1.18
9/10 of \$2.00, 1/10 of \$1.60	9/10 of \$3.85, 1/10 of \$0.10	−\$1.52
10/10 of \$2.00, 0/10 of \$1.60	10/10 of \$3.85, 0/10 of \$0.10	−\$1.85

Table 1.1 – *The ten paired lottery-choice decisions with low payoffs*

Participants were paid according to their results obtained in the lottery they chose. For example, a participant who chose option A in line one, would be paid \$2 with probability 10%, or \$1.60 with

[6] We do not go into any detail about the form that a utility function can take, however the following is a simple example. Imagine an exponential function x^a. If the coefficient a is estimated as a=1, the function is linear, and the agent is risk neutral. If a is strictly higher than 1, the agent is risk averse; moreover the higher a is, the higher the concavity of the function, and the higher the level of risk aversion. If a < 1, then the agent is a risk lover.

probability of 90%. The third column shows the difference in the expected payoffs (*i.e.* EV(option A) – EV(option B))[7]. Whenever the difference is positive (the first four lotteries) a rational, risk neutral participant should prefer option A to option B; on the other hand, for the six last lotteries they should choose option B, as it gives a higher expected payoff. Moreover, for the first line, only a dedicated risk lover would choose option B, and, in the last line, everyone should prefer option B, as it is certain that it gives a higher payoff than option A.

The authors found that even with these low stakes (the maximum gain was less than $4), about:

- ▷ 66% of participants were risk averse,
- ▷ 8% were risk lovers,
- ▷ and the remaining 25% were risk neutral.

This supports the idea that most people are risk averse. However, there are many aspects to take into account; for example, is the level of risk aversion the same for small and large amounts of money? How do participants behave if the questions are only hypothetical and do not involve real money?

Example

Low *vs* high amounts of money; real *vs* hypothetical gains

The authors controlled their experiment for higher stakes by substituting $144 and $180 (for $2 and $1.60) in option A, and $346.50 and $9 in option B. When these high stakes were hypothetical, the level of risk aversion was similar to that based on real, low stakes. However, when the stakes were high and real, the authors found a large increase in the level of risk aversion. A third of participants were not willing to take any risk at all and chose option B only in the last question.

An explanation for this behavior may be that when the potential gains are high, we become more risk averse. The difference between a certain gain of at least $144 and the potential to win only $9 makes option B a risky gamble that is not easily chosen. When the stakes are hypothetical, participants tend to be braver and typically underestimate the extent to which they will avoid risk once real payoffs are on offer.

Despite the important results of economic experiments that provide monetary incentives, in many situations we need a simpler, more direct and less costly way to access information about people's risk attitude. Many different surveys are available and used by researchers. Nevertheless, we still need to validate that the answers to these unpaid and hypothetical questionnaires are in fact good predictors of actual behavior in real situations.

Dohmen et al. carried out a study based on the German socio-economic panel (SOEP), which includes many measures of risk attitude in different contexts (general, driving, financial matters, sports and leisure, health and career, *etc.*). The panel also includes other useful information such as age, gender, wealth, income, job, education, parents' education, number and ages of children, civil status, religion, weight, height, health status and others [Dohmen et al. 2011]. The authors tested whether a very simple question could describe actual behavior in a lottery experiment similar to that carried out by Holt and Laury. Responses to a lottery experiment (where participants could win up to 300€) revealed that:

- ▷ around 78% of the population was risk averse,
- ▷ 13% risk neutral,
- ▷ and 9% risk lovers[8].

Not only were their findings similar to Holt and Laury's and other important studies on risk attitude, but the authors also found that the answer to the **general risk attitude** (GRA) question "*How willing are you to take risks, in general?*" (on a scale from 0 – 10) was a reliable predictor of risky behavior in the real-stakes lottery. Given the data available, it is interesting to look at the breakdown of answers to the GRA question. Women are, in general, more risk averse than men; risk aversion becomes more significant with age; having well-educated parents makes people more open to taking risks; and most surprisingly, taller people tend to be less risk averse.

[7] It is important to make clear that this last column was not part of the experimental instructions.
[8] A small, remaining percentage reflected participants whose answers were inconsistent with the three definitions of risk attitude.

1.7 What about "anomalies"?

All these studies help us to understand how people react to risky situations: for example, we may expect women to be more careful in risky decisions. So far, the economic theory we have described assumes that risk attitudes are heterogeneous but standardized. Consequently, we have assumed that people are either "always" risk averse or "always" inclined to take risks independently of time or situation and our theoretical model captures these elements.

Expected utility theory has been widely used in every branch of economics and economists have been quick to defend its validity. Despite this widespread belief, a great number of papers in experimental and behavioral economics based, for example, on the work of psychologists Kahneman and Tversky have found many problems that systematically violate the predictions of expected utility theory [Kahneman and Tversky 1979, 1984, 2000] .

In the following chapter we analyze a series of empirical and experimental results that depart from the predictions of expected utility theory. We focus on irregularities that result from psychological motivations which are context free (*i.e.* that are independent of a specific frame), and are thus applicable in many different circumstances. We call these irregularities "anomalies".

Definition

Anomaly

In economics, an anomaly is a behavior that is not in line with the conventional theoretical model.

The study of these anomalies with respect to EUT has led to the emergence of an alternative theory, known as prospect theory, which will be presented in chapter 2. However, not all anomalies are sufficiently widespread in the general population to be accounted for by this new general theory; thus, in chapter 3, we present some other deviations from rational behavior that have not yet been modeled, but that have a large impact on decision-making under uncertainty.

2

Discrepancies between the rational model and reality

Empirical results suggest that in general, people are risk averse. An interesting puzzle emerges when the same person buys insurance that costs more than the risk it is expected to cover (risk averse behavior) and gambles on a lottery ticket that costs more than its expected outcome (risk lover behavior). If we assume that the attitude of an economic agent is, for example, to always avoid risks, then they should never gamble and any other behavior can be seen as irrational.

In the previous chapter we discussed the role of risk aversion in decision-making under uncertainty. Most individuals are reluctant to bear risks and prefer safe options when the outcome is not 100% sure.

We introduce anomalies, and again we assume that whenever there is risk the probabilities of the alternatives are known, *i.e.* there is no uncertainty about the exact value of the probabilities involved[1].

2.1 Loss aversion

One of the most interesting and common anomalies in human behavior when faced with risk is **loss aversion**. In terms of its importance in economics and decision-making under uncertainty, it is second only to risk aversion (discussed in section 1.5).

Loss aversion arises in situations where at least one of the possible alternatives available to the decision-maker leads to a reduction in their wealth. More precisely, it assumes that situations in which the probability that an individual might suffer a loss are perceived differently than situations where risk leads to gains. As Kahneman and Tversky argued, the idea behind loss aversion is that

> “ *losses loom larger than corresponding gains [Kahneman and Tversky 1979].* ”

In other words, the pain of a loss is much higher than our experience of a gain of the same magnitude.

Example

Perception of losses and gains

> Imagine you won a car valued at 20 000€. Now, imagine the car is destroyed in an accident. Although the two situations are of the same magnitude, the negative feeling from the loss will be perceived, in absolute terms, more acutely than the positive reaction to the win.

This general psychological principle, which might be linked to our survival instinct, means that loss averse agents behave differently in the same situation depending on how it is framed – either as losses or as lost/missed gains.

