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Strategies of Information Acquisition Under Uncertainty

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May Attallah. Strategies of Information Acquisition Under Uncertainty. Economics and Finance. Université de Rennes, 2017. English. NNT : 2017REN1G023 . tel-01714007

HAL Id: tel-01714007

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THÈSE / UNIVERSITÉ DE RENNES 1
sous le sceau de l'Université Bretagne Loire

pour le grade de
DOCTEUR DE L'UNIVERSITÉ DE RENNES 1
Mention : Sciences économiques

**Ecole doctorale Sciences Économiques et sciences De Gestion
(EDGE)**

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Préparée à l'unité de recherche CREM (UMR 6211 CNRS)
Centre de Recherche en Économie et Management
Faculté des Sciences Économiques

**Strategies of
Information
Acquisition Under
Uncertainty**

**Thèse soutenue à Rennes
le 13 Octobre 2017**

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Acknowledgements

During my PhD years, I have been supported by many people, I would like to express my gratitude to all of those who supported me through this adventure.

First of all, I am deeply indebted to my supervisor Olivier L'Haridon. I would like to express my thanks to him for his support, his guidance and insights that have been essential to my dissertation and my career. I am proud to have written my thesis under his supervision. I would like also to thank Guisepe Attanasi, Laurent Denant-Boemont, Fabrice Le Lec, Brice Magdalou and Kirsten Rohde for being part of my thesis committee.

I would like to thank all the researchers of the CREM who helped me with their comments and discussions about my work. I would like to thank all the administrative staff of the CREM and of the University of Rennes 1. I have a special thought for Anne L'Azou and Cécile Madoulet. I would also like to thank my co-author Isabelle Vialle for her fruitful discussions and Elven Priour for teaching me Z-tree and helping me in conducting the experiments.

Of course, I cannot forget ALL the PhD students who made the working atmosphere so pleasant and productive. Special thanks go to my officemates Guillaume Beaurain and Romain Gaté. I always enjoyed our teamwork (solidarité de bureau!), many stimulating and inspiring discussions as well as celebrating successes and coping with failures together. After sharing The office 108 for such a long time, they have become a family to me and I am deeply indebted to them. I would also like to thank Ewen Gallic and Xuan Tran and Vincent Malardé for always being helpful and fun to be around, making the last three years a very special time in my life.

I also would like to thank my friend Nourhane who has always been there for me and supporting me till the end.

Last, but definitely not least, I would like to thank my parents Atef and Seham and my sister Sally for unconditionally supporting all my pursuits. I owe a lot to them.

Résumé en français

Stratégies d'acquisition d'information dans l'incertain

La méthode expérimentale a été pendant longtemps l'instrument d'observation empirique privilégié des travaux d'économie comportementale. Cette méthode consiste à créer un environnement contrôlé afin de réaliser artificiellement une situation reflétant les conditions d'un comportement économique. Comme toute méthode expérimentale, elle se fonde sur la formulation d'hypothèses, l'observation empirique par l'expérience et l'interprétation des résultats. Elle est désormais devenue un élément à part entière de la boîte à outils de l'économiste. A ce titre elle peut être mobilisée pour évaluer des politiques publiques, notamment concernant le marché du travail. L'avantage premier de l'économie expérimentale repose sur ses capacités de contrôle de l'observation empirique : contrôle de l'assignation aléatoire des participants, contrôle de la nature des institutions, contrôle de la spécification des variables exogènes et contrôle des processus de détermination des variables endogènes.

L'économie expérimentale et comportementale est une clé permettant de progresser notre compréhension des préférences individuelles, qui jouent un rôle primordial dans la prise de décision économique. La science économique traditionnelle repose sur les hypothèses de l'homo œconomicus, ou l'homme économique, un sujet économique rationnel et purement intéressé. Cependant, il existe de plus en plus d'évidences provenant de différentes disciplines telles que la psychologie, la sociologie ou l'économie qui révèlent les limites des modèles avec de telles hypothèses. De nombreuses études expérimentales en économie révèlent que les décideurs n'agissent pas comme prédit par les modèles de l'homo œconomicus. Ils échouent souvent à maximiser leur propre profit parce que les choix humains ne sont pas seulement motivés par l'intérêt matériel, mais aussi par des motifs tels que l'altruisme, la réciprocité et l'aversion à l'inégalité. Ces motifs sont appelés "préférences sociales". Outre la dimension des préférences sociales, il existe deux autres dimensions au sein des préférences individuelles qui ont un impact sur la prise de décision: les préférences face au risque et les préférences

temporelles. La plupart des décisions économiques majeures sont prises dans des conditions d'incertitude et affectent le futur ainsi que le présent (par exemple, le problème classique d'allocation de consommation/épargne). Les décisions optimales dépendent donc des attitudes vis-à-vis du risque ainsi que des préférences temporelles.

Le premier chapitre¹ aborde ce sujet. Conformément à la critique de [Henrich et al. \(2010b\)](#), la majorité des données et des recherches en sciences comportementales est basée sur des échantillons tirés de populations occidentales, formées, industrialisées, riches et démocratiques (en anglais l'acronyme WEIRD-bizarre- correspond à Western, Educated, Industrialized, Rich, and Democratic). Néanmoins, malgré le caractère restreint de leurs échantillons, les chercheurs tirent souvent des conclusions concernant les préférences humaines en général. Dans ce chapitre, je propose une synthèse et un point de vue sur la représentativité des résultats issus des expériences de laboratoire et de terrain qui visent à expliquer les préférences sociales, les préférences concernant le risque et le temps. Il existe effectivement des différences incontestables entre les populations d'étudiants et d'autres populations plus générales.

En comparant les étudiants avec des échantillons représentatifs des adultes, je remarque que les étudiants constituent en quelque sorte une limite inférieure de la pro-socialité dans les mesures expérimentales de confiance, d'équité ou de coopération. Dans les expériences testant la propension à coopérer, il existe deux types de variabilité dans les résultats : une variabilité inter-pays et intra-pays. Il existe une relation inverse non parfaite entre les normes de coopération et le niveau de développement d'un pays. En outre, les facteurs sociodémographiques (par exemple : âge, urbanisation, statut étudiant) déterminent le comportement de coopération au sein d'un même pays. Donc, les étudiants se comportent différemment des autres participants et les résultats expérimentaux basés sur un échantillon d'étudiants ne sont pas souvent généralisables. De même, pour les étudiants et les sujets issus des populations WEIRD, la relation entre confiance et réciprocité est positive et forte, pourtant elle est inexistante pour les adultes non étudiants et les sujets issus des populations non-WEIRD. En outre, les expériences mesurant

¹Publié dans *L'Actualité Économique* (2016)

l'équité et l'altruisme confirment que les étudiants sont un échantillon spécial. La différence entre l'offre moyenne du jeu de l'ultimatum et de celui du dictateur dans les pays en voie de développement est bien plus faible que celle des étudiants. Nous constatons donc que les résultats des étudiants sont souvent atypiques en regard des résultats sur des populations plus générales. Par ailleurs, nous avons vu que les étudiants avaient également un comportement beaucoup plus homogène dans ces jeux que les participants en population générale. La généralisation des résultats issus des études expérimentales est donc sensible, non seulement car les comportements sont potentiellement différents, mais également plus diversifiés en population générale.

La comparaison des mesures des attitudes vis-à-vis du risque et du temps entre les populations d'étudiants et les autres populations est plus délicate puisqu'il y a des différences de méthodologie, de protocole et de contexte entre les travaux. D'une part, les attitudes sont très hétérogènes, même au sein d'une population supposée homogène, comme celle des étudiants. D'autre part, les mesures réalisées des attitudes vis-à-vis du risque ou de l'impatience reposent souvent sur des méthodes très différentes les unes des autres. En plus de l'hétérogénéité individuelle et de l'hétérogénéité des populations d'origine, ces différences de méthodes de mesure créent un troisième type d'hétérogénéité, méthodologique, rendant difficile toute comparaison. Dans ce domaine également, cette analyse montre qu'une forte hétérogénéité est la règle, et de ce fait, il est nettement plus difficile de conclure à une spécificité des étudiants ou de toute autre population particulière pour ce qui concerne les attitudes face au risque ou les préférences temporelles.

Les chapitres suivants se focalisent sur les attitudes vis-à-vis du risque car elles constituent des déterminants importants de la prise de décision individuelle. La distinction entre risque et incertitude est donc importante. Celle-ci a été proposée pour la première fois par [Knight \(1921\)](#) dans son livre "Risk, Uncertainty and Profit". Selon Knight, le risque (dont il se réfère comme une incertitude mesurable) s'applique à des situations où différents états de la nature sont connus et la probabilité d'occurrence de chaque état peut être déterminée avec précision. L'incertitude (dont il se réfère comme une incertitude non mesurable), d'autre part, s'applique à des situations dans lesquelles il

n'y a presque aucune information disponible sur les différents états de la nature et/ou la probabilité d'occurrence de chaque état. L'incorporation formelle du risque et de l'incertitude dans la théorie économique a été réalisée par [Von Neumann and Morgenstern \(1947\)](#) dans leur livre "Theory of Games and Economic Behavior". Ils développent quatre axiomes de préférences selon lesquels un sujet évalue une loterie selon la valeur subjective sur tous les résultats. Ce concept est connu sous le nom de la théorie de l'utilité espérée (EUT). Une restriction majeure de la théorie de [Von Neumann and Morgenstern \(1947\)](#) est le fait que, pour calculer la valeur subjective, la distribution de probabilité sur l'ensemble des résultats doit exister et être connue. Cependant, [Savage \(1954b\)](#) a développé la théorie de l'utilité espérée subjective (SEU), où il indique que ce n'est pas un problème en soi tant que le décideur assigne des probabilités subjectives aux événements et se comporte suivant une règle d'utilité espérée. Par conséquent, il ne trouve aucune distinction valable entre le risque et l'incertitude comme Knight le décrit. Cette interprétation a trouvé un usage courant dans l'économie néoclassique.

Des travaux expérimentaux ont donc porté sur l'examen de la validité descriptive de l'EUT en testant ses axiomes. [Ellsberg \(1961\)](#) a contesté la théorie de Savage en utilisant des expériences hypothétiques pour souligner que les informations manquantes sur les probabilités, ce qui l'appelle l'ambiguïté, affecteront les comportements individuels. Ces résultats peuvent pas être expliqués par la théorie de SEU. Dans le cas de l'ambiguïté, l'information disponible ne suffit pas pour que le décideur affecte une distribution de probabilité subjective unique sur les résultats potentiels. [Ellsberg \(1961\)](#) montre que la plupart des gens sont averses à l'ambiguïté, c'est-à-dire qu'ils préfèrent une loterie avec des probabilités connues à une loterie similaire avec des probabilités inconnues, ce qui est de nouveau incompatible avec l'EUT. Diverses expériences ont été conçues pour enquêter sur d'autres violations systématiques de l'EUT, produisant de nombreuses théories alternatives proposées pour tenir compte de l'échec de l'EUT. [Kahneman and Tversky \(1979\)](#) soulignent le rôle des heuristiques dans la production de biais dans le comportement individuel et ont formalisé la Prospect Theory (PT) qui représente l'alternative la plus influente à l'EUT. Cette théorie introduit deux notions importantes pour la modélisation du comportement individuel: la notion de point de référence et celle d'aversion aux pertes. La notion de "point de référence" permet de modéliser le

fait qu'un individu évalue les conséquences monétaires d'un choix, non pas vis-à-vis de leur impact sur son niveau global de richesse, mais en termes de changement par rapport à un état de référence. L'"aversion aux pertes" fait référence à une sensibilité plus importante des individus aux pertes qu'aux gains équivalents. La notion d'aversion aux pertes a été proposée, dans le cadre de la PT, pour expliquer l'observation selon laquelle les gens refusent systématiquement d'accepter un pari qui donne, avec des chances égales, soit un gain monétaire, soit une perte de même montant. Le refus d'accepter des paris donnant un gain ou une perte de même montant, avec des chances égales, est observé également pour des sommes très faibles. L'aversion aux pertes s'avère nécessaire pour expliquer pourquoi les individus n'acceptent pas de tels paris, dans la mesure où l'aversion au risque seule, au sens de la théorie de la décision traditionnelle, est insuffisante pour expliquer un tel refus ([Rabin, 2000](#)).

La littérature sur l'aversion à l'ambiguïté montre que l'ambiguïté peut expliquer les violations empiriquement observées des théories basées sur les utilités attendues ([Camerer and Weber, 1992](#)). De nombreuses études explorent les implications de l'ambiguïté sur le comportement économique. [Alary et al. \(2013\)](#) et [Snow \(2011\)](#) montrent que l'ambiguïté à l'aversion influence le taux optimal de souscription d'assurance. En économie de la santé, [Berger et al. \(2013\)](#) trouvent que l'ambiguïté concernant le diagnostic ou le traitement de l'affection médicale affecte les choix de traitement des patients. Lorsque nous pensons à de véritables situations de prise de décision, les probabilités sont rarement connues. Les individus font face à des décisions dans un environnement incertain dans diverses situations de la vie réelle. Un exemple important est le moment où un individu recherche un emploi et devrait décider d'accepter ou de rejeter une offre d'emploi. L'ambiguïté quant aux conditions du marché du travail peut rendre les individus plus prudents et les décourager de chercher sur des périodes plus longues car ils deviennent moins confiants dans leur capacité à trouver une meilleure offre d'emploi à l'avenir ([Asano et al., 2015](#)).

Dans les modèles de recherche d'emploi, le comportement optimal est caractérisé par une règle d'arrêt, également nommée "propriété de salaire de réservation" dans la littérature expérimentale. Le comportement d'un individu en recherche d'emploi consiste

à continuer à chercher un emploi jusqu'à ce qu'il reçoive une offre de salaire supérieure ou égale à son salaire de réservation. De même, l'information sur la distribution des offres, l'horizon de recherche et la possibilité d'accéder à des offres passées, qui sont des déterminants essentiels des comportements optimaux de recherche, ne sont pas aisément identifiables dans les données d'enquête ou les données administratives. A cet égard, la méthode expérimentale apparaît comme un outil complémentaire intéressant pour tester les modèles de prospection puisqu'elle n'est pas soumise aux précédentes limites. Sur la base de ces preuves, dans le deuxième chapitre, nous analysons expérimentalement comment le risque et l'ambiguïté ont un impact sur les décisions de recherche d'emploi. Le risque et l'ambiguïté sont illustrés par les informations sur la probabilité de recevoir une offre. Notre protocole expérimental est basé sur le modèle standard de recherche d'emploi de [Lippman and McCall \(1976\)](#) et vise à éliciter les durées de recherche et les salaires de réservation. Afin d'explorer les comportements de recherche d'emploi sous risque et ambiguïté, nous utilisons deux traitements qui diffèrent dans l'information sur la probabilité de recevoir une offre. Pour les décisions en matière de risque, cette probabilité est parfaitement connue, alors que sous ambiguïté, les sujets ont pour seule connaissance un intervalle donné à cette probabilité. En comparant les comportements entre les deux traitements, nous sommes en mesure de déterminer si les sujets se comportent différemment en risque et en ambiguïté. Nous constatons que les salaires de réservation sont globalement inférieurs aux salaires de réservation théoriques et diminuent avec le temps dans le risque et l'ambiguïté. En outre, nous constatons que les sujets se comportent comme des agents neutres à l'ambiguïté, ce qui montre que l'ambiguïté n'a pas d'impact important sur les décisions de recherche d'emploi.

La comparaison sociale est un déterminant important du comportement humain. En psychologie sociale, la théorie de la comparaison sociale de [Festinger \(1954\)](#) a montré que les gens comparent leurs propres opinions et leurs capacités à celles des autres. Dans la littérature économique, [Veblen \(1899\)](#) est considéré comme l'un des premiers théoriciens à faire la lumière sur la comparaison sociale dans sa "Théorie de la classe de loisirs". Il présente l'idée que les gens s'engagent dans une consommation ostentatoire pour signaler la richesse et indiquer un meilleur statut social. [Duesenberry \(1949\)](#) a suggéré que l'indice d'utilité des individus dépendait du rapport de leur consommation

à une moyenne pondérée de la consommation des autres. Plus récemment, il existe des preuves empiriques que le revenu relatif a un impact sur le bonheur ([Vendrik and Woltjer, 2007](#)).

Le troisième chapitre explore expérimentalement l'effet de la comparaison sociale et la corrélation des risques sur les attitudes face au risque dans le domaine de gain, perte et le domaine mixte. Les risques sont corrélés lorsque la même situation de choix est sélectionnée au hasard pour déterminer la rémunération des sujets. Cependant, les risques ne sont pas corrélés lorsque la situation de choix sélectionnée au hasard pour déterminer la rémunération des sujets diffère d'un sujet à l'autre. Ce chapitre vise à combler une partie des lacunes dans l'information empirique et constitue une étape vers une meilleure compréhension des attitudes face au risque social. Des études antérieures portent sur l'effet de la comparaison sociale vis-à-vis les attitudes face au risque pour les gains et les pertes séparément. Étant donné que la plupart des décisions risquées de la vie réelle impliquent des gains et des pertes simultanément, il est important d'explorer les attitudes face au risque dans un domaine mixte où les sujets font face à des gains et des pertes dans le même choix et voir si la comparaison sociale a un impact sur les attitudes face au risque dans ce domaine. Je trouve que dans l'ensemble, l'introduction du contexte social diminue considérablement l'aversion au risque. En ce qui concerne les gains et les pertes, l'aversion au risque pour les gains est significativement plus élevée que pour les pertes comme le prédit la Prospect Theory. Lors de l'introduction du contexte social, l'aversion au risque pour les gains reste supérieure à celle des pertes. Dans le domaine mixte, lorsque les sujets font face à des gains et des pertes dans le même choix, l'introduction du contexte social diminue significativement l'aversion à la perte. Ceci signifie que les gains résonnent plus que les pertes.

