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TITLE:

Risk, Time and Social Preferences: A Behavioural and Experimental Approach to the Decisions of Individuals

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Introduction

Discount factors are one of the most relevant elements when dealing with intertemporal preferences. There are different approaches to estimate the value of discount factors and discount rates, as there are different models that are used to predict the choices of individuals. Most of these models use particular utility functions which include numerous variables within them and which are able to accurately reflect the behavior of economic agents. In this dissertation we will first try to examine some of the most recent models and formulations concerning intertemporal discount factors, comparing them with older models in order to provide a comparison between them and to observe the evolution of the studies on the subject. Furthermore, we intend to analyze the type of relations between intertemporal discount rates and social preferences and the implications that this entails. In this way we will have provided a complete view on all aspects of intertemporal preferences. To conclude, we will propose a model with empirical data in order to confirm or deny some of the last hypotheses concerning intertemporal preferences. The remainder of the paper is arranged as follows.

Chapter 1 begins by providing a review of the most important topics of literature and which are indispensable for analyzing many of the elements that will be dealt with in the following chapters. Also in Chapter 1 we deal with the intertemporal discount factor and its various formulations. Specifically, we analyze the most commonly used exponential form. We then analyzed the hyperbolic form and highlighted the differences between the two, with relative advantages and disadvantages. Continuing, we have proposed some of the most recent models for the modeling of the intertemporal preferences of individuals, analyzing their characteristics and their particularities.

In Chapter 2 we introduced decision theory with all its features and then defined the difference between "risk" and "uncertainty." Later we analyzed the axioms of rationality on which the Subjective Expected Utility is based, demonstrating, however, that there are situations in which these fail to predict the behavior of individuals. Later, analyzing the paradoxes of Allais and Ellsberg, we define the concept of ambiguity and consequently of ambiguity-aversion. Finally, we have analyzed some models that use particular functional forms to model the aversion to ambiguity.

We begin Chapter 3 by proposing two models that deal with the behavior of subjects in the presence of multiple sources of ambiguity. In the first we are in the presence of two sources of ambiguity while in the third the sources come to be three, modifying the results and the hypotheses made in the previous one. Continuing Chapter 3, we analyzed myopia or imperfect foresight and its implications in intertemporal choices in the ambit of uncertainty. Through the analysis of the Gabaix and Laibson elaborate we observed what are the characteristics of myopia and how to distinguish it from time preferences. We conclude Chapter 3 by analyzing the use of Waiting Periods as tools to push individuals to make more patient decisions.

Chapter 4 focuses on social preference and the effect they have on the intertemporal choices of subjects. Based on the work of Ponti and Rodriguez-Lara (2017), we observe how social preferences and social influence modify the decisions of subjects in a social dimension. Finally, we propose a model developed using data from the Ponti and Rodriguez-Lara experiment, based on intertemporal preferences and with the aim of verifying some of the hypotheses we have expounded during this dissertation. We conclude the paper by analyzing and commenting the results obtained by our model.

Chapter 1

In this first chapter we will examine the argument of *intertemporal choices*, especially focusing on how this topic was approached by the authors of the past, what are the relevant characteristics and the determinants of intertemporal choices, what are the principal models used to predict the behavior of economic agents and the assumptions behind these models. Furthermore, we will analyze the latest discoveries carried out by the most recent studies on the topic, highlighting the possible future topics that could bring important results in this field.[1]

We refer intertemporal choices when we are dealing with decisions that involve costs and benefits occurring at different times. A typical problem that intertemporal choices try to give an answer, and to understand the motivations behind that answer, is the question: do you prefer to have \$10 today or \$11 tomorrow? From this simple problem we can argue what are the main elements that compose *intertemporal choices*, but it is not as simple to argue what are the determinants, either psychological or sociological, that lead an economic agent to prefer a given option to another one. Highlighting and analyzing these determinants was the purpose of many economists since the XIX century. In this paper we will focus more on the economic aspects and determinants of intertemporal choices, analyzing the results of the most relevant researches, starting from the Scottish economist John Rae to arrive to nowadays economists like Richard Thaler, David Laibson, George Loewenstein and others. This first part of chapter 1 will be then focused on the

[1] We will base this first chapter on the work of Shane Frederick, George Loewenstein, Ted O'Donoghue, *Time Discounting and Time Preference: A Critical Review*, Journal of Economic Literature vol. XL, 2002, pp. 351-401.

review of previous empirical research and on the main models that were built on these assumptions and that are still nowadays object of discussion.

However, before starting it is necessary to define the concepts of *time discounting* and *time preference* that we will refer often on the course of this dissertation since they are strictly connected with *intertemporal choices*. These two are almost similar concepts but with some little but fundamental difference:

> We use the term time discounting broadly to encompass any reason for caring less about a future consequence, including factors that diminish the expected utility generated by a future consequence, such uncertainty or changing tastes. We use the term time preference to refer, more specifically, to the preference for immediate utility over delayed utility. (Frederick, Loewenstein, O'Donoghue, 2002, p. 352)

In the economic models built upon this framework, time discounting and time preference are represented mathematically using a *discount function*. Such discount function is used to weight the utility that individuals experience at different period of time: usually this function takes the exponential form even if recent works suggest other forms that may be better under some circumstances.

1.1 Historical Overview

Talking about the first studies on intertemporal choices one cannot fail to mention economists like John Rae, William S. Jevons or N. W. Senior: their contribution was essential for the early development of this argument. In his most famous work, *The Sociological Theory of Capital* (1834), Rae tries to explain the differences in wealth among nations identifying two main factors that influenced these differences: the amount of labor assigned to the production of capital and the effective desire of accumulation.[2] About the second factor Rae wrote:

[2] The amount of labor is a factor that was taken in account even by Adam Smith in his work, *The Wealth of Nation*, to explain the motive why some nations are richer than other. According

> The formation of every instrument therefore, implies the sacrifice of some smaller present good, for the production of some greater future good. If, then, the production of that future greater good, be conceived to deserve the sacrifice of this present smaller good, the instrument will be formed, if not, it will not be formed. (Rae, 1834, p. 52)

Thus, Rae explained that "the determination to sacrifice a certain amount of present good, to obtain another greater amount of good, at some future period, may be termed the *effective desire of accumulation*." Rae goes further and provided a series of psychological factors that promote *intertemporal choices*. He identified four main factors, two of them promoted the effective desire of accumulation while the other two, on the contrary, limited it. In the first category Rae included "the prevalence through the society of the social and benevolent affection [...] which leads us to derive happiness from the future good we communicate to others" and "the extent of the intellectual powers, and the consequent prevalence of habits of reflection, and prudence, in the minds of the members of the society" and they can be summarized as *bequest motive and propensity to exercise self-restraint*; on the other hand, the limiting factors can be summarized as the *uncertainty of human life*[3] and the *excitement produced by the prospect of immediate consumption*, and the following *discomfort of deferring such available gratifications*.[4] As shown, Rae's contribute was very important, not only he first recognize intertemporal choices as a distinct topic but provide also the first in-deep examination of its determinant.

Following Rae's steps other economists began to treat intertemporal choice tak-

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to Smith labor and labor's productivity are the causes that determine the wealth of a nation. See: Adam Smith, *The Wealth of Nation*, W. Strahan and T. Cadell, London, 1776.

[3]About this, Rae wrote: "when engaged in safe occupations, and living in healthy countries, men are much more apt to be frugal, than in unhealthy, or hazardous occupations [...] in this respect the general prevalence of law and order, and the prospect of the continuance of peace and tranquillity, have considerable influence". (Rae, 1834, p. 57)

[4]Keywords highlighted in italics are the synthetic elaboration of the Rae's thought made by S. Frederick, G. Loewenstein, T. O'Donoghue, *op. cit.*, p. 353.

ing as starting point Rae's writes and come out with other different views. Interesting is the view proposed by William S. Jevons.[5] He proposed that, according to Rae's view, individuals will be propense to defer immediate consumption only if the early renounce is more than compensated by the postponed gratification.

Another view that we need to mention is the abstinence perspective proposed by N. W. Senior, that assumes no discounting between consumption today and tomorrow and justifies the "impatience" (the preference for immediate consumption with respect to delayed consumption) shown by individuals with the abnegation that is necessary to defer satisfaction.

> The next perspective that we are going to analyze is brought by one of the most famous economists of the XIX century. We are talking about Eugen Bohm-Bawerk, an exponent of the Austrian School of Economics. Bohm-Bawerk had a very interesting vision about intertemporal choice which was different from the ones proposed by the economists we have analyzed until now. He supposed that individuals pose a greater weight on the present because of their inability to predict and imagine future correctly, specifying that there is a tendency to underestimate future pleasures. Another interesting aspect of his view was the fact that he considered intertemporal choices at the same level of an economic trade-off that is a "technical decision about allocating resources (to oneself) over different points in time." (Frederick, Loewenstein, O'Donoghue, 2002, p. 354)

Very important was the contribute of the American economist Irving Fisher that, in face of the crescent progress in the economic sciences and on the basis of Bohm-Bawerk's studies, succeeded at representing the intertemporal choice, related

[5]William Stanley Jevons was an English economist, known for being one of the first exponent of the marginal revolution in economics, along with Léon Walras and Carl Menger. Jevons had the conviction that economic sciences need a mathematical method to be studied, as described in his book A General *Mathematical Theory of Political Economy.*

to consumption decision between two goods, on a diagram with current consumption on x-axis and future consumption on y-axis; in this case, as explained by Frederick, Loewenstein and O'Donoghue, the result was that "a person's observed (marginal) rate of time preference – the marginal rate of substitution at her chosen consumption bundle – depends on two considerations: time preference and diminishing marginal utility."

In his work about intertemporal choices, Fisher included a view on the psychological determinants like other researchers before him did.

> Fisher begins his theory of interest with the basic determinants of time preference or impatience [...]. He divides his discussion into two parts: the influence of economic factors (i.e., income) and what he called "personal" factors. Fisher says that an individual's impatience depends on four characteristics of his income stream: the size, its time shape, its composition, and its risk. [...] Foresight and self-control are two of six personal factors that Fisher identifies as determining an individual's impatience, the others being habit, expectation of life, concern for the lives of other persons (i.e., bequest motive), and fashion.[6]

Fisher often emphasized the fact that personal factors are made of irrational components, (suggesting then that individuals do not behaves always rationally) especially fashion[7] and self-control.[8]

[6]Richard H. Thaler, *Irving Fisher: Modern Behavioral Economist*, American Economic Review, 1997, p. 439.

[7]About fashion, Fisher wrote: the most fitful of the causes at work is probably fashion. This at the present time acts, on the one hand, to stimulate men to save and become millionaires, and, on the other hand, to stimulate millionaires to live in an ostentatious manner. See: Irving Fischer, *The Theory of Interest*, Macmillan, 1930, p. 88.

[8]Fisher faced the discussion on self-control with a psychologic approach saying that: "self-control, though very distinct from foresight, is usually associated with it and has very similar effects. Foresight has to do with thinking; self-control with willing". See: R. H. Thaler, op. cit., p. 440.

1.2 The DU model

In this paragraph we will describe the model proposed by Paul Samuelson in 1937, also known as Discounted Utility Model (DU model from now on). We decided to dedicate an entire section of this paper to this model not only because it marked a turning point in the field of intertemporal choice and for the relevance that it still has nowadays but also because the assumption at the base of the model offered many interesting ideas on which recent works have been based.

As just said, the DU Model was introduced by Samuelson in an article titled "*A Note on Measurement of Utility*" published in 1937. His aim was to propose a general model that could be used for multiple time periods, improving the fisherian analysis that was limited only to two periods of time (consumption today vs consumption tomorrow). The main innovations in this model were the mathematical function used to represent the individual's intertemporal preferences over consumption profiles and the introduction of a new parameter, the *discount rate.* To better understand what we are talking about we'll display the functional form of the model below:

$$U^t(c_t, ..., c_T) = \sum_{k=0}^{T-t} D(k)u(c_{t+k}) \tag{1.1}$$

where

$$D(k) = \left(\frac{1}{1+\rho}\right)^k \tag{1.2}$$

This is the Samuelson's formulation of DU Model: $U^t(c_t, ..., c_T)$ is the intertemporal utility function which represent the intertemporal preferences of a generic individual over the consumption profiles $(c_t, ..., c_T)$; $u(c_{t+k})$ represents the utility gained from consuming a particular amount in a particular period; $D(k)$ refers to the individual's discount function and is used to describe "the relative weight she attaches, in period t, to her well-being in period $t + k$. The parameter ρ represents the individual's pure rate of time preference (her discount rate)." (Frederick, Loewenstein, O'Donoghue, 2002, p. 355) It includes individual's preferences about present and future consumption. For most individuals $\rho > 0$, meaning that they attach more weight to the present than the future; moreover, the higher is the discount rate ρ, the more the individuals discount the future.[9] It is important to notice that, unlike his predecessors, Samuelson do not provide a list of determinants or factors that explain the *time preference* of individuals. As explained by Frederick, Loewenstein, O'Donoghue, in Samuelson's simplified model, all the psychological concern discussed over the previous century were compressed into a single parameter, the discount rate.

After the description of the model, its formulation and its components, let's move to the analysis of the assumptions. First of all, the DU Model assumes that individuals do not consider alternative plans as standalone but are integrated in the existing plan they already had: this means that a certain investment project is evaluated not only on the base of its own remuneration but even in light of the changes that will bring in the individual's plan in the future. Although this is one of the central assumption in most models of intertemporal choice, in reality this may not happen because often people are unable to recompute the new optimal plan incorporating the new alternative, or eventually they just have not made any plan about consumption streams in the future. In particular, Frederick et al. collected evidences and come to the conclusion that "people evaluate the results of intertemporal choices independently of any expectations they have regarding consumption in future time periods." (Frederick, Loewenstein, O'Donoghue, 2002, p. 356)

We will focus next on two very strong assumptions that are *utility independence* and *consumption independence*, let's start with the first. Assuming utility independence means that the total value of a sequence of utilities experienced at different times is equal to the sum of the discounted utilities in each period. This implies that how the utilities are distributed over time is not relevant for the model, the only relevant thing is that utilities experienced far in the future are less important than utilities in the present, as positive *discount rate* states.[10]

[9] There can be cases in which $\rho = 0$ so that the individual is indifferent about present and future and even cases in which $\rho < 0$ that means the individual attach more weight to future than present.

[10] Excluding patterns of utilities can lead to misinterpretation of results: the implications of a flat utility profile (profiles in which utility levels are constant across time) are different from the ones of a decreasing utility profile (utility levels decrease over time) or an increasing utility profile

The assumption of *consumption independence* considers that the utility that individuals experience in a given period depends only on consumption of that period, excluding that can be influenced by consumption in previous or future periods:

> In intertemporal choice, consumption independence says that preferences over consumption profiles are not affected by the nature of consumption in periods in which consumption is identical in the two profiles. (Frederick, Loewenstein, O'Donoghue, 2002, p. 357)

The next assumption of DU Model is that the instantaneous utility function $u(c_t)$ is constant over time and that the utility produced by a certain level of consumption will stay the same in all periods. This assumption may seem unrealistic because individuals' preferences hardly remain the same during the lifespan, but they alter over time. Probably this is assumed for analytical convenience.

The independence of discounting from consumption is another assumption of DU Model and states that, as suggested by the name, the individuals discount different types of goods using the same *discount rate*. In discount function does not vary across all forms of consumption, meaning that the DU Model is assumed that the discount rate is constant over time and so is the discount function (i.e. $\rho_n = \rho$ for all n and $D(k) = (1/1 + \rho)^k$). The consequences of this constant discounting are pointed out very well by Frederick et al.:

> Constant discounting entails an even-handedness in the way a person evaluates time. It means that delaying or accelerating two dated outcomes by a common amount should not change preferences between the outcomes – if in period t a person prefers X at τ to Y at $\tau + d$ for some τ, then in period t she must prefer X at τ to Y at $\tau + d$ for all τ. The assumption of constant discounting permits a person's time preference to be summarized as a single discount rate. [...] Constant discount-

(utility levels increase over time).

ing implies that a person's intertemporal preferences are time-consistent, which means that later preferences "confirm" earlier preferences. (Frederick, Loewenstein, O'Donoghue, 2002, p. 358)

We are providing an example to better clarify this concept. Suppose to be indifferent between a \$100 reward now and \$110 reward a year from now – meaning that our (annual) discount rate is 10% - then, exponential discounting suggests that we should also be indifferent between a \$100 reward in a year and \$110 reward in two years. "According to this view, the amount people discount a future reward depends only on the length of the wait and a discount rate that is constant across different wait times."[11]

Last things we will analyze are the assumptions of diminishing marginal utility and positive time preference that imply respectively that the instantaneous utility function $u(c_t)$ is concave and that the discount rate p¿0. Although these assumptions are commonly used in many analyses of intertemporal choice, they "create opposing forces in intertemporal choice: diminishing marginal utility motivates a person to spread consumption over time, while positive time preference motivates a person to concentrate consumption in the present." (Frederick, Loewenstein, O'Donoghue, 2002, p. 359)

Thus, the DU Model was adopted as reference point for intertemporal choice studies regardless the fact that wasn't perfect under technical aspect (the assumptions of the model are often unrealistic and do not explain properly the empirical observation) but probably this happened due to its innovative formulation and its simplicity.

[11] Joseph P. Redden, *Hyperbolic discounting*, pdf.

1.3 Alternative Models

After the analysis of DU Model and the assumptions on which is based, we'll treat the models that followed. As just said, Samuelson's model became the main framework of intertemporal choice although the problems pointed out in the previous analysis, thus the successive models tried to propose alternatives that could better describe individuals' intertemporal decisions. Some of these models proposed a different set of assumptions with respect to DU Model, in order to obtain a descriptive validity; some others focused more on the characteristics of the utility function; others instead, proposed a radically different alternative approach from DU Model.

1.4 Hyperbolic Discounting

The first alternative model that we will analyze is the *Hyperbolic Discounting Model*. This model proposed an alternative discount function, different from the exponential discounting used in the DU Model. "Hyperbolic discounting refers to the tendency for people to increasingly choose a smaller-sooner reward over a larger-later reward as the delay occurs sooner rather than later in time." (Redden, pdf, p. 1)

This idea was developed on the empirically observation that discount rates are not constant over time but seem to have a decreasing pattern. The main difference from the exponential discount form relies on the fact that exponential discounting assumes that the discount rate is constant - the rate between utility at time t and $t+k$ is equal to the rate between τ and $\tau+k$, with $\tau > t$ - while hyperbolic discount rate declines as the length of time at which the reward can be claimed increases. Figure 1.1 represents this difference graphically.

"Hyperbolic discounting will generally discount future rewards more than exponential discounting for short delays, yet less than exponential discounting for long delays." (Redden, pdf, pp. 2-3)

In other words, individuals discount the present much more than future, especially when considering far away future.

Proposed by George Loewenstein and Drazen Prelec in 1992, hyperbolic dis-

Exponential vs hyperbolic discounting.

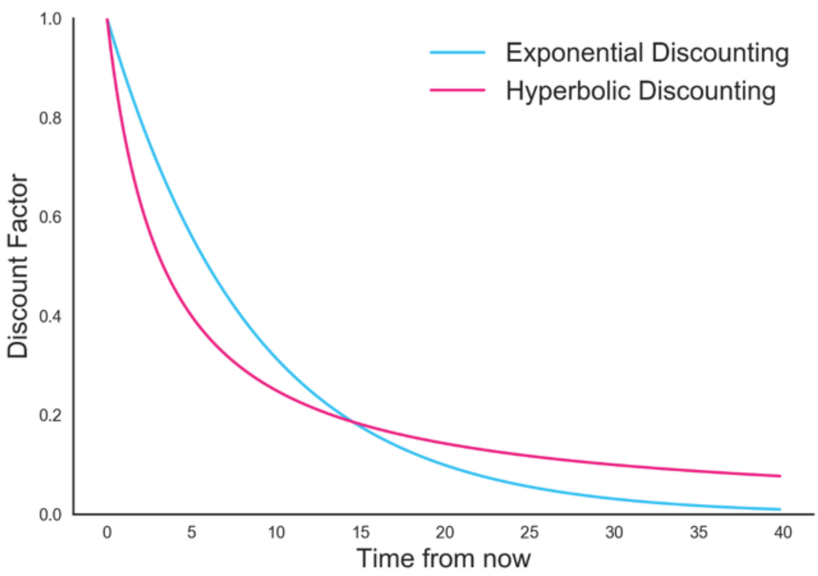


Fig. 1.1. Source: Chris Said, Hyperbolic discounting – The irrational behavior that could be rational after all, 2018.

counting adopts the following mathematical form:

$$D(t) = \frac{1}{(1+\alpha t)^{\beta/\alpha}} \tag{1.3}$$

where $\alpha > 0$ and $\beta > 0$. Anyway, other forms were proposed before this, for example the one suggested by George Ainslie (1975), $D(t) = 1/t$ or the one from Richard Herrnstein (1981), $D(t) = 1/(1 + \alpha t)$.

There are several results that prove the validity of hyperbolic discounting: evidences demonstrated that, when comparing simulated data to real-world data, this functional form can explain some stylized empirical facts better than exponential discounting. Moreover, even experimental studies concluded that "when subjects are asked to compare a smaller-sooner reward to a larger-later reward, the implicit discount rate over longer time horizons is lower than the implicit discount rate over shorter time horizons." (Frederick, Loewenstein, O'Donoghue, 2002, p. 360)

Another important result supporting hyperbolic discounting comes from the *reversal of preferences*.[12] This is one of the anomalies documented by experimental

[12]Reversal of preference is a term used to describe a behavior observed in individuals for which a preference upon a couple of reward delivered in the future reverses toward the forthcoming reward, as time approach the date at which the rewards are redeemable.

psychology literature about exponential discounting that "has been interpreted to suggest that agents have a preference for present consumption not consistent with exponential discounting. Psychologists and, most recently, behavioural economists have noted that the evidence is consistent with a declining rate of time preference, and have consequently suggested various specifications of discounting with this property, notably *hyperbolic discounting* and *quasi-hyperbolic discounting*."[13] We can then conclude that there are large empirical evidences supporting the idea that hyperbolic discounting is a better approach instead of the classic exponential discount in the studies of intertemporal choice.

Most of the recent works use a hyperbolic discount rate in their analysis proving that this type of discounting is able to describe in a more realistic way the behavior of individuals. David Laibson was one of the first experimenters that understood the potential of hyperbolic discounting and applied it in different analyses about various framework in intertemporal choice. In his famous paper, *Golden Eggs and Hyperbolic Discounting* (1997), Laibson analysed the implication of hyperbolic discounting relative to commitment, examining the behavior of an individual with a hyperbolic discount function in relation to a commitment instrument designed to help such individual to obtain higher degree of self-control.[14] The use of commitment is really useful in this context since it has been shown from Strotz (one of the first economist to implement and study commitment) that an exponential discount function doesn't push individuals to commit while a hyperbolic form does. The instrument used in this paper is an illiquid asset that pays the period of time ahead the one in which it was sold, so that if the asset is sold at period τ, the liquidity will be provided at $\tau+1$.

> In general, all illiquid assets provide a form of commitment. A pension or retirement plan is the clearest example of such an asset [...] consumers can access their assets, but they must pay an early withdrawal penalty.

[13]Jess Benhabib, Alberto Bisin, Andrew Schotter, *Hyperbolic Discounting and Self-Control: An experimental analysis*, 2004.

[14]Self-control is a very desirable feature for most people but not everybody has this capacity. People that lack of self-control can use a commitment strategy, which is one of the most used techniques to achieve self-control, in order to create one or more constraints to bind some choices.

> [...] A less transparent instrument for commitment is an investment in an illiquid asset that generates a steady stream of benefits, but that is hard to sell due to substantial transaction costs, informational problems, or incomplete markets. [...] Finally, there exists a class of assets that provide a store of illiquid value, like saving bond, and certificates of deposit. All of the assets discussed above have the same property as the goose that laid golden eggs. The asset promises to generate substantial benefits in the long run, but these benefits are difficult, if not impossible, to realize immediately. Trying to do so will result in a substantial capital loss.[15]

The use of such commitment assets together with hyperbolic discounting, allowed Laibson to analyze the behavior of a decision maker that is given the possibility to limit his available options in the future. The results obtained are really interesting. The decision maker tries, in each period, to constrain the liquidity of his future self, restraining his access to the illiquid instrument: "In this way "early" selves manipulate the cash flow process by keeping most assets in the illiquid instrument. Hence, at any given moment the consumer is effectively liquidity constrained, though the constraint is self-imposed." (Laibson, 1997, p. 455)

Another result obtained from the analysis is the presence of comovement between consumption and income. Specifically, movements in the income are usually followed by movements in the same direction for consumption.[16]

Finally, the Golden Eggs Model has provided a possible explanation for the phenomenon of declining saving rates in the 1980s. It is argued that this decline of the saving rates is related to the rapid expansion of the consumer credit market in U.S. in that years and the possibility for consumers to obtain access to instantaneous

[15] David Laibson, *Golden Eggs and Hyperbolic Discounting*, The Quarterly Journal of Economics, 1997, pp. 444-445.

[16] This relation arises from the fact that "early" self can prevent future self only the access to the assets accumulated in the past, but not to current income. This means that in period in which current income is high (low), the consumption will be high (low) too.

credit. This is supported by the evidence that the market of credit card had a rapid growth in the 1980s, reaching very high levels with respect to the previous years. Thus, the prediction of Golden Eggs Model, which states that the elimination of commitment instrument would reduce the level of capital accumulation, is consistent with empirical evidence.

1.5 Self Awareness

The idea behind this kind of models is that people may know that her preferences will change over time. About the way people can predict how their preference will change we can mention two opposed views. The first suppose that individuals cannot foresee that their preferences will change since there are completely "naïve" and believe that they will stay the same over time; the second on the other hand, proposed that individuals can predict exactly how their preference will change over time: in this sense they are said to be "sophisticated". Anyway, these are extreme considerations and it's reasonable to consider the hypothesis that people are not completely naïve neither totally sophisticated, but in the middle between them in the sense that they are aware that their preferences may change but they don't exactly know how they will be.