Let us take an example based on discounts and surcharges.

[1] The next chapter looks at ambiguity aversion, which is the desire to acquire information about unknown probabilities.

Discount and surcharge

Example

Imagine a simple situation: you are about to buy a T-shirt costing 20€ that you believe is sold at a 20% discount. You discover at the cash register that there is actually no discount. Compare this to the situation where you are about to buy a T-shirt that costs 16 € and the cashier tells you that there is a surcharge on the article and now it costs 20€.

It is usually easier to give up a discount than to accept a price increase, even if the difference is the same. Consequently, in the first situation, you would probably still be willing to buy the T-shirt, while in the second, you would not.

Another example of this type of behavior was found by Kahneman, Knetsch and Thaler [Kahneman et al. 1986]. In telephone interviews they asked participants how they judged the actions taken in the following two situations:

Real wage and purchasing power

Example

A company is making a small profit. It is located in a community experiencing a recession with substantial unemployment but no inflation. The company decides to decrease wages and salaries by 7% this year.

A company is making a small profit. It is located in a community experiencing a recession with substantial unemployment and inflation of 12%. The company decides to increase wages and salaries by only 5% this year.

In both situations there is a 7% decrease in real wages. The 5% nominal wage increase in the second situation does not compensate for the real decrease in wealth due to the 12% inflation rate. Despite the two situations being equal in real terms, judgments of the behavior of the company depend on how it is framed: 62% of participants perceived the first situation as "unfair" or "very unfair", while only 22% said the same of the second situation. A clear loss in the first case is compared to a perceived gain (an increment in nominal wages) even if the real wage and its purchasing power have decreased.

Such behavior is found in many other fields. Kahneman and Tversky addressed the issue by means of an experiment involving 307 participants [Tversky and Kahneman 1981; Kahneman and Tversky 1984]. Half (N = 152) were presented with a situation involving a health problem, the other half (N = 155) faced a similar situation framed differently. This is the first problem:

Outbreak of an Asian disease: problem 1 (N = 152)

Example

Imagine Country X is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the program are as follows:

- ▷ if program A is adopted, 200 people will be saved;
- ▷ if program B is adopted, there is a $1/3$ probability that 600 people will be saved, and a $2/3$ probability that nobody will be saved.

Which program would you prefer?

In this description, a negative event is expected to occur – 600 people are expected to die. Thus, people prefer the safe option, where 200 people are certain to be saved, rather than the risky one, where the probability is $1/3$ that they will all be saved, but $2/3$ that all 600 would die. In this case, 72% of participants preferred program A, while only 28% chose program B. As expected, the majority of people behave as a risk averse agent, although the expected number of lives saved by the two programs is the same.

Kahneman and Tversky put the following question to the remaining participants:

Outbreak of an Asian disease: problem 2 (N = 155)

Example

Imagine Country Y is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the program are as follows:

- ▷ if program C is adopted, 400 people will die;
- ▷ if program D is adopted, there is a $^1/_3$ probability that nobody will die, and a $^2/_3$ probability that 600 people will die.

Which program would you prefer?

Program C is the same as program A in terms of lives saved/ number of people dying, and program D is identical to program B in terms of its probabilities. **In fact, all four programs are equal in terms of expected numbers of lives saved**. Nevertheless, participants faced with this second problem responded differently: only 22% chose program C and 78% chose program D. Clearly, this violates expected utility theory that predicts that a risk averse agent would choose programs A and C and a risk lover would choose programs B and D. In principle, preferences between alternatives should be context-free; they should only depend on relevant differences between alternatives, and not on the way the differences are presented. This is what we call the principle of invariance, that is, in this example like in others, violated.

Principle of invariance

Definition

Different representations of the same choice problem should yield the same preference. That is, the preference between options should be independent of their description [Tversky and Kahneman 1986].

This puzzling difference is widespread and found in many different contexts. As Kahneman and Tversky observed,

> “ *The failure of invariance is both pervasive and robust. It is as common among sophisticated respondents as among naive ones, and it is not eliminated even when the same respondents answer both questions within a few minutes. Respondents confronted with their conflicting answers are typically puzzled. Even after rereading the problems, they still wish to be risk averse in the 'lives saved' version; they wish to be risk seeking in the 'lives lost' version; and they also wish to obey invariance and give consistent answers in the two versions.* ”

Next we look at an example that does not involve human lives, as talking about death tolls may have ethical implications and participants may be reluctant to take decisions involving the certain death of other human beings.

Concurrent decisions (N = 150)

Example

Imagine that you face the following pair of concurrent decisions. First examine both decisions, and then indicate the option you prefer.

- ▷ Decision (i), choose between:
  - option A - A certain gain of $240
  - option B - A 25% chance of gaining $1000 and a 75% chance of gaining nothing
- ▷ Decision (ii), choose between:
  - option C - A certain loss of $750
  - option D - A 75% chance of losing $1000 and a 25% chance of losing nothing

In decision (i) the majority (84%) of individuals chose option A and 16% chose option B, as predicted by risk aversion theory. However, in decision (ii), 87% of participants chose option D and can be classified as risk lovers, while only 13% chose a certain loss of the same expected value (option C). Since the same questions were put to all participants, we also know that 73% of respondents chose options A and D and only 3% chose options B and C. This behavior contradicts the results predicted by expected utility theory, according to which risk averse agents will choose options A and C and risk lovers will choose options B and D. The remaining 24% of respondents were more consistent: they were either risk averse (they chose options A and C), or risk lovers (they selected options B and D).

The main reasoning behind decision (ii) appears to be,

> *It's better to risk losing $1000 (I may also lose nothing) than to definitely lose $750 (without being able to do anything to change it).*

For many readers this might be reasonable; however, according to the principles of expected utility it is not at all rational.

Until recently, most economists were skeptical about results of such experiments that were carried out by psychologists. In particular, they criticized the fact that there were no monetary incentives. Nevertheless, further experiments involving real stakes (small and large gains/ losses) confirmed the inconsistencies found in earlier work.

So, are people irrational or is the theoretical model incorrect? If inconsistencies are found in many different contexts and the assumption of invariance[2] fails to be met, there might be other reasons underlying this widespread human behavior. Kahneman and Tversky created a new theory that did not completely depart from expected utility theory, but accounted for loss aversion and other manifestations of asymmetric behavior when faced with losses or gains. Before discussing this new theory (derived from loss aversion) in more detail, we introduce some other anomalies.

2.2 The endowment effect

Imagine that you are invited to participate in a very simple experiment: list five objects that you have at home and write down the price at which you would sell them. Now think again about these five objects and imagine that you are going to buy them second-hand. Are the prices at which you would sell them higher, equal to or lower than those at which you would buy them? In general, people tend to value their own objects more highly than the price they are willing to pay to buy them. Variations of this simple experiment have been carried out in many different contexts.

One of the most widely-cited experiments was carried out by Daniel Kahneman, Jack Knetsch and Richard Thaler [Kahneman et al. 1991].

Example

The coffee mug

A coffee mug was given to a group of students and they were asked to state the price (between $0.25 and $9.25) at which they would sell their newly-acquired mug. Another group of students was asked to state the price at which they would buy the same mug. The median selling price stated by the first group of students was $7.12, while $3.12 was the median price given by the potential buyers.