La corrélation des risques est une caractéristique expérimentale qui influence la prise du risque ([Schmidt et al., 2015](#)). La corrélation des risques génère une augmentation de l'aversion au risque lors de l'agrégation des choix dans les trois domaines. En examinant chaque domaine séparément, la corrélation des risques n'a pas d'impact sur les attitudes face au risque pour les gains et les pertes. Cependant, dans le domaine mixte, il génère une hausse de l'aversion au risque.

Conformément au chapitre précédent, le chapitre 4 étudie expérimentalement l'effet de la comparaison sociale ainsi que la corrélation des paiements sur les attitudes face à l'ambiguïté dans le domaine de gain, perte et le domaine mixte. Le but de ce chapitre est de compléter la recherche économique antérieure sur l'impact du contexte social sur les décisions en ambiguïté. Ceci est réalisé en corrélant les paiements entre les sujets. Ce chapitre vise à répondre aux questions suivantes: les attitudes d'ambiguïté varient-elles à travers les domaines (qu'il s'agisse de gain, de perte ou de domaine mixte). La corrélation des paiements a-t-elle un impact sur les attitudes d'ambiguïté? Les attitudes d'ambiguïté varient-elles selon la taille du groupe des sujets pour lesquels les paiements sont corrélés? Pour répondre à la première question, je mène une expérience où les sujets sont invités à choisir entre parier sur un événement sans ambiguïté et des événements ambigus de leur choix dans une version en trois couleurs d'Ellsberg (1961). Pour répondre à la deuxième et à la troisième question, les paiements sont corrélés entre les sujets pour voir si cette corrélation a un impact sur les attitudes face à l'ambiguïté. Les résultats indiquent que la corrélation des paiements diminue l'aversion à l'ambiguïté. En ce qui concerne l'aversion à l'ambiguïté dans les gains et les pertes, un passage des gains aux pertes entraîne une diminution de la neutralité face à l'ambiguïté. Cependant, un passage des gains au domaine mixte diminue la recherche d'ambiguïté lorsque les paiements sont corrélés entre les sujets. Enfin, la taille du groupe pour lequel les paiements sont corrélés n'a pas d'effet significatif sur les attitudes d'ambiguïté. La prévalence de la neutralité à l'ambiguïté est due à la tâche. Une limite de ce chapitre est la méthode utilisée pour eliciter les attitudes face à l'ambiguïté. J'ai utilisé le protocole de [Charness et al. \(2013\)](#) où ils ont constaté que la majorité des sujets sont neutres à l'ambiguïté. Selon [Trautmann et al. \(2011\)](#), les tâches de choix, qui sont utilisées dans ce chapitre, révèle une aversion à l'ambiguïté inférieure à celle des tâches d'évaluation. Par conséquent, le type de tâches utilisé a une influence importante dans la mesure des attitudes face à l'ambiguïté. Ainsi, la part des sujets averses à l'ambiguïté n'est pas suffisante pour avoir des conclusions fiables concernant l'effet des traitements sur l'aversion à l'ambiguïté. La méthode de Matching Probabilities pourraient-être utilisée pour mesurer les attitudes face à l'ambiguïté offrant des résultats plus fiables.

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²Published in *L'Actualité Économique* (2016)

³This Chapter is based on a working paper co-authored with Olivier L'Haridon and Isabelle Vialle

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General Introduction

Experimental and Behavioral Economics, the current state-of-the-art in Economics for studying human behavior, is a key to advancing our understanding of individual preferences, including social preferences, risk and time preferences. Individual preferences have been shown to be an important determinant of economic decision making. Traditional economic science has built upon assumptions of *homo economicus*, or economic man, a rational and purely self-interested economic subject. However, there is a growing body of evidence in different research disciplines such as psychology, sociology, or economics that reveal the limitation of models with such assumptions. Many experimental studies in economics reveal that decision makers do not act as predicted by models of *homo economicus*. They often fail to maximize their own material payoff because human choices are not only driven by material self-interest but also by motives such as altruism, reciprocity and inequity aversion. These motives are referred to as “social preferences”. Beside the dimension of social preferences, there are two other dimensions of individual preferences that have an impact on decision making: risk and time preferences. Most major economic decisions are made under conditions of uncertainty and affect the future as well as the present (e.g., the classical consumption/savings allocation problem). The optimal decisions thus typically depend on risk attitudes as well as on time preferences.

Chapter 1⁴ tackles this subject. It provides an overview of the main experimental literature on social preferences in three categories of experiments: the propensity to cooperate in social dilemmas; trust and reciprocity; norms of fairness and altruism as

⁴Published in *L'Actualité Économique* (2016)

well as individual risk and time preferences. Based on the criticism of [Henrich et al. \(2010\)](#), the majority of research in behavioral economics is based on samples drawn entirely from Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies. However, researchers often implicitly assume that these “standard subjects” are representative of the human population. In this chapter, I present a synthesis and a point of view on the notion of the representativeness of the experimental results with regard to these elements. I show that there are indeed undeniable differences between student populations and other more general populations. By comparing students with representative samples of adults, I find that students represent a lower bound of prosociality in experimental measures of trust, equity or cooperation.

In experiments testing the propensity to cooperate, there are two types of variability : variability between countries and within country. There is an inverse relationship between the norms of cooperation and the level of development of a country. Additionally, socio-demographic factors (eg. age, urbanization, student status) determine the behavior of cooperation within the same country. Thus, students behave differently than other participants and experimental results based on a sample of students are not often generalizable. Similarly, for students and subjects from WEIRD populations, the relationship between confidence and reciprocity is positive and strong, yet it is non-existent for non-student adults and subjects from non-WEIRD populations. Moreover, experiments measuring equity and altruism confirm that students are a special sample. The difference between the average offer of the ultimatum and dictator game in developing countries is much lower than that of the students. This shows that other individuals behavior is more affected by the norms. The generalization of the results from experimental studies is therefore sensitive, not only because behaviors in general populations are potentially different from that of student populations, but also more diverse. Regarding risk and time preferences, the comparison between student populations and other populations is more difficult because there are differences in methodology, design and context between studies.

In the following chapters, I focus on risk attitudes since they constitute important

determinants of individual decision making. The distinction between risk and ambiguity is therefore important. [Knight \(1921\)](#) has proposed for the first time the distinction between situations of probabilistic and non-probabilistic beliefs in his book *Risk, Uncertainty and Profit*.

“Uncertainty must be taken in a sense radically distinct from the familiar notion of Risk, from which it has never been properly separated. . . . 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; and there are far-reaching and crucial differences in the bearings of the phenomena depending on which of the two is really present and operating. . . . It will appear that a measurable uncertainty, or “risk” proper, as we shall use the term, is so far different from an un-measurable one that it is not in effect an uncertainty at all”

According to Knight, risk (which he refers to as measurable uncertainty) applies to situations where where probabilities could either be theoretically deduced (“a priori probabilities”) or determined from empirical frequencies (“statistical probabilities”). Uncertainty (which he refers to as non-measurable uncertainty), on the other hand, applies to situations that did not provide any such basis for objective probability measurement. The formal incorporation of risk and uncertainty into economic theory was accomplished by [Von Neumann and Morgenstern \(1947\)](#) in their book *Theory of Games and Economic Behavior*. They develop four axioms for preferences under which a subject evaluates a lottery by the expected value over all outcomes. We refer to this concept as the Expected Utility Theory (EUT). A major restriction of [Von Neumann and Morgenstern \(1947\)](#)’s theory is the fact that in order to compute the expected value, the probability distribution over the set of outcomes must exist and be known to the decision maker. However, [Savage \(1954\)](#) developed the Subjective Expected Utility (SEU) theory where he argues that this is not a problem per se as long as the decision maker has a subjective probability distribution in mind that satisfies the assumptions of the EUT. Hence, he finds no valid distinction between risk and uncertainty as Knight describes it. This interpretation has found common use in mainstream neoclassical economics.

Experimental work has thus focused on the examination of the descriptive validity of the EUT by testing its axioms. [Allais \(1953\)](#) identifies systematic violations of the EUT by demonstrating the violation of the independence axiom. This has led to the development of non-expected utility models of preferences over objective lotteries. [Ellsberg \(1961\)](#) challenged Savage's view. He used thought experiments to point out that missing information about probabilities, in his terminology *ambiguity*, will affect individuals betting behavior, which can not be explained by SEU theory. In particular, the phenomenon of ambiguity violates the hypothesis that individuals uncertain beliefs can be represented by subjective probabilities (sometimes called personal probabilities or priors). Under ambiguity, the available knowledge is not sufficient for the decision maker to assign a unique subjective probability distribution over potential outcomes. [Ellsberg \(1961\)](#) argues that most people are ambiguity-averse, that is, they prefer a lottery with known probabilities to a similar lottery with unknown probabilities which is inconsistent with the EUT.

Since then, various experiments have been designed to investigate other systematic violations of the EUT, producing many alternative theories proposed to accommodate the failure of the EUT. [Kahneman and Tversky \(1979\)](#) stresses the role of heuristics in producing biases in individual behavior and formalized the Prospect Theory (PT) which represents the most influential alternative to the EUT. The PT asserts that individuals perceive gains and losses differently, in the sense that they are risk averse in the gain domain but risk seeking in the loss domain with losses looming larger than gains. An oft-cited criticism of EUT is that it fails to take into account how the outcomes in a decision problem are presented. [Tversky and Kahneman \(1981\)](#) showed that subjects exhibit an alternate reversal of risk preferences over identical pairs of hypothetical outcomes depending on whether outcomes are presented as gains or losses. Such a phenomenon is illustrated by the Asian disease problem, as discussed by [Tversky and Kahneman \(1981\)](#). They provided subjects in their study with the following dilemma: Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimates of the consequences of the program are as follows:

- If Program A is adopted, 200 people will be saved.
- If Program B is adopted, there is $1/3$ probability that 600 people will be saved, and $2/3$ probability that no people will be saved.

Which of the two programs would you favor?

Another group of subjects were given the same story regarding an Asian disease problem, but they were provided with a different formulation of the alternative programs:

- If Program C is adopted 400 people will die.
- If Program D is adopted there is $1/3$ probability that nobody will die, and $2/3$ probability that 600 will die.

Which of the two programs would you favor?

The two pairs of prospects are stochastically equivalent. The only difference between them is that Programs A and B are phrased in terms of lives saved, whereas Programs C and D are phrased in terms of lives lost. Tversky and Kahneman reported that the majority of subjects preferred Program A to Program B and Program D to Program C. Thus, subjects preferred the certain option when alternative outcomes were phrased positively in terms of saving lives. However, when outcomes were phrased negatively in term of preventing deaths, the risky option was preferred.

The litterature on ambiguity aversion shows that ambiguity can account for empirically observed violations of expected utility-based theories (Camerer and Weber, 1992). Numerous studies explore the implications of ambiguity for economic behavior. Alary et al. (2013) and Snow (2011) show that ambiguity aversion influences optimal insurance take-up, deductible choices and self protection activities. In health economics, Berger et al. (2013) find that ambiguity about the diagnosis or the treatment of medical condition affects patients treatment choices. When we think of real decision making situations, probabilities are rarely known. Individuals face decisions in an uncertain

environment in various real life situations. A prominent example is when an individual searches for a job and should decide whether to accept or reject a job offer. Ambiguity about the prospects of labor market conditions may make individuals more cautious and discourage them from searching for longer periods because they become less confident in finding more appealing job offers in the future ([Asano et al. \(2015\)](#)).

Building on these evidence, in Chapter 2 (based on a working paper co-authored with Olivier L'Haridon and Isabelle Vialle), we analyze experimentally how risk and ambiguity impact job search decisions. Risk and ambiguity are illustrated by the information about the probability of receiving an offer. Our within-subject design is based on the standard job search model of [Lippman and McCall \(1976\)](#) and aims at eliciting both search durations and reservation wages. In order to explore job search behaviors under risk and ambiguity, we run two treatments that differ in the information about the probability of receiving an offer. For decisions under risk subjects perfectly know this probability, while under ambiguity subjects know that this probability lies in a certain interval. By comparing behaviors between both treatments, we are able to determine if subjects behave differently under risk and ambiguity. We find that reservation wages are overall lower than the theoretical reservation wages and are decreasing over time in risk and ambiguity. Moreover, we find that subjects behave as ambiguity neutral agents, suggesting that ambiguity does not have a strong impact on search decisions.

In individual decision making, the decision maker is often portrayed and treated as a separate entity that can be abstracted from her social environment ([Vieider, 2009](#)). However, social comparison is an important determinant of human behavior. In social psychology, [Festinger \(1954\)](#)'s "Social Comparison Theory" showed that people compare their own opinions and abilities to those of others. In the economic literature, [Veblen \(1899\)](#) is regarded as one of the first theorists to shed the light on social comparison in his "Theory of the Leisure Class". He presented the idea that people engage in conspicuous consumption to signal wealth and indicate better social status. [Duesenberry \(1949\)](#) suggested that individuals utility index depended on the ratio of their consumption to a weighted average of the consumption of the others. More recently, there is empirical evidence that relative income has an impact on happiness ([Vendrik](#)

and Woltjer, 2007). Given these evidence about the importance of social comparison, it is natural to expect that when evaluating the consequences of their decisions, people take into consideration not only their own outcome but also their relative outcome with respect to their peers. Tversky and Kahneman (1991) suggest that different factors may determine the reference point such as status quo, expectations, aspirations, norms and social comparisons. Hence, the income of peers may play a role in determining individual's reference point. Social reference point may motivate individuals to modify their risk preferences. Building on these evidence, I explore experimentally the impact of social comparison on decision making under risk and ambiguity in Chapter 3 and 4 respectively. I investigate how social reference points could affect the individual decision making process and thus can help to understand economic phenomena.

Chapter 3 experimentally explores the effect of social comparison and the correlation of risks on individual risk attitudes in the gain, loss and mixed domain. Risks are correlated when the same choice situation is randomly selected for all subjects to determine their earnings. However, risks are not correlated when the randomly selected choice situation differs from one subject to another. This chapter aims to fill some of this gap in empirical information and provides a step towards a better understanding of social risk attitudes. It also explores the extent to which usual findings of risk attitudes translate to social risk attitudes. Previous studies focused on the effect of social comparison on individual risk attitudes for gains and losses separately. Since most of real life risky decisions involve gains and losses at the same time, it is important to explore risk attitudes in a mixed domain where subjects face gains and losses in the same prospect and see whether social comparison has an impact on risk attitudes in that domain.

I find that overall the introduction of social context decreases significantly risk aversion. Regarding gains and losses, risk aversion for gains is significantly higher than that for losses as predicted by the Prospect Theory. When introducing social context, risk aversion for gains remains higher than that for losses. In the mixed domain, when subjects face gains and losses in the same prospect, the introduction of the social context decreases significantly loss aversion. Lastly, correlation of risks generates an increase in risk aversion when aggregating choices in the gain, loss and mixed domain. When

looking at each domain separately, correlation of risks does not change risk attitudes for gains and losses. However, in the mixed domain, it generates an increase in risk aversion.

In accordance with the previous chapter, Chapter 4 investigates experimentally the effect of social comparison on individual ambiguity attitudes in the gain, loss and mixed domain. The purpose of this chapter is to complement prior economic research on the impact of social context on individual decisions under ambiguity. I do so by correlating payments across subjects. This chapter aims to answer the following questions: Do ambiguity attitudes vary across domains (whether it is gain, loss or mixed domain). Does correlating payments have an impact on ambiguity attitudes? Do ambiguity attitudes vary with the size of the group of subjects for which payments are correlated? To answer the first question, I conduct an experiment where subjects are asked to choose between betting on unambiguous event and ambiguous events of their choice in a three-color version of [Ellsberg \(1961\)](#) experiment in a between-subjects design in three types of prospects: gain, loss and mixed prospects in accordance with the previous chapter. To answer the second and the third question, I correlate payments across subjects to see if correlation of payments has an impact on ambiguity attitudes. I find that correlating payments decreases significantly ambiguity aversion. Regarding ambiguity aversion in gains and losses, a switch from gains to losses leads to a decrease in ambiguity neutrality. However, a switch from gain to mixed domain decreases ambiguity seeking when payments are correlated across subjects. Lastly, the size of the group for which payments are correlated does not have a significant effect on ambiguity attitudes.

Finally, the section General Conclusion summarizes the results of the experimental studies and identifies their main limitations. The appendix contains the experimental instructions and supplementary material at the end of the thesis.

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Chapter 1

Représentativité et Hétérogénéité des Préférences dans les Expériences de Laboratoire¹

1.1 Introduction

Les explications de la pauvreté, de la croissance et du développement, dépendent de divers facteurs macroéconomiques et microéconomiques. Au cours des années récentes, aux côtés des facteurs traditionnels macroéconomiques : quantité de travail, capital, progrès technique, institutions et ouverture économique, une attention croissante s'est portée sur les facteurs individuels. Les déterminants du développement en particulier trouvent alors un fondement en partie microéconomique où le comportement et les préférences sociales jouent un rôle important, voire capital.

L'économie expérimentale offre des méthodes pour mesurer les préférences individuelles et tester les représentations généralement utilisées par l'analyse économique. La méthode type consiste en des expériences de laboratoire, confrontant des volontaires –

¹Published in *L'Actualité Économique* (2016)

en général recrutés parmi les étudiants – à des situations fictives, qui permettent d’observer leurs réactions et leurs choix. Au travers de ces expériences de laboratoire et du formidable développement de l’économie expérimentale, nous disposons aujourd’hui d’une accumulation de connaissances sur les préférences des étudiants. Au regard de cette accumulation de travaux, cet article cherche à faire un tour d’horizon des principaux résultats expérimentaux visant à expliquer les préférences individuelles dans les pays développés ainsi que dans les pays en voie de développement et de savoir quelle est la représentativité de ces études, reposant sur les préférences d’un groupe particulier d’individus. Cette question de la validité externe des résultats expérimentaux est cruciale lors d’études sur des phénomènes concernant la population en général, tels que la pauvreté ou le développement par exemple. Cet article représente la première tentative de comparer les populations vis-à-vis de différentes catégories de préférences, en se basant principalement, sur [Henrich et al. \(2010\)](#) et [Cardenas et Carpenter \(2008\)](#). Nous trouvons qu’en matière de préférences sociales, les résultats des étudiants sont souvent atypiques au regard des résultats sur des populations plus générales. Mais, il est nettement plus difficile de conclure à une spécificité des étudiants, ou de toute autre population particulière, pour ce qui concerne les attitudes face au risque ou les préférences temporelles.