O'Donoghue and Rabin in 2001 propose a model of *partial naiveté* reflecting this idea: they suppose that an individual is conscious that she will have self-control problems in future but underestimates their magnitude. These models of self-awareness are commonly used in the analysis of self-control problems and the implementation of public policy: "if people are sufficiently sophisticated about their own self-control problems, providing commitment devices may be beneficial. However, if people are naïve, policies might be better aimed at either educating people about loss of control (making them more sophisticated), or providing incentives for people to use commitment devices, even if they don't recognize the need for them." (Frederick, Loewenstein, O'Donoghue, 2002, p. 368)

1.6 Habit-Formation models

Habit-Formation models develop the idea of James Duesenberry (1952) that the level of utility of an individual does not depend only on current consumption but also on consumption experienced in the past. The models that adopt this assumption must then use a different utility function that takes in account in every period, all the past experienced consumptions. A typical functional form could be $u(c_\tau; c_{\tau-1}, c_{\tau-2}, ...)$ where $\partial^2 u/\partial c_\tau c_{\tau'} > 0$ for $\tau' < \tau$. "Most such models assume that all effects of past consumption for current utility enter through a state variable. That is, they assume that period-τ instantaneous utility function takes the form $u(c_\tau; z_\tau)$ where z_τ is a state variable that is increasing in past consumption and $\partial^2/\partial c_\tau \partial z_\tau > 0$. [...] z_τ is the exponentially weighted sum of past consumption, or $z_\tau = \sum_{i=1}^{\infty} \gamma^i c_{\tau-i}$." (Frederick, Loewenstein, O'Donoghue, 2002, p. 369)

Habit-formation models relax the consumption independence assumption taken in account in the DU Model, assuming that the preferences (and utilities) in current period are influenced by the nature of consumption in previous periods; furthermore, it is assumed that current consumption can both increase or decrease the level of future utility, meaning that the utility function takes into account the possibility that consumption can create "disutility" and so that an individual may even prefers decreasing or non-monotonic consumption profiles, instead of increasing profiles. This approach has been recently used to analyze interesting topics like addictive activities and products.[17]

1.7 Models with Utility from Anticipation

As for Habit-Formation Models, Anticipal Utility Models develop the idea that individuals' utility does not depend only on present consumption. The consumption independence assumption entailed in the DU Model is relaxed even in these type of models, but this time is the utility from future consumption that is incorporated in current utility such that the instantaneous utility function takes the form

[17]Interesting recent works developed by O'Donoghue and Rabin (1999a, 2000) incorporate hyperbolic discounting in the analysis of addictive products.

$u(c_\tau; c_{\tau+1}, c_{\tau+2}, ...)$ where $\partial u / \partial c_{\tau'} > 0$ for $\tau' < \tau$.

1.8 Prospect Theory and Reference-Point

The argument that we are going now to introduce has a totally different approach from all the models that we have analysed so far but is still recognized as one of the most accurate method to describe individuals' behaviour in the rational choice theory. This is the *Prospect Theory* published by Daniel Kahneman and Amos Tversky in 1979. To better understand the reasons why this theory became so important (and was even awarded with the Nobel prize in 2002) is useful a comparison with the *Expected Utility Theory* proposed by Von Neumann and Morgenstern. As we know, EU Theory is based on the idea that the individuals are rational and act to maximize their own expected utility, on the base of a set of axioms that predict how a rational economic agent should act. We can see how EU Theory follows a top-down approach since from the axioms are derived the previsions that should be verified empirically. On the other hand, Prospect Theory uses a descriptive approach that tries to describe real-life choices that common individuals make, not the optimal decisions taken from the rational individual described by normative models. In this sense it follows a bottom-up approach: starting from the empirical observation to formulate a theory that could explain them. Anyway, even if the two approach are different (EU Theory normative, Prospect Theory descriptive), this doesn't mean that one excludes the other since: "Tversky and Kahneman do not fail to emphasize that both theories are indispensable: Expected Utility Theory to characterize rational behaviour and Prospect Theory to capture the real behaviour that deviates systematically from that implied by the axioms. [...] it is only thanks to the concept of rational behaviour that is possible to identify its violation; and then analyze the way in which the choices observed are (systematically) deviated from the rational ones."[18] Let's now observe what are the fundamental characteristics of the Prospect Theory and what are their implications; remember that all the features

[18] Matteo Motterlini, Francesco Guala, *Economia cognitiva e sperimentale*, Università Bocconi Editore, 2005, p. 19.

are based on the empirical observations and the study of human behavior that for length purposes we will not incorporate in this paper.

First of all, Prospect Theory suppose that individuals, when evaluating the possible outcomes of a decision in case of uncertainty, do not care about the absolute value of the outcome itself but evaluates it based on how much it departs from a *reference point*. This reference point is not uniquely defined, it can depend on status quo, current welfare, expectations, social comparison and others.

The second feature concern the form of the value function that is made to reflect the fact that individuals have different risk attitude towards gains and losses. Indeed, the value function is concave for gains, indicating that individuals are averse to risk, and is convex for losses, so that individuals are inclined to risk. Moreover, the slope of the function is greater in the neighbourhood of the origin, meaning that small variations near to the starting point have a greater impact than big variation but far from the origin. The value function is not symmetric in the region of gains and losses since the slope is steeper for losses than for gains to reflect the fact that for most individuals to avoid a loss is preferred to attain a gain. Finally, the value function exhibits diminishing marginal utility/disutility, showing that both gains and losses procure less satisfaction or misery as they increase. To better understand these features we represent the value function graphically in Figure 1.2.

The third characteristic of Prospect Theory implies the existence of a probability weighting function that is used to transform the probabilities perceived by the individuals replicating the fact that people overvalue small probabilities while undervalue large ones.[19]

The mathematical form proposed by Tversky and Kahneman is the following:

$$V = \sum_{i=1}^{n} \pi(p_i) v(x_i) \tag{1.4}$$

[19]The introduction of a function that transforms the probabilities perceived from the individuals and that is monotonically increasing with discontinuities between 0 and 1, is consistent with the empirical observations that people are more concerned in switching probability from 0% to 1% or from 99% to 100% than switching from 42% to 43%. This has been shown even through Allais Paradox, together with the inconsistency of independence axiom.

Graphical representation of Value function.

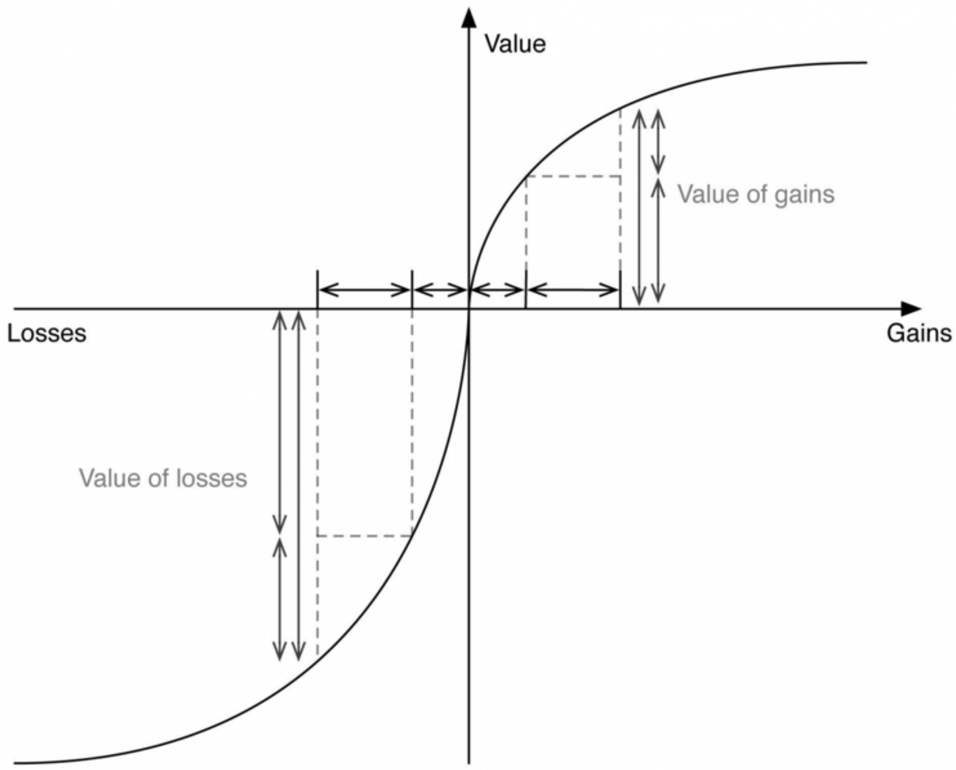


Fig. 1.2. Source: http://ui-patterns.com/patterns/Loss-aversion.

where $\pi(p_i)$ is the probability weighted function and $v(x_i)$ is the value function.

Reference-Point Models are based on the idea from Prospect Theory and their implications are really interesting since they achieve in explaining some of the anomalies addressed to the incapacity of the DU Model to explain some of the stylized facts. Especially, Loewenstein and Prelec in 1992 could explain in their model the magnitude effect, the sign effect and the delay-speedup asymmetry.

They show that if the elasticity of the value function is increasing in the magnitude of outcomes, people will discount smaller magnitudes more than larger magnitudes. [...] Consequently, even if a person's time preference is actually constant across outcomes, she will be more willing to wait for a fixed proportional increment when rewards are larger, and, thus, her imputed discount rate will be smaller for elastic than the value function for gains, then people will discount gains more than losses. [...] When delaying consumption, loss aversion reinforces time discounting, creating a powerful aversion to delay. When expediting consumption, loss aversion opposes time discounting, reducing the desirability of speedup. (Frederick, Loewenstein, O'Donoghue, 2002, p. 370)

Until now we have analysed alternative models that tried to explain intertemporal choices more precisely than the DU Model relaxing and modifying some of its assumption, using a different type of utility function or taking into account more complex discount factors. In the following sections we will provide an analysis of alternative models that depart more from the assumptions and the hypothesis of the DU Model.

1.9 Multiple-Self Models

An interesting category of models is Multiple-Self Models in which is supposed the existence of two or more selves that are in conflict in each individual facing an intertemporal choice. Usually these selves are labelled as myopic or farsighted, meaning that the first type doesn't really care about future outcome (or that she's not able to forecast future consequences correctly) while the second cares about future consequences too. The idea of these models is that the selves interact with each other alternating in taking control of behaviour and that farsighted selves often try to constrain the behavior of myopic selves predicting the action the she may undertake and trying to eliminate those actions.

The problem is that the same doesn't apply for myopic selves. Multiple-Self Models are newcomers, so there is still a little evidence to support their prediction but could be really useful in certain areas: "Specifically, multiple-self models have been used to make sense of the wide range of self-control strategies that people use to regulate their own future behavior. Moreover, these models provided much of the inspiration for more sophisticated hyperbolic discounting." (Frederick, Loewenstein, O'Donoghue, 2002, p. 376)

1.10 Temptation Utility

The models analysed until now assume that, among all the possible choices available to an individual, only the choice she made is relevant and the others are irrelevant.

This hypothesis, although used in most models of intertemporal choices, doesn't consider that individuals may suffer the disutility from renouncing to choose the option that is preferable now: this implies that a person would feel better if that specific option was not available or if it could be eliminated. This is the main idea of Temptation Utility Models and are mostly used to study preference for commitment. Indeed, most of the results emerging from these models shown that individuals may prefer to remove the tempting option in advance bearing some costs.

1.11 Uncertainty

Another assumption incorporated in the models we have analysed so far is that rewards that should occur at some point in the future will be delivered with certainty. But what happen if we add uncertainty about the delivery of the rewards? Experimental studies proved that embedding uncertainty into the delivery of rewards led to different results with respect to the usual case in which rewards are certain.[20] This means not only that introducing uncertainty about current and future rewards can alter the choices of individuals, but even that it can influences the discount rates. "Because of this subjective uncertainty associated with delay, it is difficult to determine to what extent the magnitude of imputed discount rates (or the shape of the discount function) is governed by time preference per se, versus the diminution in subjective probability associated with delay. There may be complicated interactions between risk and delay, because uncertainty about future receipt complicates and impedes the planning of one's future consumption stream." (Frederick, Loewenstein, O'Donoghue, 2002, p. 382)

[20] In their studies, Gideon Keren and Peter Roelofsma showed that adding the same level of uncertainty to both current and future rewards results in a totally different outcomes in terms of choices and discount rates. Specifically, they proposed to the first group of respondents a choice between 100 florins (a Netherland currency) today and 110 florins in a month and to the second group a choice between 100 florins with a probability of 0.5 and nothing otherwise today and 110 florins with a probability of 0.5 and nothing otherwise in a month. In the first group 82% of respondent prefer the immediate reward but in the second only 39% preferred the immediate one.

1.12 Projection Bias

As already seen in other models, it is likely that the tastes of an individual – and so the utility that she obtains from consumptions – will change over time and that correctly predicting how they will change is essential to optimally plan future consumption.[21] Interesting is the model proposed by Loewenstein, O'Donoghue and Rabin (2000) in which they assumed that, "while people may anticipate the qualitative nature of their changing preferences, they tend to underestimate the magnitude of these changes – a systematic misprediction they label *projection bias*". In this model it is supposed that the period- τ utility function is $u(c_\tau; z_\tau)$, where z_τ is a state variable that captures the effects of past consumption. For Loewenstein, O'Donoghue and Rabin, projection bias occur when tastes of individuals change over time; moreover, these should be considered in the study of intertemporal choice since the estimates could be distorted by the presence of such projection bias.

1.13 Conclusions

As we tried to explain in this chapter, intertemporal choices and time preference have always occupied a relevant position in the economic field but it is only lately that these got a wide diffusion and approval, especially thanks to the development of subjects like behavioural and experimental economy. We can mainly distinguish the development of intertemporal choices in three periods or phases. Initially, the study of intertemporal choices was founded principally on the psychological determinants that led individuals to have immediate or postponed gratification. It followed an inductive approach, observing the behavior of individuals and formulating hypothesis on the basis of such observations. In paragraph 1.1 we have seen that this is a feature of economists like Rae, Jevons, Senior and Bohm-Bawerk, which used a theorical and psychological approach.

[21]Most of the economic models assume that people can precisely forecast how their tastes will change in the future since it is assumed that they have rational expectation. However, models incorporating projection bias reject this assumption and suppose that people cannot exactly predict change of tastes.

The second period began with Fisher and Samuelson, which first introduced a quantitative multiperiodal approach to study intertemporal choices. The psychological determinants are no longer relevant in this approach: the discount factor proposed by Samuelson was only meant to mathematically represent the fact that individuals attach less weight to future rewards, as we explain in paragraph 1.2. The idea of this new approach was to formulate quantitative models that were able to represent individuals' behavior through mathematical functions. Thus, the aims of researchers were to find mathematical functions that could better represent how individuals act and that were both mathematically and economically tractable.

Finally, with the development of the behavioral and experimental economy and the prospect theory it has returned to give importance to the psychological aspects and motivations that move individuals in intertemporal decisions, trying at the same time to represent them through mathematical functions that accurately describe certain behaviors. The intertemporal discount rate is no longer the only main concept in the study of time preference (as it was for the DU Model), but there are new key concepts, on which recent models are based, that are really innovative and can reflect appropriately the choices of individuals and the empirical data.

Chapter 2

Individuals make decisions continuously in everyday life and in making these choices they have to take into account many of the variables that affect these decisions. Furthermore, it is not always easy to predict the consequences and results of these decisions due to the uncertainty that surrounds them in many cases. The purpose of this chapter is therefore to analyze and understand how individuals act in situations of choice where the results are uncertain or ambiguous. To do this we will use many of the principles of decision theory, in order to have a reference base on which to build our analysis. Then we will examine situations in which ambiguity seems to play a predominant role in the choices made by individuals. Finally we will try to identify the causes of this ambiguity and the ways to infer the attitude towards the ambiguity of individuals. In this way we should be able to get an in-depth view of one of the most significant phenomena in this sector in recent years.

2.1 Decision Theory

To proceed with our research, we need to understand the behavior of people when they are facing options to choose between. For this objective we can rely on the Decision Theory, which is a science that explains how individuals take decisions to reach their goals in presence of a plurality of options. Especially, Decision Theory focuses on the moment in which the choice is taken by the individual and on the reasons of that choice, instead of the consequences of that given decision. We can distinguish between *normative* and *descriptive* decision theory. The former explains the decisional process, the criteria or the evaluation of alternatives that an individual should make to behave in a *rational* way, the latter examines the decisional process of real individuals in real situations and tries to provide explanations or make predictions about that.

Agents are the subject of these analyses: they face decision problems based on the information and resources available to them, considering the options and actions they can take and evaluating them using their own mental schemes. Thus, we can describe decision problems using the words of Richard Bradley (2014):

> A decision maker or decision making body has a number of options before them: the actions they can take or policies they can adopt. The exercise of each option is associated with a number of possible consequences, some of which are desirable from the perspective of the decision maker's goals, others are not. Which consequences will result from the exercise of an option depends on the prevailing features of the environment.[1]

A common behavior undertaken when we choose between two or more options is to try to achieve the best possible outcome from that decision. In doing so, we usually evaluate the possible outcomes of each decision we could make using our own standard of evaluation. Decision Theory proposes two way in which this evaluation can be done: using a numerical approach or a preference relation. The first approach consists in assigning a numerical value to each of the outcomes in terms of utility so that is possible to determine the best outcome based on the highest value.[2] With the second approach the consumer's preferences are captured by a preference relation $\succsim$ that is a binary relation used to compare two alternatives with each other. For example, considering two alternatives A and B, we can write A $\succsim$ B if A is at least as good as B or we can write A $\succ$ B if A is preferred to B.

[1] Richard Bradley, *Decision Theory: A Formal Philosophical Introduction*, 2014, London School of Economics and Political Science, p. 2.

[2] The drawback of this approach is that in some cases is unclear what these numbers represent. They can be compared to the other values to understand which of the options is the one preferred, but we can't know how much that option is preferred in absolute term.

The three comparative notions "better than" ($\succ$), "equal in value to" ($\sim$) and "at least as good as" ($\succsim$) are essential parts of the formal language of preference logic. $\succ$ is said to represent preference or strong preference, $a \succsim b$ weak preference, and $\sim$ indifference. These three notions are usually considered to be interconnected according to the following two rules:

- A is better than B if and only if A is at least as good as B but B is not at least as good as A. (A $\succ$ B if and only if A $\succsim$ B and not B $\succsim$ A)
- A is equally good as B if and only if A is at least as good as B and also B at least as good as A. (A $\sim$ B if and only if A $\succsim$ B and B $\succsim$ A).[3]

The preference-based approach assumes that the preference relation $\succsim$ is rational, meaning that it must possess the *completeness* and *transitivity* properties. A preference relation is complete if for all x,$y \in X$, we have $x \succsim y$ or $y \succsim x$ (or both), meaning that the decision maker has a well-defined preference between any possible pair of alternative. A preference relation possesses the transitivity property when for all x,y,$z \in X$, if $x \succsim y$ and $y \succsim z$, then $x \succsim z$.

It is interesting to consider the information available to individuals when they are going to make a choice. In fact, the outcome of a decision does not depend just on the alternative chosen but also on some external factors that may be not under the control of the decision maker. These factors include decisions of other individuals and information about the future scenarios that are unknown to us that may influence our outcome. From this point onward we will use the term *state of world* to refer to these scenarios, where the world is the object about decision maker is concerned and the state (of the world) is the description of all relevant characteristics of the object. Knowing then that the information plays a key role inside the decision making process, we can identify at least three categories of information. We shall say that we are in the realm of decision making under:

- *Certainty* if each action is known to lead invariably to a specific outcome.

[3]Sven Ove Hansson, *Decision Theory: A Brief Introduction*, 1994, Royal Institute of Technology, p. 15.

- *Risk* if each action leads to one of a set of possible specific outcomes, each outcome occurring with a known probability. The probabilities are assumed to be known by the decision maker. For example, an action might lead to this risky outcome: a reward of $10 if a fair coin comes up head, and a loss of $5 if it comes up tails. Of course, certainty is a degenerate case of risk where the probabilities are 0 and 1.

- *Uncertainty* if either action or both has as its consequence a set of possible specific outcomes, but where the probabilities of these outcomes are completely unknown or are not even meaningful. (Luce and Raiffa, 1957, p.13)

This classification is based on the idea pointed out by the American economist Frank Knight. In his work *Risk, uncertainty and profit* he wrote:

> Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated. The term "risk", as loosely used in everyday speech and in economic discussion, really covers two things which, functionally at least, in their causal relation to the phenomena of economic organization, are categorically different. [...] The essential fact is that risk means in some cases a quantity susceptible of measurement, while at other times it is something distinctly not of this character. [...] It will appear that a *measurable* uncertainty or "risk" proper, as we shall use the term, is so far different from an *unmeasurable* one that it is not in effect an uncertainty at all. We shall accordingly restrict the term "uncertainty" to cases of the non-quantitative type. (Knight, 1921, pp. 19-20)

2.2 Expected Utility

After that we have pointed out the main differences between uncertainty and risk, we can now analyze the principal approach used in decision-making under risk that is the Expected Utility.[4]

Expected utility can also be referred as "probably-weighted utility theory" since, with this approach, each possible outcome is represented by the weighted average of its correspondent utility value and probability. Expressing this in mathematical terms: suppose there are n possible outcomes x_i and a given utility u and probability p associated to each of these outcomes. Then the EU can be expressed as

$$E[u(x)] = p_1 u(x_1) + p_2 u(x_2) + ... + p_n u(x_n) \tag{2.1}$$

Although the denomination "expected utility" and this mathematical formulation are quite recent, this theory was used since XVIII century in relation to monetary outcomes.[5] The expected utility approach was one of the dominant approaches in the field of decision theory together with the expected value approach. These were for many years the main approaches used to model the choices of individuals. These two approaches may seem similar in formulation but are totally different for the basic idea and for the results obtained when applied. The expected value approach takes into consideration the payoffs of the various states of nature and the probabilities with which they can occur: in this case the expected value of a certain event will be calculated as the weighted average of the payoffs weighed for the respective probabilities. According to the expected utility theory, on the other hand, every possible payoff enters into a function of subjective utility which therefore modifies its value to a certain degree, to then be associated with the respective probability.

Although both models are widely recognized and used, it seems that the expected utility approach is able to explain the decisions of individuals more precisely than the other approach. Specifically, there are situations in which the expected value approach fails to describe the behavior of the subjects, while using the expected utility approach in the same cases it seems possible to succeed.

One of the most famous examples of this is the St. Petersburg paradox, proposed by Nicolas Bernoulli in 1713. The dilemma proposed by this paradox is the following:

[4]This approach was dominant in both normative and descriptive decision theory since the 1950s and is still largely used today.

[5]Specifically, this analysis was applied for games of objective probabilities such that an individual should take part in the game or bet only if its expected wealth will increase.

suppose a casino offers a game of chance for a single player in which a fair coin is tossed at each stage. The initial stake starts at 2 dollars and is doubled every time heads appears. The first time tails appears, the game ends and the player wins whatever is in the pot. Thus the player wins 2 dollars if tails appears on the first toss, 4 dollars if heads appears on the first toss and tails on the second, 8 dollars if heads appears on the first two tosses and tails on the third, and so on. Mathematically, the player wins $2k$ dollars, where k equals number of tosses (k must be a whole number and greater than zero). What would be a fair price to pay the casino for entering the game?

Nicolas proposed this problem precisely to highlight the limits of the expected value approach. Indeed, we could use the expected value to calculate the average payout, but using this approach we would obtain that:

$$E = \frac{1}{2} \cdot 2 + \frac{1}{4} \cdot 4 + \frac{1}{8} \cdot 8 + ... \tag{2.2}$$

It's easy to see that using the expected value we obtain an infinite sum of 1s, meaning that the expected win of the game is an infinite amount of money. Thus any rational individual that has the possibility to play this game should pay any price to play it. But this does not give a proper solution to the paradox. The conventional solution to St. Petersburg paradox was given in 1738 by Daniel Bernoulli, Nicholas' cousin. To solve the problem he introduced a utility function that exhibits diminishing marginal utility of money, that is called log utility. The idea is that "the utility attached by a person to wealth does not increase in a linear fashion with the amount of money, but rather increases at a decreasing rate. Your first \$1000 is more worth to you than is \$1000 if you are already a millionaire". (Hansson, 1994, p.31)

Using a log utility function that incorporates the concept of diminishing marginal utility of money, Daniel Bernoulli was able to give an answer to the problem establishing a relation between the wealth of an individual that is playing the game and its willingness to pay for that game. Specifically, he found that richer people, like millionaire, should be willing to pay more with respect to poorer one.

2.3 The Savage Axioms

Starting from the idea of Daniel Bernoulli, the expected utility approach moved toward what is now known as subjective expected utility. This type of utility measures how much a risky economic opportunity is worth from the point of view of a decision maker so that this function may be different for each individual. Subjective expected utility is composed by two subjective concept that are a personal utility function and a subjective probability distribution.

An important result about subjective expected utility was achieved in 1953 by Leonard J. Savage that tried to characterize the behavior of decision makers that use this kind of expectation. He proposed a series of "axioms of rationality" and proved that if an individual adheres to these, then the subjective expected utility can be used to describe and predict the choices of that individual. To better explain this concept imagine a decision maker that respects the axioms of rationality facing risky event that has x_i possible outcomes, each of which has a utility $u(x_i)$. Then, combining this utility function with the subjective probability of each outcome $P(x_i)$ we can describe the choices of the decision maker using the formula 2.1 that we are now represent in a more elegant form:

$$E[u(x)] = \sum_i u(x_i)P(x_i) \tag{2.3}$$

An important thing to remember is that not all the people may take the same decision since they might have different subjective utility function or different subjective probability distribution from the others.

For completeness we will now provide the postulate and the description of some of the Savage axioms.