This type of bias contradicts expected utility theory predictions: the same object should offer the same utility and therefore should be valued at the same price.

This anomaly is called the **endowment effect**. This large difference in the valuation of the same object cannot be simply explained by different preferences. There is a disparity between the value that we give to a good that is in our possession and our evaluation of the same good that we do not hold. If we imagine our house or our favorite armchair, the endowment effect might be explained by the affection that we have for our goods. However, many further experiments have proved that there is a reluctance to trade even newly-acquired goods where affection should not play a role, *e.g.* coffee mugs [Kahneman et al. 1991], Swiss chocolate bars [Knetsch 1989], or bottles of wine [van Dijk and van Knippenberg 1998] where the possession effect appears instantaneously.

It was Thaler who first suggested that people value their own objects more than they value the same objects if they do not own them [Thaler 1980].

[2] In this sense, the theory is universally correct: a risk averse agent avoids risk in any situation, independent of any losses or gains.

In his paper, Thaler suggested other examples to support the hypothetical endowment effect:

A bottle of wine

Example

Mr. R bought a case of good wine in the late 1950's for about \$5 a bottle. A few years later his wine merchant offered to buy the wine back for \$100 a bottle. He refused, although he has never paid more than \$35 for a bottle of wine.

This example can be read in terms of loss aversion: giving up the bottles of wine is perceived by Mr. R as a loss, even if the price offered by the merchant is much higher than the price he himself would pay. On the other hand, buying a bottle of wine is considered a gain and is seen as less valuable. This example clearly shows that removing an item from one's endowment is perceived as a loss, and since, in general, human beings are loss averse, it has a negative impact. Consequently, the endowment effect can be seen as a specific manifestation of loss aversion.

Cure and medical research

Example

Two survey questions:

(a) *"Assume you have been exposed to a disease which, if contracted, leads to a quick and painless death within a week. The probability of developing the disease is 0.001. What is the maximum you would be willing to pay for a cure?"*

(b) *"Suppose volunteers were needed for research on the above-mentioned disease. All that would be required is that you expose yourself to a 0.001 chance of contracting the disease. What is the minimum payment you would require to volunteer for this program? (You would not be allowed to purchase the cure.)"*

Applying the same reasoning that we have seen in other examples, the two questions differ in terms of context, but they are mathematically the same. However, in this second example many respondents gave very different values in response to questions (a) and (b). Thaler's results (ibid.) showed that typical responses are \$200 for question (a) and \$10 000 for (b). Voluntarily exposing oneself to a disease is a certain loss, and the endowment is health; therefore potential participants ask for huge amount of money. On the other hand, having the disease focuses attention on the potential loss incurred in paying for the cure.

2.3 The status quo bias

Now imagine these two problems proposed by Samuelson and Zeckhauser [Samuelson and Zeckhauser 1988]:

Your rich great-uncle: problem 1

Example

You are a serious reader of the financial pages but until recently had little money to invest. Then you inherited a large sum of money from your great-uncle. You are considering different portfolios.

Your choices are:

(a) Invest in moderate-risk Company A. Over a year, their stock has 0.5 chance of increasing by 30% in value, a 0.2 chance of remaining unchanged, and a 0.3 chance of declining by 20% in value.

(b) Invest in high-risk Company B. Over a year, their stock has a 0.4 chance of doubling in value, a 0.3 chance of remaining unchanged, and a 0.3 chance of declining by 40% in value.

(c) Invest in treasury bills. Over a year, these will yield a nearly certain return of 9%.

(d) Invest in municipal bonds. Over a year, they will yield a tax-free return of 6%.

Your rich great-uncle: problem 2

Example

You are a serious reader of the financial pages but until recently had little money to invest. Then you inherited a portfolio of cash and securities from your great-uncle. A significant portion of this portfolio is invested in high-risk Company B. You are deliberating whether to leave the portfolio intact or to change it by investing in other securities. (Tax and broker commissions involved in any change are insignificant.)

Your choices are:

(a) Invest in moderate-risk Company A. Over a year, the stock has a 0.5 chance of increasing by 30% in value, a 0.2 chance of remaining unchanged, and a 0.3 chance of declining by 20% in value.

(b) Retain the investment in high-risk Company B. Over a year, the stock has a 0.4 chance of doubling in value, a 0.3 chance of remaining unchanged, and a 0.3 chance of declining by 40% in value.

(c) Invest in treasury bills. Over a year, they will yield a nearly certain return of 9%.

(d) Invest in municipal bonds. Over a year, they will yield a tax-free return of 6%.

In problem 1, all four investment alternatives are new: the great-uncle left you some money that you can invest in any of the four alternatives. We will call the situation in problem 1 the **neutral design**. In problem 2, choice (b) is the **status quo**, namely it is the alternative selected by your great-uncle at the moment when the investment choice was made. Although in both problems participants can freely (and at no cost) choose among the four investment opportunities, in problem 2 many tend to stick to alternative (b), namely the current situation, the status quo. This is evident when we compare the percentage of participants in the neutral design that chose option (b) in problem 1 (40%), to the percentage that remained in the high-risk situation in the status quo design (56%). This experiment has been repeated with different status quo conditions, other investment alternatives and alternative frames (*e.g.* alternative frame [Samuelson and Zeckhauser 1988]).

Alternative frame

Example

1- The National Highway Safety Commission is deciding how to allocate its budget between two safety research programs: i) improving automobile safety (bumpers, body, gas tank configurations, seat belts); and ii) improving the safety of interstate highways (guard rails, grading, highway interchanges, and implementing selective reduced speed limits).

It is considering four options:

(a) Allocate 70% to auto safety and 30% to highway safety.

(b) Allocate 30% to auto safety and 70% to highway safety.

(c) Allocate 60% to auto safety and 40% to highway safety.

(d) Allocate 50% to auto safety and 50% to highway safety.

1'- The National Highway Safety Commission is reassessing the allocation of its budget between two safety research programs: i) improving automobile safety (bumpers, body, gas tank configurations, seat belts) and ii) improving the safety of interstate highways (guard rails, grading, highway interchanges, and implementing selective reduced speed limits). Currently, the commission allocates approximately 70% of its funds to auto safety and 30% of its funds to highway safety. Since there is a ceiling on its total spending, its options are (check one):

(a) Maintain present budget amounts for the programs.

(b) Decrease auto program by 40% and raise highway program by like amount.

(c) Decrease auto program by 10% and raise highway program by like amount.

(d) Decrease auto program by 20% and raise highway program by like amount.

The explanation for this type of behavior does not relate to attitudes to risk, but is rather based on the tendency of people to want to remain in their current state. Individuals prefer to maintain their current condition rather than make changes. Whenever a change is in the wind, the perception of the disadvantages that may arise in giving up the current situation carries more weight than the perception of advantages related to the new state[3], even when the probabilities and benefits of the new state are known. Moreover, the status quo is chosen more frequently as the number of alternatives increases. It seems that increased confusion and the ability to choose new alternatives

[3] An example of status quo bias and ambiguity aversion is the story of the old woman of Syracuse. Unlike her fellow citizens, who prayed for the death of the tyrant Dionysius, she prayed for his safety because she was afraid that a new ruler would be even worse.

decrease the willingness of participants to change – even if a more advantageous alternative is available.