L’accumulation de résultats expérimentaux sur les préférences individuelles a été largement critiquée par [Henrich et al. \(2010\)](#). Selon ces auteurs, la richesse des bases de données est restreinte et cela remet en question la validité supposée des résultats expérimentaux. À titre d’exemple, une analyse des grandes revues spécialisées dans six sous-disciplines de psychologie de 2003 à 2007 a révélé que 68% des sujets proviennent des États-Unis, et 96% des sujets proviennent des sociétés occidentales et industrialisées, c’est-à-dire Amérique du Nord, Europe, Australie et Israël ([Arnett \(2008\)](#)). La construction de ces échantillons reflète largement le pays de résidence des auteurs, puisque 73% des premiers auteurs provenaient des universités américaines, et 99% provenaient des universités des pays occidentaux. Cela signifie que 96% des échantillons recensés par [Arnett \(2008\)](#) proviennent, au mieux, de seulement 12% de la population du monde. Au-delà de la psychologie, les sujets des expériences en économie expérimentale ne sont pas plus diversifiés.

[Henrich et al. \(2010\)](#) montrent que la majorité des données et des recherches en sciences comportementales est basée sur des échantillons tirés des populations occidentales, formées, industrialisées, riches et démocratiques (en anglais l'acronyme WEIRD- "bizarre"- correspond à Western, Educated, Industrialized, Rich, and Democratic). Ainsi, les travaux en économie comportementale, souvent implicitement, supposent que l'on compte soit peu de variations entre les populations humaines, soit que les sujets classiques issus des populations WEIRD sont représentatifs de toute autre population. En examinant les bases de données comparatives des sciences comportementales, [Henrich et al. \(2010\)](#) affirment qu'il existe une variabilité importante des résultats expérimentaux au niveau des populations : ceux qui font référence aux sujets issus des populations WEIRD sont inhabituels par rapport au reste du monde et représentent des observations aberrantes. Par conséquent, il ne règne a priori aucune raison évidente pour supposer qu'un échantillon d'une seule sous-population puisse être la base d'un comportement particulier universel. La validité externe des expériences de laboratoire, notamment en ce qui concerne les résultats sur les préférences individuelles, serait donc très limitée.

Afin de proposer une approche plus formelle de la question de la validité externe, [Brunswik \(1956\)](#) a introduit la notion de "Protocole représentatif" (en anglais Representative design) en psychologie comprenant deux dimensions. Premièrement, les sujets d'une expérience doivent être représentatifs de la population à laquelle nous souhaitons généraliser les résultats. Deuxièmement, les situations hypothétiques rencontrées par ces sujets doivent également être représentatives de leurs environnements. Selon [Hogarth \(2005\)](#), les économistes ont été moins intéressés à intégrer la deuxième dimension dans leurs expériences. Le non-respect de ce dernier a conduit à des échecs expérimentaux en psychologie, à partir desquels, l'économie pourrait apprendre. Une inférence valide ne peut être atteinte que par un échantillonnage d'une manière représentative basée sur ces deux dimensions.

Dans cet article, nous explorons cette question et nous proposons une synthèse et un point de vue sur la représentativité des résultats expérimentaux en matière de préférences. Pour cela, nous procédons en trois temps. En premier, nous présentons une

série d'expériences de laboratoire et de terrain qui visent à expliquer les préférences sociales : la coopération, la confiance et la réciprocité, et l'équité, et l'altruisme, dans les pays développés ainsi que dans les pays en voie de développement. Dans un deuxième temps, nous présentons une autre série d'expériences expliquant les préférences concernant le risque et le temps. La dernière partie présente la notion de la représentativité des résultats expérimentaux au regard de ces éléments.

1.2 La représentativité des préférences sociales

1.2.1 Expériences testant la propension à coopérer dans les dilemmes sociaux

Comprendre les sources de la coopération humaine est une question fondamentale dans les sciences sociales. Une connaissance empirique solide de ses déterminants est donc un élément important pour le développement des théories du choix et l'explication de la coopération.

La recherche concernant la coopération des individus s'est historiquement fondée en économie expérimentale sur deux types d'expériences : le dilemme du prisonnier et le jeu du bien public. Chaque jeu représente un dilemme social pour les participants où une des stratégies mène à l'optimum social tandis que la stratégie dominante mène à une situation socialement inefficace. Le Dilemme du Prisonnier est bien connu. C'est un jeu à deux participants symétriques qui choisissent entre deux stratégies : coopérer et ne pas coopérer où la non-coopération est la stratégie dominante. Le jeu du bien public (ou VCM, "Voluntary Contribution Mechanism") est un jeu de contribution volontaire à un bien public. Ce jeu permet de mesurer expérimentalement la coopération des joueurs et le comportement prosocial dans un contexte de groupe². Le jeu du bien public présente

²Dans ce jeu, chaque participant dispose de jetons à placer soit dans un compte privé, soit dans un compte public dont tout le groupe peut bénéficier. Le rendement global du compte public dépend de l'ensemble des contributions.

la tension entre le bien-être collectif et la motivation individuelle. La théorie économique prévoit ici que les individus ne vont pas contribuer volontairement au bien public, et se comporteront en passagers clandestins. Pourtant, de nombreuses expériences, par exemple celles de [Fehr et al. \(2002\)](#), [Fehr et Fischbacher \(2004\)](#) et [Gächter et Herrmann \(2009\)](#), trouvent des résultats contradictoires avec cette prédiction. Typiquement, les études expérimentales concluent à une participation au bien public comprise entre 40 et 60% de la dotation. Autrement dit, il existe une coopération substantielle entre les individus, émergeant de manière endogène. Les individus ont donc des préférences sociales et pas seulement des préférences centrées sur leur niveau de consommation. De plus, ces résultats montrent également une certaine variabilité dans les comportements observés. Les motivations pour coopérer sont donc hétérogènes et la théorie doit prendre cet état de fait en considération³.

[Cardenas et Carpenter \(2008\)](#) proposent une méta-analyse des expériences de la littérature visant à expliquer les préférences sociales dans plusieurs pays en voie de développement et dans plusieurs pays développés. Ils trouvent que globalement à peu près un tiers des participants coopère dans le jeu de dilemme du prisonnier et que les participants dans le jeu de bien public contribuent en moyenne à hauteur de la moitié de leur dotation. Nous considérons ici un pays comme "développé" si son Indice de Développement Humain (IDH)⁴ est supérieur à 0,9. Le tableau 1 montre les différents niveaux de coopération issus des expériences de jeu de dilemme de prisonnier et de jeu de bien public dans des pays en voie de développement et développés.

Le tableau 1 montre que pour juger de la validité externe du comportement prosocial observé dans le dilemme du prisonnier et dans le jeu du bien public, il est nécessaire de prendre en compte deux types de variabilité dans les résultats de ces expériences :

³Les récents travaux de recherche suggèrent également qu'il existe une hétérogénéité individuelle importante concernant le comportement prosocial dans ce contexte de coopération. Ces différences inter-individuelles peuvent expliquer le comportement agrégé et les différences au niveau des groupes [Fischbacher et Gächter \(2010\)](#).

⁴L'IDH est un indicateur synthétique du niveau de développement des pays. L'intérêt de l'IDH a été de s'imposer face à la mesure de la seule richesse monétaire (typiquement le produit intérieur brut par habitant) pour évaluer le niveau de développement ou de "bien-être" des populations. Avec la richesse monétaire, l'IDH prend en effet en compte deux autres aspects essentiels du développement humain : la santé et l'éducation.

Type de Jeu	Auteurs	Pays	Etudiants	Taux moyen de coopération
Jeu du Dilemme du Prisonnier	Cooper et al. (1996)	Etats-Unis	Oui	22%
	Hemesath et Pomponio (1998)	Etats-Unis	Oui	25%
		Chine	Oui	54%
	Tyson et al. (1988)	Afrique du Sud	Oui	45% avec les participants noirs et 37% avec les blancs
	Falk et al. (2005)	Suisse	Oui	63%
Jeu du Bien Public	Andreoni (1995)	Etats-Unis	Oui	33% de dotation
	List (2004)		Non	Les personnes âgées contribuent à hauteur de 43% de leur dotation
		Etats-Unis	Non	Les jeunes contribuent par 32% de leur dotation
	Barr (2001)	Zimbabwe	Non	48% de dotation sans sanction sociale et 58% avec sanction sociale
	Barr et Kinsey (2002)	Zimbabwe	Non	53% de dotation pour les Femmes
			Non	48% de dotation pour les hommes
	Carpenter et al. (2004)	Vietnam	Non	72% de dotation sans sanction sociale et 76% avec sanction
		Thaïlande	Non	61% de dotation sans sanction sociale et 73% avec sanction sociale
	Ensminger (2000)	Kenya	Non	58% de dotation
			Oui	44% de dotation
	Gächter et al. (2004)	Russie	Non	52% de dotation
	Henrich et Smith (2004)	Pérou	Non	23% de dotation
		Chili-Mapuche	Non	33% de dotation
		Chili – Huinca	Non	58% de dotation
Sefton et al. (2007)	Etats-Unis	Oui	53% de dotation	
Gächter et Herrmann (2011)	Russie	Oui	37% de dotation	
		Non	51% de dotation des jeunes ruraux	
		Non	54% de dotation des urbains âgés	
		Non	53% de dotation des ruraux âgés	

TABLE 1.1: Niveau de coopération dans les pays en voie de développement et les pays développés

premièrement une variabilité inter pays et deuxièmement une variabilité au sein d'un même pays.

Il existe une variabilité remarquable des résultats des expériences entre les différents pays. Nous remarquons que le taux de coopération est élevé chez les participants d'Afrique et Asie du Sud-Est tandis qu'il est modéré chez les étudiants aux États-Unis. Ainsi, il existe apparemment une relation inverse entre les normes de coopération et le niveau de développement. Cependant, cette relation n'est pas parfaite puisque par exemple, le taux de coopération des horticulteurs pauvres au Pérou est assez faible.

Il existe également une variabilité dans les résultats des expériences au sein du même pays. Il semble que les étudiants coopèrent moins que les autres participants. Les résultats montrent que ceci n'est pas dû à l'éducation mais plutôt à l'âge. En se concentrant sur les non-étudiants, [List \(2004\)](#) trouve que l'âge et les préférences sociales sont corrélés. Les individus les plus âgés aux États-Unis sont plus coopératifs que les jeunes puisqu'ils contribuent davantage au bien public. [Gächter et al. \(2004\)](#) trouvent le même résultat pour la Russie. La variabilité des contributions semble également liée à d'autres facteurs. [Gächter et Herrmann \(2011\)](#) trouvent une différence de comportement de coopération entre les habitants urbains et ruraux et aussi entre les jeunes et les plus âgés en Russie. Ils constatent que les résidents ruraux et les participants plus âgés sont plus coopératifs que les résidents urbains et les jeunes. Dans ces jeux, les possibilités de punition modifient les résultats de façon remarquable et tendent à orienter également les sujets vers la coopération. Au niveau agrégé, on trouve que les taux moyens de coopération pour les étudiants et les non étudiants sont respectivement 41,33% et 50,7% et ceux pour les populations WEIRD et les non-WEIRD sont respectivement 38,9% et 50,5%. Ceci montre que les étudiants et les populations WEIRD coopèrent moins que les autres.

Pour examiner la possibilité de généraliser ces résultats, [Herrmann et al. \(2008\)](#) ont fait des expériences avec des étudiants provenant des différentes populations. Leurs données expérimentales se composent de 1120 participants venant de quinze pays aux caractéristiques socio-économiques et culturelles diverses : des pays asiatiques (Chine et Corée), des pays arabes (Oman et Arabie Saoudite), des pays anglophones (Australie,

Etats-Unis et Royaume-Uni), d'Europe de l'Est (Ukraine, Russie et Biélorussie), d'Europe centrale germanophone (Suisse et Allemagne), des pays scandinaves (Danemark) et d'Europe du Sud-Est (Grèce et Turquie). En plus de trouver des différences de volonté de coopération des sujets au niveau de la population, [Herrmann et al. \(2008\)](#) découvrent dans la moitié de ces échantillons, un phénomène de punition antisociale qui n'est pas observé chez les étudiants suisses servant de population de référence. Les individus peuvent punir les passagers clandestins, tout comme les individus prosociaux et extrêmement coopératifs. La sanction antisociale est due au fait que les individus n'acceptent pas la punition et cherchent donc à se venger. Ce comportement affecte négativement le niveau de coopération pour ces populations. Dans la majorité des pays, la possibilité de punition altruiste⁵ ne génère pas de niveaux élevés de coopération. Cependant, les sujets d'un certain nombre de pays occidentaux, tels que les États-Unis, le Royaume-Uni et l'Australie se comportent comme les étudiants de Zurich où la punition augmente le niveau de coopération. Alors, on peut en conclure que les résultats de l'échantillon de Zurich sont généralisables à d'autres populations WEIRD, mais ils ne peuvent pas être étendus au-delà.

1.2.2 Expériences testant la confiance et la réciprocité

Dans le jeu de confiance ou "trust game", les joueurs sont dotés d'une somme d'argent et organisés par paire. Dans chaque paire, l'un des individus joue le rôle d' "envoyeur" et l'autre celui de "receveur". Pour chaque somme reçue, le receveur a la possibilité d'en renvoyer une partie à l'envoyeur⁶. La confiance est illustrée par le fait que l' "envoyeur" donne le montant qu'il souhaite de sa dotation à un receveur anonyme. Puis, la réciprocité est présentée par la volonté du receveur de renvoyer le montant qu'il souhaite dans la deuxième étape. Le receveur n'a, bien sûr, aucun intérêt à renvoyer une somme d'argent. Par induction à rebours, l'envoyeur, suivant cette logique, ne va rien envoyer. L'unique prédiction d'équilibre de Nash pour ce jeu, avec information

⁵La punition altruiste veut dire que les individus punissent même si la punition est coûteuse pour eux et ne leur donne aucun gain matériel ([Fehr et Gächter \(2002\)](#)).

⁶La somme renvoyée peut être multipliée par un facteur donné.

parfaite, est d'envoyer zéro. Malgré cette prédiction, [Berg et al. \(1995\)](#) trouvent que les "envoyeurs" envoient environ 50 % de leurs dotations et les "receveurs" renvoient 30%. Malgré la déviation vers la pro-socialité, le fait que l'envoyeur envoie de l'argent au receveur n'est pas un investissement rentable pour l'envoyeur puisqu'il récupère en général 90% seulement du montant qu'il envoie.

La figure 1.1 se fonde sur le tableau de [Cardenas et Carpenter \(2008\)](#) (présenté en tableau 10 en Annexe) et résume les différents résultats des expériences de jeux de confiance faites dans les pays développés et en voie de développement. Nous présentons une méta-analyse de ces résultats expérimentaux. La Figure 1.1 montre qu'il existe une relation positive entre le taux moyen d'envoi et celui de retour de dotation, autrement dit entre la confiance et la réciprocité. La relation monotone positive entre le taux moyen d'envoi et celui de retour de dotation est forte pour les étudiants (Spearman $\rho = 0,88$ et $p < 0,01$) et les sujets issus des populations WEIRD (Spearman $\rho = 0,92$ et $p < 0,01$). Pourtant, elle est faible voire inexistante pour les non-étudiants (Spearman $\rho = 0.18$ et n'est pas statistiquement significatif⁷) et les sujets issus des populations qui ne sont pas WEIRD (Spearman $\rho = 0,44$ et $p < 0,1$). Dans un cas extrême, selon l'expérience d'[Ashraf et al. \(2006\)](#) avec des étudiants de l'Afrique du Sud, les envoyeurs envoient une fraction faible de leur dotation et les receveurs renvoient significativement moins que ce qu'ils ont reçu. À l'autre extrême, selon [Danielson et Holm \(2007\)](#), les non-étudiants de la Tanzanie envoient plus que la moitié de leurs dotations et renvoient en moyenne 40%. Les comportements de confiance et de réciprocité sont donc extrêmement hétérogènes en dehors des populations non-WEIRD.

De même, les normes diffèrent d'une communauté à une autre. Par exemple, [Greig et Bohnet \(2009\)](#) montrent que la norme dans les bidonvilles de Nairobi est la réciprocité équilibrée, qui est la disposition à donner quelque chose de valeur équivalente à ce que l'on a reçu. Au contraire, la majorité des données des pays développés suit la norme de la réciprocité conditionnelle, dans le sens où plus on a confiance en une personne, plus elle donne en retour et donc agit d'une manière réciproque. La relation entre les deux parties est considérée comme un partenariat dans lequel les deux joueurs accumulent du

⁷Le taux moyen d'envoi et celui de retour de dotation sont indépendants.

profit. Dans le premier cas, il n'y a pas de relation entre la confiance et la réciprocité mais dans le deuxième, ils sont positivement corrélés.