Axiom 1: Complete ordering of gambles, or actions. Very straightforward, the first axiom demands that there must be an order of preference between all the actions. This means that taking in consideration 2 gambles or actions A and B, we can have that A is preferred to B (A $\succ$ B), B is preferred to A (B $\succ$ A) or A and B are indifferent (A $\sim$ B). Moreover, if we consider a third action C and we have that A is preferred to B and B is preferred or indifferent to C (A $\succ$ B $\succ$ C or A $\succ$ B $\sim$

C), then A is preferred to C (A $\succ$ C).

Axiom 2: The choice between two actions must be unaffected by the value of pay-offs corresponding to events for which both actions have the same pay-off. This is one of the most important axioms, even known as sure-thing principle. This principle states that if decision maker would select a given action supposing that an uncertain event E will occur and the same decision maker would select the same action even if the event E will not occur, then the decision maker should choose that action even if he has no information about the event E.

> A businessman contemplates buying a certain piece of property. He considers the outcome of the next presidential election relevant. So, to clarify the matter to himself, he asks whether he would buy if he knew that the Democratic candidate were going to win, and decides that would. Similarly, he considers whether he would buy if he knew that the Republican candidate were going to win, and again finds that he would. Seeing that he would buy in either event, he decides that he should buy, even though he does not know which event obtain, or will obtain, as we would ordinarily say. It is all too seldom that a decision can be arrived at on the basis of this principle, but except possibly for the assumption of simple ordering, I know of no other extralogical principle governing decisions that finds such ready acceptance. (Savage, 1954, p.21)

Axiom 3: Independence of probabilities and payoffs. This one explains that a decision maker should not be influenced by the size of the price when choosing on which event to bet.

Axiom 4: Rejection of dominated actions. This one includes the admissibility into the analysis, making the decision maker rejecting the dominated actions and choosing only the dominant ones.

For our analysis we mention just these four axioms even because it is possible to determine the decision maker preference using just these we mention. In fact, if the choices of an individual satisfy these axioms, "his preference for A $\succ$ B may safely be interpreted as sufficient evidence that he regards alpha as not less probable than beta," where the relation not less probable than "will have all the properties of a qualitative probability relationship." (Ellsberg, 1961, p.650)

In this section we are focusing on the qualitative aspects of the probability relation, so we will not mention other axioms that are necessary to describe the numerical properties. Savage's axioms were tested to verify their validity through a variety of hypothetical situations and the results support the fact that they can predict some choice behaviors with accuracy. Anyway, these postulates are not foolproof since there are situation in which they fail to describe some behaviors. Some experiments have shown that many individuals do not behave in a manner consistent with Savage's axioms. We will provide a description of these situation using the Allais paradox (1953) and the Ellsberg paradox (1961).

2.4 Violations of Savage's Axioms

We have seen that in situations where there are not objective probabilities it is still possible to infer the behavior of decision makers thank to the method of Subjective Expected Utility proposed by Savage in 1954 with the formulation of the axioms of rationality. Anyway, there are some cases in which these axioms fail to work, since observed choices were different from the prediction of the axioms.

Consider two pairs of gambles: the first implies a choose between the certainty of winning \$1 million or the chance of winning \$5 millions with a probability of 10%, winning \$1 million with a probability of 89% and win nothing with 1% probability; the second gamble implies the choice between a chance of winning \$1 million with a probability of 11% and win nothing with 89% probability or the chance of winning \$5 millions with a probability of 10% and win nothing with 90% probability. The following table shows the two pairs of gambles.

Empirical studies have shown that in this situation the majority of individuals would prefer Gamble 1A over 1B and Gamble 2B over 2A, but this is inconsistent with the precepts of the axioms: a decision maker acting accordingly to Savage's

Table 2.1: Graphic representation of Allais paradox

	Gamble 1A	Gamble 1B	Gamble 2A	Gamble 2B
Winnings	Probability			
\$1 M	100%	89%	11%	-
\$0	-	1%	89%	90%
\$5 M	-	10%	-	10%

axioms should maintain his order of preferences, preferring then Gamble 1A over 1B and Gamble 2A over 2B, or vice versa. In this case we can see that the only difference between the two pairs of gambles is that the probability of winning \$1 million was added in Gamble 1A and 1B, replacing the 89% probability of \$0 in Gamble 2A and 2B. Thus, an individual that prefers 1A over 1B should prefer 2A over 2B since 1A and 2A can be seen as the same choice, like 1B and 2B, as prescribed by the axiom of independence.

This experiment, known as "Allais paradox", was proposed in 1953 by Maurice Allais as counterexample to Savage's axioms. For completeness, we will provide a simple mathematical proof to show the inconsistency of such pair of choices: suppose that an individual prefers 1A over 1B and 2B over 2A. In terms of utility of each pair, this can be written as:

$$1 \cdot U(\$1) > 0.89 \cdot U(\$1) + 0.01 \cdot U(\$0) + 0.1 \cdot U(5) \tag{2.4}$$

$$0.89 \cdot U(\$0) + 0.11 \cdot U(\$1) < 0.9 \cdot U(\$0) + 0.1 \cdot U(5) \tag{2.5}$$

Rearranging the terms in equation (2.5) we obtain:

$$0.11 \cdot U(\$1) < 0.01 \cdot U(\$0) + 0.1 \cdot U(5);$$

$$1 \cdot U(\$1) - 0.89 \cdot U(\$1) < 0.01 \cdot U(\$0) + 0.1 \cdot U(5);$$

$$1 \cdot U(\$1) > 0.89 \cdot U(\$1) + 0.01 \cdot U(\$0) + 0.1 \cdot U(5) \qquad (2.6)$$

Comparing equations (2.4) and (2.6) the contradiction is clear, meaning that this pattern of choice is inconsistent with the axioms.

Consider now a hypothetical situation where there are two urns that contain red and black balls. An individual is asked to choose from which urn a ball will be randomly draw and to bet on the color of that ball. The individual knows that the first urn contains a total of 100 balls but he does not know the exact proportion between red and black balls, while in the second urn there are exactly 50 red balls and 50 black balls. If the individual guesses the color of the ball drawn he wins a prize, for example \$100, otherwise he wins nothing. In this situation there are four possible actions: choose the first urn and bet on red ball, choose the first urn and bet on black ball, choose the second urn and bet on red ball, choose the second urn and bet on black ball. Now suppose that we do not know the level of information of this individual about the distribution of the red and black balls inside the two urns and want to infer his subjective probabilities about that. A simple way to do that is asking some question to the individual. In Ellsberg experiment, the decision maker was asked if he prefers to bet on red or black or if he is indifferent when drawing a ball from the first urn and the same question was asked about drawing from the second urn. So far no problem arises, but when asking to the decision maker what he considers more likely between the draw of a red ball from the first urn or the draw of a red ball from the second urn, some problem may arise and we will explain why.

First thing to consider is that most individuals answered that they are indifferent on the first two questions.[6] But when was asked them if they prefer to bet on a red ball drawn from the first urn or a red ball drawn from the second urn (or a black ball from first urn and a black ball for the second urn), the results were different

[6]This is a common answer to that questions since for the urn that contains 50 red and 50 black balls the expected value of drawing a red or a black ball is the same. The answer is still valid for the case of the first urn because the proportion of balls is unknown to the decision maker; having no other information about the urn he might be indifferent on which color to bet on.

from what expected. Only a minority of respondent answered to be indifferent eve in this case, in contrast with the results obtained from the previous two questions. This time the majority answered to consider more likely the drawn of a red ball from the second urn than from the first urn and similarly, the drawn of a black ball from the second urn than from the second urn. In this case there is clearly a violation of the Savage's axioms.

> Suppose that, betting on red, you preferred to draw out of Urn II.[7] An observer would infer tentatively that you regard Red2 as "more probable than" Red1. He then observes that you also prefer to bet on Black2 rather than Black1. Since he cannot conclude that you regard Red2 as more probable than Red1 and, at the same time, not-Red2 as more probable than not-Red1, this being inconsistent with the essential properties of probability relationships, he must conclude that your choices are not revealing judgments of "probability" at all. So far these events are concerned, it is impossible to infer probabilities from your choices. (Ellsberg, 1961, p.651)

The same reasoning applies for those who prefer to bet on Red1 and Black1 instead of Red2 and Black2. This means that, if a decision maker considers the draw of a red or black ball from urn I equally probable events like the draw of a red or black ball from urn II, he should be indifferent between a red (or black) ball drawn from urn I and a red (or black) ball drawn from urn II. In the other two cases the axiom of complete ordering of actions and the sure-thing principle are violated, then it is not possible to follow the axiomatic approach to infer preferences.

[7] In this passage, Savage calls urn I the one that contains an unknown proportion of red and black balls and urn II the one that contains 50 red balls and 50 black balls. Moreover, uses the terms Red1, Red2, Black1 and Black2 to refers respectively to betting on the draw of a red ball from urn I, the draw of a red ball from urn II, the draw of a black ball from urn I and the draw of a black ball from urn II.

2.5 Ellsberg Paradox

On the basis of the results obtained in the "two-color" problem, Ellsberg proposed a further experiment to verify the previous results and to explain that kind of behavior. There is an urn containing a total of 90 balls, 30 of which are known to be red with certainty and the remaining 60 are black and yellow in unknown proportion. A ball will be drawn from this urn and is asked to the decision maker on which of two event he prefers to bet. The first event is "red ball will be drawn" while the second is "black ball will be drawn". We represent the scenario in the following matrix:

Table 2.2: Payoff of the first lottery of Ellsberg paradox.

	Red	Black	Yellow
Action I	$100	$0	$0
Action II	$0	$100	$0

Action I and action II are respectively the decision to bet on red and on black. After this lottery, the decision maker is asked to choose on which outcome to bet in a new lottery on the same urn. Now, the two new possible actions are to bet on red or yellow ball (Action III) and to bet on black or yellow (Action IV). As usual we represent this lottery in matrix form:

Table 2.3: Payoff of the second lottery of Ellsberg paradox.

	Red	Black	Yellow
Action III	$100	$0	$100
Action IV	$0	$100	$100

The results of this experiment were very interesting since the majority of the respondents said to prefer action I to action II and action IV to action III. This combination of preferences is inconsistent with Savage's axioms because they violate the sure-thing principle. In this case the problem is that under the sure-thing principle the order of the preference should be the same for the two lotteries. Specifically, if an individual prefers action I to action II in the first lottery, he should prefer action III to action IV in the second lottery, or vice versa.[8] A small portion of respondents answered that they prefer action II to action I and action III to action IV, but this pattern of preferences still violates the sure-thing principles for the same reason we just explained. Once again, we cannot infer qualitative probabilities from these choices using the axiomatic approach. That is because, analyzing the pattern of choices, we are led to think that the individual considers the event "Red" more probable than "Black" in the first lottery, but in the second one we can say that he considers the event "not-Red" more probable than "not-Black", leading to a contradiction. Specifically, if one prefers "Red" over "Black" in the first lottery, we can infer that he considers the probability of that event, which is known to be $1/3$, to be greater than the probability of drawing a black ball. Anyway, preferring action IV to action III in the second lottery, one is saying that he considers less probable the draw of a red ball than the draw of a black one, meaning that he thinks that the probability of drawing a black ball is greater than the probability of drawing a red ball, which is known to still be $1/3$.

Thus, is clear that is not possible to determine a qualitative probability relationship for the individuals that have this kind of preferences since two of the properties that distinguish this kind of relation are violated.[9] Moreover, it is not possible to describe this behaviors using a quantitative approach like the maximization of the expected utility. In fact, replacing the payoffs \$100 and \$0 respectively with 1 and

[8]Looking at the payoffs of the lotteries it is clear that the first two column are the same in both cases. The payoffs of the third column changes from the first to the second lottery but they should still irrelevant for the decision because the payoffs are still the same for both actions: if a yellow ball is drawn you always get \$100, whatever actions you decide to choose. Then, for the sure-thing principle, if an individual prefers to bet on red instead of black when the payoffs of drawing a yellow ball are null, he must maintain his ordering of preference when the payoffs increases (or decreases) by a constant amount for all the possible actions.

[9]The properties we are referring to are the following: (1) If event A is more probable than event B, then "not-A" (the complement of A) is less probable than "not-B" (the complement of B) and, if event A is equally probable than its complement not-A and event B is equally probable than its complement not-B, then A and B are equally probable. (2) If events A and C are mutually exclusive and so are events B and C and if A is more probable than B the union $A \cup C$ is more probable than the union $B \cup C$.

0, we have that the expected values of the four actions are:

$$EV[ActionI] = Prob.(Red)$$

$$EV[ActionII] = Prob.(Black)$$

$$EV[ActionIII] = Prob.(Red) + Prob.(Yellow)$$

$$EV[ActionIV] = Prob.(Black) + Prob.(Yellow)$$

It is clear that there is not any combination of probabilities $P_i \geq 0$, with $\sum_i P_i = 1$ that can satisfy the system:

$$\begin{cases} Prob.(Red) > Prob.(black) \\ Prob.(Red) + Prob.(Yellow) < Prob.(Black) + Prob.(Yellow) \end{cases}$$

So far, we understood that the majority of individuals do not act following the Savage's axioms and so they "are simply not acting as though they assigned numerical or even qualitative probabilities to the event in question." (Ellsberg, 1961, p.656)

Now the problem is to understand what are the reason that move all these decision makers to behave differently from the Savage's axioms. To find an answer to this problem, Ellsberg interviewed the decision makers that acted in violation of the axioms and the responses showed a very interesting feature.

The respondents justified their decisions saying that it did not just depend on the subjective probability of the events and on the expected value of gains, but especially on the information that they had about the likelihood of the events.

> Responses from confessed violators indicate that the difference is not to be found in terms of the two factors commonly used to determine a

> choice situation, the relative desirability of the possible payoffs and the relative likelihood of the events affecting them, but in a third dimension of the problem of choice: the nature of one's information concerning the relative likelihood of events. What is at issue might be called ambiguity of this information, a quality depending on the amount, type, reliability and "unanimity" of information, and giving rise to one's degree of "confidence" in an estimate of relative likelihoods. (Ellsberg, 1961, p.657)

The results obtained by Ellsberg was really important because he proved that the subjective expected utility theory, which was mainly used for decisions under uncertainty since its formulation by Savage, was not universally applicable in these cases. He also proved that the violations of the axioms were consciously made by the decision makers: questioning those who made the violations and making them reflect on the reasons that led them to make that choices, he found that a very little part of them reconsidered his decisions and decided to follow the axioms, thinking that their initial decision was wrong. Instead, most of the violators said that they would have persist with their decision and not changing their opinion since those were their real preferences, implying then that the axioms were wrong. The fact that many individuals decided to confirm their choices is an important signal, especially because "this includes people who previously felt a first-order commitment to the axioms, many of them surprised and some dismayed to find that they wished, in these situations, to violate the sure-thing principle." (Ellsberg, 1961, p.656)

Therefore Ellsberg used the term ambiguity of information to refer to this particular situation. In fact, the type of information that the decision maker had in the experiment cannot be labeled neither as risk or ignorance.[10] In this case the decision maker knows that 1/3 of the total balls in the urn are red and this led him to exclude some probability distribution (for example, he can exclude the possibility that the balls in the urn are all black or all yellow), giving him a certain

[10]Recall that we refer to decision under risk when the decision maker knows the probabilities of all the outcomes that may occur, while decision under ignorance if he does not have any information about the likelihood of the events.

degree of certainty. Anyway, he has still a lot of possible distribution that seems plausible. In this example he might assume that all the distributions contained in the set $[P_r = \frac{1}{3}; P_b \in (0, \frac{2}{3}); P_y = 1 - P_r - P_b]$ where P_r, P_b, P_y are respectively the distribution of the red, black and yellow balls, are potentially true and he cannot conclude that a certain distribution is more probable than the others.

Then, it can be concluded that, in situations of information ambiguity, we cannot use rules like minimax, minimax regret or maximax to describe the behavior of a decision maker.[11] That is because these rules are working in situations of complete ignorance, when the decision maker has no information about the probabilities of the events, but fail to work in presence of ambiguity of information.

Knowing that the violations of the Savage's axioms were voluntarily made by most of the decision makers because of the ambiguity of the information, Ellsberg provided a possible justification to this behavior. He argued that ambiguity did not depend on the quantity of information available to decision makers, but mostly on the quality of information. Thus, a high level of information does not reflect a low level of ambiguity: there can be high level of ambiguity, and then low confidence in the probability distribution, even in a situation in which the decision makers are a lot informed.

The presence of ambiguity is determined by the reliability and the confidence instead of the quantity of that information. Situations in which an individual has low level of confidence about some probability distributions may be caused by the fact that the beliefs of that individual on that given problem are vague or unsure, as defined by Ellsberg. Therefore, it is common to observe this "self-consistent" behavior that leads decision makers to violate the Savage's axioms in presence of high levels of ambiguity.

[11]Minimax, minimax regret and maximax are decision rules that describe three different behavior in decision theory. Minimax rule involves the selection of the alternative which minimizes the possible lost considering the worst possible scenario that could happen; Minimax regret is a rule that minimizes the maximum regret, where the regret is considered as the opportunity loss that verifies if a wrong decision is made; Maximax involves the selection of the alternative which has the highest payoff available.

> In reaching his decision, the relative weight that a conservative person will give to the question, "What is the worst expectation that might appear reasonable?" will depend on his confidence in the judgements that go into his estimated probability distribution. The less confident he is, the more he will sacrifice in terms of estimated expected payoff to achieve a given increase in "security level"; the more confident, the greater increase in "security level" he would demand to compensate for a given drop in estimated expectation. (Ellsberg, 1961, p.664)

After these considerations on ambiguity, it is not wrong to consider it as a subjective variable, since different individuals may have different level of confidence and reliability on the same problem with same information for all. Furthermore, it is possible to identify situations in which there are high levels of ambiguity in an objective manner: for example detecting cases where information is highly unreliable or cases where there is a low confidence in the estimated probabilities or even cases where the expectations of the decision makers are very different between them.

2.6 A Simple Decision Rule

So far, we have analyzed the behavior of the violators of the axioms and the motivations behind them, and we have guessed that this behavior was the result of the ambiguity in the information that they had, and lastly we provided some features and justifications about this ambiguity. We even said that decision rules that was used to predict the behaviors in case of uncertainty did not work in presence of ambiguity, so now the question is whether there is a rule to predict behaviors when decision makers face ambiguity.

Ellsberg proposed a simple decision rule on the basis that all the relevant factors in the analysis are linearly combined to form this decision rule. Then, the decision rule had the following form:

$$\rho \cdot est_x + (1 - \rho) \cdot min_x \tag{2.7}$$

Where ρ is the degree of confidence that an individual has on a given estimated distribution y_0 in a state of ambiguity, est_x is the expected payoff to the act x corresponding to the estimated distribution y_0, and min_x is the minimum expected payoff to the act x. We can use this formula to obtain a certain index for each action x and then we have to choose the action associated with the highest index. It is important to point out that ρ , y_0, and Y_0 (that is the set of all possible probability distributions) are subjective data that must be inferred from the decision maker.[12] Then, using the subjective value to measure such indexes, it turns out that an individual should prefer action I to action II and action IV to action III, like most of the decision makers did. Finally, what emerges from the results is that the decision maker "does not actually expect the worst, but he chooses to act as though the worst were somewhat more likely than his best estimates of likelihood would indicate." (Ellsberg, 1961, p.667)

This implies that most of individuals, in a scenario of ambiguity, prefer to adopt a conservative approach, preferring decisions with high but known risk with respect to decisions in which the probabilities of the outcomes are unknown. The preference for risk instead of uncertainty can be motivated from the fact that, when dealing with uncertain events, the likelihoods of all events must be estimated, and this is not a simple task without any evidence or prior. Even if one is able to obtain a certain evaluation, this is not enough to rely doubtless on that estimate right because there is no solid basis to confirm it.

Other reasons might be that individuals tend to be pessimistic about their estimations in case of ambiguity, selecting then the option with known probabilities since it give them better protection in the case where their own estimates are completely wrong; or simply that because most of us feel more comfortable when knowing the effective risk that we are taking instead of making decision blindly without any hints. Taking into account all these considerations, the decision rule proposed by Ellsberg was constructed to reflect this behavior, preferring an action in which

[12] In his example, Ellsberg proposed $\rho = \frac{1}{4}$ such that the decision rule became $\frac{1}{4} \cdot est_x + \frac{3}{4} \cdot min_x$.

the probabilities are known than one in which there are no information about the distribution. This do not mean that this rule precludes decision makers to select the latter option, "but it will definitely bias the choice away from such ambiguous ventures and toward the strategy with known risk." (Ellsberg, 1962, p.666)

A final consideration about this decision rule is that ρ is an important factor that describes the degree of confidence that a decision maker has in his estimate. It can be said that it represents the level of ambiguity perceived by the individual. Thus, for low levels of ambiguity, ρ get closer to 1 and without ambiguity $\rho = 1$: in this case the decision rule will observe the Savage's axioms principles meaning that we can still use it to infer the estimated probabilities of the decision makers.

In conclusion, Ellsberg's results were really important because he proved that individuals show a certain degree of *ambiguity aversion*, which is the preference for known risks instead of unknown ones. A person that is ambiguity-averse will choose situations in which the probability distributions of the outcomes are known, acting if he is placing a premium on such type of outcomes. These results were replicated from many other researchers even in different field to further prove their validity and their applicability.

2.7 Ambiguity Aversion Models

The introduction of ambiguity aversion mechanisms in the decisional process of individuals has started a whole new literature on the argument. Initially, experimental literature was focused on finding and analyzing cases where there was the presence of ambiguity but then, researches moved toward the reasons that lead individuals to adopt this type of behavior. A lot of models concerning ambiguity and with different characteristics were developed lately.

In this paragraph we mention one of the most famous models that has been used as a basis for future analysis always in the ambiguity field, that is the model of maxmin expected utility proposed in 1989 by Gilboa and Schmeidler. Furthermore, we will also introduce one of the best tools used to elicit the attitude towards the ambiguity of the subjects during the experiments, the *multiple price list*.

Gilboa and Schmeidler in their work affirm that a maxmin expected utility decision rule is one of the best approaches to model decisions in the presence of ambiguity. Starting from the results of Ellsberg's classic "two-color" experiment, they tried to understand the motivations that led the subjects to act differently from what was predicted by the expected utility theory and by the Savage's axioms. The most accredited explanation from their point of view is that:

> In case of urn B, the subject has too little information to form a prior. Hence he considers a set of priors as possible. Being uncertainty averse, he takes into account the minimal expected utility (over all priors in the set) while evaluating a bet. For instance, one may consider the extreme case in which our decision maker takes into account all possible priors over urn B. In this case the minimal utility of each one of the bets Ab, AR is $50, while that of bets BB and BR is $0, so that the observed preferences are compatible with the maxmin expected utility decision rule.[13]

Thus, they proposed that preference relations over acts could be represented by the function:

$$J(f) = min\{\int u \circ f dP \mid P \in C\} \tag{2.8}$$

where f is an act, u is a von Neumann-Morgenstern utility over outcomes and C is a closed and convex set of finitely additive probability measures on the states of nature. Using such equation it is supposed that individuals have multiple priors and therefore the expected utility is given by the minimum value of all the set of priors. In this situation, individuals appear to be pessimistic about their estimations since they expect the lowest value to be realized. The authors of the papers argued that in case of uncertainty:

[13]Itzhak Gilboa and David Schmeidler, *Maxmin Expected Utility With Non-Unique Prior*, 1989, Journal of Mathematic Economics (18), p.142.

the subject has too little information to form a prior, hence he considers a set of prior as possible. Being uncertainty averse, he takes into account the minimal expected utility (over all priors in the set) while evaluating a bet. (Gilboa and Schmeidler, 1989)

Thus, in the multiple-prior model of Gilboa and Schmeidler (1989), beliefs are represented using a set of probability measures.

Although there are many other models that deserve to be mentioned, in this paper we will focus on the model proposed in 2015 by Uri Gneezy, Alex Imas and John List in their work. Their purpose was to formulate a method to obtain data on decision in case of ambiguity with the aim of analyzing the attitudes of individuals in presence of ambiguity. The central idea of this method is to use double multiple price list applied to a series of decisions to obtain information about risk and ambiguity attitudes of individuals. *Multiple price list* format allows to present the gambles in the form of a list of options whose expected value increases (or decreases) from the current option to the next one, and in which two or more mutually exclusive alternatives are proposed. Usually, with multiple price list decision makers are asked to determine their personal *switching point*, that is the point where one prefers to move from one gamble to the other.

The idea of using multiple price list to elicit risk preferences was developed first in 2002 by Holt and Laury.[14] They proposed a multiple price list made of ten choices between pairs of lotteries to measure the degree of risk aversion of the interviewed subjects. We are reporting the multiple price list used in their experiment to furnish an example.

This format allows to easily compare the different behaviors of the individuals both in cases of real or hypothetical incentives and to identify the different attitude toward risk preferences.

[14] The same method was used in 1990 by Kahneman, Knetsch and Thaler to elicit prices for commodity and in 1999 by Coller and Williams to elicit discount rates.

Table 2.4: The ten paired lottery of Holt and Laury's experiment.

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

Source: Charles A. Holt and Susan K. Laury, Risk Aversion and Incentive Effects, 2002, American Economic Review, p. 1645.

2.8 Estimation of Ambiguity Aversion

As said before, Gneezy, Imas and List formulated a model to estimate the levels of ambiguity aversion of individuals: using a double multiple price list they could obtain data on the risk aversion parameter r and the ambiguity aversion parameter α, that were then estimated using a model of α-maxmin expected utility (α-MEU), which is a kind of model that "represents the utility of an outcome as the convex combination of the expected utilities given the set of priors the individual holds." (Gneezy, Imas and List, 2015, p.2)

The general idea of this work is to prove that multiple price list is an optimal method to elicit the risk and ambiguity attitudes of decision makers because of its simplicity and capacity of generating good data for the estimations of the model. Moreover, they wanted to show that the estimates obtained using multiple price list are the same for both experiments with real and hypothetical incentives. They asked the subjects to make decisions over two different multiple price list. For the first one they used the same multiple price list used by Holt and Laury (2002), that we reported in Table 2.4, to estimate the risk attitudes of the subjects.