Samuelson and Zeckhauser define this position as the "status quo bias" [Samuelson and Zeckhauser 1988]. It is related to the tendency to avoid changing current conditions; either to buy a new good that is not in our possession, or to sell a good that is in our possession. Like the endowment effect, it can be traced back to a manifestation of loss aversion.

2.4 A general theory: prospect theory

As we mentioned earlier, Kahnemann and Tversky suggested a new theoretical approach to economic decision-making under uncertainty, based on a modification to expected utility theory that is consistent with the empirical and experimental evidence.

Key issue

What do experimental studies show

The experimental economic studies of uncertainty that we have described so far can be summarized by two main conclusions:

- individual utility seems to be associated not with wealth or well-being, but with a variation in that wealth or well-being with respect to an initial reference point;
- changes that make the initial situation worse (losses) seem to carry more weight than improvements with respect to the same initial situation (gains).

The first conclusion is directly linked to anomalies such as the status quo bias and the endowment effect. This creates a reference ("zero") point for each individual when they evaluate a risky situation; it represents their *ex ante* wealth (*i.e.* the wealth of the individual before making the decision). We call this reference state Ro.

The second conclusion implies that there is a sharp change in the utility function whenever we are close to Ro: in this situation losses appear larger than corresponding gains. From a mathematical point of view, this translates into the fact that the utility function is much steeper for losses than it is for gains.

Moreover, as we have seen in previous examples, people generally tend to be risk averse in the domain of gains, but risk lovers in the domain of losses. The reference point separates the two domains and mathematically, means that the utility function has to be concave in the positive quarter and convex in the negative quarter.

Figure 2.1 shows a typical curve proposed for the model:

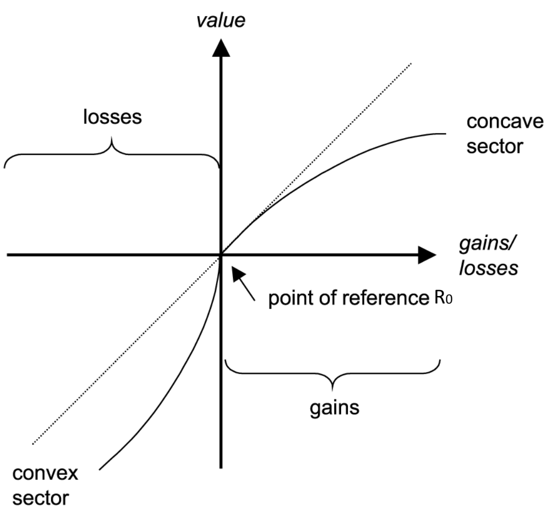

Figure 2.1 – *Graph of a typical curve for prospect theory (based on the work of Kahnemann and Tversky)*

The graph includes all the characteristics that appear as anomalies in expected utility theory.

Kahnemann and Tversky suggest that the process by which people make choices follows two steps:

- first they construct the context for their choice;
- then, they make their decisions according to the basic principles of prospect theory.

This first step is called **framing**. Framing is where people choose the reference point and, thus, how to represent the available alternatives. As we have seen, framing is not only influenced by real issues (*e.g.* wealth, real losses or gains, the status quo), but also by the "fictitious" way in which a situation is presented. Changing "death rate" to "survival rate" should simply be a question of style. However the perception that is established in the person's mind changes how the problem is framed and, consequently, the choice of the decision-maker. Usually when people see the context in terms of losses (death rate) they tend to be a risk lover and choose the risky alternative; however, when the context is one of gains (survival rate) people are usually risk averse and choose the safe alternative.

One case in which the framing process can be potentially very influential in the outcome of the decision occurs when it modifies the reference point. In this case, it increases the influence of the context and can have a large impact on the decision-maker, who can become either risk averse or a risk lover according to the position of alternatives relative to the reference point.

2.5 Loss aversion: human or animal behavior?

An important question posed by researchers in different fields (economics, psychology, anthropology, biology, *etc.*) is whether this widespread behavior is innate, or if it is a bias derived from the environment or affected by social norms. Experiments on laboratory animals provide an opportunity to conduct controlled experiments that investigate economic theories, and the ability to replicate experiments with human participants.

For example, in a series of papers Chen, Lakshminarayanan and Santos found qualitatively similar behavior in primates [Chen et al. 2005, 2006; Lakshminarayanan et al. 2008; Lakshminarayanan et al. 2011].

Example

Capuchin monkeys

They presented capuchin monkeys with risky choices similar to the experiments we have presented in this chapter. The monkeys learned to exchange tokens for pieces of apple: they could gamble and trade, and understood the concept and value of "money" as something that could be exchanged for food. In their 2011 paper, Chen, Lakshminarayanan and Santos focused on framing effects and risk aversion [Lakshminarayanan et al. 2011]. Initially, each monkey was given an amount of tokens to spend in exchange for food. In order to set the reference point, the experimenter had in one hand a plate with a given amount of apple slices. The primate had to put one token in the experimenter's other hand in order to get the plate (the safe option). To represent risky choices, the number of slices on the plate increased or decreased after the payment was made: for losses, the experimenter removed some slices from the plate; slices were added to represent gains.

In these experiments Chen, Lakshminarayanan and Santos found that,

> "*when capuchins are faced with [...] risky gambles, they display many of the hallmark biases of human behavior, including reference-dependent choices and loss-aversion.*"

They argued that this supports the theory that loss aversion is,

> "*an innate function of how our brains code experiences, rather than learned behavior or the result of misapplied heuristics [Chen et al. 2005].*"

As it is not within the scope of this document to provide a detailed answer to the question of whether this behavior is innate or learned, we invite the interested reader to refer to other books and articles, for example:

- *Economic Choice Theory. An Experimental Analysis of Animal Behavior* [Kagel et al. 1995];
- *Animals' Choices Over Uncertain Outcomes: Further Experimental Results* [MacDonald et al. 1991];

▷ *Great Apes' Risk-Taking Strategies in a Decision Making Task* [Haun et al. 2011].

To conclude, this chapter has shown how anomalies that are widespread in human (and animal) behavior can be modeled without departing widely from expected utility theory.

Key issue

What drives a decision

What is important to remember is that an individual's decision may be driven not only by the stakes involved in the choosing process when the outcome is uncertain, but it can also be deeply and strongly influenced by the frame, the situation and the status quo.

3

Other anomalies in risk attitude

We give a brief description of some other interesting anomalies of human behavior that depart from the rational model of standard economic theory. These biases concern the perception of probability by individuals, for example when we see their computational limits; it also concerns agents' behavior when faced with choices if event probabilities are ambiguously defined.

One of the most rigid assumptions of both expected utility and prospect theory is that of the **complete information framework**: previous chapters have consistently highlighted that in all situations we assume that the decision-maker is aware of the probabilities of the events they are considering. All the experiments we have discussed so far have given clear information about the probabilities of lottery success or failure or the frequency of occurrence of risky events.

However, if the same experiments and questionnaires are presented to participants and not given explicit probabilities or only a vague idea of the frequency of events, the nature of the problem clearly changes and the decision-maker's choices might be different.