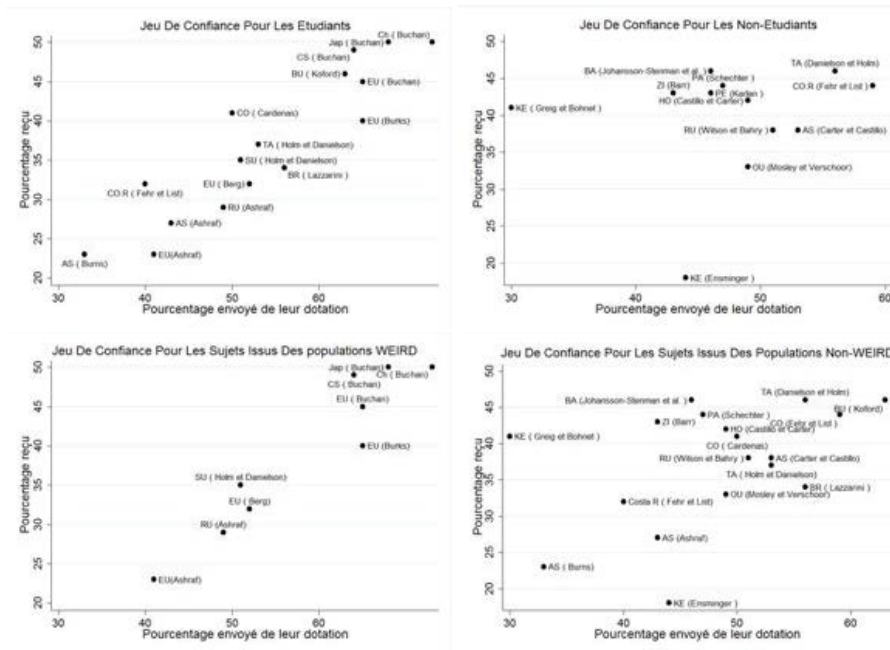


FIGURE 1.1: Illustration des expériences de jeu de confiance par pays et population⁸.

1.2.3 Expériences testant l'équité et l'altruisme

Il existe deux façons de penser les normes qui peuvent influencer les interactions entre les individus. Dans le cas le plus simple, les normes d'altruisme dictent comment une personne doit traiter une autre quand la deuxième a peu, voire aucune, possibilité de contrôler le résultat. Ces normes dirigent beaucoup d'actes philanthropiques. Cependant, la situation devient plus compliquée quand la deuxième personne a assez de pouvoir pour se venger des injustices. Afin de différencier les normes qui dictent le comportement dans cette situation, nous utilisons le terme "d'équité". Les expérimentalistes ont développé deux moyens pour mesurer les normes d'équité et d'altruisme :

⁸Fondé sur Cardenas et Carpenter (2008) (Tableau 10 de l'Annexe)

le jeu de l'ultimatum⁹ et le jeu de dictateur¹⁰. Un résultat connu depuis longtemps est qu'il existe des différences substantielles de comportement entre les pays (Roth et al. (1991)) et que la plupart des individus dévient de l'équilibre parfait en sous-jeux. Ce qui est intéressant d'un point de vue du développement est la variété des normes et les facteurs économiques qui déterminent ces normes. Les tableaux 11 et 12 (en Annexe) montrent les différents résultats des expériences des jeux de l'ultimatum et du dictateur. L'allocation moyenne de l'offreur est considérablement supérieure à zéro dans les deux jeux.

Dans Carpenter et al. (2005) et Henrich et al. (2006), les étudiants offrent légèrement plus que 41% en moyenne de leur dotation dans le jeu de l'ultimatum mais, seulement, 25% et 32% dans le jeu du dictateur. Cependant, la différence entre l'offre moyenne du jeu de l'ultimatum et de celui du dictateur dans les pays en voie de développement est bien plus faible. Ceci montre que les étudiants des États-Unis sont plus sensibles aux différences de l'environnement stratégique d'un jeu mais aussi que le comportement d'autres individus est plus influencé par les normes. En particulier, les données de Henrich et al. (2006) montrent notamment la puissance de normes locales. Dans certains cas, les participants rejettent des offres qui sont trop élevées ou bien trop faibles.

Pour étudier l'interaction entre normes et institutions, Henrich et al. (2001) mènent une étude dans 15 sociétés de petites tailles. Ils trouvent que la récompense de la coopération et le degré d'intégration dans le marché expliquent 68% de la variation des offres dans le jeu de l'ultimatum. Les sociétés où le travail en équipe est nécessaire pour la production (les pêcheurs de baleine de Lamalera par exemple) ont des normes de partage importantes tandis que les sociétés composées de petits groupes de familles indépendantes et isolées, comme les Matskigenkas, ne sont pas généreux envers les étrangers et ne s'attendent à ce que les étrangers le soient envers eux. Il semble donc

⁹Le jeu de l'ultimatum est une interaction, unique, entre une paire de sujets anonymes disposant d'une certaine somme d'argent. L'un des deux, l'offreur, peut offrir une partie de cette somme à l'autre sujet, le répondeur. Ce dernier décide d'accepter ou bien de rejeter l'offre. S'il accepte, il gagne ce qui lui est proposé et l'offreur à son tour, garde le reste. Sinon, ni l'un ni l'autre ne gagne. Puisque les sujets sont motivés uniquement par leur propre intérêt, le répondeur devrait toujours accepter une offre positive, et l'offreur doit offrir le plus petit montant non nul.

¹⁰Celui-ci est semblable au jeu de l'ultimatum sauf que le second joueur ne peut pas rejeter l'offre. Si les sujets sont purement motivés par leur propre intérêt, ils offriraient zéro dans le jeu de dictateur.

que les différences au niveau des communautés expliquent davantage la variabilité de comportement que les différences individuelles. Cela confirme l'idée que les normes sont locales et dépendent des conditions économiques locales.

La figure 7 (en annexe), illustre la variabilité des résultats des expériences de jeu de l'ultimatum (JU) et du dictateur (JD). Le comportement des adultes non-étudiants américains occupe l'extrémité de la distribution dans tous les cas. Pour le jeu du dictateur, les États-Unis ont l'offre moyenne la plus élevée suivie par la ville de Sanquianga en Colombie. Les offres des États-Unis correspondent au double de celles des chasseurs-cueilleurs de Hadza en Tanzanie et des horticulteurs de Chimane -Amazonie Bolivienne. En ce qui concerne le jeu de l'ultimatum, les États-Unis ont la deuxième offre moyenne la plus élevée après les populations Sursurunga (Papouasie-Nouvelle-Guinée). Le troisième graphique montre la possibilité de punition du jeu de l'ultimatum à travers les offres de maximisation de revenu de chaque population. L'offre de maximisation du revenu est celle qu'un offreur propose s'il connaît la probabilité de rejet pour chaque possibilité d'offre. Les États-Unis et le peuple Sursurunga de Papouasie-Nouvelle-Guinée ont le même niveau d'offre de maximisation des revenus qui, par rapport à la majorité des autres sociétés, est 5 fois plus élevé. Les populations des pays industrialisés occupent souvent l'extrémité de la distribution de comportement humain. [Henrich et al. \(2010\)](#) constatent que le degré d'intégration du marché par la population peut engendrer des offres plus élevées. De même, la taille de la communauté est positivement corrélée avec un degré de punition plus fort. [Henrich et al. \(2006\)](#) ont observé une tendance à exclure les offres très élevées dans à peu près la moitié des sociétés de petites tailles étudiées. Cette tendance à refuser les "offres hyper-équitables" s'accroît quand les offres augmentent de 60% à 100% de dotation. Celle-ci existe aussi bien dans les populations russes ([Bahry et Wilson, 2006](#)), chinoises ([Hennig-Schmidt et al., 2008](#)) puis, dans une moindre proportion, chez les adultes non-étudiants en Suède, Allemagne ([Güth et al., 2003](#)) et les Pays-Bas ([Bellemare et al., 2008](#)).

1.3 Préférences individuelles face au risque et au temps

Dans de nombreuses situations, la prise de décisions économiques optimales dépend des attitudes vis-à-vis du risque ainsi que des préférences temporelles. Dans cette partie, nous présentons une série d'expériences de laboratoire et de terrain mesurant les attitudes vis-à-vis du risque et les préférences temporelles. Comme précédemment, nous comparons les résultats habituellement obtenus sur les sujets WEIRD aux résultats obtenus pour des populations plus générales.

1.3.1 Les préférences individuelles face au risque

Les préférences face au risque et à l'incertain occupent une position centrale pour comprendre le comportement économique. Par exemple, elles sont essentielles comme déterminant non seulement des comportements d'investissement et d'assurance mais également des choix d'emploi, familiaux, et éducatifs. Dans la littérature sur la prise de décision, le concept de risque est généralement identifié aux situations où les probabilités sont données et connues d'une façon objective. Nous retenons ici les études expérimentales renvoyant explicitement à de telles situations de risque.

Plusieurs chercheurs ont mené des expériences dans les pays en voie de développement pour expliquer les situations individuelles par les préférences des agents. La littérature en économie du développement souligne le risque d'une "culture de la pauvreté" : les pauvres dans les pays en voie de développement le restent non seulement du fait de leurs taux d'escompte élevés mais également de leur aversion au risque (Lewis, 1975). Ainsi, les préférences individuelles seraient sources de trappes à développement où il serait impossible pour les individus d'épargner et de prendre le risque nécessaire à l'accumulation du capital. Parmi les mesures expérimentales des préférences face au risque, deux grandes méthodes ont été largement utilisées. La première méthode est celle, bien connue, de Holt et al. (2002). Dans cette expérience, les participants font une série de choix entre deux loteries, lorsque les probabilités de gain varient. Une des loteries est systématiquement plus risquée que l'autre et la domine en termes d'espérance et de

variance de gain. L'ensemble des choix proposés permet de mesurer simplement le coefficient d'une fonction d'utilité du type CRRA. En moyenne, [Holt et al. \(2002\)](#) trouvent que les étudiants ont un coefficient d'aversion relative au risque compris entre 0,68 et 0,97. Ce niveau représente une forte aversion au risque. Parallèlement à cette méthode bien connue, la seconde méthode employée repose sur un simple choix de loterie. Dans cette méthode, les participants doivent choisir une loterie dans une liste permettant un arbitrage en fonction de l'importance du gain espéré. Le choix d'une loterie particulière révèle alors le degré d'aversion au risque. Cette méthode est la méthode traditionnelle en économie du développement. Elle a été proposée initialement par [Binswanger \(1980\)](#) dans le cas de paysans en Inde.

1. La variabilité des préférences face au risque au sein d'un pays

Plusieurs chercheurs ont étudié les préférences face au risque sur des populations autres que des étudiants. [Tanaka et al. \(2010\)](#) proposent une expérience dans les villages vietnamiens montrant comment sont corrélées les préférences avec les circonstances économiques qui affectent les individus. Les auteurs ont collecté expérimentalement des mesures de préférences puis ont déterminé la relation entre ces mesures et des variables démographiques et économiques (notamment le revenu) issues d'une précédente enquête auprès des ménages. Les résultats montrent que le revenu moyen d'un village est lié à l'aversion au risque de ses habitants : ainsi, les habitants des villages plus riches ont un degré moins élevé d'aversion au risque que les habitants des villages plus pauvres. À un niveau plus individuel, [Carlsson et al. \(2013\)](#) étudient la prise de décision des couples en Chine. Ils constatent que les conjoints ont des préférences individuelles de risque plus semblables, lorsque le ménage est plus riche et que la contribution de la femme au revenu est plus grande. C'est également le cas lorsque les deux conjoints sont membres du parti communiste. Cependant, ces découvertes ne devraient pas dissimuler le fait que les préférences individuelles de risque des conjoints étaient identiques pour seulement 6% des ménages. De ce fait, il y a un grand degré d'hétérogénéité au sein des ménages. Cette grande hétérogénéité des préférences

face au risque rend ainsi difficile leur interprétation en tant que caractéristique globale de tel ou tel pays ou de telle ou telle communauté.

Afin d'obtenir des mesures sur des populations autres que les traditionnelles populations étudiantes, [Von Gaudecker et al. \(2011\)](#) analysent les préférences de risque à l'aide d'une expérience avec un échantillon représentatif de la population néerlandaise. Ils modélisent l'hétérogénéité dans toutes les préférences et les paramètres d'erreurs comme une fonction des caractéristiques observées et non observées. Ils trouvent que les préférences face au risque dans la population sont très hétérogènes, et seulement une petite partie de cette hétérogénéité peut être capturée avec les variables standards telles que l'âge, le genre, l'éducation, le revenu et la richesse. En outre, la courbure de la fonction d'utilité s'avère être le principal déterminant des choix individuels dans le contexte du risque.

Par ailleurs, il est possible que le modèle de décision, de type utilité espérée, supposé dans les mesures les plus populaires de l'aversion au risque, ne soit pas adapté. Ainsi, [De Brauw et Eozenou \(2014\)](#) étudient les préférences face au risque des agriculteurs en Mozambique à l'aide d'une expérience de terrain. Ils rejettent l'hypothèse que les préférences des agriculteurs suivent une fonction d'utilité CRRA et ils trouvent que les trois quarts des agriculteurs de l'échantillon ont des préférences face au risque suivant le modèle d'utilité dépendante au rang. Un tel résultat, avec des proportions très proches, a également été trouvé sur des populations d'étudiants chinois ou suisses ([Bruhin et al., 2010](#)). Ce résultat semble donc relativement stable entre les différentes populations.

2. La variabilité des préférences face au risque entre différents pays

[Vieider et al. \(2015\)](#) présentent des données collectées dans des expériences contrôlées avec 2939 étudiants dans 30 pays mesurant les attitudes envers le risque et l'incertitude par des mesures incitatives aussi bien que par enquête. Ils trouvent que les données de l'enquête visant à mesurer les attitudes face au risque sont corrélées avec les décisions lorsque de l'argent réel est en jeu. Les données d'enquête et les mesures incitatives sont également corrélées au sein de la plupart des 30 pays et entre ces pays. Les résultats montrent également une forte relation

entre la tolérance au risque et le PIB par habitant. De même, les attitudes face à l'incertitude sont liées dans la plupart des contextes et des domaines.

Dans la même veine, [Rieger et al. \(2014\)](#) présentent des résultats d'une enquête internationale à grande échelle sur les préférences vis-à-vis du risque conduite dans 53 pays. Conformément à la Prospect Theory de [Kahneman et Tversky \(1979\)](#), ils trouvent dans tous les pays, en moyenne, une attitude d'aversion relative au risque dans les gains et une recherche du risque dans les pertes, le degré d'aversion au risque varie significativement entre pays. De plus, les attitudes face au risque dans leur échantillon dépendent non seulement de conditions économiques, mais aussi de facteurs culturels. Il semble que la culture de l'individualisme et de l'incertitude favorise la prise de risque.

[l'Haridon et al. \(2016\)](#) analysent l'hétérogénéité dans les préférences face au risque à travers plusieurs dimensions : entre les individus, entre les contextes de décisions et entre pays. Les préférences dans les pays non-occidentaux diffèrent systématiquement de ceux dans pays occidentaux, considérées universelles. De même, les caractéristiques individuelles expliquent peu l'hétérogénéité des préférences. Les facteurs macroéconomiques peuvent expliquer la plupart de l'hétérogénéité.

1.3.2 Les préférences individuelles face au temps

[Eckel et al. \(2005\)](#) utilisent des données d'enquêtes et des données expérimentales d'un échantillon de travailleurs canadiens ayant de faibles revenus afin d'étudier les attitudes face au risque et au temps. Les auteurs trouvent que les individus ayant une forte aversion au risque ont une préférence plus marquée pour le présent. Le principal facteur pour appréhender le comportement des travailleurs à faibles revenus est leur contrainte monétaire actuelle. Les auteurs trouvent que les décisions expérimentales prises pour un horizon de court terme permettent de prédire les arbitrages réalisés par les participants

entre le présent et des décisions de long terme. En particulier les préférences des travailleurs à faible revenu semblent caractérisées par des taux d'escompte extrêmement élevés.

Dans les villages vietnamiens, [Tanaka et al. \(2010\)](#) trouvent que le revenu moyen d'un village est corrélé non seulement à une aversion au risque modérée, mais également à un taux d'escompte faible. Autrement dit, les habitants de villages les plus riches sont plus patients. De même, le revenu du ménage est corrélé à la patience, mais pas à la préférence face au risque. Ces résultats sont cohérents avec ceux obtenus de longue date par [Binswanger \(1981, 1980\)](#). Par ailleurs, les préférences face au risque et au temps peuvent affecter le succès des programmes du microcrédit. [Bauer et al. \(2012\)](#) proposent une série d'expériences ayant pour but de mesurer le taux d'escompte et l'aversion au risque pour 573 villageois en Karnataka au sud de l'Inde. Leurs résultats montrent qu'il existe, pour les femmes, une corrélation positive robuste entre la préférence pour le présent et la demande des prêts auprès d'une institution de microcrédit.

1.4 Discussion

Les chercheurs font souvent face à un dilemme de validité externe de leurs résultats concernant la mesure des préférences des individus. Faire une expérience avec des milliers de sujets est difficile à mettre en œuvre étant donné les coûts administratifs et financiers que cela représente. À l'opposé, les données des enquêtes ou des expériences faites avec des centaines de sujets ne sont pas toujours fiables puisque l'échantillon est relativement petit et doté d'une puissance statistique faible. La preuve de la fiabilité des mesures expérimentales est une question non résolue. Il existe d'ailleurs un débat considérable sur l'exactitude des questions hypothétiques et les circonstances dans lesquelles elles sont susceptibles de bien fonctionner ([Camerer et Hogarth \(1999\)](#), [Manski \(2004\)](#)).