As can be seen from the table, decision makers have to face ten pairs of lotteries in which the payoffs are constant in all ten cases, but the probability of obtaining the highest value of each gamble increases moving from top to bottom of the table. Instead, to estimate ambiguity aversion, they used a second multiple price list always made of ten pairs, but in this case one column is composed by lotteries with known probabilities while in the other column the probabilities are not known: moreover, the payoffs of the column with known probabilities are constant while the ones in the column with unknown probabilities increases moving from top to bottom of the table. Let's now see what are the information that subjects had about the gamble in the second multiple price list.

> Participants were presented with two urns. Urn A contained 50 red balls and 50 black balls; Urn B contained 100 red and black balls, but the distribution of colors was not known. They were asked to choose a color, red or black, which would act as their success color, and then make a series of 20 decisions between drawing a ball from Urn A or Urn B. If the color of the ball drawn from the chosen urn matched their success color, then they would win the prize corresponding to that decision. If the drawn color did not, then they would win nothing. (Gneezy, Imas and List, 2015, p.5)

As you can see, the format is the same as the "two-color" problem proposed by Ellsberg, that we have analyzed in section 2.4 of this chapter. The payoffs of this multiple price list were determined so that a subject should prefer to start drawing from Urn A instead of Urn B.[15] Then, he should decide to switch toward Urn B at some point, before the last choice: such point, known as switching point, characterizes the ambiguity attitude of the subject.

Assuming that an individual prefers the urn A in the first decision, we can define his degree of aversion to ambiguity based on his own switching point: if he prefers

[15]There could still be individuals that prefer to start drawing from Urn B instead of Urn A. This is the case of ambiguity lover individuals or individuals that have extremely positive priors about the distribution of the balls.

to pass from the urn A to the urn B in one of the last decisions implies that it is very ambiguity averse, while a switching point in the first decisions indicates a low degree of aversion to ambiguity.

An important thing to say about the experiment is that it is designed such that the subjects are allowed to switch from Urn A to Urn B just one time. For example, an individual cannot decide to start drawing from Urn A, switching toward Urn B at some point in the middle and then switch back to Urn A before the last decision: "allowing individuals to switch freely between the options for each decision row has been shown to produce a significant number of inconsistent decisions, where participants switch more than once." (Gneezy, Imas and List, 2015, p.6)

Using the data collected from the subjects the authors estimated the coefficients α_i and r_i , that we remember to be respectively the ambiguity attitude and the risk aversion of individual i. Then, assuming von Neumann-Morgenstern utility with constant relative risk aversion they came up with the following specification:

$$V_i(x;\alpha,r) = \alpha_i \frac{x_{max}^{1-r_i}}{1-r_i} + (1-\alpha_i)\frac{x_{max}^{1-r_i}}{1-r_i} \tag{2.9}$$

where x_{min} and x_{max} represents respectively the smallest and the highest payoff of the pairs of gambles.

The results obtained from the data "suggested substantial risk aversion in the population" and that the subjects of the experiment showed "a significant amount of ambiguity aversion." (Gneezy, Imas and List, 2015, p.8)

Moreover, is interesting the fact that the estimates of α were smaller when risk and ambiguity attitudes were estimated jointly and were higher when estimated assuming risk neutrality. Finally, another interesting result is that the estimates of the experiment with hypothetical incentives are no different from the ones obtained with real incentives. This could depend on the low size of the stakes, since in the experiment of Holt and Laury (2002) it is shown that when there are large monetary stakes the estimates of risk aversion increase.

To conclude, Gneezy, Imas and List proved with their results that the double multiple price list is an optimal instrument that can be used to elicit ambiguity attitudes thanks to its simplicity and the capacity of generating data.

2.9 Conclusions

During the second chapter we provided a detailed analysis on the phenomenon of ambiguity. We started from Ellsberg's experiments, in which he demonstrated the presence of this factor within the decisions of individuals, to be able to affirm that most individuals prefer to avoid, when they have the possibility, situations in which they do not have information on the frequency of events: it can therefore be concluded that these are to some extent adverse to ambiguity. Finally, we analyzed some of the most recent studies and models in this regard, especially that conducted by Gneezy, Imas and List in 2015 to understand the approaches that have been used in this field to study ambiguity and to formulate decision models able to describe accurately the behavior of individuals in the presence of ambiguity.

Those highlighted in the chapter are very important results for the sector, and have allowed further developments regarding the modelling of decision-based behavior. Furthermore, this advancement has allowed the creation and development of new tools and techniques to obtain more reliable data and in a simpler way by the subjects during the experiments. An example that we reported in the chapter is precisely that of multiple price lists, thanks to which it is possible to obtain good quality data with relative simplicity. Or again, the new types of utility functions, such as the α-MEU model with fixed priors (Ghirardato et al., 2004), thanks to which it is possible to estimate the parameters more precisely.

Chapter 3

As seen, we focused the analysis of the second chapter on the ambiguity and the effects it has on the decisions of individuals. We have also observed the tools we have available to study and model these behaviors. In this third chapter we will take a step forward, analyzing models in which there are multiple sources of ambiguity so as to be able to verify the effects on decision makers and compare the results with those obtained in the case of a single source of ambiguity. This comparison is very important in our analysis because from the results obtained it is possible to obtain more refined and precise models of uncertainty, as this phenomenon is very complex and very rarely we are faced with choices in which the source of ambiguity is unique.

In addition to concluding our analysis of uncertainty in decisions, we will study another very interesting and relatively recent phenomenon, namely myopia in the choices of individuals. This myopia is understood as the poor ability to predict the subjects, who cannot accurately predict the effects that will occur in the future caused by a choice in the present. Specifically, it appears that most of the subjects underestimate these effects because of their erroneous forecasts and this can lead to undesirable as well as unexpected effects. A classic example of myopia is one in which a driver driving his car sees a hole in the distance but, estimating to be small, decides not to change the trajectory of the vehicle. However, as he gets closer and closer, he notices that his predictions were not exact and that the hole is larger than expected, unfortunately it is too late to avoid it and this causes damage to the vehicle. As we can see from this example, the driver's decision not to steer in time did not depend on uncertainty but on his poor ability to forecast. Finally we will analyze some methods that can be used to counter myopic choices and we will observe the effects of these methods on the subjects through experiments made on the subject.

3.1 Multiple source of ambiguity

In Section 2.4 we have presented some situations in which Savage's rationality axioms cannot be applied to infer the preferences of individuals. The explanation provided by Ellsberg for these situations is the presence of ambiguity within the information held by the subjects and the fact that the latter show a certain degree of aversion to ambiguity. In fact, as evidenced in the "two-color" experiment, the subjects who preferred to bet on the urn with 50 red balls and 50 black balls, were classified as ambiguity averse.

As we have seen, this experiment reflects a very simplistic situation in which there is only one source of ambiguity within the decision. In reality the sources of ambiguity can be numerous and can cover many aspects: in Ellsberg's experiment the only source of ambiguity concerned the content of Urn B and therefore the information on the probability distribution of the red and black balls. Now, our goal is to verify the behavior of the subjects in the event that a further source of ambiguity is inserted. To do this we will rely on the work published in 2015 by Eichberger, Oechssler and Schnedler. They used the "two-color" experiment as a basis and added a second source of ambiguity on the payoffs to verify the possible effects on the behaviors and decisions of individuals. In addition to extending Ellsberg's experiment, they have also considered three different situations concerning the new source of ambiguity, so as to be able to compare the results obtained in each situation. Let's look at the specifics now.

> Subjects decide on an urn (H or U) and a color (black or red). If their color matches that of the ball drawn from the respective urn, subjects receive an envelope that is marked with an equal sign (=). If not, they receive a (different) envelope that is marked with an unequal sign (≠).

> We consider three situations. In situation O (for open envelope), subjects see the content of the envelopes. There are 3 euro in the envelope with = sign and 1 euro in the other envelope. [...] In situation S (for sealed envelope), subjects only know that one of the two envelopes contains 3 euro and the other 1 euro but they do not know which amount is in which envelope. In situation R (for random), subjects know that the content of envelope (3 euro or 1 euro, respectively) will be determined by flipping a fair coin after they have made their choice on which urn to bet. (Eichberger, Oechssler and Schnedler, 2015, p. 340)

Let's analyze the three situations separately. First, we can see that the situation O corresponds exactly to the Ellsberg experiment, as the subjects are aware of the contents of the two envelopes, so even in this case ambiguity averse individuals should prefer to bet on the urn containing the 50 red balls and black. The reason why a scenario has been inserted practically identical to that proposed by Ellsberg is that of obtaining data that can be used as a benchmark to be able to compare them with the data obtained from the other two scenarios. In fact, during the course of this experiment, participants were asked to make decisions in each of the three situations, in order to obtain a "within" subject treatment. Specifically, some of the subjects dealt with "OS-treatment", where they were asked to make decisions first in scenario O and then in scenario S, while the other part performed the "SO-treatment" in which the order of the scenarios is reversed. At the end of both treatments, scenario R was presented to each participant.

As for situation R, we expect the subjects to be indifferent about which urn and which color to choose due to the fact that the contents of the two envelopes will be randomly decided by the toss of a coin: this means that the decisions taken on color and on the urn are irrelevant since the subjects will still have a 50% chance of winning the larger sum and 50% of winning the smaller sum, whatever decision they make. The fact that individuals should be indifferent is also supported by studies performed in earlier jobs. Eichberger, Grant and Kelsey (2007) argued that ambiguity can be derived from uncertainty about missing information on the probability distributions of some events, but "once an event is known to have obtained, the only remaining ambiguity the individual faces relates to uncertainty about the probabilities of subevents of that event. [. . .] past (or borne) uncertainty one may have had about the probability of counterfactual event and its subsets are no longer relevant".[1]

Finally in situation S we could expect the subjects to be indifferent as in situation R: since they are not aware of which of the two rewards is in which envelope, they should not be interested in getting the envelope $=$ rather than the envelope $\neq$, or vice versa. This means that, whatever the outcome of the draw (ie that the subject guesses the color of the ball or not), he cannot know which of the two rewards he will receive until the envelope is opened, so he should not even be interested in which of the two urns bet.[2]

Finally, we need to compare the results of the O and S scenarios to see if the additional source of ambiguity changes the decisions of individuals with respect to the situation with a single source of ambiguity. Eichberger, Oechssler and Schnedler decided to use the Maxmin Expected Utility approach with multiple priors (Gilboa and Schmeidler, 1989) to represent ambiguity aversion.

Now that we have analyzed the 3 scenarios and defined our expectations on the behavior of the subjects, we move on to analyze the results obtained, in order to verify whether the ambiguity averse individuals will continue to prefer the urn with known distribution of balls (Urn H) even in the case of a second source of ambiguity, that is the case in which the content of the envelopes is uncertain.

After analyzing the results, it was found that the latter did not completely reflect the considered expectations. As for situation O, about 2/3 of the subjects proved to be ambiguity averse, ie they preferred to bet on the urn H: this is a fairly common result in this type of experiment. But in situation S things are different. Specifically, the results showed that the share of ambiguity averse subjects decreased significantly

[1] Jürgen Eichberger, Simon Grant and David Kelsey, *Updating Choquet beliefs*, 2007, Journal of Mathematical Economics (43), p. 890.

[2] The authors imagined that, when taking decision in situation S, an individual may think: "Given that I have no way of knowing what I win if I win, I should not care whether I win."

compared to the situation O. This seems to mean that the ambiguity related to the content of the envelopes somehow manages to "obscure" the ambiguity relative to the choice of the urn, leading the decision makers to be on the whole less ambiguity averse. Even in situation R, the forecasts have not been confirmed: only a small number of participants declared to be indifferent in the choice of the urn, while most preferred to bet on the urn H, thus showing a certain degree of ambiguity aversion in this case. We can observe more in detail the results obtained from the experiment in Table 3.1.

Table 3.1: Percentage of subjects choosing the urns in the different situations.

	Urn choices in %		
	Urn *H*	Urn *U*	Indifferent
Treatment "within"			
Situation *O*	62.5	22.9	14.6
Situation *S*	39.6	35.4	25.0
Situation *R*	52.1	25.0	22.9
Treatment "between"			
Situation *O*	62.5	33.3	4.2
Situation *S*	45.5	45.5	9.1
Situation *R*	48.0	36.0	16.0

Source: Jürgen Eichberger, Jörg Oechssler and Wendelin Schnedler, How do subjects view multiple sources of ambiguity?, 2015, Theory and Decision (78), p. 350.

The table represents in percentage the preferences of choice of the subjects on the two urns in the two treatments. Recall that in the "within" subjects treatment, individuals were subjected to all three situations: specifically, they were asked to make decisions first in the OS-treatment (or in SO-treatment) and then in scenario R. In the treatment "between "subject each subject has had to make decisions in only one of three situations. Looking specifically at the "within" subjects treatment data it is possible to note that the percentage of subjects who preferred to bet on the urn H is very high and corresponds to 62.5%. Then, "in line with the customary notion, we classify subjects as ambiguity averse if they choose to bet on urn H rather than on urn U in this situation." (Eichberger, Oechssler and Schnedler, 2015, p. 347)

The situation changes substantially when we look at the data of situation S. Unlike the expectations, we can see how the percentage of subjects who preferred to bet on the urn h decreased considerably, reaching 39.6%, while the percentages of subjects who have bet on the urn U and of the subjects that have declared to be indifferent they are increased regarding situation O.

As we have already said, these results go against the expectations of the authors. They assumed that the preferences of the individuals are represented by the Maxmin Expected Utility model with multiple priors (Gilboa and Schmeidler, 1989), such that the expected utility of a bet f perceived by a decision maker has the form:

$$MEU(f) = \min_{\pi \in P} \sum_{s \in S} \pi_s u(f(s)) \tag{3.1}$$

where P is a set of priors obtained by the product measure of the probability distributions over states. Moreover, they assumed that "an MEU-maximizer has non-degenerate set of priors in each dimension for which no objective probabilities are known" (Eichberger, Oechssler and Schnedler, 2015, p. 346), so that the following conditions holds on the set of priors:

$$Q \cap [0, \frac{1}{2}) \neq 0 \quad and \quad Q \cap (\frac{1}{2}, 1] \neq 0 \tag{3.2}$$

where Q is the set of priors for the probability that a black ball is drawn from urn U. Finally, they used as a benchmark an hypothetical subject which preference is described by a Subjective Expected Utility with a unique prior. These preferences can be represented using the following equation:

$$SEU(f) = \sum_{s \in S} \pi_s u(f(s)) \tag{3.3}$$

Using these hypotheses, they mathematically proved that, in situation S, the decision makers whose preferences were represented by equation 3.1 and that respected condition 3.2 strictly prefer to bet on urn H, unlike the SEU-maximizers subjects, which weakly prefer to bet on urn U. Therefore, Eichberger, Oechssler and

Schnedler (2015) have stated that subjects who are classified as ambiguity averse because they choose H in situation O will also choose H in situation S. Anyway, the results were completely different from the expectation, as we have seen from Table 3.1.

Finally, in situation R was expected that most of the subjects would be indifferent regarding the choice of the urn: this is valid both for the MEU and MEU subjects. But looking at the results in the table we see that they do not correspond to expectations. The percentage of subjects who declared to be indifferent turned out to be 22.3% while those who preferred the urn H and the urn U were 52.1% and 25.0% respectively. If we compare these results to those obtained in situation O we can see that the differences are not many, the percentage of indifferent subjects has increased relatively little compared to expectations.

Considering therefore the contrasts obtained between expectations and the data obtained, the authors have summarized the results of their work by stating that "significantly fewer subjects have a strict preference for urn H in situation S than in situation O" and that "the preferences for H in situations O and R are not significantly different." (Eichberger, Oechssler and Schnedler, 2015, p. 352)

From these results we can therefore assume that, with multiple source of ambiguity, the decisions of subjects are different from what predicted by function like the Maxmin Expected Utility with multiple priors or the Subjective Expected Utility with unique prior. This may depend on the assumptions that have been made on the set of priors, since to build such a set it was assumed that the decision makers considered the events of the various phases of the experiment independent of each other.[3] However, we cannot exclude that the subjects consider such events to be dependent on each other. If this is the case it would be necessary to further investigate the concept of independence in the event that ambiguity is present. Another possible solution is to represent the preferences of the subjects in a different way,

[3]This is a reasonable assumption since, from the point of view of an external observer, it is quite obvious that the extraction of a red ball from the urn H or U is an event independent of the extraction of a black ball from the same urn, as well as the content of the envelopes is independent of the color of the ball extracted from any urn.

thus using other utility functions.

3.2 Multiple vs single source of uncertainty

In the previous analysis we observed that the subjects make different decisions when facing choices in which there are multiple sources of ambiguity with respect to the choices in which there is a single source. Furthermore, we have been able to verify that the utility functions that seem to succeed in describing the behavior of individuals in the case of a single source of ambiguity, fail when these sources increase in number.

To better understand what happens in the decision-making process of the subjects when we pass from one to more ambiguous sources, we should therefore consider and analyze situations in which the sources of uncertainty do not exclusively concern the probabilities of the events, as in the models we have analyzed so far, but also concerning other dimensions. Some possible dimensions in which uncertainty may arise are the amount of rewards for decision makers or the date of payment, ie the time frame between the winning of a sum and the actual delivery of the latter.

Therefore, based on the experiment made by Ellsberg, it is possible to insert in this case more sources of uncertainty, such as those just described, in order to study the behavior and decisions of decision makers having as benchmark the results obtained in the models previously analyzed in our work. To this end, we will also observe the results obtained by Eliaz and Ortoleva (2016), who proposed an experiment of this kind aimed at studying the behavior of individuals on the basis of different and multiple sources of ambiguity.

Considering these additional sources, our job will be to understand how individuals perceive these dimensions of uncertainty: if they are therefore ambiguity averse not only in the case where the probabilities are not known, but also when the winnings or the payment date they are uncertain.[4]

Furthermore, we will also need to check if the correlations between the various

[4]Moreover, we should investigate if the fact that an individual is ambiguity averse toward one dimension leads him to be ambiguity averse even in other dimensions.

sources of uncertainty affect the decisions and how they do it. To make the concept clearer, let us suppose that a decision maker can decide whether to remove or maintain uncertainty about probabilities, as in the Ellsberg experiment in which subjects can decide whether to bet on the urn with the known composition of balls by removing the uncertainty or not. In this case we should understand how the other sources of uncertainty influence the decision on the possibility of removing the uncertainty relating to the probabilities.

Finally, we will have to verify the preferences of the subjects towards situations in which there are more sources of ambiguity, in order to understand if decision makers continue to be ambiguity adverse even in such situations or if they prefer to make decisions in presence of multiple sources with respect to a unique source.

As already mentioned, to investigate these behaviors we will base on the work of 2016 by Eliaz and Ortoleva, specifically on the variations proposed by them to the classic Ellsberg experiment. Their idea is to insert sources of uncertainty on various dimensions in order to observe how the subjects compare themselves with the different situations proposed. They considered an urn containing 60 poker chips and informed the subjects that 20 of those chips are black while the remaining 40 can be both red and green, but the proportion between the two colors is unknown. Finally, after that the subjects decided on which color to bet, a chip will be randomly extracted from the urn. Let's now observe the variations introduced.

> In one variation, a participant is paid only if a black chip is drawn, but he is paid a number of dollars equal to the number of chips in the urn of his chosen color: if X is the number of chips in the urn that have the color chosen by the participant, he wins $X if a black chip is drawn. In this case the prob-ability of winning is not uncertain, because the lottery is paid only if a black chip is drawn, but the amount won is. In another variation, the participant is again asked to choose a color, and is paid if a chip of that color is extracted, a number of dollars equal to the number of chips of that color in the urn. In this variation, there is a sense in which the uncertainty is on "two dimensions": not only the

likelihood of winning, but also the amount won. In yet another variation, if the participant guesses correctly, he wins $X, but is paid X days from the date of the experiment. Here we have added uncertainty on a "third dimension": how soon the prize is paid.[5]

Considering these variations we can analyze the behavior of the subjects in the different treatments proposed and then compare the results. In this way we will try to understand how decision makers are influenced by multiple sources of ambiguity and if there is a decisional pattern for these situations.

Analyzing the data obtained in the experiments, the first thing that emerges is that most of the subjects prove to be averse to uncertainty if there is only one source of ambiguity. Again, an individual is labeled as ambiguity averse if he prefers to bet on the option that has the most objective information. Furthermore, this aversion to uncertainty concerns all three dimensions (probability, prize and date of payment) even if the proportion of adverse subjects is different for each dimension. These data are in line with the results obtained by Ellsberg and other researchers in presence of a single source of ambiguity.

Further analyzing this data, it is possible to distinguish four groups of individuals according to their preferences: the first group is formed by subjects that are not averse to uncertainty in any dimension; then there is the group of individuals who show aversion to uncertainty solely on the prizes; the third is the group of subjects adverse to uncertainty about prices and probabilities; finally, the last group includes the individuals who are adverse to all the ambiguities considered and is made up of 52% of the interviewed subjects. We can therefore affirm that the larger set is the one that contains the decision makers averse to having uncertainty about prices, while the group of the subjects who are uncertainty averse about probabilities can be considered a subset of the previous one, as well as the group of individuals uncertainty averse about the payment date is a subset of both the previous ones.

[5]Kfir Eliaz and Pietro Ortoleva, Multidimensional Ellsberg, 2016, Management Science (62), pp. 2179-2180.

The second important result that emerges from the analysis concerns the separability of the dimensions of uncertainty. One of our goals was to verify how the presence of a fixed source of ambiguity influenced the choices of subjects in the other dimensions of ambiguity: analyzing the data obtained from Eliaz and Ortoleva it is possible to obtain an answer to this question. They compared the data of two slightly different treatments to see if the subjects maintained their choices or not. Thus, they used as benchmark their replica of the Ellsberg experiment in which individuals must choose which color to bet on to win the fixed prize of $20 and compared it to the same situation with the only difference that the prize won in this case is equivalent to the number of red chips in the urn, that is uncertain.[6]

Recall that in the Ellsberg experiment in which subjects can choose whether to face uncertainty or avoid it by choosing the option with defined probabilities, the majority of individuals preferred the latter. However, by inserting a new dimension of uncertainty with a fixed value, as just explained, it significantly changes the behavior of the subjects. In fact, in this case the subjects no longer prefer to avoid the first source of uncertainty by choosing the option with known probabilities, but instead tend to choose the option for which both uncertainties are perfectly correlated, thus preferring the gamble with the most exposure to the uncertain variable.[7]

Preferring options in which the sources of uncertainty are perfectly correlated means that the subjects prefer to increase their exposure to uncertainty rather than reduce it. If in fact they wanted to hedge and reduce the exposure, probably the subjects would have preferred to bet on the green color in the second scenario because of the present uncertainty on the number of red chips and therefore on the

[6]To represent the gambles in numerical way the authors used a triplet $(p, \$m, t)$ the gamble that pays $m in t days with probability p, and $0 otherwise. Using this description we can represent the two treatments as the sets that contain the following gambles: S(1)={(20/60,$20,0); (r/60,$20,0); (g/60,$20,0)} and S(2)={(20/60,$r,0); (r/60,$r,0); (g/60,$r,0)} where r and g are respectively the numbers of red and green chips inside the urn . (Eliaz and Ortoleva , 2016)

[7]For an individual, preferring the gamble with most exposure means, "when the date is known, [...] choosing a gamble where the prize and probability both depend positively on the same color; by contrast, when the date is uncertain, choosing the option for which the date depends on a different color than the prize or the winning probability." (Eliaz and Ortoleva, 2016)

amount of the prize: with this strategy an individual could win a small prize but with a high probability if there are a few red chips or a large prize but with a low probability if there are many red chips. However, since the results show a propensity to an increase in exposure, we can say that in this case the subjects prefer to bet on the red color in the second scenario, in order to have a high probability of winning a large prize in case there are many red chips in the urn, or have a low probability of winning a small sum if there are few red chips.

Eliaz and Ortoleva (2016) have summarized this result in the following observation: "Compared to a choice problem that includes a gamble with no uncertainty (and where two of the three dimensions are fixed and certain), making one of the dimensions uncertain (but fixed) leads to a significant change in behavior, most of which is in direction of more exposure." (Eliaz and Ortoleva, 2016, p. 2188)

Looking at the data, we can see that, in the situation with fixed price of \$20 and no delay in payment, 76% of decision makers decided to bet on black and only 11% bet on red. But when the prize changes into \$$r$ only 28% of the subjects continued to bet on black, preferring the gamble with the least uncertainty, while all the others switch to bet on red, confirming the fact that they prefer more exposure.

Up to this point we have analyzed the behavior of the subjects, first in the case in which they had to choose between a gamble without uncertainty and one with a single source of uncertainty, and then in the case in which the choice was between a gamble with a single dimension of uncertainty and one having more dimensions of uncertainty. To conclude the analysis we will now examine the behavior of the decision makers in the event that they face a choice between a gamble without uncertainty and one with multiple sources of uncertainty, so as to have analyzed all the possible cases.

From the results obtained in the experiments, Eliaz and Ortoleva (2016) stated that comparing options with uncertainty in multiple dimensions against options with no uncertainty, the majority of participants prefer the option with no uncertainty. However, compared to the previous situations, it is interesting to note that the percentage of decision makers who prefer the gamble with no uncertainty instead of the one with multiple dimension of uncertainty, is smaller than the percentage of the ones that prefer no uncertainty instead of uncertainty in a single dimension.

Comparing the three principal results that emerge from the experiment it is possible to define the type of approach that the subjects seem to use when facing decisions in the presence of multiple sources of ambiguity.