Example

Lottery

Imagine, for example, that you buy a lottery ticket with a possible gain of 50€ at a price of 1€. If you know that the probability of winning is say, 10%, then (if you are not extremely risk averse) you would probably buy the ticket (EV = 5). However, if you are told that the probability of winning can vary from 0 – 20%, then you might not be so keen to buy the ticket. Moreover, if you do not have any idea of the probabilities then you might even abandon the idea of participating[1].

We refer to this uncertainty about the likelihood that an event occurs as **ambiguity** and it is the most important aspect of risk decision theory after attitude to risk. We discuss its implications for decision-making in the first part of this chapter.

Although ambiguity exists in many of life's situations, the assumption that in some way we can correctly infer the likelihood that certain events will occur is not unrealistic, especially when we consider simple episodes in daily life. As we have already stressed, it is important to know precise probabilities, or at least to be able to make a confident prediction. In general, we assume that we are able to infer the probability of an event in daily life through being in continuous contact with our environment, either directly or indirectly.

Example

Familiar events

For example, we might be confident about the probability of a car accident on our way to work, the chance of winning the national lottery, the likelihood of a domestic accident or of being robbed in our neighborhood, as well as the probability of a rainy day in mid-February in the town where we have lived for decades.

Even if our predictions are not totally correct, we feel confident in making them, either because of our personal knowledge or because we are familiar with these events. They are easy to imagine and our familiarity is mainly linked to experience: either directly or indirectly, we acquire information

[1] We are not considering lotteries held to raise money for charity, in which case the driving force behind the decision to buy a ticket might be generosity or some other form of altruism.

about the surroundings that we continuously observe. Our judgment and our choices are highly dependent on our environment or past history.

Whenever information about the frequency of a risky event is missing, another way to eliminate ambiguity (apart from inference from personal experience) is to provide the lacking information. Governments, the media and other institutions make great efforts to reduce the level of ambiguity or vagueness concerning certain events.

Example

Nuclear accidents

Imagine that people living in the neighborhood of a nuclear power plant would like to know the probability of an accident. Even if they are educated through exposure to studies and probabilities, it is still possible that they do not apprehend the actual risk; first, because they lack trust in the people providing the information; and/or, second, because of an incorrect perception of exact probabilities.

Therefore, here we address the **problem of trust**, and present some experiments that examine **biases in computing correct probabilities**. These issues affect how people make the appropriate choice, namely the one that gives them the highest expected utility.

3.1 Uncertainty/ambiguity aversion

Ambiguous situations arise in the absence of information about the correct probabilities. In both expected utility theory and prospect theory models, economists and psychologists assume that the decision-maker "knows" subjective probabilities and that they are able to evaluate the problem that they face by taking action that maximizes their utility given these probabilities. Thus, these models completely ignore the possibility that there is an aversion to incertitude (*i.e.* ambiguity aversion) from both a descriptive and normative point of view.

Nevertheless, ambiguity in the information relative to financial or monetary risk (for example) has an effect on economic decisions. This is also true in situations concerning, for example, technological risks, especially when new technologies are developed and we have no previous knowledge upon which to base our beliefs or ideas. A typical example is wireless network antennas and their possible effects on health. Widespread public concern has emerged, in part generated by ignorance about the diffusion of new technologies for which there is no previous experience. Fear can emerge from this lack of knowledge and, in general, most people prefer to know the risks.

The first study of this widespread behavior was carried out by Daniel Ellsberg[2], who speculated that individuals preferred to bet in lotteries with known probabilities than to gamble in draws with ambiguous outcomes [Ellsberg 1961]. His hypothesis has been validated by many experiments, and has proved transferable to other contexts.

[2] Daniel Ellsberg is also known for having released a top-secret Pentagon study, the Pentagon Papers, concerning United States' government policy in the Vietnam War. Ellsberg's attempt to inform the population and, thus, influence public opinion about the war was driven by his belief in revealing the truth (clearly in line with his work on ambiguity). It was evident from the top-secret documents that victory was unattainable and that the number of expected casualties was much higher than predicted. In 2006, Ellsberg was awarded the Right Livelihood Award, "*… for putting peace and truth first, at considerable personal risk, and dedicating his life to inspiring others to follow his example*."

Consider the following problem:

Example

Urns

There are two urns in front of you, urn I and urn II, each containing 100 balls. The balls can be either red or black. Urn I contains red and black balls. Urn II contains 50 red balls and 50 black balls.

You can choose one of the two urns in the following situations. After you have chosen, a ball is randomly drawn from the chosen urn and the color of the ball determines whether you win $100 or $0.

Choice A. You must choose one of two gambles:

- ▷ a1 – ball is drawn from urn I, you win $100 if red, $0 if black.
- ▷ a2 – ball is drawn from urn II, you win $100 if red, $0 if black.

Choice B. You must choose one of two gambles:

- ▷ b1 – ball is drawn from urn I, you win $100 if black, $0 if red.
- ▷ b2 – ball is drawn from urn II, you win $100 if black, $0 if red.

The only difference between urn I and urn II is what we know about the number of black and red balls: we know that urn II contains exactly the same number of red and black balls, thus that the probability of drawing a particular color is 50%; on the other hand, we are uncertain about the probability distribution of the two colors in urn I. Most participants in the experiment prefer to gamble with the second urn that, although risky, has a known probability of success. In fact, usually around 75% of participants prefer a2 to a1 and b2 to b1[3]. This preference is called **ambiguity aversion**: participants avoid the lottery where the stakes are the same but the probabilities are unknown or vague.

Key issue

The safe option

This shows that the safe option is not linked to the level of risk associated with the event, but rather to awareness of how risky the event is.

Participants are certain about the 50% probability of the contents of urn II. In both cases they prefer to draw from this urn, in other words they prefer "known" risky events to "unknown" ones.

Ambiguity aversion is inconsistent with expected utility theory because it leads to "irrational" behavior. Theoretically, if a participant prefers (in this case) option a2 to a1, they are actually saying that they believe that urn II contains more red balls than urn I and that the expected outcome of urn II is favorable to them. However, if they are also asked to choose between b1 and b2, then, if they really believe that urn II contains more red balls than the other, they should prefer b1 to b2. However, ambiguity aversion makes the participant eager to eliminate the uncertainty; this irrational behavior is not consistent with subjective beliefs about the contents of the urns.

For those interested in the details of the argument, the following shows the inconsistencies that can arise.

[3] The experiment described here is slightly simplified. Nevertheless, there are many papers that support this finding, even when participants are asked if they are indifferent to the outcome. The results of such studies are qualitatively the same as those we describe here.