D'après [Siedler et Sonnenberg \(2010\)](#), la sélection de l'échantillon représente également une limite majeure de la plupart des expériences puisqu'ils sont basés sur des échantillons d'étudiants, qui s'auto-sélectionnent dans l'étude et qui ne sont donc pas

Auteurs	Pays	Type d'expérience	Résultats Principaux
Eckel et al. (2004)	Canada	L'étude combine des aspects d'expérience de terrain et de laboratoire	<ul style="list-style-type: none"> • Les individus ayant une forte aversion au risque ont une préférence plus marquée pour le présent. • Les préférences des travailleurs à faibles revenus semblent caractérisées par des taux d'escompte extrêmement élevés. • Les travailleurs à faibles revenus semblent avoir des taux d'escompte extrêmement élevés.
Tanaka et al. (2010)	Vietnam	Expérience de terrain	<ul style="list-style-type: none"> • Le revenu moyen d'un village est lié à l'aversion au risque : les habitants des villages plus riches ont un degré moins élevé d'aversion au risque que les habitants des villages plus pauvres. • Le revenu moyen d'un village est corrélé à un taux d'escompte faible : les habitants des villages plus riches sont plus patients.
De Brauw et Eozenou (2011)	Mozambique	Expérience de terrain	<ul style="list-style-type: none"> • Ils rejettent l'hypothèse que les préférences des agriculteurs suivent une fonction d'utilité CRRA. • Les trois quarts des agriculteurs de l'échantillon ont des préférences de risque suivant l'utilité dépendante au rang.
Von Gaudecker et al. (2011)	Pays-Bas	Enquête sur internet et expérience de laboratoire	<ul style="list-style-type: none"> • Les préférences du risque dans la population sont très hétérogènes, et seulement une petite partie de cette hétérogénéité peut être capturée avec les variables standards tels que l'âge, le genre, l'éducation, le revenu et la richesse.
Bauer et al. (2012)	Inde	Expérience de terrain	<ul style="list-style-type: none"> • Il existe, pour les femmes, une corrélation positive robuste entre la préférence pour le présent et la demande de prêts à une institution de microcrédit
Carlsson et al. (2013)	Chine	Expérience de terrain	<ul style="list-style-type: none"> • Les conjoints ont des préférences individuelles de risque plus semblable, lorsque le ménage est plus riche et que la contribution de la femme au revenu est plus grande ou quand les deux conjoints sont membres du parti communiste.
Rieger et al. (2014)	53 Pays	Expérience de Laboratoire	<p>Il existe une attitude d'aversion au risque dans les gains et de la recherche du risque dans les pertes, conformément à la Prospect Theory de Kahneman et Tversky (1979).</p> <ul style="list-style-type: none"> • Le degré de l'aversion au risque montre des différences significatives au niveau des pays. • Les attitudes, face au risque dans leur échantillon, dépendent non seulement de conditions économiques, mais aussi de facteurs culturels.
Vieider et al. (2014)	30 Pays	Expérience de Laboratoire	<ul style="list-style-type: none"> • Les données de l'enquête visant à mesurer les attitudes face au risque sont corrélées avec les décisions avec de l'argent réel est en jeu. • Les attitudes face à l'incertitude sont liées dans la plupart des contextes et des domaines. • Une forte relation entre la tolérance du risque et le PIB par habitant.

TABLE 1.2: Un tour d'horizon des études des préférences face au risque et au temps.

représentatifs de la population adulte. En réalité, en raison de l'auto-sélection, les études expérimentales basées sur des étudiants pourraient même ne pas être représentatifs de l'ensemble de la population étudiante. Les auteurs discutent des avantages de combiner les méthodes expérimentales avec des bases de données représentatives afin de surmonter cette limite des expériences en laboratoire. En premier lieu, les enquêtes représentatives peuvent servir de données de référence pour les chercheurs qui collectent leurs propres données afin d'évaluer le potentiel biais de sélection de l'échantillon. Cela permettra donc de savoir dans quelle mesure les études expérimentales basées sur des échantillons d'étudiants peuvent être généralisées. En second lieu, les travaux de recherche mesurant à la fois les préférences révélées et les préférences déclarées permettent aux chercheurs de valider leurs mesures. Par exemple, [Fehr et al. \(2002\)](#), [Ermisch et al. \(2009\)](#) et [Naef et Schupp \(2009\)](#) trouvent que les réponses aux questions relatives aux attitudes concernant la confiance envers les étrangers prédisent le comportement réel de confiance dans l'expérience. Les études d'[Eckel et Grossman \(2000\)](#) et [Roe et Just \(2009\)](#) montrent l'importance de l'auto-sélection dans les études expérimentales. Leurs études suggèrent que les résultats des expériences de laboratoire pourraient ne pas être généralisés à l'ensemble de la population.

L'étude de [Dohmen et al. \(2011\)](#) représente un autre exemple démontrant les avantages de combiner des méthodes expérimentales incitatives avec les données d'une enquête représentative. L'objectif est de valider les mesures de risques issues d'une enquête du Panel Socio-économique (SOEP) de 2004, basée sur un échantillon représentatif de 22 000 individus de la population adulte allemande à l'aide des données d'une expérience de terrain. Les auteurs trouvent que les mesures de l'enquête SOEP ayant pour but de tester le comportement de prise de risque individuelle sont pertinentes et constituent une bonne mesure de prédiction du comportement vis-à-vis du risque dans l'expérience. Pour [Dohmen et al. \(2006\)](#), il est ainsi possible de valider les mesures issues des enquêtes lors d'une expérience de laboratoire avec des étudiants, ce qui est relativement plus facile à réaliser et moins coûteux. Ceci ne résout pas pour autant la question de la validité externe. En effet, la validation est "valide" uniquement pour un sous-groupe de la population totale. Par ailleurs, les résultats de [Dohmen et al. \(2011\)](#) ne permettent pas de conclure à la validité externe des mesures de risque en dehors d'un

pays développé tel que l'Allemagne. [Andersen et al. \(2008\)](#) ont également essayé de résoudre le problème de validité externe des mesures de préférence face au risque en constituant un échantillon représentatif de la population danoise âgée entre 19 et 75 ans. [Andersen et al. \(2008\)](#) appliquent ainsi les mesures habituelles des expériences en laboratoire, du type [Holt et al. \(2002\)](#), avec des expérimentations de terrain et trouvent des résultats similaires pour un individu représentatif.

[Exadaktylos et al. \(2013\)](#) démontrent plutôt le contraire. Leurs résultats suggèrent que les étudiants auto-sélectionnés constituent un échantillon approprié pour l'étude du comportement social. Ils utilisent les données d'une enquête expérimentale basée sur un échantillon de 5 765 individus représentatifs de la population de la ville de Grenade. Les données comprennent des étudiants et des non-étudiants ainsi que des bénévoles et des non-bénévoles. Ils examinent séparément les effets de statut étudiant et bénévole sur le comportement, qui permet de comparer *ceteris paribus* entre les étudiants qui s'auto-sélectionnent (étudiants*bénévoles) et la population représentative. L'échantillon d'étudiants auto-sélectionnés produit des résultats qualitativement et quantitativement précis.

Les expériences de laboratoire sont souvent basées sur des échantillons très homogènes (généralement des étudiants qui étudient le même sujet à la même université) et fréquemment des informations potentiellement importantes, sur les caractéristiques socioéconomiques des sujets, sont manquantes, ou manquent de diversité. Une autre limite des expériences de laboratoire est le manque d'anonymat. Dans la plupart des expériences de laboratoire, les étudiants jouent les uns contre les autres et savent que l'autre joueur est un étudiant. Par conséquent, le degré de l'anonymat est plutôt faible. Le degré d'homogénéité et d'anonymat pourraient influencer les préférences sociales révélées ([Sapienza et al., 2007](#)). Afin d'atteindre une meilleure diversité d'échantillon et mener des expériences sociales interculturelles, les expérimentalistes, en sciences économiques, trouvent que l'internet est un outil très pratique dans cette mise en œuvre. [Hergueux et Jacquemet \(2015\)](#) mènent une expérience en ligne et dans le laboratoire visant à renforcer la validité interne des décisions générées sur Internet. Ils trouvent d'ailleurs un fort parallélisme des préférences révélées dans les deux expériences. Ces

résultats sont importants pour les chercheurs qui souhaitent mener leurs expériences sur Internet.

La question de la validité externe et de la généralisation des résultats reste une question ouverte et seule l'accumulation d'expérience de terrain permettra d'avoir une vue claire des méthodes et des protocoles gardant un sens au-delà du laboratoire d'expérimentation de telle ou telle université.

1.5 Conclusion

Pour conclure, nous avons vu qu'il existait des différences incontestables entre les étudiants et les adultes non-étudiants dans le domaine de l'économie comportementale. En comparant les étudiants avec des échantillons représentatifs des adultes, nous avons remarqué que les étudiants constituent en quelque sorte une limite inférieure de la prosocialité dans les mesures expérimentales de confiance, d'équité ou de coopération.

Dans les expériences testant la propension à coopérer, il existe deux types de variabilité dans les résultats : une variabilité inter pays et intra pays. Il existe apparemment une relation inverse non parfaite entre les normes de coopération et le niveau de développement d'un pays. En outre, les facteurs sociodémographiques (par exemple : âge, urbanisation, statut étudiant) déterminent le comportement de coopération au sein d'un même pays. Donc, les étudiants se comportent différemment des autres participants et les résultats expérimentaux basés sur un échantillon d'étudiants ne sont pas souvent généralisables. De même, pour les étudiants et les sujets issus des populations WEIRD, la relation entre confiance et réciprocité est positive et forte, pourtant elle est inexistante pour les adultes non étudiants et les sujets issus des populations non-WEIRD. En outre, les expériences mesurant l'équité et l'altruisme confirment que les étudiants sont un échantillon spécial. La différence entre l'offre moyenne du jeu de l'ultimatum et de celui du dictateur dans les pays en voie de développement est bien plus faible que celle des étudiants. Ceci montre que les étudiants des États-Unis sont plus sensibles aux

différences de l'environnement stratégique d'un jeu, mais aussi que le comportement d'autres individus est plus influencé par les normes.

On constate que les résultats des étudiants sont souvent atypiques en regard des résultats sur des populations plus générales. Par ailleurs, nous avons vu que les étudiants avaient également un comportement beaucoup plus homogène dans ces jeux que les participants en population générale. La généralisation des résultats issus des études expérimentales est donc sensible, non seulement car les comportements sont potentiellement différents, mais également plus diversifiés en population générale.

La comparaison des mesures des attitudes vis-à-vis du risque et du temps entre les populations d'étudiants et les autres populations est plus délicate puisqu'il y a des différences de méthodologie, de protocole et de contexte entre les travaux. D'une part, les attitudes sont très hétérogènes, même au sein d'une population supposée homogène, comme celle des étudiants. D'autre part, et contrairement aux situations de jeu, les mesures réalisées des attitudes vis-à-vis du risque ou de l'impatience reposent souvent sur des méthodes très différentes les unes des autres. En plus de l'hétérogénéité individuelle et de l'hétérogénéité des populations d'origine, ces différences de méthodes de mesure créent un troisième type d'hétérogénéité, méthodologique, rendant difficile toute comparaison. Dans ce domaine également, notre analyse montre qu'une forte hétérogénéité est la règle, et de ce fait, il est nettement plus difficile de conclure à une spécificité des étudiants ou de toute autre population particulière pour ce qui concerne les attitudes face au risque ou les préférences temporelles.

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Chapter 2

Job search behaviors under risk and ambiguity: An Experimental Test¹

2.1 Introduction

Search problems occur frequently in economic life: consumers search for the lowest price and workers search for the highest wage. Job search models imply that the agents' information on the distribution of wage offers, the length of search horizons, and the feasibility of recalling past wage offers are central determinants of an optimal search strategy (Cox and Oaxaca (2000)). The optimal strategy for a risk-neutral searcher is to continue searching as long as the expected marginal benefit of another search exceeds its expected marginal cost. A consistent finding in the literature is that people search too little compared to the amount of search prescribed under risk neutrality (Braunstein and Schotter (1981, 1982), Cox and Oaxaca (1989), Hey (1987)). Braunstein and Schotter (1981) and Cox and Oaxaca (1989) suggest that early stopping can be explained by risk aversion. Risk aversion can be interpreted as the willingness to accept lower average earnings in exchange for a lower variability of the earnings. Job search models have been developed for infinite and finite search horizons. The principal difference between

¹This Chapter is based on a working paper co-authored with Olivier L'Haridon and Isabelle Vialle

infinite and finite search horizon models is that the reservation wage is constant in the former and decreasing in the latter (Lippman and McCall, 1976).

In this chapter, we conducted a laboratory search experiment to study how risk and ambiguity impact job search decisions. Our within-subject design is based on the standard job search model Lippman and McCall (1976) and aims at eliciting both search durations and reservation wages. In order to explore job search behaviors under risk and ambiguity, we run two treatments that differ in the information about the probability of receiving an offer. For decisions under Risk subjects perfectly know this probability, while under Ambiguity there is an uncertainty about the probability of receiving an offer. By comparing behaviors between both treatments, we are able to determine if subjects behave differently under Ambiguity and under Risk. The main findings of this chapter are that reservation wages are overall lower than the theoretical reservation wages and are decreasing over time in risk and ambiguity. Moreover, we find that subjects behave as ambiguity neutral agents.

The remainder of the chapter is structured as follows. Section 2.2 presents a literature review. Section 2.3 presents the theoretical framework. Section 2.4 explains the experimental design. Section 2.5 discusses the results and section 2.7 concludes.

2.2 Related research

Sequential search models has been used to interpret field data on unemployment durations since Lippman and McCall (1976). Braunstein and Schotter (1981, 1982) were the first to conduct lab search experiments and presented experimental tests of many hypotheses derived from the survey by Lippman and McCall (1976). Their design reproduced an infinite horizon search model. Subjects engaged in search for a wage drawn from a known distribution. The number of searches that the subjects could undertake was not limited and they could accept any of the offers they had received (i.e there was unlimited recall of past offers). The optimal strategy in an infinite horizon search model predicts a constant reservation wage. Braunstein and Schotter (1981,

1982) elicited reservation wages by asking workers to bid for the right to search. On average, these reservation wages were very close to the theoretical optimum for a risk neutral researcher. Actual search behavior conformed to these elicited reservation wages. They also observed that subjects reacted to variations of the environment as predicted by theory, even though the duration of search was often lower than that predicted by the theory. Additionally, reservation wages were decreasing over time which violates the theoretical predictions. Hey (1982) conducted a consumer search experiment similar to Schotter and Braunstein's. The offers were drawn from an unknown distribution. 40% of the subjects stopped searching with the first price below the theoretically optimal reservation price.

Cox and Oaxaca (1989, 1992) studied behavior in search experiments in a finite horizon model. They argued that subjects in Braunstein and Schotter's experiments had not actually believed in the infinite horizon and had rather perceived the experiment as a finite horizon game, in which optimal reservation wages decreases over time. Cox and Oaxaca (1989) presented a finite horizon version of the theory of sequential search that focused upon the opportunity costs associated with the foregone earnings from rejecting an offer when it was received. They found that 77% of 600 search terminations were consistent with the varying predictions of the risk-neutral model over several treatments, whereas 94% were consistent with the weakly risk-averse version of the theory. Cox and Oaxaca (1992) induced observable reservation wages. Subjects responses consisted of stated minimum acceptable offers for which they were willing to make binding pre-commitments of acceptance. Their experiment consisted of two parts. In the first part, subjects were asked to record either an S (for stop the search) or C (for continue the search) during each period in which a trial was in progress. The C response indicated that the offer, if any, in that period was rejected. The S response indicated that the subject accepted the offer, if any, received in that period. In the second part, subjects were asked to record the minimum acceptable offer during each period in which a trial was in progress. If the subject received an offer that exceeded the recorded reservation wage, the offer was accepted and the trial ended. However, if the subject did not receive an offer that was equal or exceeded their reservation wage, they continued the search. Cox and Oaxaca (1992) found the directly elicited reservation wages to be lower than

predicted and concluded that a model with risk aversion explains their observations best. However, [Sonnemans \(1998\)](#) showed that a fully rational model of risk-averse search is not consistent with the search strategies that participants chose in a finite search model experiment.

[Cox and Oaxaca \(2000\)](#) tested experimentally the finite horizon models of job search in which wage offer distribution is unknown. Thus, the reservation wage property may not exist. This may occur when the subject does not know in advance whether the search is from a relatively favorable or unfavorable wage offer distribution. They found that the predictions of search theory continue to hold up when search is from an unknown distribution and that the success or the failure of search theory is not dependent on the presence or the absence of the reservation wage property.

[Brown et al. \(2011\)](#) identified the impact of both search time and accumulated search cost on reservation wage in a stationary environment. Since these two variables are highly colinear, they conducted two treatments to isolate their respective impact. They compared subjects behavior in a treatment where subjects wait uncertain amounts of time for offers but accumulate no search costs to one where offers arrived immediately but with a stochastic cost. They found that the waiting treatment generated a downward trend in reservation wages. This implies that a lengthy search spell might be discouraging, or searchers might accumulate subjective search costs not captured in standard models.

[Boone et al. \(2009\)](#) studied experimentally job search behavior in the presence of unemployment benefits sanctions. They identified the ex-ante and ex-post effects of the sanction system. The ex-post effect was that if confronted with a reduction of the benefits, an unemployed worker would be more likely to accept a given job offer. However, the ex-ante effect was that due to the threat of receiving a benefit sanction, a worker would be more likely to accept a given wage offer than he would be if his benefits would be constant and no system of benefit sanctions existed. In their experiment, a subject who accepted an offer was employed for a given period and then returned to the search process. He then received the full unemployment benefit for the period following the employment phase. As soon as he refused an offer, he took the risk of being

sanctioned in the following period and thus seeing the amount of unemployment benefit decreased. The penalty had a given probability that was of common knowledge. Their results showed that sanctions accelerated the return to employment. Following the introduction of penalties ranging from 25% to 75% of the unemployment benefit, the rate of return to employment increased on average by 28%. In addition, the introduction of sanctions has two distinct effects. On one hand, subjects accepted an offer more quickly after receiving a sanction (ex-post effect). On the other hand, the introduction of a possible sanction acted as a threat and led subjects to reduce their search time before they were even punished (ex-ante effect). The magnitude of the ex-ante effect was greater than that of the ex-post effect.