> Our findings suggest that individuals tend to exhibit one particular pattern of behavior: aversion to single-dimensional uncertainty, (milder) aversion to multidimensional uncertainty, and a preference for multidimensional uncertainty over single-dimensional uncertainty. Put differently, when subjects have the option to remove all uncertainty, the majority opt for that option. When uncertainty cannot be completely removed, the majority of subjects prefer perfectly correlated uncertainty on several dimensions to having only one uncertain dimension. (Eliaz and Ortoleva, 2016, p. 2181)

After analyzing the behaviors and preferences of the subjects in the experiments, our goal is to verify whether these decision patterns are compatible with the predictions of the ambiguity aversion models. We will focus especially on the Maxmin Expected Utility model by Gilboa e Schmeidler (1989) as it is one of the best models in the analysis of uncertainty decisions, as we have seen in the previous chapter of this paper. Let us remember that the MEU model presupposes that individuals have a set containing multiple priors, a function of subjective utility to evaluate the attractiveness of the various outcomes and that the value of a gamble is equal to the expected minimum utility of that gamble, that is given by the minimum value of all the priors in the set.

We provide a representation of the value V of the gamble $h(x) = (p(x), m(x), 0)$ considered during the treatment with uncertain dimension in probability and prize, with $x \in [r, g]$ and where Π represent the set of priors.

$$V(h(x)) = \min_{\pi \in \Pi} \sum_{x=0}^{40} \pi(x) \cdot p(x) \cdot u(m(x)) \tag{3.4}$$

In this situation, the only restrictions that must be imposed on the set of priors concern the probabilities of the various colors: in fact, any prior contained in the set must assign a probability of 20/60 to the extraction of a black chip. However, considering that using MEU the evaluation of each gamble is given by the product of its expected utility and the most pessimistic prior belonging to the set Π, the authors noted that, if no other restrictions are applied to the set of priors Π, the gambles with double positively correlated uncertainty are the ones with the highest value. Thus, following the prediction of MEU, individuals should always prefer double positively correlated uncertainty in prize and probability over any other type of uncertainty, and even over the situation with no uncertainty. But this is not supported by the data that emerged from the experiment as over 65% of decision makers preferred to bet in situations with no uncertainty instead of situations with double positively correlated uncertainty.

Eliaz and Ortoleva (2016) proposed an explanation to the fact that the predictions of the MEU model were inconsistent with the data of the experiments, explaining that in evaluating an option, two opposing forces come into play. The first concerns the aversion to ambiguity, which leads subjects to prefer options that contain the most objective information. The second one concerns the pessimism of the subjects' priors about the expected value and the variance of the option: in this case, the variance of such priors should be relatively high because the subjects know that they are pessimistic in their evaluations and they also know that they could make a mistake by acting in this way.[8] To better explain the concept:

> Although subjects can act as if they are pessimistic about the number of red or green balls—they have a prior with a low expected value—they cannot act as if they are sure about this pessimistic valuation: they should incorporate in this prior the awareness that they are being pes-

[8]Knowing this, we can guess that the MEU model assigns high values to the options with double positively correlated uncertainty since the high variance leads to a high expected utility even with pessimistic priorities. So, if the variance is high enough, these options are attractive precisely because in the MEU the utility and the probability are multiplied by each other.

simistic, and hence incorporate some variance in the priors. In particular, they cannot incorporate beliefs that put support only in the "pessimistic" side. On the other hand, for how much variance they incorporate, their pessimism must still be strong enough to lead them to prefer no uncertainty to double uncertainty, which takes place only if the variance is not too high; that is, even if they do recognize that incorporating some variance could improve the valuation of some options, they are still not ready, to prefer them to the options with no uncertainty. We refer to this behavior as *skeptical pessimism*. (Eliaz and Ortoleva, 2106, p. 2195)

To conclude this analysis, we can summarize the results obtained from the experiments below. First we have verified that most subjects prefer situations with no uncertainty with respect to any other type of situation with uncertainty, whether uncertainty comes from a single source or whether the sources are multiple: this is valid for the dimension of uncertainty too, as we have seen for the three different cases of uncertainty in prize, probability and date of payment. Secondly, we observed that subjects prefer positively correlated uncertainty on multiple dimension to uncertainty on any single dimension. Lastly, we showed that the MEU model with the set of pessimistic priors is unable to predict the behavior of individuals in multiple uncertainty framework. This is probably due the fact that individuals exhibit what is called *skeptical pessimism*: a possible solution to this problem is to impose further restriction on the set of priors and to include priors that are not only pessimistic and that satisfy some condition on variance.

3.3 Myopia or Imperfect Foresight

At this point, we have shown in our analysis how uncertainty is an extremely important factor to be taken into consideration when studying the choices and behaviors of subjects during decision-making processes. With the help of some models, we were able to understand how individuals consider the sources of uncertainty and how they relate to them. The most common observed behavior is the aversion to uncertainty: in all the models and experiments analyzed, the majority of subjects preferred to choose options and bets in which the information was the most objective possible. Furthermore, we have seen how many authors have tried to model this decision pattern. In our work we focused mainly on the MEU model of Gilboa and Schmeidler (1989) that in situations of uncertainty behaves well in describing the decisions of the subjects, above all thanks to the presence of the set composed of the multiple priors that are born precisely because of uncertainty.

Now, the results we have shown in the field of uncertainty will be useful for us to proceed with our analysis. Our goal for the rest of the chapter will be to analyze another very relevant phenomenon in the field of decision theory. We are referring to the so-called "myopia" or *imperfect foresight*. Myopia has been considered one of the main justifications for the fact that individuals prefer immediate rewards than those postponed, in the field of intertemporal preferences. Specifically, we assume that our preference for early rewards is caused by our myopia, that is, by the fact that our intellect is not able to perfectly predict the future consequences of an action or a decision. Failing to accurately predict the consequences that occur in a more or less distant future, individuals are more likely to rely on immediate consequences that are easily predictable and almost certain. As for uncertainty aversion, the imperfect information that we find in this type of choice influences the subjects, leading them to prefer rewards that are purely certain in the immediate respect to those less certain that will occur in the future.[9]

The same Böhm-Bawerk (1890), which we mentioned in paragraph 1.1, argued that "we possess inadequate power to imagine and to abstract, or that we are not willing to put forth the necessary effort, but in any event we limn a more or less incomplete picture of our future wants and especially of the remotely distant ones."

An important aspect of myopia, on which research and experiments are still carried out, is the fact that this can appear simply as impatience in the eyes of an

[9] In this case, the imperfect information comes from the imperfect ability to predict the future of the subject which prevents them from getting a correct estimate of future values. Instead, in case of uncertainty aversion, imperfect information is due to the lack of objective information on or more aspects of the problem.

external observer: ”if delayed consequences are typically harder to foresee than immediate consequences, then decision makers will appear to be impatient.” (Gabaix and Laibson, 2017, p. 3)

In these situations, it is therefore very difficult to distinguish between behaviors that derive from imperfect foresight and those deriving from time preference. In fact, in both cases the subjects prefer a smaller sooner reward to a larger later reward, but while for the time preference this happens because the subjects discount the future rewards at a high rate compared to the immediate ones, in the case of imperfect foresight the reason is that subjects underestimate future rewards because of their limited ability to make long-term predictions. Gabaix and Laibson (2017) called this seemingly impatient behavior *as-if discounting*, and showed in their work that such behavior has the same characteristics of the behavior arising from deep time preference.

In the next section we will examine the model on myopia proposed by Gabaix and Laibson in 2017. This model is very interesting for the purposes of our analysis because, in addition to demonstrating that the behaviors arising from the imperfect foresight almost perfectly replicate those arising from time preferences, provides a method to distinguish between myopic behavior and intertemporal preferences.

3.4 Myopia and Time Preferences

To support their claims, Gabaix and Laibson (2017) proposed a simple approach: they considered a decision maker who at zero time had to decide between two mutually exclusive options. The first, called *Early*, can be obtained at time $t > 0$ while the second, called *Late*, will be available at time $t + \tau$, where $\tau > 0$. The value of both rewards is not known by the decision maker, for this we will indicate with u_t the true value of Early and with $u_{(t+\tau)}$ the true value of Late. Furthermore, it is assumed that the decision maker is perfectly patient in order to exclude intertemporal preferences from the analysis.[10]

[10]Perfectly patient means that the decision maker evaluates equally two rewards that have the same amount but different date of payment. Specifically, the discount factor of such individual is

In this framework, we assume that the decision maker makes estimates about the values of Early and Late rewards, since he does not know the true value of them. In this way he generates *noisy*, *unbiased signals* which are then combined with his priors to form posteriors. The signals about the values of the rewards can be represented as $s_t = u_t + \varepsilon_t$ for the Early reward and $s_{t+\tau} = u_{t+\tau} + \varepsilon_{t+\tau}$ for the Late reward: ε_t and $\varepsilon_{t+\tau}$ are simulation noises associated with the rewards and it is assumed that there is no correlation between them. Moreover, let's consider an assumption about the variance of the simulation noises: in this case we suppose that the variance will increase as the time horizon increases. This is a fairly realistic assumption as short-term forecasts of events are usually more accurate than long-term forecasts.

Observing the time horizons t and $t + \tau$, taken into consideration in the model, we can state that

$$var(\varepsilon_t) < var(\varepsilon_{t+\tau}) \tag{3.5}$$

and that

$$\lim_{t\to\infty} var(\varepsilon_t) = \infty \tag{3.6}$$

Finally, Gabaix and Laibson (2017) assumed linearity of the variance, meaning that the variance of the simulation noise increases proportionally to the time horizon, and can be represented in the form:

$$var(\varepsilon_t) = \sigma^2_{\varepsilon_t} = t \cdot \sigma^2_{\varepsilon} \tag{3.7}$$

$$var(\varepsilon_{t+\tau}) = \sigma^2_{\varepsilon_{t+\tau}} = (t + \tau) \cdot \sigma^2_{\varepsilon} \tag{3.8}$$

As specified before, the authors assumed that the decision makers combine their mental simulation with the Bayesian priors over utility events: in this way, Bayesian posteriors are generated.[11] Gabaix and Laibson (2017) provided a mathematical

$\rho = 1$ such that: $u(x_t) = \rho \cdot u(x_{t+\tau})$

[11]In this case, it is assumed that Bayesian priors take the form of a normal distribution $u \sim N(\mu, \sigma^2_u)$, with mean μ and variance σ^2_u.

representation of the Bayesian posteriors obtained combining Bayesian priors and the mental simulation of the subjects, that is $u_t \sim N(\mu + D(t)(s_t - \mu), (1 - D(t))\sigma_u^2)$, with:

$$D(t) = \frac{1}{1 + \frac{\sigma_{\varepsilon_t}^2}{\sigma_u^2}} \tag{3.9}$$

The authors defined $D(t)$ the agent's as-if discount function, where $\sigma_{\varepsilon_t}^2$ is the variance of the simulation noise of a decision maker and σ_u^2 is the overall variance. We can notice that equation 3.9 is decreasing in t because of the assumption that the simulation noise's variance $\sigma_{\varepsilon_t}^2$ is increasing in t. Finally, it was assumed that the signals s_t are unbiased, meaning that on average they converge to u_t.

Let's now focus on the assumption of linearity that implies that the variance of the simulation noise increases proportionally to the simulation horizon, as specified before. The reason of this choice is that it produces *hyperbolic as-if discounting*, meaning that the resulting behavior of subjects can be misinterpret as impatience arising from time preference although we have assumed that decision makers are perfectly patient. Recalling the properties of hyperbolic discounting that we have analyzed in paragraph 1.9 and considering the linearity assumption it is possible to express the agent's as-if discount function as

$$D(t) = \frac{1}{1 + \alpha t} \tag{3.10}$$

where

$$\alpha = \frac{\sigma_\varepsilon^2}{\sigma_u^2} \tag{3.11}$$

is the one-period noise-to-signal variance ratio.

From equation 3.10 we can obtain the instantaneous discount rate, that is $\alpha/(1 + \alpha t)$. From the instantaneous discount rate, we can note that at initial time $t = 0$ the discount rate is α, while as $t \to \infty$ discount rate approaches 0.

3.5 Effects of myopia on the choices of agents

After analyzing the model's assumptions and determining the agent's as-if discount function, let's look at the predictions of the model on the choices of the subjects.

In this framework, the choices of the decision makers will be influenced by the noisy unbiased signals and by the as-if discount function, leading them to prefer a reward over the other based on the highest value. Then, we can say that an individual will choose Early reward if and only if

$$D(t)s_t \geq D(t+\tau)s_{t+\tau} \tag{3.12}$$

Rearranging the terms knowing that $s_t = u_t + \varepsilon_t$ and $s_{t+\tau} = u_{t+\tau} + \varepsilon_{t+\tau}$, as specified in the assumptions, it is possible to express the probability that a subject chooses Early reward as

$$P[Early] = P[D(t)(u_t + \varepsilon_t) \geq D(t+\tau)(u_{t+\tau} + \varepsilon_{t+\tau})] \tag{3.13}$$

Then, if we consider the case in which $t = 0$, meaning that the Early reward is immediately obtainable, equation 3.13 becomes

$$P[Early] = P[u_0 \geq D(\tau)(u_\tau + \varepsilon_\tau)] \tag{3.14}$$

In this case, if it is assumed $\tau \to \infty$, which means that Late reward will be delivered in a very distant future compared to Early reward, we have that

$$\lim_{\tau \to \infty} P(Early) = 1_{u_0 > 0} \tag{3.15}$$

"This implies that the agent chooses the Early reward with probability one if three properties hold: (i) the Early reward is available immediately ($t = 0$), (ii) the Late reward is available arbitrarily far in the future ($\tau \to \infty$), and (iii) the Early reward is strictly positive ($u_0 > 0$). In other words, the agent behaves as if she places no value on the (infinitely) delayed Late reward." (Gabaix and Laibson, 2017, p. 12)

Now consider $t > 0$, which means that the Early reward is not immediately delivered to the subject. In this case we have that

$$\lim_{\tau \to \infty} P(Early) = P[u_t + \varepsilon_t > 0] \tag{3.16}$$

If we assume $\tau \to \infty$ as in the previous situation, also in this case we will get that a decision maker chooses the Early reward over the Late reward if and only if the former is strictly positive.

Thus, considering equation 3.15 and 3.16 we can agree with the authors on the idea that subjects prefer Early reward because it seems that they assign no value to the Late reward.

Next step is to verify the presence of preference reversal behavior arising in the model. For this purpose, Gabaix and Laibson (2017) considered two further assumption that are $u_{t+\tau} > u_t > 0$ and $u_t > D(\tau)u_{t+\tau}$ and showed that, for high values of t, if the decision makers are obliged to make a choice immediately after the proposal, they prefer Late over Early reward. This can be seen mathematically since:

$$D(t)u_t - D(t+\tau)u_{t+\tau} = \frac{u_t}{1+\alpha t} - \frac{u_{t+\tau}}{1+\alpha(t+\tau)} < 0 \tag{3.17}$$

The latter inequality is verified for the assumption made, $u_{t+\tau} > u_t > 0$.

Although we have verified that the subjects prefer the Late reward if the two options occur in a distant future, it is important to note that with the progress of time, when approaching time t, all subjects would prefer to change their choice towards Early reward, if they had the chance. The reason is the second assumption that the authors considered: $u_t > D(\tau)u_{t+\tau}$. This behavior shows preference reversal because the decision makers initially prefer Late over Early immediately after the question was asked, but prefer Early over Late when approaching the time in which the Early reward should be delivered. "More precisely, if agents were not forced to choose in advance, but were instead given the chance to choose at time t , all would choose Early." (Gabaix and Laibson, 2017, p. 13)

Anyway, in contrast with other models of time preferences, in this framework preference reversal do not arise from time inconsistencies in the preference of the subjects but from the fact that they possess imperfect information about the value of the rewards. In this case the difference is clear: with preference reversal arising from time inconsistency the decision makers show willingness for commitment, for example having some of the options removed from the choice set, as pointed out from many studies on the argument. Conversely, in this model the preference reversal comes from a forecasting problem of the agent and not from a self-control problem, thus there is no reason to reduce the set of choices.[12] About absence of commitment, Gabaix and Laibson (2017) stated that their model on myopia "predicts that agents will exhibit as-if hyperbolic discounting with preference reversal and no willingness to pay for commitment."

We have therefore seen how the preference reversals are a phenomenon also present in this model even if in this case they derive from the imperfect foresight and not from a self-control problem of the agents. Other important implications of the model can be derived based on the differences between subjects and their forecasting abilities. The idea is that the subjects who are more skilled in making predictions will have a lower discount rate. In this sense, an individual skilled in forecasting will have low simulation noises ε_t and $\varepsilon_t + \tau$ and therefore the generated signals will be approximately equal to the various value, i.e. $s_t \cong u_t$ and $s_{t+\tau} \cong u_{t+\tau}$. Thus, the variance of the simulation noise $\sigma^2_{\varepsilon_t}$ is lower for this type of agent and from equation 3.9 we know that $\sigma^2_{\varepsilon_t}$ and $D(t)$ are inversely correlated, meaning that the agents are discounting less.

In this framework, it is showed that an individual's ability to make prediction may depend on various factors, for example intelligence: more intelligent decision makers should generate and consider more simulations about future outcomes so as to reduce the variance of the average simulation, since this value must be divided by the number of simulations generated. Moreover, observing the results of the model, it is possible to conclude that "agents with more domain-relevant experience, and hence better within-domain forecasting ability, will exhibit less discounting; [...] older agents – who generally have more life experience and consequently better forecasting skill – will exhibit less discounting; [...] people who experience cognitive decline (e.g., due to normal aging) will exhibit more discounting; [...] agents who

[12] A possible situation in which an individual might decide to reduce his set of choices occurs when such individual has an incentive to do so, for example in exchange for monetary compensation.

are unable to think carefully about an intertemporal tradeoff – e.g., due to a cognitive load manipulation or the effects of alcohol – will exhibit more discounting; [. . .] agents who are encouraged to spend more time thinking about a future tradeoff will exhibit less discounting; [. . .] rewards delivered in future periods that are cognitively well-simulated will exhibit less discounting." (Gabaix and Laibson, 2017, pp. 17-18)

So far we have seen how the combination of Bayesian priors and noisy, unbiased signals generates as-if hyperbolic discounting that seem to show dynamically inconsistent time preference due to preference reversal. To conclude the analysis, we will compare these results with those obtained in the case of time preferences associated with extrinsic risks, in order to determine a distinction between the different cases. One of the first studies on the argument was that conducted in 1965 by Menahem E. Yaari: he proposed that "a consumer who makes plans for the future must, in one way or another, take account of the fact that he does not know how long he will live."[13] For example, in the model we are analyzing, an individual who expects to live T years would certainly choose the Early over Late reward if $t < T < t + \tau$. Thus, the choice of the nearest reward does not depend on time preferences but is associated with extrinsic risk or mortality. Anyway, an external observer is led to think that the individual has deep time preferences even if he is perfectly patient, since the resulting behavior is the same in both cases. To solve this confusion about the causes of the declining sensitivity to delayed rewards, one can notice that there are empirical methods to distinguish between behaviors caused by extrinsic risk, time discounting and myopia. For our purpose we will focus principally on learning dynamics, experience or expertise in each of the three cases.

A possible way to distinguish extrinsic risk from other mechanisms is to directly measure the sources of such risk since in this case learning dynamics do not give us a clear pattern of preference because the perception of extrinsic risk can increase or decrease depending on the expertise. For time discounting and myopia things are different: although the behavior arising from these two mechanisms are practically

[13]Menahem E. Yaari, *Uncertain Lifetime*, Life Insurance, and the Theory of the Consumer, 1965, The Review of Economic Studies (32), p. 137

equivalent, they lead to very different learning dynamics. Specifically, in case of time discounting, experience does not bring the agent to modify his time preferences but if such time preferences are dynamically inconsistent, learning dynamics can lead the agent to adopt a commitment strategy to avoid self-control problems. This does not happen in case of myopia because learning dynamics and experience bring the subject to exhibit less as-if discounting, as we have previously shown in case of more intelligent agents or agents with more domain-relevant experience. Moreover, such learning dynamics do not generate preference for commitment.

> In summary, it is possible to empirically distinguish between true time preferences and myopia by studying learning dynamics. With true time preferences, learning generates no change in the time preferences and, if the time preferences are dynamically inconsistent, learning engenders a taste for commitment. With myopia, learning generates less (as-if) discounting and no taste for commitment. (Gabaix and Laibson, 2017, p. 27)

To conclude, assuming unbiased noises in the signals bring individual to put more weight on his priors and less weight on his simulation. Thus, combining Bayesian priors with simulations they get expectations that exhibit as-if discounting, meaning that the agents seem to behave "as-if" they are discounting future rewards, miming the classic behavior that arise with time preference. Anyway, when an agent becomes more skilled in making prediction (his experience improves with time), he seems to behave as-if he has become more patient.

3.6 Waiting periods and patient choices

In the last model we have analyzed, we have seen how myopia influences the decisions of individuals and we have shown how this phenomenon is able to explain some behaviors of subjects in the case of imperfect information or limited forecasting capacity. Furthermore, the results obtained by the authors have shown how the predictions of the model are reflected with the empirical evidence. Finally, we have seen some mechanisms to distinguish the effects of myopia from those deriving from time preferences and extra-risk risk. Now that we have provided an in-depth analysis of the phenomenon of myopia, let us analyze the possible mechanisms capable of pushing decision makers to take more "patient" choices. Already in the previous paragraph we have mentioned some of these mechanisms able to decrease the myopia present in the choices, for example the experience gained over time regarding the relevant domain. In this section we will concentrate instead on waiting periods, a tool introduced just for this purpose and which seems to bring excellent results in this direction.

Waiting periods are an instrument designed to temporally separate the moment in which the information relating to a given choice is given to a subject and the moment in which that subject must make the choice. The idea is that a decision maker should make more patient decisions if he has not the possibility to choose immediately: a waiting period should help the decision maker in this sense, allowing him to have a time frame to think about the decision and the consequences.

The usefulness of this instrument is widely recognized, in fact waiting periods are applied in real situations in which the effects of imperfect foresight can be harmful to consumer. Luca, Malhotra and Poliquin (2017) reported in their work that in U.S. states that impose waiting periods between the initiation of a purchase and the final acquisition of a firearm the number of homicides caused by firearms is significantly lower with respect to states that do not require waiting periods: in this situation, waiting periods reduce gun homicides by roughly 17%. "These policies are predicated on the idea that inserting a delay between when a choice set first comes into focus and when the choice can actually be made may prompt a shift towards more deliberative thinking, and lead to a change in the final decision." (Imas, Kuhn and Mironova, 2017, p. 2)

Thus, waiting periods are an effective tool in pushing subjects to reflect in certain situation. Our goal is to determine if they are able to influence the decisions of the subjects regarding intertemporal choices and to do so we will observe the model proposed by Imas, Kuhn and Mironova (2017) in which they studied the impact of deliberation time on intertemporal choice. They wanted to observe what effects the insertion of waiting periods has on the choices of individuals constructing an experiment in which the subjects were asked to decide how to distribute work and rest sessions during the experiment.

They run two treatments in which the information given to subjects and the choices they could make were the same in both, the only difference being that in the first treatment the subjects could make their choice immediately after they get the information while in the second they could make a choice only after a waiting period of one hour. Each treatment is made of two one-hour working period, named WP1 and WP2, in which subject have to decide how to allocate binding and effortful tasks and leisure. Moreover, Imas et al. (2017) built the experiment so that "delaying tasks to a later work period resulted in a greater total task requirement, while choosing to allocate tasks to the earliest available period minimized total work time." After the allocation choice, subjects must complete all the tasks that decided to pick for the first period and could not proceed to the second period until the time expires, even if all the tasks were completed. Anyway, the time lapse between the end of the tasks allocated in WP1 and the beginning of WP2 can be used for leisure activities.

About the set of choices, this experiment is structured such that each subject has to choose an allocation in four convex time budgets that slightly differ from each other on the number of tasks to be completed in WP2 and thus in the implied interest rate for delaying tasks from WP1 to WP2. However, in each of the four sets, the maximum number of tasks that can be performed in WP1 is 40. In Table 3.2 we represent the four budgets used in the experiment. The number of options' column in Table 3.2 represent how many different convex combinations of the extremes of each budget are proposed to the decision makers.

The authors implemented four treatments in the experiment, but for our purpose we will examine only the "Immediate treatment" and the "Waiting Period treatment". The first treatment was made so that the participants could make their

Table 3.2: Composition of the four budgets.

Budget	Max Tasks WP1	Max Tasks WP2	# of Options	Interest Rate
1	40	60	11	50%
2	40	50	11	25%
3	40	45	6	12.5%
4	40	40	11	0%

Source: Alex Imas, Michael A. Kuhn, Vera Mironova, Waiting to Choose, 2017.

own choices on the allocation of the tasks immediately after receiving the information on the budgets. The second treatment was structured so that, after receiving the information, the subjects must wait an hour before being able to confirm their choice and start performing the tasks.

Our aim is to compare the results obtained in the two treatments to see if the presence of a waiting period in the second case affects the choices of the decision makers. However, before analyzing the results, we want to see what the theoretical predictions of the model are in this situation using the classic hypotheses of time preferences models.

Therefore, we will consider a decision maker with a discount function $D(t)$ and a utility function $U_k(x_0, x_1, x_2) = \sum_{t=k}^{2} D(t-k)u(x_t)$, where x_t are the tasks that can be allocated in the working periods at time $t = 0, 1, 2$ and k is the time period in which the evaluation is made. Then, we assume that $u(0) = 0$ and $D(0) = 1$.