Proof

Example

Although the probability distribution is factually unknown, we have subjective beliefs about it. For example, we can assume that there are more red balls than black balls in urn I:

$$P(\text{red} \mid \text{Urn I}) > P(\text{black} \mid \text{Urn I})$$

thus

$$P(\text{red} \mid \text{Urn I}) > 50\%.$$

If a player prefers a2 > a1, we can evaluate the expected utility of their choice as:

$EU(a2) = U(100\$) * P(\text{Red} \mid \text{Urn II}) + U(0\$) \times P(\text{Black} \mid \text{Urn II}) >$

$EU(a1) = U(100\$) * P(\text{Red} \mid \text{Urn I}) + U(0\$) \times P(\text{Black} \mid \text{Urn I})$

$U(100\$) \times P(\text{Red} \mid \text{Urn II}) + U(0\$) \times (1 - P(\text{Red} \mid \text{Urn II})) >$

$U(100\$) \times P(\text{Red} \mid \text{Urn I}) + U(0\$) \times (1 - P(\text{Red} \mid \text{Urn I}))$

As usual, we assume $U(100\$) > U(0\$)$

$P(\text{Red} \mid \text{Urn II}) * [U(100\$) - U(0\$)] > P(\text{Red} \mid \text{Urn I}) \times [U(100\$) - U(0\$)]$

Which implies that

$$P(\text{Red} \mid \text{Urn II}) > P(\text{Red} \mid \text{Urn I})$$

If the same player prefers b2 > b1, the same procedure shows that

$$P(\text{Red} \mid \text{Urn II}) < P(\text{Red} \mid \text{Urn I})$$

which is a contradiction of a2 > a1 implying that

$$P(\text{Red} \mid \text{Urn II}) > P(\text{Red} \mid \text{Urn I}).$$

In his paper Ellsberg discusses the evidence for these common behaviors [Ellsberg 1961]. He also defines ambiguity aversion as a “preference for specificity” and emphasizes the importance of dividing uncertainty into two main categories:

- ▷ one concerned with risk
- ▷ and the other with ambiguity.

He argues that risk aversion and ambiguity aversion are different concepts and lead to different choices in the decision-making process. The following example will help us to understand the possible implications and make predictions about ambiguity aversion.

Risky activities

Example

Suppose that there are two risky activities (A and B) that can lead to a gain of 10 000€ or 5 000€ respectively. Both probabilities are unknown but we know that pA, namely the probability of gaining 10 000€ from activity A, is between 40 – 60%. Thus, the complementary probability (1 - pA) of gaining 5 000€ is also between 40 – 60%. Moreover, we know that pB, the probability of gaining 10 000€ from activity B, is in the range 30 – 70%.

Although the mean probability that either activity will gain 10 000 or 5 000€ is 50%, an ambiguity averse agent would prefer activity A to activity B, because it has less variability. Note that the same agent would prefer another activity (C) to either A or B if the outcomes were the same but the probabilities were 50%.

A question that naturally arises is whether there is a difference in the perception of ambiguity with respect to losses and gains. Like attitudes to risk, although ambiguity aversion is most common, there are differences depending on whether the context is one of potential losses or gains. However, the difference is not as clear as it is for risk attitude: ambiguity aversion is widespread in both contexts. Nevertheless, we observe that agents tend to be more tolerant of ambiguity when there are potential gains rather than losses. This asymmetry is more consistent when people are faced with smaller probabilities rather than larger ones. In fact, the magnitude of the probability has a large impact on choices made under ambiguity. The following example demonstrates small probabilities.

Ambiguity tolerance

Example

Consider two urns with 1 000 balls in each. In Urn 1, each ball is numbered from 1 to 1 000, and the probability of drawing any number is 0.001. In Urn 2, there are an unknown number of balls each bearing any single number. For example, the proportion of balls numbered 687 could vary from zero to one.

Suppose there is a prize for drawing number 687 from an urn. Which urn do you prefer to draw from, Urn 1 or Urn 2? Source: [Einhorn and Hogarth 1986].

Clearly, there is no ambiguity in Urn 1, since we know that the probability of drawing the number 687 is exactly 0.1%. On the contrary, in Urn 2 the probability of winning is unknown: there is ambiguity as all the probabilities of winning are equally likely (from 0 – 100%).

Participants faced with this type of problem tend to prefer Urn 2, which contradicts previous findings related to diffuse ambiguity aversion. On the other hand, we note that if the problem had been framed as a loss, participants would have preferred the unambiguous urn.

3.2 Ambiguity in comparable contexts

Craig Fox and Amos Tversky investigated ambiguity aversion. They found that ambiguity aversion arises particularly where there is a comparison with a similar unambiguous event [Fox and Tversky 1995].

For example, they asked participants to value the price of a lottery ticket in Ellsberg's urn experiment. Participants had to answer the following hypothetical questions:

Lottery

Example

The most that I would be willing to pay for a ticket to draw from Urn I (50 red balls and 50 black balls) is:

The most that I would be willing to pay for a ticket to draw form Urn II (? red balls and ? black balls) is:

Half of the participants had to answer both questions at the same time. A quarter of participants were only asked the first question (the non-ambiguous bet); the remaining quarter were only asked the question concerning the vague bet (where the probabilities were not known).

The average results are shown in the following table:

	Clear/Unambiguous Bet	**Vague/Ambiguous Bet**
Comparative	\$24.34 (N=67)[4]	\$14.85 (N=67)
Non Comparative	\$17.94 (N=35)	\$18.42 (N=39)

Table 3.1 – *Responses to ambiguous/ unambiguous betting scenarios [Fox and Tversky 1995].*

When people evaluate tickets from both urns (the comparative case), the difference between the two bets is very high (more than \$6). However, when people are asked to price the lotteries separately, their evaluation is similar (both about \$18). This is an important result because it provides more detail about the motivations that lead to certain choices under risk and a better understating of human behavior.

4 N is the number of participants.

According to this hypothesis, which is supported by the experimental evidence, ambiguity aversion arises when the individual perceives a difference between their limited knowledge of an event and the greater knowledge of someone else. For example, this suggests that people who are knowledgeable about sports prefer to bet on sporting events rather than other events; and that financial experts prefer to speculate on financial activities than gamble on the results of elections. An individual who sees themselves as an expert in a specific field is more tolerant of ambiguity in their field: however, when the context changes or they must make a comparison between similar situations with different levels of ambiguity, they become ambiguity averse.

3.3 Ambiguity, trust and optimism

It is important to notice that ambiguity aversion can be linked to both individual and subjective trust — or, in other cases — to a lack of trust in other people, information systems, institutions, *etc.*

Trust is one of the most important motivations for interaction with other people; therefore, it is worth investigating its role in decision-making under risk. However, we need to distinguish between trust in friends, relatives and acquaintances, and trust in strangers or unknown people. Since, in general, we are interested in situations where the agents who interact do not know each other, the majority of experiments in economics are based on anonymous interactions in order to observe what an individual would do in an environment which is "out of the ordinary". It has been suggested that the decision to trust an anonymous agent is associated with the individual's attitude to risk.

However, the relationship between trust and risk attitude has not been widely studied. One notable example is the work of Eckel and Wilson who tried to link measures of risk attitude to measures of trust in others. They found no correlation between the decision to trust and risky behavior [Eckel and Wilson 2004]. On the other hand, Corcos et al. investigated the link between trust and ambiguity aversion. They argued that as trust in others follows an anonymous procedure, the level of uncertainty could be seen as ambiguous: trusting an unknown person with whom we have never interacted (and probably will never interact with again) is different to trusting, for example, a friend with whom we interact regularly and whose behavior we know [Corcos et al. 2012].

Trust can be measured using the well-known experiment called the trust game.

Example

The trust game

Two anonymous agents take part. Player 1 has, for example, 10€ and can choose to give any amount (all, none or some of it) to player 2. The amount received by player 2 is tripled (*e.g.* if player 1 gives 4€, player 2 receives 12€). Next, player 2 decides how much of this amount to keep and how much to give back to player 1. Player 1's decision is used by researchers as a measure of trust, namely how much player 1 believes that player 2 should be trusted (the higher the amount given, the higher the level of trust).