Some studies explored search behavior under risk and ambiguity. According to [Nishimura and Ozaki \(2004\)](#)'s model an increase in risk, increases the reservation wage. Thus, an unemployed worker was inclined to keep searching for a job when risk had increased. In contrast, they formulated Knightian uncertainty in such a way that the worker did not have confidence that a given wage distribution was the true one, and that instead they assumed a set of probability distributions and maximized the minimum of expected utilities based on each probability distribution. They then showed that the reservation wage was decreased when Knightian uncertainty increased, and hence, the worker tended to accept the job offer more quickly.

[Asano et al. \(2015\)](#) conducted an experiment to test the result of [Nishimura and Ozaki \(2004\)](#). They explored the effect of ambiguity on subject's search behavior in a finite horizon sequential search model. The effect of ambiguity was represented by an unknown point distribution. Subjects faced games of 20 rounds by way of a finite horizon sequential search model in which recall was not allowed. In the direct response treatment, a point was drawn from an unknown distribution, and the subject then "accepted" or "rejected" the wage offer. If a subject accepted the point, the search activity ended and the accepted point was converted to a payment. However, if the subject rejected the point, they moved to the second round where another point was drawn from a given distribution. Points were discounted over rounds. In the twentieth round, if a subject refused the point drawn, the search activity ended automatically and no point was

obtained. In the strategy-method treatment, subjects were asked ex-ante to declare their reservation point at each round and then began in the actual search based on the reservation point they had already entered. [Asano et al. \(2015\)](#) found that the presence of ambiguity in point distribution significantly decreased reservation points for consistent subjects.

[Schunk \(2009\)](#) conducted two experiments combining a lottery-based preference elicitation mechanism with a price search task, in order to link information from an independent measure of individual preferences with information on sequential decision behavior. Both experiments differ mainly in the preference elicitation method. Each experiment consisted of three parts. The first one served to elicit risk attitudes in gain lottery tasks. The second one served to elicit loss aversion in mixed lottery tasks. The third one consisted of a series of repeated price search tasks used to elicit subject's search behavior. At the end of the third part, they add a question to see if subjects evaluate the next step of the search process as a gain lottery or as a mixed lottery. Hence, subjects behaving in a manner that is consistent with the Expected Utility theory evaluated the next step of the search process as a gain lottery. However, subjects behaving in a manner that is consistent with a model which subjects set utility reference points evaluated the next step of the search process as a mixed lottery. [Schunk \(2009\)](#) found considerable heterogeneity of search rules and predominance of early stopping in the population ([Cox and Oaxaca \(1989\)](#); [Hey \(1987\)](#); [Sonnemans \(1998\)](#)). This heterogeneity can be linked to heterogeneity in individual preferences, specially loss aversion, whereas risk aversion is not related to search behavior.

[Schunk and Winter \(2009\)](#) explored the reasons why in many of these studies agents stop searching earlier than what is theoretically optimal derived under risk neutrality. They found that the specifications of the generalized search model with risk aversion could not fully describe the observed search behavior. While individual risk parameter did not correlated with the individual search parameters, loss aversion parameter did correlate with observed search behavior. There are two possible explanations for that finding. First, loss aversion can be measured better than risk aversion in their experimental tasks. This explanation is in line with [Rabin \(2000\)](#) who provided theoretical

arguments that loss aversion can account better for observed decision behavior over modest stakes than the standard notion of risk aversion. A second explanation is that individuals set reference points during the search process. This explanation is in line with laboratory and field evidence on myopic loss aversion in dynamic decision tasks (Benartzi and Thaler (1995)).

In summary, there is strong evidence of early stopping in search and decreasing reservation wage over time.

2.3 Theoretical framework

We consider a basic job search model with discrete time and infinite horizon. In each period, the probability that the unemployed worker receive a job offer is p . When a job offer arrives the searcher receives a wage offer w . The wage offers are randomly drawn from a discrete uniform distribution with density function $g(w)$ (with \underline{w} and \bar{w} the (finite) infimum and supremum of the support of $g(w)$). If the wage offer is rejected, the worker remains unemployed and continues the search. The rejected wage offer cannot be recalled. If the wage offer is accepted, the worker is employed at that wage forever. So we assume that an employed worker cannot be hired or search on the job. We also assume that the workers are risk neutral.

Given our assumptions, Bellman equation for the lifetime utility of employment at wage w :

$$W_t(w) = w_t + \beta W_{t+1}(w) \quad (2.1)$$

In a steady state:

$$W_t(w) = \frac{w}{1 - \beta} \quad (2.2)$$

$$U_t = (1 - p)\beta U_t + p\beta \sum_{\underline{w}}^{\bar{w}} \max\{U_t, W_t(w)\} g(w) \quad (2.3)$$

Where $W_t(w)$ is the lifetime utility of employment at wage w and U_t is the expected lifetime utility of unemployment. β is the discount factor. The reservation wage is such as the payoff from accepting a wage w_R is equal to the payoff from rejecting it and continuing job search : $W_t(w_R) = U_t$.

Substituting $U_t = \frac{w_R}{1 - \beta}$ and $W_t(w) = \frac{w}{1 - \beta}$ in (2.2) and simplifying, we have:

$$w_R = \frac{p\beta}{1 - \beta} \sum_{w_R}^{\bar{w}} (w - w_R) g(w) \quad (2.4)$$

This equation characterizes the optimal search strategy. Using a uniform distribution $g(\cdot)$, we get a quadratic equation defining the reservation wage:

$$0 = p\beta w_R^2 - [p\beta(1 + 2\bar{w}) + 2(1 - \beta)(\bar{w} - \underline{w} + 1)] w_R + p\beta\bar{w}(1 + \bar{w}) \quad (2.5)$$

We also can define the expected search duration:

$$D = \frac{1}{p \sum_{w_R}^{\bar{w}} g(w)} \quad (2.6)$$

Given the parameters in our experiment:

- The rate of interest: $r = 0.1$
- The wage offer distribution: a uniform discrete distribution from 1 to 25
- The probability of receiving an offer: $p = \{0.1; 0.3; 0.5; 0.7; 0.9\}$

We can derive theoretical values of reservation wage (w_R) and expected search duration (D) according to the probability of receiving an offer p :

p	w_R	D
0.1	7	13.16
0.3	12	5.95
0.5	14	4.17
0.7	16	3.57
0.9	17	3.09

2.4 Experimental design

We explore job search behavior under risk and ambiguity through a repeated search game. Each subject completes 14 search spells with infinite horizon². We use a version of this game that allows to elicit subjects' reservation wages in an incentive-compatible manner. Our approach is similar to the one used by [Cox and Oaxaca \(1992\)](#) and [Brown et al. \(2011\)](#) except that we elicit subject's reservation wage in each search period whether he receives an offer or not³. Our job search game is described as follows.

2.4.1 The search game

Each search spell is divided into search periods. The number of periods is not restricted. As long as the subject does not accept an offer, he continues the search. In each period, the subject receives a job offer with a probability p . This probability is the same from one period to another, but it can change between the search spells. Without knowing if he would receive an offer, the subject has to decide which offers he is

²Most theoretical and experimental literature consider infinite job search horizon. One exception is [Cox and Oaxaca \(1989, 1992, 2000\)](#) that conducted experiments based on a job search model with finite horizon.

³Except [Cox and Oaxaca \(1992\)](#) and [Brown et al. \(2011\)](#), previous experiments on search behaviors used observations of search duration, search income and accepted wages but not reservation wages that are not observed ([Braunstein and Schotter, 1981, 1982](#), [Cox and Oaxaca, 1989, 2000](#), [Boone et al., 2009](#))

willing to accept and which to reject. The subject makes a decision (acceptance or rejection) for each possible wage offer that allows to reveal his reservation wage which is the minimum wage offer he is willing to accept.

Then a random draw is performed to determine whether the subject receives an offer or not in this period. If the subject does not receive an offer, he starts similarly the next period. However, if he receives an offer, a wage offer is randomly drawn. The wage offers are drawn from a discrete uniform distribution ranging from 1 to 25. The offered wage is compared with the subjects reservation wage that he has reported at the beginning of the current period. If the subject receives a wage offer lower than his reservation wage, the wage offer is automatically rejected and the subject starts the next period where he continues the search. By contrast, if the subject receives a wage offer that equals or exceeds his reservation wage, the wage offer is automatically accepted. The subject's payoff in this spell corresponds to the discounted present value of accepted wage offer. The present value of an offer depends on the value of the offer that the subject has accepted as well as the period in which he has accepted this offer. It is calculated as follows:

$$\text{Present value} = \frac{\text{Offer}}{0.1 * (1.1)^{\text{Period's number}-2}}$$

The present value increases with the offer amount and it decreases over periods. The subject has finished this search spell and he starts the next that takes place in the same way.

2.4.2 The treatments *Risk* and *Ambiguity*

Our experiment includes two treatments aiming to compare search behavior under *Risk* and *Ambiguity*. We implement a within-subject design, meaning that each subject completes both treatments. Both treatments, called *Risk* and *Ambiguity*, differ in the information about the probability of receiving an offer. Under *Risk*, the subject perfectly knows this probability, while under *Ambiguity* there is an uncertainty about it.

In both treatments, the probability of receiving an offer is revealed to the subject using an urn that contains 10 balls that are either red or blue. In each period, a random draw is performed in the urn to determine whether the subject receives an offer or not. Subject states which color they prefer to bet on. For example, if they prefer red, they receive an offer if the drawn ball is red but not if it is blue. The content of the urn is the same across all periods of a search spell, but it can vary between search spells. In each period, the urn is displayed on subject's screen before making his decision.

Under *Risk*, the subject perfectly knows the content of the urn, i.e. the color of the 10 balls. Hence, the perfectly know the probability of receiving an offer. However under *Ambiguity*, the content of the urn is only partially revealed to the subject. The urn still contains 10 balls, either red or blue, in unknown proportions. In other words, they are split into red balls, blue balls and indeterminate color balls that are either red or blue. So the subject does not perfectly know the probability of receiving an offer, but they only know a range of values including this probability. For example, if the urn includes 2 red balls, 2 blue balls and 6 balls of indeterminate color, the subject only knows that the probability of receiving an offer ranges from 0.2 to 0.8.

Under *Risk*, the subject completes 6 search spells. The first five spells implement 5 different probabilities of receiving an offer: $p = 0.1, 0.3, 0.5, 0.7, 0.9$. The occurrence of each probability is randomly chosen for each subject. For consistency check, the last spell implements the same probability as in the third spell. The 5 urns under *Risk* are the following:

Urn's code	Number of red balls	Number of blue balls	Probability of receiving an offer p
K_1	1	9	0.1
K_3	3	7	0.3
K_5	5	5	0.5
K_7	7	3	0.7
K_9	9	1	0.9

Under *Ambiguity*, the subject completes 8 search spells. In the first seven spells, we use 7 different urns that differ in either the range of values including p or the actual value of p . As under *Risk*, the urns are randomly displayed on the subjects screen through search spells and the last spell replicates the urn used in the tenth spell. The 7 urns under *Ambiguity* are the following:

Urn's code	Number of red balls	Number of blue balls	Number of indeterminate color balls	Range of values including p	Actual value of p
U_1	1	1	8	[0.1, 0.9]	0.1
U_5	1	1	8	[0.1, 0.9]	0.5
U_9	1	1	8	[0.1, 0.9]	0.9
U_1^L	1	5	4	[0.1, 0.5]	0.1
U_5^L	1	5	4	[0.1, 0.5]	0.5
U_5^H	5	1	4	[0.5, 0.9]	0.5
U_9^H	5	1	4	[0.5, 0.9]	0.9

For the sake of simplicity, we use codes to refer to each urn. Under *Risk*, the urn is denoted by K since the probability p is known and K_i is the urn where p is equal to $0.i$. For example, K_3 represents the urn where the probability of receiving an offer is known and equal to 0.3. Under *Ambiguity*, urns are denoted by U since the probability p is not perfectly known. The uncertainty differs between the urns U_i , U_i^L , U_i^H . Figure 2.1 presents the range of values including p for those 3 urns:

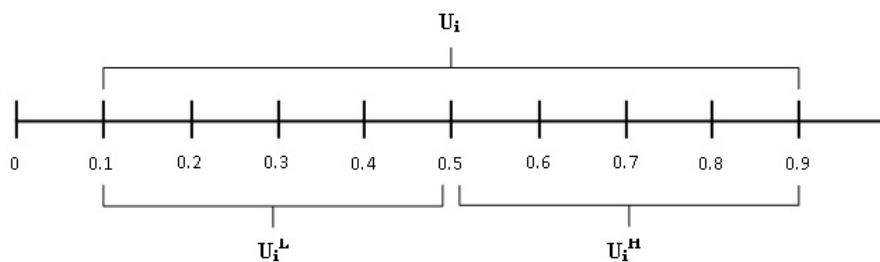


FIGURE 2.1: Range of values including p

For each out of these urns, the subscript i indicates the actual value of p . For example, U_1 means that the probability of receiving an offer is 0.1 but the subject does not have this information and they just know that the probability is between 0.1 and 0.9. Likewise, U_5^H means that the probability of receiving an offer is 0.5 but the subject does not have this information and they just know that the probability is between 0.5 and 0.9.

In figure 2.1, 3 different urns are shown to the subject: an urn with symmetric uncertainty (U_i), an urn with asymmetric uncertainty and low range of probabilities (U_i^L) and an urn with asymmetric uncertainty and high range of probabilities (U_i^H). In fact, the urns U_1 , U_5 and U_9 are similar on the subjects screen since only the actual value of p differs. The same applies to U_1^L , U_5^L and U_5^H , U_9^H .

Moreover, when comparing the urns under both treatments, the probabilities under *Risk* correspond to either the lower bound, the middle or the higher bound of the interval including p under *Ambiguity*. Hence, by comparing the behavior under *Risk* and *Ambiguity*, we are able to determine if under *Ambiguity* subjects behave as if the probability is the lowest (ambiguity averse) or as if it is in the middle (ambiguity neutral) or as if it is the highest (ambiguity lover).

2.4.3 Experimental procedures

The experiment was conducted at the CREM-CNRS (LABEX) institute of the University of Rennes 1. A total of 114 subjects participated in 8 sessions. The participants were undergraduate students from business, economics, law, engineering, medicine and literature. Each subject participated in only one session. The experiment was run in a computerized interface using the Z-tree platform (Fischbacher, 2007). Each session lasted around 75 minutes and the average gain is 20.13 Euros, including a show-up fee of 4 Euro.

Upon arrival, the participants were randomly assigned to a computer. The written instructions were then distributed and read aloud, so that it is common knowledge that everybody is involved in the same experiment. The wording of the instructions is as

neutral as possible regarding the job search. We use the terms market and offer, but not the terms job, search and wage.

Each subject participates in both treatments, *Risk* and *Ambiguity*. To check order effect, we reverse the order of the treatments across sessions. The half of subjects completed the six risky markets first, then the eight ambiguous markets. The other half of subjects did the opposite. In both cases, the subjects were given the whole instructions before starting the experiment. Moreover, to improve the understanding of the experiment, the subjects completed 8 trial markets including three risky markets and five ambiguous markets. These markets are not taken into account for subjects final earning.

The subjects final earning consists of three parts. The first part is a 4 euros show-up fee for participation. The subjects also have the opportunity to earn 3 additional euros by answering a simple quiz performed at the beginning of the experiment. The third part of the payment is the most important and it depends on subjects choices during the experiment.

Before starting the experiment, each subject randomly drew an envelope that contains an urn corresponding to one out of 14 markets they completed during the experiment. The subjects were told that they must not open their envelope at risk of being excluded from the payoff. When a subject has finished the experiment, they have to raise his hand and the experimentalist comes to open his envelope. The subjects earning is equal to the present value of the offer that they have accepted in the market corresponding to the content of his envelope. To know his earning in the randomly drawn market, the subject has to insert a code that is written on a paper in his envelope into the computer.

Throughout the experiment, the subjects can refer to two tables by clicking on buttons that are displayed on their screen. The first table shows the subject the present value of the 25 possible offers in the current period and in a period of his choice. The subjects are thereby able to know the present value of each offer in all periods without making calculations. The second table shows a summary of previous periods of the market. For each period, this summary table displays the minimum offer the subject decided to

accept, if the subject received an offer or not, the offer amount and the corresponding present value. When the subject accepts an offer, the market is closed and the summary table is cleared.

At the end of the experiment, the participants were asked to answer a questionnaire providing their individual characteristics (gender, age, etc.). After completing the questionnaire, subjects were privately paid their earnings, calculated according to the conversion rate of 10 experimental points to 1 Euro. The participants were privately paid before leaving the experimental laboratory.

2.5 Findings

2.5.1 Behavior under *Risk*

2.5.1.1 Do subjects select the theoretical reservation wage?

First we compare the reservation wages reported by subjects with the theoretical values. For each probability of receiving an offer ($p \in \{0.1; 0.3; 0.5; 0.7; 0.9\}$), table 2.1 displays the theoretical reservation wage for each probability of receiving an offer.

TABLE 2.1: Reservation Wage under *Risk*

Urn	Probability	Theoretical Reservation Wage
K_1	0.1	7
K_3	0.3	12
K_5	0.5	14
K_7	0.7	16
K_9	0.9	17

Average reservation wages per period for the urns K_1 , K_3 , K_5 , K_7 and K_9 are represented in tables from 2.2 to 2.6 respectively. Average reservation wages are denoted with *, ** and *** if they are significantly lower than the theoretical reservation wage for each urn at 1%, 5% and 10% significance level respectively.

Overall, subjects select reservation wages below the theoretical values. In the urn K_1 , the average reservation wage reported in table 2.2 for the 114 subjects in the first period is 6.72 which is not significantly different from 7, the theoretical reservation wage for the urn K_1 . The average reservation wages decrease over period and become significantly lower than 7.

For the urn K_3 , all reported reservation wages in table 2.3 are significantly lower than 12. Similarly in urn K_5 in table 2.4, all reported reservation wages are significantly lower than 14.