Given these assumptions, we suppose that in the "Immediate treatment" the decision maker at time $t = 0$ tries to choose the allocation that minimize the tasks to complete in WP1 and WP2. Thus, we can describe the decision problem in the "Immediate treatment" as

$$\min_{x_0 x_1} U_0(x_0, x_1) = u(x_0) + D(1)u(x_1) \tag{3.18}$$

$$s.t. \quad x_0 + \frac{x_1}{1+r} = 40$$

The constrain implies that the minimum number of tasks to be completed is 40, as we specified in the description of the experiment and r represents the interest rate through which the tasks moved from WP1 to WP2 increase. Instead, considering the "Waiting Period treatment", we can describe the decision problem as

$$\min_{x_1 x_2} U_1(x_1, x_2) = u(x_1) + D(1)u(x_2) \tag{3.19}$$

$$s.t. \quad x_1 + \frac{x_2}{1+r} = 40$$

The two problems differ in the fact that in the second treatment the choice is shifted one period ahead. For completeness, we will compare the results of equations 3.18 and 3.19 considering both the case in which the decision maker has an exponential discount function, such that $D(t-k) = \delta^{t-k}$, and the case of quasi-hyperbolic discounting in which $D(t-k) = \beta^{1(t>k)}\delta^{t-k}$ and where $\beta \in [0, 1)$ is a parameter that is used to further discount the utility that is not received immediately.[14]

Hence, considering constant, exponential discounting "the decision maker in the Waiting Period treatment solves the same decision problem subject to the same constraint as in the Immediate treatment, with the labels shifted by one period. In turn, under exponential discounting the allocations should be the same in both treatments." (Imas, Kuhn and Mironova, 2017, p. 10)

With quasi-hyperbolic discounting we have to consider that in "Waiting Period treatment" the decision maker receives the information and begins to think about how to allocate tasks at $t = 0$ even if he will have to make the choice at $t = 1$. Therefore, at $t = 0$ the decision maker solves the following problem:

$$\min_{x_1 x_2} U_0(x_1, x_2) = D(1)u(x_1) + D(2)u(x_2) \tag{3.20}$$

$$s.t. \quad x_1 + \frac{x_2}{1+r} = 40$$

[14]The hypothesis of $0 < \beta < 1$ was considered by Laibson (1997) who explained that with this assumption the qualitative properties of hyperbolic discounting are maintained. This is useful to model self-control and procrastination problems.

where $D(1) = \beta\delta$ and $D(2) = \beta\delta^2$. As we can see, in this case the discount function multiplies the utility obtained at $t = 1$, since the decision maker is evaluating the allocation from $t = 0$. Thus, with $k = 0$ the allocation of the two treatments may differ under quasi-hyperbolic discounting. Anyway, there is a problem: as just said, this is the allocation that the decision maker faces in the moment he received the information, but it is required that he submits the decision after the waiting period elapsed, that is at $t = 1$. Hence, if decision maker can not commit to the decision taken at $t = 0$, he ends up with the problem described in equation 3.19 after the waiting period elapsed. "In turn, absent the ability to commit, both exponential and quasi-hyperbolic discounting models predict that a waiting period should not affect the allocation decision." (Imas, Kuhn and Mironova, 2017, p. 11)

Therefore, from the hypothesis of the model we get that waiting periods do not influence the decision maker choices, absent the ability to commit, that is $x_1^{WP} = x_0^I$, where the left side of the equation represent the tasks allocated at t=1 in "Waiting Period treatment" while the right side represent the tasks allocated in t=0 in the "Immediate treatment".

However, analyzing the predictions of the model in light of the results obtained by Gabaix and Laibson (2017) about myopic choices, we can think that the use of waiting periods can push subjects to make more patient decisions. As we explained in paragraph 3.3, if a subject is uncertain about the future realization of utility he generates signals or forecasts about the future and combines them with his priors to obtain Bayesian posteriors. In this case we are assuming that waiting periods prompt deliberation and this should lead the decision makers to think more carefully about the choices, giving them the opportunity to generate more simulations.

This should reflect in more patient and less myopic choices because, as explained and showed by Gabaix and Laibson (2017), people that are encouraged to spend more time thinking about a future tradeoff will exhibit less discounting. The decision makers should then allocate more tasks to WP1 when they are in presence of waiting periods, meaning that $x_1^{WP} > x_0^I$.

Next step is to observe the result of the experiment to observe if one of the two hypotheses ($x_1^{WP} = x_0^I$ and $x_1^{WP} > x_0^I$) is more accredited than the other. The first thing that emerges from the results is that the decisions of the subjects were responsive to interest rates, meaning that they prefer to allocate more tasks in WP1 as the interest rate increased in the four convex budgets (Table 3.2 shows the value of interest rate for each of the four budgets). Focusing on the difference between the two treatments we have analyzed, we can see that decision makers allocated more tasks to WP1 in the "Waiting Period treatment" than in the "Immediate treatment" when the interest rates were positive, that is in three out of four budgets. From this result it is possible to say that waiting periods lead subjects to allocate more tasks to the earlier period, but that is not all.

> Waiting periods only led to significantly earlier allocations if this resulted in fewer tasks to complete overall – on budgets with positive interest rates. [. . .] When the interest rate is positive, waiting periods lead to more tasks being allocated to the sooner period; when the interest rate is negative, tasks are (directionally) more likely to be allocated to the later period. Together, these results offer suggestive evidence for individuals becoming better calibrated after waiting periods, rather than just shifting tasks to the later period in general. [. . .] These results suggest that introducing a waiting period between information about a choice and the choice itself leads to more patient decision. (Imas, Kuhn and Mironova, 2017, p. 16)

Then, we can conclude rejecting the first hypothesis of $x_1^{WP} = x_0^I$ and accepting $x_1^{WP} > x_0^I$.

3.7 Conclusion

In this chapter we have analyzed some interesting models, first in the field of uncertainty and then in that of myopia. In the model of Eichberger, Oechssler and Schnedler (2015) we saw how the introduction of a second source of uncertainty concerning the possible winnings influences the decisions of the subjects: comparing the results obtained in their experiment with the results obtained in the experiments with a single source of uncertainty we note that on average the subjects exhibit a lower degree of ambiguity aversion, leading us to conclude that the presence of a second source of uncertainty makes the subjects more indifferent towards the first source.

To confirm these hypotheses, we have considered models that include up to three sources of uncertainty, such as the one proposed by Eliaz and Ortoleva (2016) in which the ambiguity concerns prizes, probabilities and payment date. The results of this model are very interesting because it confirms the fact that the subjects exhibit ambiguity aversion in the presence of a single source of uncertainty, no matter what type it is. Furthermore, it is shown that in presence of a source of uncertainty that it is not possible to remove, the subjects prefer to add a second source of uncertainty perfectly correlated with the first, thus increasing their exposure and their risk but at the same time increasing the chances of a large reward. Particularly interesting is the definition that the authors give to the behavior that the subjects adopt in presence of multiple sources of uncertainty, that is skeptical pessimism: with this term they refer to the fact that the subjects incorporate in their assessments the very pessimistic priors, as if they were taking considering the worst possible scenario. However, individuals are aware of the fact that they are pessimistic in their evaluations and that they may be wrong in their estimates, so the variance is very high in this case, leading them to prefer the double perfectly correlated uncertainty option to no uncertainty.

Then, we introduced myopic choices and the idea that individuals have an imperfect ability to predict future: this is an important feature for Decision Theory since myopia and imperfect foresight can give an alternative explanation to the empirical evidence that individuals have a preference for earlier reward over later reward. The model of Gabaix and Laibson (2017) is one of the most important on the argument since they proposed a model in which the decision makers do not know for sure the realization of two rewards in the future. They have noisy, unbiased signals about the future values that, combined with their priors, form Bayesian posteriors. Considering the key assumption that the variance increases linearly with the time horizon, it is shown that the subjects behave as-if they are discounting future utility, replicating the effects of time preferences even if the subjects are perfectly patient. In this case we could say that the as-if discounting behavior derives from the agent's imperfect foresight of the future utilities. Finally, another important result of this work is that learning dynamics do not bring myopic agents to have a preference for commitment, contrarily to impatient agents that may be prompted to adopt commitment strategy if their time preferences are dynamically inconsistent.

To conclude, we have analyzed the so-called waiting periods, a tool that is used to temporally separate the moment in which an individual receives information relative to a choice and the moment in which he will have to make that choice. We wanted to examine if waiting periods can be used to prompt subjects toward more patient decisions. To do so, we analyzed the work of Imas, Kuhn and Mironova (2017) where they proposed an experiment in which agents have to allocate effortful tasks over two working periods. We considered the treatment in which agents have to make an immediate decision after receiving the information and the treatment with a waiting period between the moment in which they receive the information and the allocation decision. Even in this case, the results are very interesting since, comparing the two treatments, we can see that majority of subject preferred to allocate more tasks to the earlier period with a waiting period than without one. This result his consistent with the prediction of Gabaix and Laibson (2017) that agents who are encouraged to spend more time thinking about a future tradeoff will behave more patiently, leading us to think that waiting periods are an effective tool to prompt individuals to make more patient decisions.

Chapter 4

4.1 Social Preferences

At this point, we analyzed most of the novelties in the field of behavioral and experimental economics during this dissertation, starting with the now recognized hyperbolic discounting up to consider models of ambiguity and myopia. Wanting to continue on this path, it is interesting to dwell on social preferences, a topic that has found room in recent years and that in our opinion could have interesting implications for future studies on the behavior and decisions of individuals. We will begin by describing this topic from a general point of view and then going into specifics by looking at some interesting models. As we know, behavioral economics is a science that aims to describe or regulate the behavior of economic agents through the use of economic, mathematical and psychological concepts. However, the concept of economic agent understood as the homo oeconomicus of classical economics is not representative of the decision-making dynamics observed empirically in various contexts, both economic and non-economic. This difference is mainly due to the characteristics attributed to homo oeconomicus, specifically to rationality and the exclusive pursuit of one's personal interests. Therefore, in order to describe as accurately as possible the choices and behavior of economic agents, studies in the field of behavioral economics relax these two very strong assumptions. Currently we can distinguish two main approaches within behavioral economics. The first, that of the bounded rationality, corresponds to what we have analyzed so far and, as we have seen in the previous chapters, assumes that the subjects have a limited rationality that can manifest itself in different forms.[1]

The second approach is that of social preferences and requires that personal preferences should be combined with social preferences, such as equity or envy. Canonically it is possible to distinguish two types of social preferences: distributive preferences and reciprocal preferences. We refer to the first category when we focus on equity, efficiency or altruism related to the final distribution of the outcome. The second category includes the behavior of the subjects who have the objective of rewarding or punishing the counterpart in certain situations.

4.2 A model of social preferences

As we have seen in the previous paragraphs of this chapter, it is not uncommon to observe changes in decisions due to concerns about fairness and altruism when we consider the choices of subjects in social environments. Let's now analyze a recent model on social preferences proposed by Rodriguez-Lara and Ponti in 2017. The idea proposed by the authors is very interesting and innovative considering that their goal is to show that social preferences have effect on intertemporal decisions (concerns and inclinations) and not only on decisions regarding monetary or material outcomes. Going to study this type of influence is very interesting since it is an analysis that differs substantially from the literature on social preferences that we have observed so far. In fact, as just specified, the purpose of the authors is to study the implications of social preferences on the degree of risk aversion or discounting of subjects rather than on the material consequences of decisions. To do this, the authors built an experiment with various phases and various treatments based on the Dictator Game that we will now describe.

The authors' initial objective is to obtain individual risk and time preferences for each subject, in order to obtain a benchmark for comparing the results of subsequent treatments. To obtain time and risk preferences, Rodriguez-Lara and Ponti used two different and independent multiple price lists: "one MPL over lotteries paid off at the same time of the experiment, another intertemporal MPL of certain

[1]Uncertainty, ambiguity and myopia are the hypothesis that we analyzed in Chapters 2 and 3.

monetary payoffs paid off at different times." (Rodriguez-Lara and Ponti, 2017, p. 179)

The two MPLs represent the first two phases of the experiment to which all participants must undergo to obtain individual time and risk preferences. As already mentioned, these two phases are necessary to obtain data that will then be used to observe the probable differences with the data obtained in subsequent treatments, in which a social dimension is present. In fact, after the two MPLs, the subjects are grouped in pairs and within each pair the roles of "Dictator" and "Recipient" are assigned. The assignment of pairs and the choice of roles is random.[2]

At this point, the subjects assigned the role of Dictator will again be subjected to the problem encountered in the first two phases, namely the MPL on risk and time preferences. The main difference with the previous phases lies in the fact that now the decisions of the Dictator will also be applied to the corresponding Recipient which is obliged to accept the choice without the possibility of replication, as in the classic Dictator Game. In addition to incorporating the social dimension into the decisions of the Dictators, the authors decided to include four different treatments with the aim of identifying the effects deriving from social motives and social influences.[3]

We propose the following four treatments developed by Rodriguez-Lara and Ponti.

> In the baseline treatment (T_0, INFO-SOCIAL), Dictators make their intertemporal choices after being informed of what their assigned Recipient had chosen in the first two stages of the experiment;
> in the BELIEF-SOCIAL treatment (T_1), before deciding for the pair, Dictators go through an additional stage in which we elicit their beliefs

[2] *Random Matching* is the main coupling method used, although the authors considered and used two other methods: *Dissortative Matching* and *Efficient Random Matching*. For the purposes of this dissertation we will skip the last two and will consider only the Random Matching. For further information see: Rodriguez-Lara and Ponti, 2017, p. 182.

[3] To examine the effects of social motives the authors inserted payoff externalities in some of the treatments while to verify for social influences they let the Dictators to know about the decisions of their respective Recipients in the previous phases.

on risk and time concerns of their assigned Recipients;
in the INFO-PRIVATE treatment (T_2), subjects receive (exactly as in the baseline) information on risk/time individual choices of their group-mate, but no payoff externalities are imposed on others;
in the NO INFO-SOCIAL treatment (T_3), Dictators make their intertemporal decisions for the pair without prior knowledge (or elicited belief) of the Recipient's risk/time decisions. (Rodriguez-Lara and Ponti, 2017, p. 178)

Each subject participates in only one of the four treatments offered, in addition to the first two phases of the experiment. The additional stage in the T_1 treatment must obviously be carried out exclusively by the subjects assigned to that treatment and has the purpose of eliciting the beliefs about risk and time preferences of their own partners. Finally, a debriefing questionnaire with questions concerning *socio-demographics standards*, *proxies of cognitive ability* and *proxies of social capital* was submitted to all participants.

After briefly describing the structure, let's analyze the way in which the first two phases with the respective MPLs were built. The first MPL encountered by the subjects is the one designed to elicit individual risk preferences. Similar to the one introduced by Holt and Laury (2002), the MPL built by Rodriguez-Lara and Ponti provides a binary choice between eleven pairs of lotteries and is structured in such a way that "the risky option is increasingly more profitable, as the probability of the highest prize grows in probability, and so is falling the expected payoff difference between options A and B." (Rodriguez-Lara and Ponti, 2017, p. 180)

By examining the subjects' switching points, their risk preferences can then be determined, knowing that the MPL is constructed so that a risk neutral subject should place his switching point from lottery A to lottery B at the sixth decision. Thus, a switching point after decision 6 will indicate risk aversion for the subject.[4]

[4]We recall that the MPL is structured so that a rational subject indicates a single switching point, as already explained in paragraph 2.8. Subjects who entered more than one switching point between lottery A and lottery B were labeled as "inconsistent".

In the second phase of the experiment, the participants are subjected to the second MPL, this time in order to elicit time preferences. In this case, the structure is different from the previous MPL because the subjects are not asked to choose between pairs of lotteries but to show their preference between an amount of money to be received immediately or a higher amount to be received in the future. Specifically, the participants are subjected to 10 rounds of decisions, each with a different time horizon that varies from 1 day to 180 days of waiting for the payment; in addition, each round presents twenty possible alternatives.

The amount of money offered in the first column of the MPL remains unchanged and is equivalent to €100, while the amount offered in the second column is equivalent to €100$[(1 + i_k/365)^\tau]$, where τ represents the number of days of delay in payment.[5]

An important remark is that "contrary to what happens in Stage 1, subjects make only one decision for MPL, in that they are simply asked to indicate their switching point (if any) from option A (€100 today) to option B (€100$[(1 + i_k/365)^\tau]$ in τ days)." (Rodriguez-Lara and Ponti, 2017, p. 181)

After dealing with the first two phases, the subjects are paired and given the role of Dictator or Recipient and each couple participates in one of the four treatments listed above. We remind you that the subjects participating in the BELIEF-SOCIAL treatment (T_1) will have to participate in a further phase in which they will have to predict the choices made by the respective partner in phases 1 and 2 of the experiment before proceeding with the treatment. Following the instructions of the relative treatment to which they have been assigned, all the subjects will have to make decisions related to the same sequence of MPLs they encountered on stage 1 and 2: in this case also the subjects with the role of Recipients will have to make the choices but aware of the that their decisions do not affect the outcome of the couple.

For clarification purposes, we report the table provided by Rodriguez-Lara and

[5]The term i_k indicates the sequence of Annual Interest Rates which in this case can vary from 2% to 300%. However, the authors decided not to disclose the value of the Annual Interest Rate to the subjects, so we will skip it in our analysis.

Table 4.1: Treatment conditions.

Cod.	Treat.	Info	Pay. ext.	#Session	(RM/DM/ERM)	#Subj. (dict.)
T_0	INFO-SOCIAL	Yes	Yes	6	(1/2/3)	288(144)
T_1	BELIEF-SOCIAL	Beliefs	Yes	2	(2/0/0)	96(48)
T_2	INFO-PRIVATE	Yes	No	3	(1/1/1)	144(144)
T_3	NO INFO-SOCIAL	No	Yes	2	(2/0/0)	96(48)
			Total	13	(6/3/4)	624(384)

Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

Ponti that summarizes the four treatments with their own characteristics.

4.3 Data and results

After having described in detail the structure of the experiment proposed by Rodriguez-Lara and Ponti (2017), let us analyze the data obtained from this experiment so as to be able to draw conclusions on the research objective of the authors.

First of all, let's start by analyzing the data of the first two phases, obtained by using MPLs to elicit risk and time preferences. For the data obtained from the subjects to be tractable and meaningful there is a need for the subjects' behaviors and the respective decisions to satisfy certain conditions. Specifically we will have two main conditions that must be met, the first in relation to the MPL of phase 1 while the second relating to the MPL of phase 2. The behaviors and decisions that do not respect one or the other or both conditions are labeled as inconsistent behaviors. Let's look at the two conditions in detail:

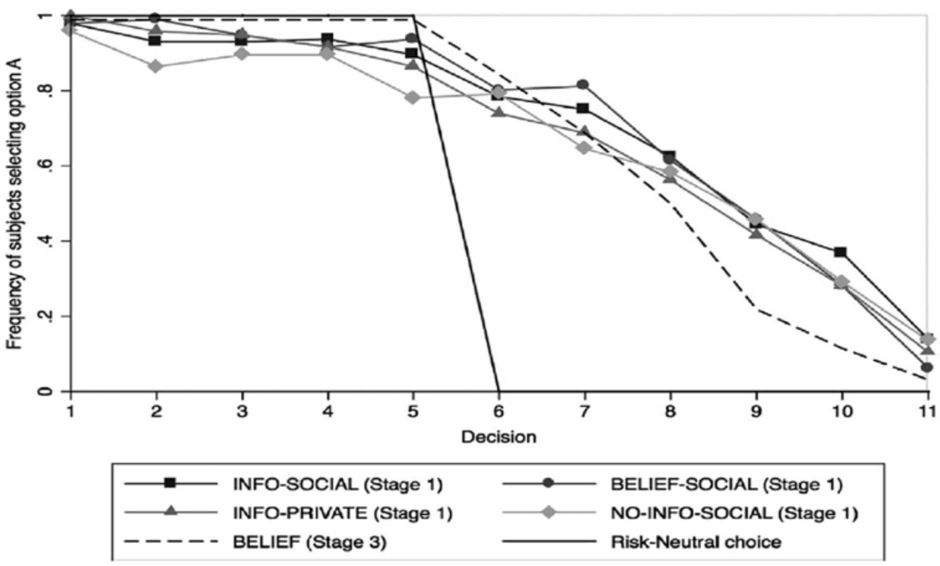
> *Condition 1.* A subject should choose option A in the first row, option B in the last row, and switch from option A to B once – and once only – along the sequence.
>
> *Condition 2.* If a subject prefers €100 today against any higher amount €x at some point τ in the future, then, for all $\tau' > \tau$, he should never

prefer €$x' < x$ against €100 today. (Rodriguez-Lara and Ponti, 2017, p. 185)

Analyzing the two conditions in detail, we can see that the first simply provides that a consistent and rational decision by the subjects is to make a single switching point from column A to B. In the second stage the subjects are asked to indicate their switching directly point in each round, so in this case the "time consistency" is imposed by the authors within each MPL; however condition 2 is required to have time consistency also across MPL. From the data obtained it was observed that approximately 60% of subjects respected both conditions and demonstrated consistent behavior.

Now let's look at the results related to risk and time preferences. Regarding risk preferences, the authors considered the frequency with which subjects selected option A and built a graph to show the results of the analysis of these data. We reported the results in Figure 4.1.

Figure 4.1: Aggregate behavior in the lottery tasks.

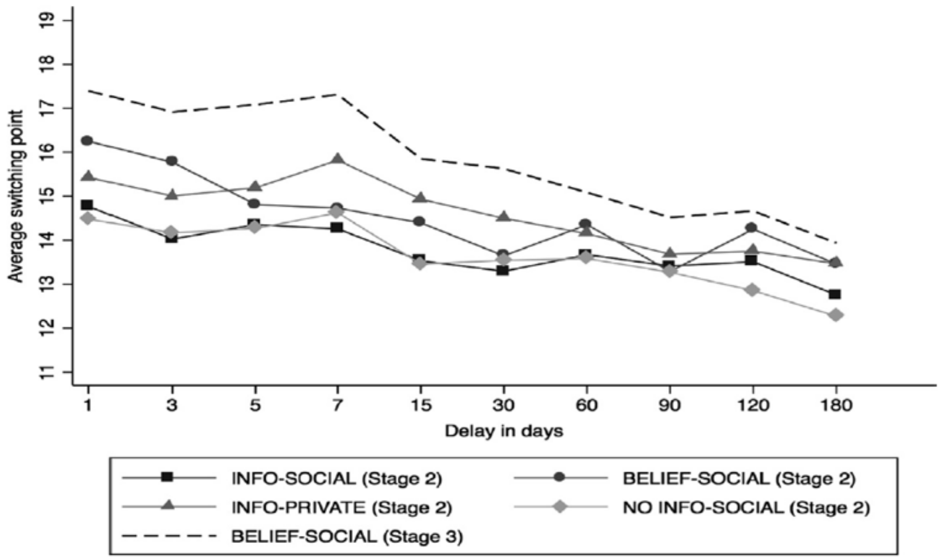


Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

In this case were considered the data relating to the MPLs of stage 1 of all the treatments (from T_0 to T_3), also including the data obtained from the additional stage to which the participants of the BELIEF-SOCIAL treatment (T_1) were subjected.

As shown in the figure, the subjects demonstrated an aggregate risk aversion behavior: this is noted by the fact that the shift from option A to B occurs very slowly and gradually, especially when compared to the optimal behavior under risk neutrality which is always shown in the figure. The situation based on individual time preferences is slightly different. Also in this case we report the distribution of the data in Figure 4.2.

Figure 4.2: Aggregate behavior in the aggregate task.



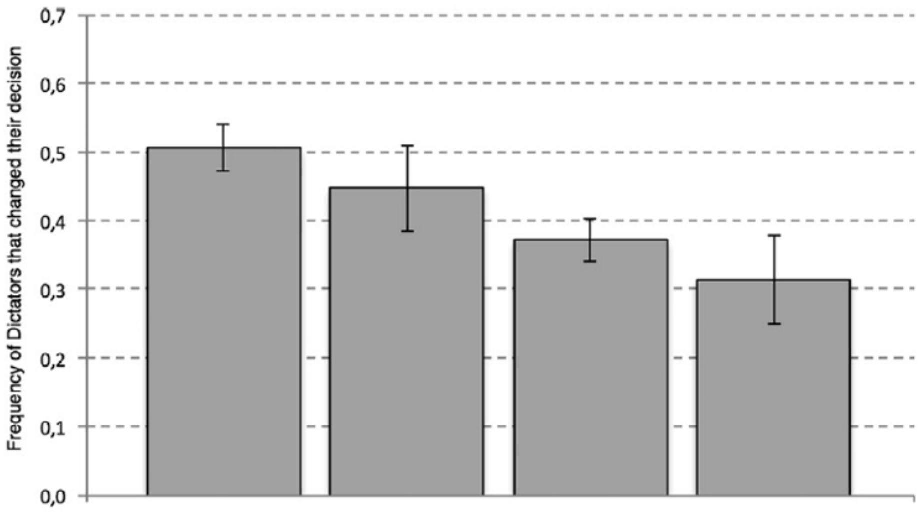
Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

As expressed by Rodriguez-Lara and Ponti (2017), Fig.2 "summarizes subjects' behavior in stages 2 (all treatment) and 3 (treatment T_1), with the vertical axis representing the distribution of "average switching points", that is, the first decision (out of a sequence of 20) for which subjects express their preference for the delayed payment."

The data shown in the graph show how the average switching point decreases as waiting time to receive payment increases. This is an interesting result because it supports the literature of hyperbolic discounting in contrast to exponential discounting, showing that individuals do not discount present and future equally, but they pose more value on sooner rewards and less value on later rewards.

After these considerations on the first phases of the experiment, we pass to analyze the data obtained in Stage 4, which includes the four treatments with the pairs of Dictators and Recipients. We remind you that the previously obtained individual risk and time preferences data will be useful to observe any differences in the behavior of the same subjects in the presence of social motives and social influences. About that, Rodriguez-Lara and Ponti (2017) estimated "the relative frequency of rounds where the decisions of consistent Dictators in Stages 4 differ from those in Stage 2" and represented it graphically.

Figure 4.3: Likelihood of changing decision of Stage 2.