Authors argue that, although the game involves risk (player 1 risks getting nothing back) it is not based on pure probabilities, but involves a human dimension. Player 1, who does not know the other player, has no idea of the probability that their offer will be reciprocated. This is an uncertain and ambiguous, rather than risky situation and, in fact, they found that the higher the player's level of ambiguity aversion, the lower the amount sent to player 2.

This result is important in an analysis of the issue of ambiguity and trust in other contexts. No matter how much information we receive to complete our knowledge about a risky event, if we do not trust the "informer", it may be ignored. To understand the importance of trust, the following example is from the field of economics. The link between trust and economic growth has long been debated by academics and many empirical studies have proved that there is a positive relationship between the two. A high level of trust in institutions has important consequences for policy choices at a national level; on the other hand, a perception of being cheated can reduce investment levels.

Another interesting link between personal attitudes and ambiguity has been found by Bier and Connell in 1994. They investigated an ambiguous medical scenario where decisions had to be made about treatment options. Assuming that there are differences in individual aversion to ambiguity they looked at the reasons for these differences. They established a personality measure that they thought might correlate with ambiguity aversion and found that more optimistic agents tended to be ambiguity seeking. The simplest explanation for this difference in behavior is that optimists are ready to gamble in uncertain situations, believing that they will benefit from it [Bier and Connell 1994].

3.4 Bayesian inference

In previous chapters we have assumed that when probabilities are known, individuals correctly process the information they receive and, consequently are able to predict its effect on future outcomes. Even when a problem is ambiguous, in order to make a decision, we need to assume some kind of probability distribution (for example that all events are equally likely to occur – a uniform distribution). When we have to predict the occurrence of future events, we need to rely on computational capabilities in order to calculate future outcomes. When two events are independent, for example two consecutive throws of a (fair!) die the occurrence of one event does not influence the probability of the other. For example, the first throw of the die does not affect the probability of an even number in the second throw. On the other hand, when two events are not independent, the outcome of one changes the probability of the other.

Example

Conditional probabilities

For example drawing, without replacement, a red card from a deck of cards affects the probability of drawing another red card. The outcome of the second draw is dependent on that of the first draw in this case because there is one less red card in the deck.

Dependent events are linked by conditional probabilities.

In both expected utility and prospect theory, we have used probabilities both to calculate expected values and evaluate expected utilities related to different choices. We have assumed that individuals are able to correctly evaluate probabilities, both for dependent and independent events, and to update these probabilities whenever new outcomes occur or each time they receive new information. However, when two events are dependent, evaluating probabilities becomes computationally complex for agents who are usually unfamiliar with statistics and probabilities. Making decisions about future events based on old information can be complicated, even in relatively simple cases. Economic and psychological models often assume that individuals update their beliefs according to Bayesian principles. This will be explained in the following sections, but in simple terms it means that they are able to compute conditional probabilities on the basis of new information received before the outcome of the event is known.

Let us take an example used in a well-known experiment that investigates the ability of humans to evaluate the probabilities of dependent events [Kahneman and Tversky 1982].

Consider the following hypothetical question.

Example

Green cabs, blue cabs

A cab was involved in a hit-and-run accident at night. Two cab companies, Green and Blue, operate in the city. You are given the following data:

(a) 85% of the cabs in the city are Green and 15% are Blue.

(b) A witness identified the cab as Blue. The court tested the reliability of the witness in the same conditions that existed on the night of the accident, and concluded that the witness correctly identified the color of the cab 80% of the time and failed 20% of the time.

What is the probability that the cab involved in the accident was Blue rather than Green?

The median answer to the question is 80%, suggesting that people give greater importance to the testimony of the witness, rather than the fact that only a small percentage of city cabs are blue and, thus, that is less likely that the cab was blue. However, 80% is only the probability that the witness is correct, **independently of other things**. It is not the probability that the witness is correct – given that there only 15% of cabs in the city that are blue. The conditional probability is much smaller than the median answer. Next we look at how to correctly evaluate the probability statistically. The link between two dependent events and their conditional probabilities is given by Bayes' law (or theorem or rule). Bayes' rule says that two conditional probabilities are linked and that we can infer (predict) the other given one of the two.

Let us analyze it formally. Suppose A and B are two dependent events (*i.e.* the occurrence of one event is linked with the occurrence of the other). P(A) and P(B) are, respectively, the probability that event A and event B occur. The conditional probability of A given B, P(A|B), represents the probability that event A occurs given that event B has already occurred. On the other hand, P(B|A) is the conditional probability of B given A.

Bayes' rule links the two conditional probabilities:

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \text{and} P(B|A) = \frac{P(A|B) \times P(B)}{P(A)}$$

So how can we estimate the correct probability in the cab example given above? First of all, it is important to understand the information provided:

- ▷ the probability that a cab in the city is blue is: P(Blue) = 15%
- ▷ the probability that the witness correctly identifies a Blue cab is: P(identifiedBlue|Blue) = 80%[5]
- ▷ the conditional probability that the cab is Blue, given that the cab has been identified by the witness as Blue is given by: P(Blue|identifiedBlue)

Using Bayes' theorem, the correct answer is given by:

$$P(Blue|identifiedBlue) = \frac{P(identifiedBlue|Blue) \times P(Blue)}{P(identifiedBlue|Blue) \times P(Blue) + P(identifiedBlue|Green) \times P(Green)}$$

$$P(Blue|identifiedBlue) = \frac{80\% \times 15\%}{80\% \times 15\% + 20\% \times 85\%} = 41\%$$

The difference between the correct answer (41%) and the median answer (80%) is very high, suggesting that agents are not usually able to compute relatively simple Bayesian conditional probabilities. To understand whether this finding is context-free, other participants were asked to respond to a slightly different problem in which statement (a') replaced statement (a):

(a'). Although the two companies are roughly equal in size, 85% of cab accidents in the city involve Green cabs and 15% involve Blue cabs.

In this case, the median answer was close to 60%. Although agents still do not use Bayes' law, they rely less on the witness and focus on the higher number of accidents caused by Green cabs.

Gerd Gigerenzer and Ulrich Hoffrage in 1995 suggested that evolution is behind the difficulty humans have in computing these types of statistical problems [Gigerenzer and Hoffrage 1995]. Probabilities, statistical inference and algorithms are a recent introduction in human history (they only appeared in the XVIII century) and, typically, human beings do not acquire information using these notions. The "natural" way to acquire information is based on experience and frequency that is used to update and evaluate the likelihood of events. Even if Bayes' law is explained to participants in experiments, they still seem to find it difficult to reason in terms of probabilities and find the correct answer. In a series of experiments, Gigerenzer and Hoffrage showed that presenting the problem in terms of frequency increased the number of participants who could correctly predict the answer. As the human mind is used to frequencies, it is better able to understand the problem in terms of the number of times that the witness can correctly or incorrectly identify a cab.

To see how the idea works, we can represent the cab example in terms of frequencies (see figure 3.1 below). Suppose there are 1 000 cabs in the city; 850 are green and 150 blue. If we ask the witness to identify all 1 000 cabs, they will correctly identify 680 of the 850 Green cabs and the remaining 170 will be identified as Blue (because they are only right 80% of the time). Then, among the 150 Blue cabs, they will correctly identify 120 as Blue and the remaining 30 as Green. Thus, the witness would identify a total of 710 Green cabs and 290 Blue.