For the urn K_7 , all reported reservation wages in table 2.5 are significantly lower than the theoretical reservation wage which is equal to 16 except at the third period, 60 subjects terminated the search and 52 continued. For these 52 subjects, in the first period, the average reservation wage is not significantly lower than 16. Similarly, at the fourth period, 19 subjects terminated the search and 33 continued. For these 33 subjects, the average reservation wage in period 1, 2 and 3 is not significantly different than 16, hence subjects who remain in the job search are those who choose relatively higher reservation wages.

Finally, for the urn K_9 , for all 114 subjects, the average reservation wage is significantly lower than 19. Out of the 114 subjects, 64 continued the search. For these 64 subjects, in the first period, the average reservation wage is not significantly different than the theoretical one. Out of these 64 subjects, 40 continued the search. For these 40 subjects, the average reservation wage in the first period is also not significantly different than the theoretical one.

It is difficult to compare with previous papers due to difference in experimental design as described in literature. But overall it is consistent with previous experiments that directly elicit reservation wages. Indeed, [Cox and Oaxaca \(1992\)](#) also found that the directly reported reservation wages were lower than the theoretical predictions with risk-neutral agent⁴. They attributed this result to subjects risk aversion. Conversely, [Brown](#)

⁴On the other hand, [Cox and Oaxaca \(1989\)](#) found search duration and income very close to the theoretical values when they did not directly elicit subjects reservation wages. Indirect tests based on search duration seemed less powerful since search durations were strongly influenced by randomly draws.

et al. (2011) found no difference during the first search spell in the first environment⁵. However, this result did not hold when they aggregated all environments and all the search spells, they found that subjects set reservation wages that were lower than the theoretical predictions.

TABLE 2.2: Difference between average reservation wage and theoretical reservation wage over periods for the urn K_1

Period \ Subjects	114	107	100	88	81	72	67	64	56	53
1	6.72	6.76	6.67	6.78	7.09	7.37	7.57	7.73	7.41	7.57
2		5.99**	6.09**	6.09**	6.33	6.35	6.46	6.58	6.7	6.87
3			6.11**	6.15**	6.39	6.51	6.6	6.67	6.48	6.62
4				5.92*	6.14**	6.25*	6.31	6.39	6.29	6.38
5					5.85***	6.04**	6.15*	6.2*	6.11*	6.13*
6						6.07**	6.18*	6.23*	6.16*	6.21
7							5.78**	6**	5.8**	5.74**
8								6.14*	5.95**	5.91**
9									6.16*	6.06*
10										5.77**

TABLE 2.3: Difference between average reservation wage and theoretical reservation wage over periods for the urn K_3

Period \ Subjects	114	90	72	57	47	38	28
1	8.54***	8.54***	8.64***	9.53***	10.17***	9.95***	10.36**
2		8.21***	8.42***	9.19***	9.68***	9.47***	9.79***
3			7.86***	8.54***	9.25***	9***	9.25***
4				8.3***	9.02***	8.68***	8.86***
5					8.64***	8.42***	8.75***
6						8.05***	8.29***
7							8.25***

Even though we elicit reservation wages, we can briefly compare theoretical and observed search duration. For each probability of receiving an offer, table 2.7 displays the mean search duration as well as the theoretical search duration. However as search durations depend on random draws of offers and wages, we also report the theoretical search durations taking into account the actual draws. To calculate these durations, we

⁵In Brown et al. (2011), each subject completed five consecutive search spells in 3 different environments (between each environment parameters vary and are randomly chosen)

TABLE 2.4: Difference between average reservation wage and theoretical reservation wage over periods for the urn K_5

Period \ Subjects	114	70	48	38
1	11.17***	11.71***	12.15***	12.24***
2		11.26***	11.75***	11.82***
3			11.27***	11.18***
4				10.5***

TABLE 2.5: Difference between average reservation wage and theoretical reservation wage over periods for the urn K_7

Period \ Subjects	114	82	52	33
1	13.35***	14.76***	15.63	16.3
2		13.95***	14.5***	15.97
3			14.08***	15.3
4				13.91***

TABLE 2.6: Difference between average reservation wage and theoretical reservation wage over periods for the urn K_9

Period \ Subjects	114	64	40
1	14.39***	16.37	16.65
2		15.75***	15.95*
3			15.15***

proceed as [Cox and Oaxaca \(1989\)](#). We compare the theoretical reservation wage to randomly drawn offers to determine when the subject would have stopped the search if they behaved optimally. For subjects who stop the search too quickly, we cannot proceed thereby because there is no longer wage offers after leaving the search process. In this case we use the theoretical duration in the current period.

Overall, observed search durations are lower than the theoretical predictions with or without controlling the draws. The differences are all significant except for the probability 0.1. We therefore conclude that overall subjects leave the search process faster

than predicted by theory unless the probability of receiving an offer is very low. This result is in line with what is observed for reservation wages: if subjects set reservation wages lower than those predicted by the theory, they leave faster the search process.

TABLE 2.7: Search Duration under Risk

Probability	Theoretical Search Duration	Theoretical Search Duration taking into consideration the draws	Observed Search Duration
0.1	13.16	11.92	11.97
0.3	5.95	6.02	4.93
0.5	4.17	3.78	2.94
0.7	3.57	3.43	2.96
0.9	3.09	3.06	2.54

2.5.1.2 Is the reservation wage constant over time?

The standard search model with infinite horizon predicts a constant reservation wage⁶. However, this prediction is challenged by most experiments on job search (Braunstein and Schotter, 1981, 1982, Brown et al., 2011) that showed a decreasing reservation wage over time.

Average reservation wages over periods for urns K_1 , K_3 , K_5 , K_7 and K_9 are represented in the appendix in tables from 13 to 17 respectively. We use paired t-test to see if there is a significant decrease in average reservation wage between period 1 and period t as well as between period t as well as period $t - 1$. For all the urns, average reservation wages decrease over periods.

This result is also confirmed by the estimation of mixed models that show a negative and significant effect of periods on reservation wage. Therefore, we confirm the results observed in previous experiments: contrary to the theoretical predictions, we find evidence of declining reservation wage over periods.

⁶Unlike the finite horizon where reservation wage is decreasing over time.

2.5.1.3 Do subjects learn from one spell to another?

If there is a learning process over time, the spells are not then independent and there is an order effect. In order to test the presence of learning, we introduce a repeated spell at the end of each treatment. In the last spell of each treatment, each subject has the same probability of receiving an offer as in the spell played in the middle of treatment. For example, if a subject faces the urn K_1 in spell 3 under Risk, they will face this urn again in the spell 6 under Risk. We proceed likewise in Ambiguity treatment. The urn used in spell 10 is repeated at the last spell. Repeated urns are not used in the analysis of results but they are used to test the learning effect during the course of the experiment.

Table 2.8 shows average reservation wages over period for repeated spells. We find no significant difference in average reservation wages between repeated search spells. This result is also confirmed by the estimation of mixed models that do not show significant differences between repeated spells.

TABLE 2.8: Learning in Risk treatment: Average reservation wages in repeated spells

Period	114	88	63	36
1	10.69	11.14	11.36	11.88
1	10.48	10.78	10.9	11
2		10.3	10.46	11.05
2		10.02	10.1	10.05
3			10.23	10.86
3			9.81	10.17

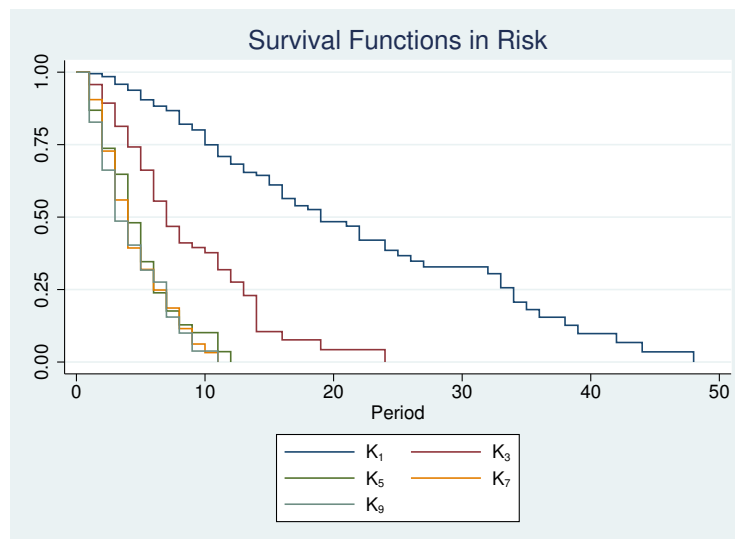
2.5.1.4 Does the probability of receiving an offer affect the behavior of subjects?

We compare, by using paired t-test, average reservation wages reported by subjects for a certain urn with that of the rest of the urns. For example, table 18 in the appendix shows average reservation wages per period for urns K_1 and K_3 . Paired t-test shows that the difference between average reservation wages per period in urn K_1 and K_3 is significant at 1% significance level. Similarly, from table 19 to table 27, the differences

between average reservation wages are all significant at 1% significance level. Hence, the probability of receiving an offer affects significantly subjects reservation wages.

We also investigate the effect of the probability of receiving an offer on search duration. Table 2.7 provides search durations in Risk treatment. As predicted by the theory, we find that the search duration tends to decrease with the probability of receiving an offer. However, the differences observed between the probabilities 0.5, 0.7 and 0.9 are not significant. This result is confirmed by figure 2.2 which shows the survival functions for each level of probability. The survival functions show for each period the proportion of subjects who are still in the search process. Wilcoxon tests for the equality of survival functions confirms the existence of significant differences in levels of low probability but no significant difference between the probabilities 0.5, 0.7 and 0.9.

FIGURE 2.2: Survival functions in Risk



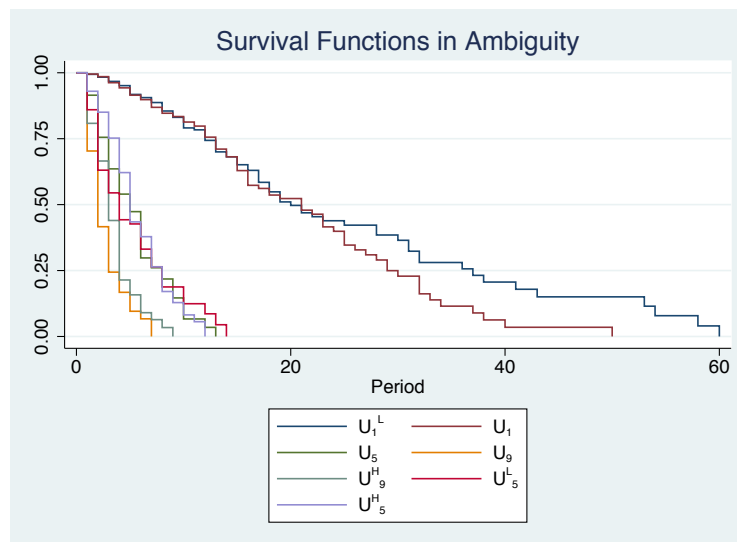
2.5.2 Behavior under *Ambiguity*

2.5.2.1 Do subjects select the theoretical reservation wage?

We compare the reservation wages reported by subjects with the theoretical values. Theoretical reservation wages in Ambiguity treatment are calculated based on subjects

updating their beliefs about probability distribution. For all urns, reported average reservation wages are significantly lower than the theoretical ones at 1% significance level. The results for the urns U_1 , U_5 , U_9 , U_1^L , U_5^L , U_5^H and U_9^H are shown from table 2.9 to table 2.15. Regarding search durations, Figure 2.3 shows the survival functions for each urn. Wilcoxon tests for the equality of survival functions confirms the existence of significant differences between urns. There is also a significant difference between the urns of low probability [0.1-0.5], high probability [0.5-0.9] and the urns of probability range [0.1-0.9].

FIGURE 2.3: Survival functions in Ambiguity



Tables from 2.9 to 2.11 present average reservation wages reported by subjects with the theoretical values for the urns where the probability interval is [0.1-0.9] and the actual value of probability is 0.1, 0.5 and 0.9 respectively .

TABLE 2.10: Average reservation wage over periods versus the theoretical reservation wage for the urn U_5

Period \ Subjects	114	82	52	37
1	10.57	11.28	12.08	12.38
1 Theoretical	14	14	14	14
2		10.73	11.58	12.03
2 Theoretical		13.41	13.35	13.32
3			11	11.22
3 Theoretical			13	13.08
4				10.62
4 Theoretical				13.08

TABLE 2.11: Average reservation wage over periods versus the theoretical reservation wage for the urn U_9

Period \ Subjects	114	52
1	10.19	12.6
1 Theoretical	14	14
2		11.65
2 Theoretical		14.5

Table 2.12 and 2.13 present average reservation wages reported by subjects with the theoretical values for the urns where the probability interval is [0.1-0.5] and the actual value of probability is 0.1 and 0.5 respectively .

TABLE 2.13: Average reservation wage over periods versus the theoretical reservation wage for the urn U_5^L

Period \ Subjects	114	70	34
1	8.91	9.01	10.68
1 Theoretical	12	12	12
2		8.69	10.5
2 Theoretical		11.43	11.41
3			10.03
3 Theoretical			10.65

Table 2.14 and 2.15 present average reservation wages reported by subjects with the theoretical values for the urns where the probability interval is [0.5-0.9] and the actual value of probability is 0.5 and 0.9 respectively .

TABLE 2.14: Average reservation wage over periods versus the theoretical reservation wage for the urn U_5^H

Period \ Subjects	114	84	67	53	39
1	12.27	13.48	14.09	14.19	14.77
1 Theoretical	16	16	16	16	16
2		13.26	13.94	14.04	14.62
2 Theoretical		15.32	15.33	15.3	15.33
3			13.37	13.55	13.97
3 Theoretical			14.46	15.45	15.51
4				12.57	12.92
4 Theoretical				15.3	15.33
5					11.59
5 Theoretical					15.44

TABLE 2.15: Average reservation wage over periods versus the theoretical reservation wage for the urn U_9^H

Period \ Subjects	114	63	44
1	12.61	13.87	14.55
1 Theoretical	16	16	16
2		13.3	14.2
2 Theoretical		15.84	15.9
3			13.11
3 Theoretical			16

2.5.2.2 Is the reservation wage constant over time?

For all urns, average reservation wages decrease over periods. Similarly as in Risk, we test if there is a significant decrease in the average reservation wage between period t and period 1 as well as between period t and $t - 1$. Tests for the difference in average reservation wages between period t and period 1 for urns U_1 , U_5 , U_9 , U_1^L , U_5^L , U_5^H and U_9^H are presented in the appendix from table 28 to 34 respectively. Tests for the difference in average reservation wages between period t and period $t - 1$ are presented from table 35 to 40 in the appendix.

2.5.2.3 Do subjects learn from one spell to another?

Table 2.16 shows average reservation wages over period for repeated spells. We find no significant difference in average reservation wages between repeated search spells. This result is also confirmed by the estimation of mixed models that do not show significant differences between repeated spells.

We also check this result by comparing average reservation wages when subjects face identical urns on their screen. For example, we can compare the average reservation wages for urns U_1 , U_5 , U_9 all including a red ball, blue ball and 8 balls of indeterminate

TABLE 2.16: Learning in Ambiguity treatment: Average reservation wages in repeated spells

Period \ Subjects	114	92	69	56	43	36	31
1	10.15	10.39	10.63	10.47	10.68	10.18	10.4
1	10.61	10.88	10.86	10.43	10.68	10.09	10.37
2		10.22	10.54	10.54	10.4	9.64	9.83
2		10.43	10.37	10.37	10.23	9.64	9.93
3			10.47	10.04	10.04	9.34	9.69
3			10.42	9.72	9.71	9.16	9.52
4				10.38	9.08	9.08	8.9
4				10.05	8.38	8.84	9.07
5					9.23	7.84	7.84
5					9.12	7.64	7.65
6						8.56	8.62
6						8.11	8.03
7							8.13
7							7.58

color. We do the same with U_1^L and U_5^L and with U_5^H and U_9^H . We find no significant difference in reservation wages when subjects face identical urns on their screen except for average reservation wages in period 1 between urn U_1 and U_9 and in period 2 between urn U_1 and U_5 at 10% significance level. Results are reported in the appendix from table 41 to 44.

2.5.3 Behavior under Risk and Ambiguity

In this section, we compare subjects behavior under risk and ambiguity. We find that for most of the urns in the Ambiguity treatment, subjects behave as if the probability of receiving an offer is at the middle of the probability interval. Hence, subjects behave as ambiguity neutral individuals.

For each urn in the Ambiguity treatment, we compare the reported average reservation wages with those of the Risk treatment. For the urn U_9^H in the Ambiguity treatment,

the probability of receiving an offer ranges from 0.5 and 0.9. Hence, we compare average reservation wages in this urn with those of the urns K_5 , K_7 and K_9 in the Risk treatment where the probability of receiving an offer is equal to 0.5, 0.7 and 0.9 respectively. When comparing between urns U_9^H and K_9 in table 45 in the appendix, we find that average reservation wages in urn U_9^H of the Ambiguity treatment are significantly lower than those of the urn K_9 of the Risk treatment. Hence, in the urn U_9^H , subjects behave as if the probability of receiving an offer is lower than 0.9.

Then, we compare between average reservation wages in urn U_9^H and those of the urn K_5 . We find that average reservation wages in urn U_9^H of the Ambiguity treatment are significantly higher than those of the urn K_5 of the Risk treatment. Results are reported in table 46. Hence, in the urn U_9^H , subjects behave as if the probability of receiving an offer is higher than 0.5.

Finally, we compare between urns U_9^H and K_7 in table 47, we find that average reservation wages in urn U_9^H are significantly lower than those of the urn K_7 in the first one for 114 subjects. In period 2, there is no significant difference between average reservation wages in both urns. Hence, in the urn U_9^H , subjects behave as if the probability is close to 0.7 which is the middle of the probability range [0.5-0.9].