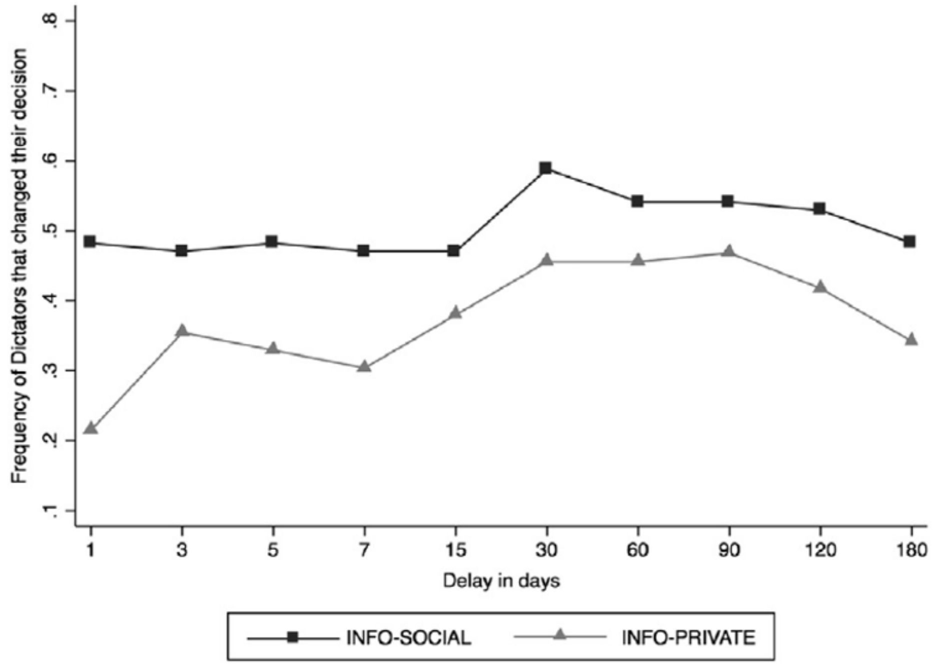
Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

Figure 4.3 is really interesting, let's explain why. First of all, it should be clear that the four bars in the figure represent the percentage of Dictators that made a different choice in each of the four treatments of Stage 4 (from left to right: T_0 INFO-SOCIAL, T_1 BELIEF-SOCIAL, T_2 INFO-PRIVATE, T_3 NO INFO-SOCIAL) with respect to the decision made in Stage 2. Then, we can make a comparison between treatments T_0 INFO-SOCIAL and T_2 INFO-PRIVATE since in both cases Dictators have information about the preferences of the corresponding Recipients, with the difference that in T_0 there is the presence of payoff externalities while in T_2 there are not. The results show that Dictators are more inclined to change their decision in presence of payoff externalities: the percentages are 50.6% for T_0 and 37.1% for T_2, as shown in Figure 4.3.

The other comparison is between T_1 BELIEF-SOCIAL and T_1 BELIEF-SOCIAL. In both cases Dictators make their decisions for the pair with no information about the preferences of the Recipients but, in treatment T_1, they are asked to make predictions about Recipients' preferences before making the choice. In this case, the results show that Dictators are more likely to change their decisions when the beliefs are elicited, that is in treatment T1. Following the percentages reported in Figure 4.3 we have 44.7% for T_1 and 31.4% for T_3.

The authors went further to find other evidences to support the preliminary results. They examined the frequency of Dictators that changed decision with respect to the time delay of the payment. Thus, confronting again T_0 with T_2 and T_1 with T_3 , they could obtain some evidence to support the results represented in Figure 4.3. Specifically, in Figure 4.4 it is possible to observe that Dictators informed on the Recipients' preferences are going to change their decisions more frequently in presence of payoff externalities than in absence of them, confirming the preliminary results. Considering these results, Rodriguez-Lara and Ponti could conclude that social motives seem stronger than social influence.

Figure 4.4: Social motives vs social influence (T_0 vs T_2).

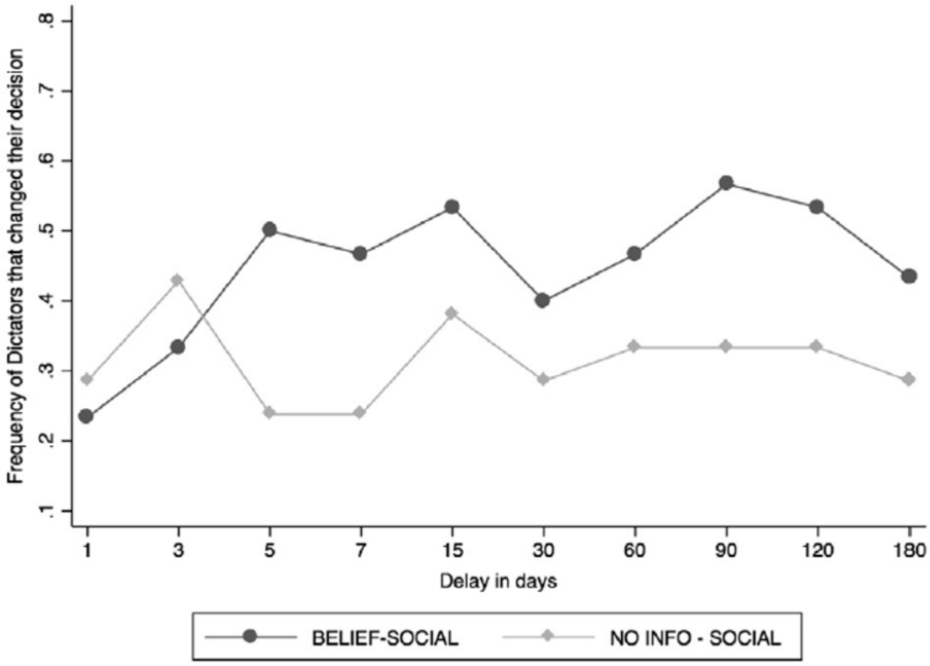


Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

A similar pattern seems to appear when considering the comparison between

BELIEF-SOCIAL and NO INFO-SOCIAL treatments. Looking at Figure 4.5 we can see that the Dictators with no information about Recipients' preferences that are prompted to elicit the beliefs of the counterpart are going to switch their decision more frequently.

Figure 4.5: Belief elicitation and focusing effect (T_1 vs T_3).



Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

Even in this case the authors obtained a confirmation of the preliminary results. Furthermore, this result is consistent with the "focusing" conjecture, formulated by Krupka and Weber (2009). Following this conjecture, "forcing subjects to form beliefs over the time preferences of others is sufficient to move behavior in the direction of beliefs." (Rodriguez-Lara and Ponti, 2017, p. 192)

After the analysis of the data obtained in the four treatment we have found that the social influences has effects on the behavior and the choices of the subjects, leading them to modify the decisions that were made previously. So far in this paragraph, we have analyzed the percentage of subjects that changed their mind picking a different option in Stage 4 from the one selected in Stage 2. What we are going to see now is the quality of these new decisions. In fact, Rodriguez-Lara and Ponti examined the direction of the changes in decision made by the subjects in the experiment: this is a very interesting analysis because it allows us to have more information on the effects of social motives and social influence in this context. Thus, the authors divided the Dictators' choices in Stage 4 in three categories – i) choices that move toward, ii) choices that perfectly match, iii) choices that move against – and reported for each category the frequency of switch in Stage 4. In this case is possible to verify in which treatment the preferences of the Recipients are better matched by the choices of the Dictators. Table 4.2 shows the results obtained by Rodriguez-Lara and Ponti (2017).

Table 4.2: Choice of Dictators in Stage 4 compared with those of Recipients in Stage 2.

	T_0 INFO-SOCIAL	T_1 BELIEF-SOCIAL	T_2 INFO-PRIVATE	T_3 NO INFO-SOCIAL	POOL DATA
Frequency of Recipients' choices matched by Dictators who moved their choices in Stage 4					
Choices move towards the Recipients' choices	0.67	0.56	0.56	0.29	0.29
Recipients' choices are perfectly matched	0.15	0.09	0.14	0.06	0.06
Choices move against the Recipients' choices	0.18	0.36	0.30	0.65	0.65

Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

As you can see from Table 4.2, most of the subjects who changed their decision with respect to Stage 2 met the Recipients' preferences. Specifically, with the exception of treatment T_3, it can be said that more than half of the subjects' choices moved towards the Recipients: treatment T_0 is the one with the highest frequency among all (0.67). Moreover, if we add to this the fraction of subjects that perfectly matched the choices of the Recipients, we obtain very high frequencies for T_0, T_1 and T_2 in contrast with the frequency of the choices that move against Recipients' choices.

4.4 Structural estimations

Considering the estimates reported in Table 4.2, one can argue that are based only on the observed behavior on intertemporal decisions, without considering individual risk preferences. This is true since the authors analyzed the results obtained in Stage 4 only with the ones emerging from Stage 2. This may result in a problem of Dictators' heterogeneity in own risk concerns and for this reason Rodriguez-Lara and Ponti tested the robustness of their results using structural estimations in which they "frame (consistent) Dictators' behavior as maximizing various parametric random utility functions, some related with the individual decisions of stages 1 to 3, others which include both the individual ("selfish") utilities of the Dictator and the Recipient as a result of some social preference – or social influence – process of joint utility maximization, depending on the treatment." For this purpose, the authors used the indifference condition proposed by Andersen et al. (2006), aimed at equalizing the utility of two monetary outcomes occurring at different periods using a discount factor. This condition has the form:

$$u_i(M_0) = \Delta_i(\tau)u_i(M_\tau) \tag{4.1}$$

where $u_i(x) = x^{1-\rho_i}/1-\rho_i$ with $\rho_i \neq 1$ and $\Delta_i(\tau) = \beta_i/(1+\delta_i)^\tau$. The utility function is a standard (time independent) CRRA and ρ is the risk aversion coefficient: $\rho_i = 0$ describes a risk neutral individual, $\rho_i > 0$ describes an individual that is risk averse and $\rho_i < 0$ a risk loving subject. For the discount factor $\Delta_i(\tau)$ we have that $\beta_i = 1$ in case of exponential discounting and $\beta_i < 1$ for hyperbolic discounting. Finally, the estimations made by Rodriguez-Lara and Ponti followed the standard maximum likelihood approach.

At this point, following the procedures just described, the authors estimated the parameters of risk ρ and intertemporal preferences β, δ using the data obtained in stages 1 to 3. Then, considered three different model of estimation. In the first, namely Model 1, they imposed exponential discounting for all the observations ($\beta_i = 1$); conversely, in Model 2 they imposed hyperbolic discounting ($\beta_i < 1$). For Model 3, Rodriguez-Lara and Ponti (2017) considered a "binary mixture model" to estimate the parameters of risk and intertemporal preferences ρ, β and δ plus the "ex-ante probabilities that each individual observation is an independent draw from Model 2" denoted by π.[6]

[6]Clearly, $1 - \pi$ represent the complementary probability referred to an individual observation

Table 4.3 shows the value of the estimated parameters in each of the three models and for each of the treatments.

Table 4.3: Structural models of individual behavior (Stages 1 to 3).

	(1) Exponential discounting		(2) Hyperbolic discounting			(3) Mixture model			
	Risk (ρ)	Time (δ)	Risk (ρ)	Time (δ)	Time (β)	Risk (ρ)	Time (δ)	Time (β)	π
Private "own" decisions (Stages 1 and 2)									
Pooled data	0.853***	0.898***	0.858***	0.261***	0.848***	0.825***	0.992***	0.690***	0.231***
	(0.008)	(0.099)	(0.008)	(0.026)	(0.007)	(0.009)	(0.025)	(0.014)	(0.019)
INFO-SOCIAL (T_0)	0.874***	1.133***	0.878***	0.195***	0.860***	0.848***	0.837***	0.725***	0.244***
	(0.012)	(0.215)	(0.012)	(0.033)	(0.011)	(0.014)	(0.028)	(0.026)	(0.035)
BELIEF-SOCIAL (T_1)	0.859***	1.133***	0.864***	0.219***	0.836***	0.837***	0.927***	0.634***	0.246***
	(0.02)	(0.214)	(0.020)	(0.069)	(0.022)	(0.024)	(0.065)	(0.025)	(0.063)
INFO-PRIVATE (T_2)	0.829***	1.179***	0.833***	0.382***	0.861***	0.791***	1.151***	0.674***	0.173***
	(0.015)	(0.132)	(0.015)	(0.062)	(0.013)	(0.019)	(0.050)	(0.023)	(0.032)
NO INFO-SOCIAL (T_3)	0.825***	1.682***	0.831***	0.335***	0.808***	0.799***	1.352***	0.687***	0.323***
	(0.021)	(0.231)	(0.021)	(0.072)	(0.016)	(0.026)	(0.088)	(0.023)	(0.048)
Beliefs about Recipients (Stage 3)									
BELIEF-SOCIAL (T_1)	0.809***	1.259***	0.812***	0.495***	0.872***	0.766***	1.368***	0.742***	0.172***
	(0.020)	(0.163)	(0.021)	(0.103)	(0.021)	(0.026)	(0.061)	(0.048)	(0.063)

Notes. Robust standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

Interesting results can be obtained from the values in Table 4.3. In Model 1, the value of the estimates of ρ and δ of the consistent subject participating in the experiment is in line with other empirical results, especially with the results obtained by Coller et al. (2012). Even the estimates of β (that is smaller than 1) in Model 2 seem to confirm the empirical evidence that supports hyperbolic discounting in spite of exponential discounting. Finally, considering the estimates of the Mixture model, Rodriguez-Lara and Ponti (2017) found that the probability π of the model with hyperbolic discounting to be the correct one is about 23%.[7]

Lastly, the authors found evidence that "risk (ρ) and time (δ) preferences are strongly correlated: more risk averse subjects turn out to be also more patient." (Rodriguez-Lara and Ponti, 2017, p. 191)

To conclude the analysis, we are going to observe how the authors treated the decisions of Dictators in Stage 4. They implemented a welfare function that is a linear convex combination of the risk and intertemporal preferences of the Dictator and its assigned Recipient. Thus, Dictators' choices should maximize the function

to be an independent draw from Model 1.

[7] We recall that Model 3 is made by the probability-weighted average of exponential discounting model and hyperbolic discounting model.

$$v_i^k(\tau) = (1-\alpha_i)\Delta_i(\tau)\Big(\frac{x(\tau)^{1-\rho_i}}{1-\rho_i}\Big) + \alpha_i\Delta_j(\tau)\Big(\frac{x(\tau)^{1-\rho_j}}{1-\rho_j}\Big) \quad (4.2)$$

where ρ_j and $\Delta_j(\tau)$ are the parameters of the Recipient j associated to Dictator i. Using the maximum likelihood approach on the data obtained from Stages 1 and 2, the individual parameters of risk (ρ_i) and time (δ_i) preferences were estimated. After obtaining these parameters, Rodriguez-Lara and Ponti (2017) estimated "the probabilities that any given consistent Dictator i in Stage 4 resolves the same sequence of intertemporal decisions assuming that i is maximizing the welfare function, derived as the convex linear combination between the utilities of Dictator i and Recipient j." (Rodriguez-Lara and Ponti, 2017, p. 191) The estimates of the parameter α are reported in Table 4.4.

Table 4.4: Structural model.

	TR_0 INFO-SOCIAL	TR_1 BELIEF-SOCIAL	TR_2 INFO-PRIVATE	POOL
(a) Estimates of α for Consistent Dictators (CD)				
Const.	0.739***	0.612	0.394*	0.527
	(0.214)	(0.999)	(0.204)	(0.413)
(b) Estimates of α for Consistent Dictators, conditioned on (In)Consistent Recipients				
Const.	0.758***	0.612	0.101	0.245
	(0.270)	(0.999)	(0.102)	(0.457)
Inc. Rec.	−0.070	N/A	0.769***	0.589
	(0.292)		(0.113)	(0.469)

Notes. Robust standard errors (clustered at the individual level) in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Ismael Rodriguez-Lara and Giovanni Ponti, Social motives vs social influence: An experiment on interdependent time preferences, Games and Economic Behavior 105 (2017) 177-194.

Panel (b) of Table 4.4 differs from Panel (a) since it considers whether consistent Dictators are matched with consistent or inconsistent Recipients. To do so, they used a dummy that assumes positive value in case of matching between consistent Dictator and inconsistent Recipient. Looking at the values of Panel (a) we can see that α is always positive but with different level of confidence for each column. Situation in Panel (b) is slightly different since the constant is positive and significant in T_0 but not in T_2.[8] Now, considering that Rodriguez-Lara and Ponti (2017) observed that "the effect of being matched with an inconsistent Recipient is negligible in T_0

[8]This means that the behavior of consistent Dictators in treatment T_0 do not seem to vary depending on the consistency of their Recipients.

and highly significant in T_2" it can be concluded that *social motives are stronger than social influence.*

To summarize, the authors considered in their analysis the main conjectures about the influence of others in individual intertemporal decisions: these are the "social motives" conjecture, the "social influence" conjecture and the "focusing" conjecture. The results obtained from the experiment and the following descriptive analysis supported all these conjectures to different degrees:

> Changes in behavior (in the direction of the Recipient) are more likely in the presence of i) information about others' decisions (even in absence of any payoff externality), ii) belief elicitation (even in absence of any information about others' decisions) and iii) payoff externalities (especially in conjunction with information about others' decisions). (Rodriguez-Lara and Ponti, 2017, p. 191)

Anyway, as shown by the result of the structural estimation, *social influence and focusing conjecture seems to have a weaker effect on influencing the behavior of subject compared to social motives.*

4.5 Intertemporal preferences in our model

In the previous paragraph we presented one of the most interesting and innovative experiments in the social preferences panorama. The results reached by Rodriguez-Lara and Ponti not only bring further evidence in favor of theories that have been consolidated in recent years - for example hyperbolic discounting and direct correlation between risk aversion and patience - but they also come to define which are the main effects and elements that trigger social preferences, opening up many scenarios for future research on the subject.

At this point, we can say that we have explored and analyzed the main aspects of intertemporal decisions, starting from the Samuelson model (1937) to arrive at extremely recent and innovative models such as those of Laibson (2017) and Rodriguez-Lara and Ponti (2017). To conclude this dissertation we will therefore try to confirm some of the most interesting results we have been able to analyze during our work. To do this, we will borrow the data of the experiment conducted by Rodriguez-Lara and Ponti (2017), specifically the ones regarding the intertemporal preferences and the socio-demographic data of the subjects participating in the experiment. Concerning intertemporal preferences we recall that, as explained in section 4.2, these are obtained from the MPLs of Stage 2 in which subjects were asked to indicate their own switching points from the columns of options A and B. In this case time consistency is verified within each MPLs but not across MPLs: we need to impose Condition 2 described in paragraph 4.3 to get rid of inconsistent answers.

Instead, socio-demographic data are taken from the debriefing questionnaire that was proposed to the participants at the end of all the sessions of the experiment. We are going to use for our analysis data about age, gender, years of study in university (q4 from now on) and the answers to the Cognitive Reflection Test questions (CRT). As the name suggests, age represents how old the subjects are: ages of subjects participating in the experiment ranged from 18 to 62 even if we will probably restrict the range getting rid of inconsistent subjects. Gender is a binary variable that assumes value 0 for male subjects and value 1 for female subjects. Variable q4 refers to the number of years of study at university: we considered this factor to examine if agents with greater experience and knowledge show less discounting. The CRT variable allows us to analyze the relation between intertemporal preferences and impulsive/reflective agents and since it is a variable that is positively correlated with intelligence, we can observe whether more intelligent individuals discount future less or more with respect to less intelligent ones.[9]

[9]Cognitive reflection test was developed in 2005 by Shane Frederick. The test consists in a set of three questions that have an obvious but wrong answer and an effortful but correct response. Subjects that give the obvious response are considered impulsive while the ones that give the correct answer are considered reflective. The mechanism of the test is structured such that a subject has to spend some effort in reflecting on the obvious incorrect answer to understand that is not the correct one. It is demonstrated that CRT has a moderate positive correlation with intelligence.

Table 4.5: Summary statistics of age, gender and q4.

Variable	Obs	Mean	Std. Dev.	Min	Max
age	10,501	22.43977	5.310808	18	54
gender	10,501	.491477	.4999512	0	1
q4	10,501	3.312066	2.13792	0	20

We have 10,501 observation for each variable after getting rid of inconsistent subjects. The average age of our sample is 22 years, including subjects ranging from 18 to 54 years. As said before, gender is a dummy variable assuming value 0 for males and 1 for females: in our sample 49% of subjects are female. About q4 we have that our subjects spent in average 3 years studying at university.
For CRT we provided a different table to show the percentage of impulsive and reflective agents.

Table 4.6: CRT categories.

CRT	Freq.	Percent	Cum.
0	5,513	52.50	52.50
1	2,614	24.89	77.39
2	2,374	22.61	100.00
Total	10,501	100.00	

In Table 4.6 are reported the categories proposed by Frederick in his CRT: 1 represents the category of impulsive agents that in this case correspond to the 24.89% of the total, while 2 represent the category of reflective agents, that are 22.61% of the total. The category represented by the 0 is the residual, that includes the subjects that cannot be labeled as impulsive nor reflective.

Next step, we are presenting the correlation between all the variables considered. In Table 4.7 we constructed the correlations matrix and reported the values obtained.

Analyzing the values obtained between the dependent and the independent variables we can see that there is a positive correlation between *firstbf2* (our dependent variable that represent the switching point in Phase 2) and age. Even between firstbf2 and q4 we have a positive value but in this case there is a problem: the sig-

The three CRT questions were inserted in the debriefing questionnaire at the end of the experiment of Rodriguez-Lara and Ponti (2017).

Table 4.7: Matrix of correlations.

	firstbf2	age	gender	q4	CRT
firstbf2	1.0000				
age	0.1195 0.0000	1.0000			
gender	-0.1282 0.0000	0.0704 0.0000	1.0000		
q4	0.0119 0.4986	0.2999 0.0000	-0.0084 0.3879	1.0000	
CRT	-0.0344 0.0498	0.0725 0.0000	-0.1256 0.0000	0.0526 0.0000	1.0000

nificance level is 0.4986 meaning that probably there is no correlation between these two variables. Conversely, the minus sign in the values obtained between firstbf2 and gender is telling us that there is a negative correlation; the same applies between firstbf2 and CRT but in this case the value is very small.

Looking at the values of the correlation between the independent variables we can see that the correlation between q4 and gender has a significance level that is not that optimal and that lead us to think that the two variables are not correlated. The remaining values do not present other problems.

Overall, the values are acceptable: the only drawback is that the values are not so high, probably meaning that a linear model cannot explain properly the relations between dependent and independent variables. We will confirm this hypothesis only after running our linear regression to observe the values.

4.6 Results

In the previous paragraph we presented our model, explained and described the characteristics of the variables and analyzed the correlations between them. Now we are going to use a linear regression where the intertemporal preferences of the subjects (firstbf2) is the dependent variable and the independent variables are age, gender, years of study in university (q4) and CRT. In Table 4.8 we report the results of the regression.

For our analysis we are interested in the coefficient and the p-value. Looking

Table 4.8: Results of linear regression.

firstbf2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
age	.1734505	.0217999	7.96	0.000	.1307074	.2161935
gender	-1.860944	.2215456	-8.40	0.000	-2.295327	-1.42656
q4	-.1053866	.0538239	-1.96	0.050	-.2109189	.0001456
CRT	-.48815	.1363698	-3.58	0.000	-.7555298	-.2207703
_cons	11.83286	.4815915	24.57	0.000	10.8886	12.77711

Number of obs	=	3,249	R-squared	=	0.0381
F(4, 3244)	=	32.10	Adj R-squared	=	0.0369
Prob > F	=	0.0000	Root MSE	=	6.2404

at the coefficient we can see that age is the only positive value, meaning that it is positively correlated with intertemporal preferences. Conversely, gender, q4 and CRT are negatively correlated: they tend to decrease if time discounting increases.

Analyzing the results we observe that older subject tend to have higher discount rate compared to younger ones; considering that our sample is comprensive of subjects aging from 18 to 54, in average 22 years, we should investigate further on the relations between these two variables. A possible solution could be to divide our sample in subgroups based on discriminants like endowment or income to furnish a motivation that can explain the relation between age and discount factor. Anyway, this seems to be in contrast with the hypothesis of Laibson (2017) that older agents, who generally have more life experience and consequently better forecasting skill, will exhibit less discounting.

Looking at the coefficient of gender we can argue that female agents discount future less than male subjects.[10]

Even the coefficient of q4 is negative, meaning that subject that spent more years studying at university discount future less and this is in line with the idea proposed by Laibson (2017).

Finally, the coefficient of CRT is negative which means that agents labeled as reflective have a lower intertemporal discount rate than subject labeled as impulsive. This result is very interesting since it confirms the idea proposed by Laibson (2017) that reflective agents or agents that are encouraged to spend more time thinking

[10]We recall that gender is a dummy variable that assumes value 0 for males and 1 for females. Since the coefficient of our regression is negative we have a negative correlation between discount rate and female agents, meaning that in average, females discount future less than males.

about a intertemporal decision will show less discounting than agents that take an immediate decision.

The results obtained from the coefficient seems to give credit (at least a little) to some of the hypothesis that we reported and analyzed in the previous chapter of this dissertation. Furthermore, observing the p-value in Table 4.8 we can reject the null hypothesis and confirming that the data are statistically significant: $\rho < 0.01$ for all the independent variables with the exception of q4 where $\rho < 0.05$.

The only problem that cannot be ignored is that the R-squared reports a very low value and this is a unequivocal signal that the data do not fit the model very well. A possible explanation is that the relation between the variables is not linear so that using a linear regression in this case do not give us optimal results.

To solve this problem we moved on a model with a non-linear regression and analyzed the relations of each single independent variable with the intertemporal preference. Using this approach we should be able to confirm or not our idea that the variables are not correlated in a linear fashion.

For our purpose we used a simple exponential function, avoiding more complex functional form that could bring different problems in the analysis. The function considered has the form $y = b_1 \cdot b_2^x$ where y is the dependent variable, x is the independent variable and b_1 and b_2 are the coefficients of the regression. Table 4.9 reports the results of the non-linear regressions.

In this case, conversely to the linear regression, we obtain an optimal value for the R-squared value, meaning that this model fits the data very well. Even in this case the p-values in each regression lead us to reject the null hypothesis ($\rho < 0.01$ for all independent variables).

This results confirm our previous idea that the relations between the variables considered is not linear. Knowing this, our work could be used as a basis for future works aimed at investigating these relations more in details, for example considering more complex non-linear functions that could give a better insight of the problem.