[5] We can also deduce that: $P(identifiedBlue|Green) = 1 - P(identifiedBlue|Blue) = 100\% - 80\% = 20\%$ and $P(Green) = 1 - P(Blue) = 100\% - 15\% = 85\%$

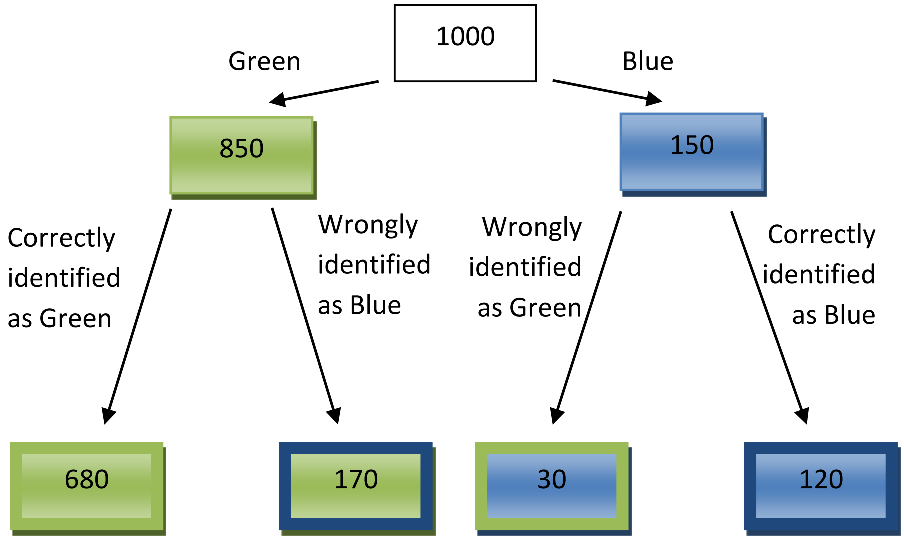

Figure 3.1 – *The application of Bayes' theorem to calculate conditional probabilities*

If we want to evaluate how many times the witness correctly identifies a Blue cab when it is Blue, we need to know the number of cases where the cab is Blue and it is correctly identified (120), and the number of times it is identified as Blue, although it is Green (170). In other words, we need to count all the times that the witness rightly or wrongly identified a Blue cab (120 + 170), and all the times they were right (120). Thus, the conditional probability is simply:

$$P(Blue|identifiedBlue) = \frac{Blue \,\&\, identifiedBlue}{Green \,\&\, identifiedBlue + Blue \,\&\, identifiedBlue} =$$

$$P(Blue|identifiedBlue) = \frac{120}{170 + 120} = 41\%$$

Looking at the frequency of events can be much more intuitive than standard statistical approaches.

Key issue

Translate into frequency

The lesson to be learned is that it is important to teach people to translate problems presented in terms of probability into a frequency approach in order to improve forecasting and inference accuracy.

3.5 The "law" of small numbers

In this last section, we present one more limitation of human reasoning related to the computation of probabilities. We start with an example from an experiment by Kahneman and Tversky [Kahneman and Tversky 1982].

Example

Hospitals

A certain town is served by two hospitals. In the larger hospital about 45 babies are born each day, and in the smaller hospital about 15 babies are born each day. As you know, about 50% of all babies are boys. However, the exact percentage varies from day to day. Sometimes it may be higher than 50%, sometimes lower.

Over a period of one year, each hospital recorded the days on which more than 60% of babies born were boys.

Which hospital do you think recorded more such days?

In the experiment, 22% of participants answered that the larger hospital was more likely to record such days, 56% of them thought that both hospitals had the same probability and only 22% gave the correct answer, which is that it is much more likely that the small hospital had more days where more than 60% of males were born.

To understand why the small hospital is more likely to depart from the average, we need to introduce the law of large numbers.

Definition

The law of large numbers

In probability theory, the law of large numbers states that, if we perform a large number of experimental trials, the average result should be close to expected values; moreover, the higher the number of trials, the closer the results will be to expected values.

Imagine tossing a (fair) coin four times. The predicted result is to throw a head half the time, and a tail the other half. However, you may throw three heads and one tail, and if you compute the frequency at which heads occur (75%) the value is far from the expected value of 50%. However, it is less likely that you will toss 75% of heads with 200 tosses of the coin: by increasing the number of trials it is more likely that you will toss an equal number of heads and tails.

In the hospital example, however, people tend to rely on the **law of "small" numbers**. Many people believe that even in small samples, probabilities are similar to those of the entire population. Rabin explains:

> *The law of "small" numbers implies that people exaggerate the likelihood that a short sequence of flips of a fair coin will yield roughly the same number of heads as tails. What is commonly known as "the gambler's fallacy" is a manifestation of this bias: if a fair coin has not (say) come up tails for a while, then on the next flip it is "due" for a tails, because a sequence of flips of a fair coin ought to include about as many tails as heads. When the underlying probability distribution generating observed sequences is uncertain, the fallacy leads people to over-infer the probability distribution from short sequences. Because we exaggerate how likely it is that a bad financial analyst making three predictions will be wrong at least once, we exaggerate the likelihood that an analyst is good if she is right three times in a row [Rabin 1996].*

Summary

Risk and uncertainty are important decision variables in everyday life. The environment in which we live is mostly indeterminate and our decisions are influenced by our risk perception and our tendency to act safely or riskily. In this document, we have described some important economic theoretical results about decision-making under uncertainty. We categorized people into three groups, and focused on the differences between those who are averse to risk and those who are risk-seeking, in order better to understand their divergent behaviors when faced with the same problem. A general theory makes it possible to classify a population with respect to its risk attitude, understand the determinants of the level of risk aversion (for example age or gender) and predict the effectiveness of, for example, government policy. Although it is important to have a general theoretical model that can predict the behavior of different types of agents, sometimes predictions are biased by hypotheses that are too strict, or the fact that people change their behavior according to the setting in which they find themselves.

An initial departure from the general model is presented in chapter 2. The standard model is revisited, taking into account empirical and experimental evidence. Individual attitudes to risk change depending on whether they face a loss or a gain. In general, loss aversion, the endowment effect and the status quo bias are three facets of the same problem: human beings tend to avoid risk when they might make a gain; on the other hand, when they might make a loss their actions are more risky. This is inconsistent with the forecasts of the standard model. Moreover, this behavior is found in different contexts (from everyday life to sporadic events) and across all parts of the population. Therefore it leads to another general theoretical model, known as prospect theory.

Following our discussion of these two pillars of economic theoretical modeling, chapter 3 is dedicated to experimental evidence of the limitations of human beings in evaluating probabilities and decision-making under uncertainty. Perceptions of risk and evaluation of the probabilities are important not only for the single individual who needs to judge a risky situation and evaluate what action to take, but also for policy-makers who must strategically anticipate the effectiveness of a policy, depending on how it is presented to citizens.

To conclude, this document does not aim to be an exhaustive description of the topic of decision-making under risk and uncertainty; rather, its aim is to give a flavor of some important insights from economics and psychology that are linked with risk and uncertainty.

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