Table 4.9: Results of non-linear regressions.

(a) Non-linear regression of firstbf2 and age.

firstbf2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b1	11.4161	.3365012	33.93	0.000	10.75632	12.07587
/b2	1.009393	.001239	814.69	0.000	1.006964	1.011823

Number of obs =	3,249	Root MSE =	6.31312
R-squared =	0.8337	Res. dev. =	21191.67
Adj R-squared =	0.8336		

(b) Non-linear regression of firstbf2 and gender.

firstbf2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b1	14.91423	.1555561	95.88	0.000	14.60924	15.21923
/b2	.8906585	.0140615	63.34	0.000	.8630882	.9182288

Number of obs =	3,249	Root MSE =	6.307218
R-squared =	0.8340	Res. dev. =	21185.59
Adj R-squared =	0.8339		

(c) Non-linear regression of firstbf2 and q4.

firstbf2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b1	13.9817	.207829	67.28	0.000	13.57421	14.38919
/b2	1.002603	.0036108	277.66	0.000	.9955235	1.009683

Number of obs =	3,249	Root MSE =	6.359253
R-squared =	0.8312	Res. dev. =	21238.98
Adj R-squared =	0.8311		

(d) Non-linear regression of firstbf2 and CRT.

firstbf2	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
/b1	14.29882	.1476107	96.87	0.000	14.0094	14.58824
/b2	.980922	.0096347	101.81	0.000	.9620314	.9998127

Number of obs =	3,249	Root MSE =	6.355945
R-squared =	0.8314	Res. dev. =	21235.6
Adj R-squared =	0.8313		

Conclusions

In the course of this dissertation we carried out an extremely detailed analysis regarding intertemporal preferences, starting from the first models formulated on the subject up to analyzing the most recent formulations with their implications. We have also seen how this topic has numerous approaches and applications, all different from each other.

In Chapter 1 we analyzed the most recent approaches and ideas regarding time preferences models, explaining the features and peculiarities that distinguish them from the previous approaches. We focused mainly on the Prospect Theory of Kahneman and Tverski, which is one of the most recognized and used approaches in this context: they proposed that individuals evaluate the possible outcomes of a decision based on a reference point and not in absolute value. Furthermore, they observed that subjects have different risk attitudes toward gains and losses (gains are discounted more than losses) and included this idea in the formulation of the Prospect Theory. Then, we focused our attention on the discount factor. The main approach used for the formulation of the discount factor is the one proposed by Samuelson (1937), named exponential discount factor. This approach was largely used in many models of intertemporal choices thanks to its semplicity and elegance. Anyway, recent studies have shown that individuals do not seem to discount future at a constant rate: this has been proved in many experiments that aimed at evaluating the discount rate of agents with different time horizons. The results supported the idea that individuals discount future rewards differently, specifically they discount future following an hyperbolic discount factors. This means that they disount more the rewards in the near future and discount less rewards that are far away in the future, instead of using the same discount factor for all the horizons. Using this approach it has been shown that it is possible to make better prediction about the decisions of the agents.

In Chapters 2 and 3 we have delved further into the subject and analyzed one of the most important concepts on the subject, namely uncertainty about the future. As we also explained in Chapter 1, uncertainty and ambiguity are fundamental concepts for modeling the intertemporal decisions of individuals precisely because they significantly influence the choices of subjects, as has been demonstrated by numerous experiments.

In Chapter 2 we introduced ambiguity and showed that it is a common behavior for individuals facing decisions in presence of uncertainty. Large empirical evidence arising from field and experimental studies suggest that majority of the individuals are averse to ambiguity. Famous examples are the Allais and the Ellsberg paradoxes, that we have analyzed in detail in section 2.4 and 2.5. The demonstration of the fact that individuals are ambiguity averse to some extent has led to a reconsideration of some of the theories and models used up until then as well as the creation of other models and ways to study and model ambiguity.

We therefore proposed and analyzed a useful tool to elicit risk and intertemporal preferences of the subjects, the Multiple Price Lists. MPLS are constructed in such a way that subjects must make decisions between consecutive binary options, usually arranged in two columns and having increasing or decreasing values, moving from the first couple of decisions to the last. This tool is highly appreciated and used in experiments for its simplicity and ability to collect data. Furthermore the use of the switching point allows to solve the problems related to inconsistent choices, that is the cases in which the subjects show discount rates that are not monotonically increasing or decreasing.

In Chapter 3 we have deepened the discussion on ambiguity, analyzing cases in which the source of ambiguity is not unique. First we added a second source and then we studied a model with three different sources of ambiguity. Comparing the results we obtained that in presence of two sources of ambiguity the share of subjects showing ambiguity aversion decreases significatively compared to the case in which the source is unique. This is probably due to the fact that the model is structured so that the second source of ambiguity obscures the first, leading the subjects to be more indifferent with respect to the case with a single source of ambiguity.

Adding the third source of ambiguity we get results that are still different compared to the previous case. Specifically, we have shown that, in the presence of multiple sources of ambiguity, individuals show an aversion to ambiguity but in a lighter form than in the case where the source is single. It is also surprising that subjects prefer to make decisions in situations with multiple sources of ambiguity compared to situations with a single source. Obviously it is less surprising that subjects prefer the absence of ambiguity to situations with one or more sources of it, but this is useful to confirm the results of this analysis.

At this point we analyzed some of the most recent innovations regarding intertemporal choices. The most interesting is undoubtedly the hypothesis of myopia or imperfect foresight. This in fact provides an explanation for the fact that subjects prefer smaller but immediate rewards instead of larger but postponed rewards. Until now the commonly accepted justification is that individuals are impatient and this leads them to prefer the more immediate rewards: this impatience is measured by the discount rate which varies from individual to individual. This explanation is generally valid when we face choices in conditions of certainty but it may not be the only explanation when we move on to choices in conditions of uncertainty. In this case, myopia could provide an alternative justification, namely that preferences for the most immediate rewards depend on the subjects' poor ability to make predictions about the future. Due to the uncertainty about future events, such as the actual realization of the winnings, individuals would be more inclined to choose the "safer" alternative, that is the one on which they are more certain, even if this leads to a smaller gain. Since the forecasting capacity is not perfect, it is relatively simple to make predictions about events that will occur in the near future but it becomes increasingly complicated as the time horizon increases. Furthermore, if we consider that individuals generally tend to be risk-averse and ambiguity-averse, as already amply demonstrated, it is possible to affirm that individuals prefer the closest rewards in terms of time.

As explained, the hypotheses of myopia and time preferences can both justify the preference of individuals for immediate rewards and this could create confusion regarding the modeling of behaviors, since the underlying intentions are different. The work of Gabaix and Laibson (2017) addresses this topic in detail, concluding that it is possible to distinguish between time preference and myopia. The differences between the two approaches can be seen in learning dynamics and preference for commitment: learning generates no change in the time preference and, if the time preference is dynamically inconsistent, learning engenders a taste for commitment. With myopia, learning generates less (as-if) discounting and no taste for commitment.

In the fourth chapter we analyzed the social preferences and the implications these have on the decisions of the subjects. In the previous chapters we analyzed the choices of individuals in different conditions, without however considering the presence of other agents in the context. However, when we consider more individuals who have to make decisions in the same context, we know that the decisions of each subject will influence those of the other subjects. This is dealt with extensively in Game Theory, where cooperative or competitive scenarios are hypothesized between multiple players who usually have to make decisions that will influence the outcome of all participants. In our case we are interested in observing the effects of social motives and social influence on the decisions of individuals.

In the fourth chapter we analyzed the social preferences and the implications these have on the decisions of the subjects. In the previous chapters we analyzed the choices of individuals in different conditions, without however considering the presence of other agents in the context. However, when we consider more individuals who have to make decisions in the same context, we know that the decisions of each subject will influence those of the other subjects. This is dealt with extensively in Game Theory, where cooperative or competitive scenarios are hypothesized between multiple players who usually have to make decisions that will influence the outcome of all participants. In our case we are interested in observing the effects of social motives and social influence on the decisions of individuals.

For this reason we have considered the experiment conducted by Ponti and Rodriguez-Lara (2017), to whom the merit goes of having succeeded in combining social preference with intertemporal preferences. Using two MPLs to elicit intertemporal and risk preferences, first individually and later in a social dimension, Ponti and Rodriguez-Lara obtained extremely interesting data regarding the effects of social motives and social influences on subject decisions.

The participants to the experiment were divided into pairs and within them the roles of Dictator and Recipient were assigned, as in the classic Dictator Game. The Dictators were then assigned the task of making decisions for themselves and for the respective Recipient, which would in no way respond to the choice made by the Dictator. Looking at the decisions made by the Dictators, we were able to verify that most of them moved towards the Recipients' preferences, meaning that there are strong effects of social motives and social influences.

After having verified that social preferences have a strong influence on the choices of the subjects, we want to verify if there is a conjecture among those considered that is stronger than the others. Analyzing the data using a statistical model it is possible to affirm that the stronger effect derives from social motives, while sociale influence and focusing conjecture have a weaker influences on the decisions of Dictators.

Finally, using the dataset granted to us by Ponti and Rodriguez-Lara, we have developed a model to test some of the hypotheses we observed during this paper. Always focusing on intertemporal preferences, we used the data obtained from the individual intertemporal MPL to obtain the switching points of each participant. Then, we considered some socio-demographic variables including age, gender and years of study at the university, obtained thanks to the questionnaires that the participants answered at the end of the experiment. In addition to these, we also considered the answers given by the subjects to the Cognitive Reflection Test questions, assigning a value between 0, 1 and 2 to each subject based on the answers: 1 represents the subjects that are defined as impulsive according to CRT standards, 2 represents the subjects defined reflexive and 0 the residual group. At this point we runned a linear regression to observe the relations between switching points (dependent variable) and age, gender, years of study and CRT values (independent variables).

The results we obtain from the regression seem to support the hypotheses made in the previous chapters, especially those brought by Gabaix and Laibson, relative to myopia and its implications..

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Executive Summary

Chapter 1

In Chapter 1 we analyzed the most recent approaches and ideas regarding time preferences models, explaining the features and peculiarities that distinguish them from the previous approaches. First of all we focused our attention on the discount factor. The main approach used for the formulation of the discount factor is the one proposed by Samuelson (1937), named exponential discount factor. This approach was largely used in many models of intertemporal choices thanks to its semplicity and elegance. The formulation proposed by Samuelson is the following:

$$U^t(c_t, ..., c_T) = \sum_{k=0}^{T-t} D(k)u(c_{t+k})$$

where

$$D(k) = \left(\frac{1}{1+\rho}\right)^k$$

Anyway, recent studies have shown that individuals don not seem to discount future at a constant rate: this has been proved in many experiments that aimed at evaluating the discount rate of agents with different time horizons. The results supported the idea that individuals discount future rewards differently, specifically they discount future following an hyperbolic discount factors. This means that they disount more the rewards in the near future and discount less rewards that are far away in the future, instead of using the same discount factor for all the horizons.

Hyperbolic discountig can explain some stylized empirical facts better than exponential discounting: experimental studies concluded that when subjects are asked to compare a smaller-sooner reward to a larger-later reward, the implicit discount rate over longer time horizons is lower than the implicit discount rate over shorter time horizons.

One of the most iteresting models that we analyzed is the Prospect Theory proposed by Kahneman and Tversky (1979). Prospect Theory suppose that individuals, when evaluating the possible outcomes of a decision in case of uncertainty, do not care about the absolute value of the outcome itself but evaluates it based on how much it departs from a reference point. This reference point is not uniquely defined, it can depend on status quo, current welfare, expectations, social comparison and others.

The second feature concern the form of the value function that is made to reflect the fact that individuals have different risk attitude towards gains and losses. Indeed, the value function is concave for gains, indicating that individuals are averse to risk, and is convex for losses, so that individuals are inclined to risk. Moreover, the slope of the function is greater in the neighbourhood of the origin, meaning that small variations near to the starting point have a greater impact than big variation but far from the origin. The value function is not symmetric in the region of gains and losses since the slope is steeper for losses than for gains to reflect the fact that for most individuals to avoid a loss is preferred to attain a gain. Finally, the value function exhibits diminishing marginal utility/disutility, showing that both gains and losses procure less satisfaction or misery as they increase.

The third characteristic of Prospect Theory implies the existence of a probability weighting function that is used to transform the probabilities perceived by the individuals replicating the fact that people overvalue small probabilities while undervalue large ones. The mathematical form proposed by Tversky and Kahneman is the following:

$$V = \sum_{i=1}^{n} \pi(p_i)v(x_i)$$

where $\pi(p_i)$ is the probability weighted function and $v(x_i)$ is the value function.

To conclude, we analyzed some models that incorporated uncertainty in various dimensions, model of multiple-self and commitment, models incorporating utility from anticipation and model of projection bias. Each model analyzed in this section shows one or more innovative and noteworthy features, especially looking at the forms of the proposed utility functions.

Chapter 2

In Chapter 2 we introduced ambiguity and showed that it is a common behavior for individuals facing decisions in presence of uncertainty. Large empirical evidence arising from field and experimental studies suggest that majority of the individuals are averse to ambiguity. Famous examples are the Allais and the Ellsberg paradoxes: these provide empirical evidences that Savage Axioms fail to predict the behaviors of individuals in some circumstances. This usually happens when agents make decisions in situation in which there is a source of ambiguity: in the Ellsberg paradox there is uncertainty on the probability distribution of balls in one of the urn. After these considerations on ambiguity, it is not wrong to consider it as a subjective variable, since different individuals may have different level of confidence and reliability on the same problem with same information for all.

The demonstration of the fact that individuals are ambiguity averse to some extent has led to a reconsideration of some of the theories and models used up until then as well as the creation of other models and ways to study and model ambiguity. We have shown how the axioms of rationality proposed by Savage fail to correctly predict the choices of agents in conditions of ambiguity.

Then, we consider how recent paper modeled ambiguity and elicit ambiguity-aversion. Gilboa and Schmeidler (1989) proposed an interesting functional form to represent preference relations over outcomes. The function has the form

$$J(f) = min\{\int u \circ f dP \mid P \in C\} \tag{1}$$

where f is an act, u is a von Neumann-Morgenstern utility over outcomes and C is a closed and convex set of finitely additive probability measures on the states of nature. The idea behind it is that the subject has too little information to form a prior, hence he considers a set of prior as possible. Being uncertainty averse, he takes into account the minimal expected utility (over all priors in the set) while evaluating a bet: for this reason, individuals appear to be pessimistic about their estimations since they expect the lowest value to be realized.

In the end, we analyzed Multiple Price Lists and their capacity to estimate ambiguity aversion. In the experiment proposed by Gneezy, Imas and List (2015) a

MPL was used to elicit the degree of ambiguity-aversion of the participants. Subjects faced series of 20 decisions between drawing a ball from Urn A or Urn B knowing the probability distribution of the balls inside the first urn but not the distribution of the second urn. Each decision differs from the precendent in the payoff obtained in case of correct guess.

Assuming that an individual prefers the urn A in the first decision, we can define his degree of aversion to ambiguity based on his own switching point: if he prefers to pass from the urn A to the urn B in one of the last decisions implies that it is very ambiguity averse, while a switching point in the first decisions indicates a low degree of aversion to ambiguity. Using the data collected from the subjects the authors estimated the coefficients α_i and r_i (the ambiguity attitude and the risk aversion of individual i) of the following function:

$$V_i(x;\alpha,r) = \alpha_i \frac{x_{max}^{1-r_i}}{1-r_i} + (1-\alpha_i)\frac{x_{max}^{1-r_i}}{1-r_i} \tag{2}$$

where x_{min} and x_{max} represents respectively the smallest and the highest payoff of the pairs of gambles.

The results obtained from the data suggested substantial risk aversion in the population and that the subjects of the experiment showed a significant amount of ambiguity aversion. Moreover, is interesting the fact that the estimates of α were smaller when risk and ambiguity attitudes were estimated jointly and were higher when estimated assuming risk neutrality.

Chapter 3

In Chapter 3 we analyzed some of the most recent innovations regarding intertemporal choices. The most interesting is undoubtedly the hypothesis of myopia or imperfect foresight. This in fact provides an explanation for the fact that subjects prefer smaller but immediate rewards instead of larger but postponed rewards. Until now the commonly accepted justification is that individuals are impatient and this leads them to prefer the more immediate rewards: this impatience is measured by the discount rate which varies from individual to individual. This explanation is generally valid when we face choices in conditions of certainty but it may not be the only explanation when we move on to choices in conditions of uncertainty. In this case, myopia could provide an alternative justification, namely that preferences for the most immediate rewards depend on the subjects' poor ability to make predictions about the future. Due to the uncertainty about future events, such as the actual realization of the winnings, individuals would be more inclined to choose the "safer" alternative, that is the one on which they are more certain, even if this leads to a smaller gain. Since the forecasting capacity is not perfect, it is relatively simple to make predictions about events that will occur in the near future but it becomes increasingly complicated as the time horizon increases. Furthermore, if we consider that individuals generally tend to be risk-averse and ambiguity-averse, as already amply demonstrated, it is possible to affirm that individuals prefer the closest rewards in terms of time.

As explained, the hypotheses of myopia and time preferences can both justify the preference of individuals for immediate rewards and this could create confusion regarding the modeling of behaviors, since the underlying intentions are different. The work of Gabaix and Laibson (2017) addresses this topic in detail. They considered a decision maker who at zero time had to decide between a Early option that can be obtained at time $t > 0$ and a Late option available at time $t + \tau$, where $\tau > 0$. The value of both rewards is not known by the decision maker, for this we will indicate with u_t the true value of Early and with $u_{(t+\tau)}$ the true value of Late. In this framework, we assume that the decision maker makes estimates about the values of Early and Late rewards, since he does not know the true value of them. In this way he generates noisy, unbiased signals which are then combined with his priors to form posteriors. In this case we suppose that the variance of the simulation noise will increase as the time horizon increases: this is a fairly realistic assumption as short-term forecasts of events are usually more accurate than long-term forecasts.

At this point it is assumed that agents have a discount function of this form:

$$D(t) = \frac{1}{1 + \frac{\sigma^2_{\varepsilon_t}}{\sigma^2_u}}$$

where $D(t)$ is defined the agent's as-if discount function, $\sigma^2_{\varepsilon_t}$ is the variance of the simulation noise of a decision maker and σ^2_u is the overall variance.

Now consider two situations: $t = 0$ and $t > 0$. In the first case we have that the agent chooses the Early reward with probability one if three properties hold: (i) the Early reward is available immediately ($t = 0$), (ii) the Late reward is available arbitrarily far in the future ($\tau \to \infty$), and (iii) the Early reward is strictly positive ($u_0 > 0$). In other words, the agent behaves as if she places no value on the (infinitely) delayed Late reward. For the second situation, if we assume $\tau \to \infty$ as in the previous situation, also in this case we will get that a decision maker chooses the Early reward over the Late reward if and only if the former is strictly positive.

Although we have verified that the subjects prefer the Late reward if the two options occur in a distant future, it is important to note that with the progress of time, when approaching time t, all subjects would prefer to change their choice towards Early reward, if they had the chance. Anyway, in contrast with other models of time preferences, in this framework preference reversal do not arise from time inconsistencies in the preference of the subjects but from the fact that they possess imperfect information about the value of the rewards. In this case the difference is clear: with preference reversal arising from time inconsistency the decision makers show willingness for commitment, for example having some of the options removed from the choice set, as pointed out from many studies on the argument. Conversely, in this model the preference reversal comes from a forecasting problem of the agent and not from a self-control problem, thus there is no reason to reduce the set of choices.

Anyway, an external observer is led to think that the individual has deep time preferences even if he is perfectly patient, since the resulting behavior is the same in both cases. To solve this confusion about the causes of the declining sensitivity to delayed rewards, one can notice that there are empirical methods to distinguish between behaviors caused by time discounting and myopia. The differences between the two approaches can be seen in learning dynamics and preference for commitment: learning generates no change in the time preference and, if the time preference is dynamically inconsistent, learning engenders a taste for commitment. With myopia, learning generates less (as-if) discounting and no taste for commitment.

Chapter 4

In this chapter we will consider the effects of social preferences on intertemporal choices. This is a very innovative approach and there are still few studies on the subject. In our analysis we will therefore try to analyze some of the aspects that need to be investigated.

One of the most important works on the subject is certainly the one presented by Ponti and Rodriguez-Lara (2017) in which an original experiment was performed with the aim of studying the effects of social preferences and social influence on the intertemporal decisions of the subjects. The experiment was constructed to obtain the individual risk and intertemporal preferences of each subject in the early stages of the experiment. The data was collected through the use of two Multiple Price Lists, one for risk preferences and the other for intertemporal preferences. At the end of this phase, the subjects were divided into pairs and within each pair the roles of Dictator and Recipient were randomly assigned. The division into roles recalls that which takes place in the classic Dictator Game, that is an important subject of Game Theory.

At this point, the Dictators are released information on the risk and intertemporal preferences of the Recipients fees. This information differs depending on the treatment in which the subjects participate. In total, four treatments were prepared: in the baseline treatment (T_0, INFO-SOCIAL), Dictators make their intertemporal choices after being informed of what their assigned Recipient had chosen in the first two stages of the experiment; in the BELIEF-SOCIAL treatment (T_1), before deciding for the pair, Dictators go through an additional stage in which we elicit their beliefs on risk and time concerns of their assigned Recipients; in the INFO-PRIVATE treatment (T_2), subjects receive (exactly as in the baseline) information on risk/time individual choices of their groupmate, but no payoff externalities are imposed on others; in the NO INFO-SOCIAL treatment (T_3), Dictators make their intertemporal decisions for the pair without prior knowledge (or elicited belief) of the Recipient's risk/time decisions.

Once the Dictators have obtained the information required by the treatment in which they participate, they must again take decisions regarding risk and intertemporal preferences with the difference that in this case their choices and the outcome that will derive will also be applied to their matching. Even in this situation, the same MPLs that the subjects encountered in the previous phase will be used to collect the decisions and obtain the data.

From the results obtained by analyzing the data collected, it is noted that more than half of the Dictators decided to change the initial preference to move towards the Recipients. This behavior is evident above all in T_0, while in the remaining treatments the frequency decreases while remaining significant. We can compare treatments T_0 and T_2 since in both cases Dictators have information about the preferences of the corresponding Recipients, with the difference that in T_0 there is the presence of payoff externalities while in T_2 there are not. The results show that Dictators are more inclined to change their decision in presence of payoff externalities (50.6% for T_0 vs 37.1% for T_2). Next, we can compare treatmens T_1 and T_1 because in both cases Dictators make their decisions for the pair with no information about the preferences of the Recipients but, in treatment T_1, they are asked to make predictions about Recipients' preferences before making the choice. In this case, the results show that Dictators are more likely to change their decisions when the beliefs are elicited, that is in treatment T1 (44.7% for T_1 vs 31.4% for T_3). Furthermore, analyzing the directions of the switches of Dictators, we obtain that, with the exception of T_3, a clear majority of choices has changed in direction of the Recipients' preferences.

To conclude, Ponti and Rodriguez-Lara proposed that Dictators' choices should maximize the welfare function:

$$v_i^k(\tau) = (1-\alpha_i)\Delta_i(\tau)\Big(\frac{x(\tau)^{1-\rho_i}}{1-\rho_i}\Big) + \alpha_i\Delta_j(\tau)\Big(\frac{x(\tau)^{1-\rho_j}}{1-\rho_j}\Big)$$

where ρ_j and $\Delta_j(\tau)$ are the parameters of the Recipient j associated to Dictator i. These parameters were estimated using the maximum likelihood approach on the data obtained from Stages 1 and 2. Using the estimated individual parameter profile (ρ_i, δ_i) in the welfare function we can estimate the estimates for α. The results showed that the estimated value of α is positive in all cases, suggesting that social motives are more important than social influence when we consider pairs composed by a consistent Dictator and a consistent Recipient.

In conclusion, the social motives, social influence and focusing conjectures seem to influence to a certain degree the behavior of Dictators. With social influence and focusing conjectures, decisions in direction of the Recipients seem more likely, anyway we obtain a stronger effect when social motives are present.

In the last part of this dissertation we proposed a model of intertemporal preferences to test some of the hypothesis that we mentioned in the previous chapters. Using the data obtained from the individual intertemporal MPL in the experiment of Ponti and Rodriguez-Lara, we derived the switching points of each participant and the relative discount factor. Then, we considered some socio-demographic variables including age, gender and years of study at the university, obtained thanks to the questionnaires that the participants answered at the end of the experiment. In addition to these, we also considered the answers given by the subjects to the Cognitive Reflection Test questions, assigning a value between 0, 1 and 2 to each subject based on the answers: 1 represents the subjects that are defined as impulsive according to CRT standards, 2 represents the subjects defined reflexive and 0 the residual group. At this point we runned a linear regression to observe the relations between switching points (dependent variable) and age, gender, years of study and CRT values (independent variables).

The results of the linear regression are showing that older subject tend to have higher discount rate compared to younger ones; considering that our sample is comprensive of subjects aging from 18 to 54, in average 22 years, we should investigate further on the relations between these two variables. A possible solution could be to divide our sample in subgroups based on discriminants like endowment or income to furnish a motivation that can explain the relation between age and discount factor. Anyway, this seems to be in contrast with the hypothesis of Laibson (2017) that older agents, who generally have more life experience and consequently better forecasting skill, will exhibit less discounting.

Looking at the coefficient of gender we can argue that female agents discount future less than male agents; this result is in line with other experiment made on the subject.

The coefficient of q4 is negative, meaning that subject that spent more years studying at university discount future less: this is consistent with the idea proposed by Gabaix and Laibson (2017) which explains that agents with more domain-relevant experience, and hence better within-domain forecasting ability, will exhibit less discounting.

Finally, the coefficient of CRT is negative which means that agents labeled as reflective have a lower intertemporal discount rate than subject labeled as impulsive. This result is very interesting since it confirms the idea proposed by Laibson (2017) that reflective agents or agents that are encouraged to spend more time thinking about a intertemporal decision will show less discounting than agents that take an immediate decision.