For the urn U_5^H , the probability of receiving an offer ranges from 0.5 to 0.9. Hence, we compare average reservation wages in that urn with those of the urns K_5 , K_7 and K_9 where the probability of receiving an offer is equal to 0.5, 0.7 and 0.9 respectively. Results are reported in tables 48, 49 and 50 respectively in the appendix. We find that average reservation wages in urn U_5^H are significantly higher than those of the urn K_5 and lower than those of the urn K_9 . Average reservation wages in urn U_5^H are significantly lower than those of the urn K_7 in period 1. In period 2 and 4, there is no significant difference between average reservation wages of both urns. Hence, in the urn U_5^H , subjects behave as if that the probability of receiving an offer is close to 0.7 which is the middle of the probability range [0.5-0.9].

For the urn U_5^L , the probability of receiving an offer ranges from 0.1 to 0.5. We compare average reservation wages with those of the urns K_1 , K_3 and K_5 in the Risk

treatment where the probability of receiving an offer is equal to 0.1, 0.3 and 0.5 respectively. Results are reported in tables 51, 52, 53 respectively in the appendix. Average reservation wages in urn U_5^L are significantly higher than those of the urn K_1 and lower than those of the urn K_3 . However, average reservation wages are not significantly different than those of the urn K_3 of the Risk treatment in period 1 for 114 subjects. For the 51 subjects who remain in the search process in both urns, we find a significant difference in reservation wages. Hence, in the urn U_5^L , subjects behave as if that the probability of receiving an offer is close to 0.3 which is the middle of the probability range [0.1-0.5].

For the urn U_1^L , the probability of receiving an offer ranges from 0.1 to 0.5. We compare average reservation wages with those of the urns K_1 , K_3 and K_5 where the probability of receiving an offer is equal to 0.1, 0.3 and 0.5 respectively. Results are reported in tables 54, 55 and 56 respectively in the appendix. Average reservation wages in urn U_1^L are significantly higher than those of the urn K_1 and lower than those of the urn K_5 . However, average reservation wages in urn U_1^L are not significantly different than those of the urn K_3 in period 1. Hence, in the urn U_1^L , subjects behave as if the probability of receiving an offer to be close to 0.3.

Similarly, for the urn U_1 , the probability of receiving an offer ranges from 0.1 to 0.9. In table 58 in the appendix, we compare then average reservation wages in the urn U_1 with those of the urn K_5 where the probability of receiving an offer is equal to 0.5. Average reservation wages are not significantly different than those of the urn K_5 in period 1. Moreover, we compare average reservation wages in urn U_5 and U_9 where the probability of receiving an offer ranges from 0.1 to 0.9 with those of the urns K_5 . Average reservation wages in urn U_5 are significantly higher than those of the urn K_5 in period 1 in table 60 and not significantly different than those of the urn K_5 for subjects who remain in the search in period 2 for both urns. Average reservation wages in urn U_9 are significantly lower than those of the urn K_5 in period 1 and not significantly different than those of the urn K_5 for subjects who remain in the search in period 2 for both urns. Hence, subjects behave as if the probability of receiving an offer to be close to 0.5 which is the middle of the probability range in the urn U_1 , U_5 , U_9 .

[Asano et al. \(2015\)](#) designed a laboratory experiment of a finite-horizon sequential search model with ambiguity in the sense that an offer distribution is unknown and tested whether ambiguity affects reservation points. They found that the presence of ambiguity in point distribution significantly decreases the reservation points when the sample is limited to consistent subjects. In our experiment, search horizon is infinite and ambiguity is present in the probability of receiving an offer in each search spell. We find that subjects behave as if the probability is in the middle of the interval, hence, they are ambiguity neutral.

2.6 Conclusion

In this chapter, we designed a laboratory experiment of an infinite horizon search model to elicit reservation wages as well as search durations under risk and ambiguity. The two treatments of risk and ambiguity differ in the information about the probability of receiving an offer. Under risk, this probability was known, however, under ambiguity this probability was unknown.

Under risk and ambiguity, we find that reservation wages are less than the theoretical predictions and are decreasing over the course of an unemployment search spell. The result of decreasing reservation wages is inconsistent with the constant reservation wage implication of the infinite horizon search model but it is consistent with the decreasing reservation wage path of finite horizon search models. Additionally, observed search durations are lower than the theoretical predictions except when the probability of receiving an offer is 0.1. We therefore conclude that overall subjects leave the search process faster than theoretical predictions unless the probability of receiving an offer is very low. This result is in line with what is observed for reservation wages: if subjects set reservation wages lower than those predicted by the theory, they leave faster the search process. [Braunstein and Schotter \(1981\)](#) and [Cox and Oaxaca \(1989\)](#) suggest that early stopping can be explained by risk aversion. Risk aversion can be interpreted as the willingness to accept lower average earnings in exchange for a lower variability of the earnings.

The contribution of this chapter is to explore the effect of ambiguity on job search behavior. This is important because the prospects of labor market conditions are hardly known. The ambiguity about the prospects of labor market conditions may make individuals more cautious and discourage them from searching for longer periods because they become less confident in finding better job offers in the future. To date, only one research paper studied the effect of ambiguity on reservation wages. [Asano et al. \(2015\)](#) introduced ambiguity in their experiment in the sense that offer distribution is unknown. They found that the presence of ambiguity in point distribution significantly decreases the reservation points. In this chapter, risk and ambiguity were presented by the information about the probability of receiving an offer. Under ambiguity, the probability of receiving an offer was unknown, subjects only knew a range including this probability. There were 3 probability ranges of ambiguity: [0.1-0.9], [0.1-0.5] and [0.5-0.9]. Hence, by comparing the behavior under Risk and Ambiguity, we are able to determine if under Ambiguity subjects behave as if the probability is the lower bound (ambiguity averse) or as if it is in the middle (ambiguity neutral) or as if it is the higher bound (ambiguity lover) of the probability range. We find that under ambiguity, subjects behave as if the probability of receiving an offer is in the middle of the probability range. Hence, they behave as ambiguity neutral agents and ambiguity does not have an impact on reservation wages. Hence, this result is not in line with [Asano et al. \(2015\)](#).

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Chapter 3

Social influence in gain, loss and mixed domain

3.1 Introduction

Social comparison is an important determinant of human behavior. In social psychology, [Festinger \(1954\)](#)'s "Social Comparison Theory" showed that people compare their own opinions and abilities to those of others. In the economic literature, [Veblen \(1899\)](#) is regarded as one of the first theorists to shed the light on social comparison in his "Theory of the Leisure Class". He presented the idea that people engage in conspicuous consumption to signal wealth and indicate better social status. [Duesenberry \(1949\)](#) suggested that individuals utility index depended on the ratio of their consumption to a weighted average of the consumption of the others. More recently, there is empirical evidence that relative income has an impact on happiness ([Vendrik and Woltjer, 2007](#)).

Given these evidence about the importance of social comparison, it is natural to expect that when evaluating the consequences of their decisions, people take into consideration not only their own outcome but also their relative outcome with respect to their peers. The focus of this chapter is on decisions under risk. According to the most prominent model of decision making under risk [Kahneman and Tversky \(1979\)](#)'s

Prospect Theory, in private environment, people evaluate their outcomes relative to a reference point. Translating this to a social context, [Tversky and Kahneman \(1991\)](#) suggested that outcomes of others can serve as a reference point for individual choice.

Few studies have explored the effect of social comparison on individual risk attitudes ([Rohde and Rohde \(2011\)](#); [Linde and Sonnemans \(2012\)](#); [Schmidt et al. \(2015\)](#)). This chapter aims to fill some of this gap in empirical information and provides a step towards a better understanding of social risk attitudes. It also explores the extent to which usual findings of risk attitudes translate to social risk attitudes. Previous studies focused on the effect of social comparison on individual risk attitudes for gains and losses separately. Since most of real life risky decisions involve gains and losses at the same time, it is important to explore risk attitudes in a mixed domain where subjects face gains and losses in the same prospect and see whether social comparison has an impact on risk attitudes in that domain. Furthermore, there is evidence that correlation of risks decreases risk aversion in gain situations ([Friedl et al. \(2014\)](#) and [Schmidt et al. \(2015\)](#)). Hence, this chapter investigates the impact of correlation of risks on risk attitudes in gain, loss and mixed domain.

To do so, in this chapter, I conducted an experiment (Initial Experiment) based on [Linde and Sonnemans \(2015\)](#) to elicit risk attitudes in three types of domains: gains (all outcomes are positive), losses (all outcomes are negative), and mixed domain (where outcomes can be gains or losses). In the first part of the experiment, subjects faced a set of binary risky choices individually. In the second part, social comparison was introduced. In this experiment, risks were correlated in the first part (Individual treatment) as well as the second part (Social treatment). I find that social context has a significant effect on risk attitudes in the gain and mixed domain. Nevertheless, in the loss domain, no significant effect was found.

To see if correlation of risks has an effect on risk attitudes, I conducted another experiment (Robustness experiment) that has the same design as the initial experiment except that risks are not correlated in the first part of the experiment (Individual treatment).

The main findings of this chapter are that overall the introduction of social context decreases significantly risk aversion. Regarding risk aversion in gains and losses separately, risk aversion for gains is significantly higher than that for losses as predicted by the Prospect Theory. When introducing social context, risk aversion for gains remains higher than that for losses. This finding is not in line with [Linde and Sonnemans \(2012\)](#), [Bault et al. \(2008\)](#) and [Vendrik and Woltjer \(2007\)](#) who found the opposite of the prediction of the Prospect theory with a social reference point. In the mixed domain, when subjects face gains and losses in the same prospect, the introduction of the social context decreases significantly risk aversion and loss aversion.

Lastly, correlation of risks generates an increase in risk aversion when aggregating choices in gain, loss and mixed domain. This result is however not in line with [Schmidt et al. \(2015\)](#) and [Friedl et al. \(2014\)](#) who found that risk aversion increases when risks are uncorrelated. When looking at each domain separately, correlation of risks does not change risk attitudes for gains and losses. However, in the mixed domain, it generates an increase in risk aversion.

The remainder of the chapter is structured as follows. Section [3.2](#) presents the theoretical background. Section [3.3](#) presents the hypotheses. Section [3.4](#) explains the experimental design. Sections [3.5](#) and [3.6](#) discuss the results and the structural estimation of the initial and the robustness experiment. Section [3.7](#) concludes.

3.2 Theoretical background

3.2.1 Prospect Theory and Reference dependence

Reference dependence is the central assumption of [Kahneman and Tversky \(1979\)](#)'s Prospect Theory and plays a crucial role in explaining people's attitudes towards risk. More recently, [Rabin \(2000\)](#) and [Rabin and Thaler \(2001\)](#) raised an important issue concerning coherence of the application of concave expected utility theory to explain risk-averse behavior for both small and large stakes gambles. [Rabin \(2000\)](#) presented

a calibration theorem for a concave expected-utility model. If an expected utility maximizer is averse to a small-stakes gamble at every wealth level, then he must exhibit unrealistic levels of risk aversion when facing large-stakes gamble. [Rabin \(2000\)](#)'s argument is that within the expected utility framework, refusing small-stakes gamble implies that the marginal utility of money must diminish very quickly for a small change in wealth. A rejection of a 50-50 lose \$10/gain \$11 gamble at every wealth level means that from any initial wealth level, the decrease in utility from losing \$10 must exceed the increase in utility from winning \$11. The aggregate decreases in utility from losses must then accumulate quickly contrary to the increases in utility from gains. [Rabin \(2000\)](#)'s analysis yields that the decrease in utility from a loss of \$1000 exceeds the increase in utility from any large gain ($\$ \infty$). [Rabin \(2000\)](#) provided a proof by calibration that expected-utility theory can be a misleading interpretation of risk attitudes over modest stakes ([Barberis \(2013\)](#)). He stated that "loss aversion, is a departure from expected-utility theory that provides a direct explanation for modest scale risk aversion. Loss aversion implies that people are significantly more averse to losses relative to the status quo than they are attracted by gains, and more generally people's utilities are determined by changes in wealth rather than absolute level". Loss aversion is the most well known effect of reference dependence. Loss aversion has been confirmed by various studies (e.g [Tversky and Kahneman \(1992\)](#); [Abdellaoui et al. \(2007\)](#)).

Another phenomenon predicted by the Prospect Theory, that shows the importance of reference dependence is the "reflection effect". [Kahneman and Tversky \(1979\)](#) found that a replacement of all positive payoffs by their negatives, so that all gains are replaced by equal losses, reverses the choice pattern. The choices of any given individual should be mirror images of the choices made between the positive prospects. The reflection effect hence implies risk aversion in the positive domain and risk seeking in the negative domain. For example, a choice between a 90% chance of getting 3000 and a 45% chance of getting 6000 would be replaced by a choice between a 90% chance of losing 3000 and a 45% chance of losing 6000. Thus, the reflection effect would imply a preference for relatively safe gain (higher probability of a 3000 gain), but a reversed preference for the risky lottery in the loss domain (lower probability of 6000 loss). [Kahneman and Tversky \(1979\)](#) reported that 86% of subjects chose the safe lottery in the gain domain.

However, when all payoffs were transformed into losses, only 8% chose the safe lottery when all payoffs were transformed into losses. [Tversky and Kahneman \(1992\)](#) proposed a modified version of the Prospect Theory known as “Cumulative Prospect Theory” because the original version of the Prospect Theory was subject to violation of first-order stochastic dominance. The major difference of the Cumulative Prospect Theory from its original version is that the concept of weighting is introduced in the cumulative probability distribution function as in the rank-dependent expected utility theory and not applied to the probabilities of individual outcomes ([Quiggin, 1982](#)).

The most famous illustration of the reflection effect is the “Asian disease problem” by [Tversky and Kahneman \(1981\)](#). Two alternative programs to combat an unusual Asian disease have been proposed to subjects. Some subjects were presented with options A and B. If Program A is adopted, 200 people will be saved. If Program B is adopted, there is a 1/3 probability that 600 people will be saved and a 2/3 probability that nobody will be saved. Other subjects were presented with options C and D. If Program C is adopted, 400 people will die. If Program D is adopted, there is a 1/3 probability that nobody will die and a 2/3 probability that 600 people will die. Subjects thus have to choose between a risky and a certain option of equal expected value. The reference point is manipulated in a way such that options A and B are perceived as gains however options C and D are perceived as losses. They found a “choice reversal” caused by the framing effect where subjects preferred the certain option when alternative outcomes were phrased positively in terms of saving lives (Option A and B). However, when outcomes were phrased negatively in term of preventing deaths, the risky option was preferred (Option C and B). This choice reversal is explained in terms of Prospect Theory ([Kahneman and Tversky \(1979\)](#)) where subjects are risk-averse in gain domain and risk-seeking in loss domain. There is evidence that the reference point has an important role in determining risk preferences. [Tversky and Kahneman \(1991\)](#) suggest that different factors may determine the reference point such as status quo, expectations, aspirations, norms and social comparisons. Hence, the income of peers may play a role in determining individual’s reference point. Social reference point may motivate individuals to modify their risk preferences.

A popular theory of reference-dependent preferences, introduced by [Kőszegi and Rabin \(2006\)](#). They propose a model in which a decision-maker's recently held rational expectations determine their reference point. They incorporate "gain-loss utility" component of the Prospect Theory with standard "consumption utility". A person's utility depends not only on their consumption bundle but also on a reference bundle. According to [Kőszegi and Rabin \(2006\)](#), a person's *personal equilibrium*¹ captures the endogenous determination of the reference point by rational expectations. It assumes that a person correctly predicts both the environment they face and their own reaction to this environment and taking the reference point generated by these expectations as given maximizes expected utility.

[Maccheroni et al. \(2012\)](#) give an axiomatic representation of interdependent preferences in the presence of a social value function. They generalize the standard subjective expected utility model to a social context by allowing decision makers preferences to depend on the outcomes of their peers. They assume that the value function of decision makers consists of an individual and a social component. It depends on the intrinsic utility that they derive from the outcome of his decision as well as the satisfaction they derive from comparing their outcome to that of their peers.

Both of the models [Kőszegi and Rabin \(2006\)](#) and [Maccheroni et al. \(2012\)](#) involve a comparison to a reference distribution: [Kőszegi and Rabin \(2006\)](#) assume that the distribution is of expected outcomes, however [Maccheroni et al. \(2012\)](#) assume that it is the outcomes of peers.

3.2.2 Related research

Various studies explored social comparison and decision making in a social context, whereas few studies applied social comparison to risky situations (see [Trautmann and](#)

¹[Kőszegi and Rabin \(2006\)](#) define *Personal equilibrium* as situation where the stochastic outcome implied by optimal behavior conditional on expectations coincides with expectations. Moreover, *Preferred personal equilibrium* selects the personal equilibrium with the highest expected utility.

Vieider (2012) for an overview of this literature). Recent studies have explored the effect of risk correlation on individual risk preferences.

Schmidt et al. (2015) studied the effect of social comparison on risk taking, more specifically, whether this effect is gender-specific. According to their model, the correlation structure of risks between subjects has an impact on their risk taking decisions and this difference varies between men and women. To test this hypothesis, they used a between-subject design with two treatments. In the uncorrelated treatment, subjects faced risks that were uncorrelated with the risks faced by their peers. In the second treatment, risks were perfectly positively correlated in such a way that all subjects were hit by the same "fate" and direct social comparison was possible. To measure risk aversion, subjects were endowed with €6 and elicited the willingness to pay (WTP) for a 50-50 lottery where they could either win €10 or receive nothing. Subjects had to indicate whether they would buy the lottery ticket on a choice list with increasing prices ranging from €3.55 to €5.80. They found that 90% of the subjects were risk averse in a way that they were willing to pay less than €5 for the lottery, whereas 10% were willing to pay more than €5. When risks were uncorrelated, only 5% were willing to pay more than €5 (risk seeking subjects). When they were correlated, the share of risk seeking subjects increased to 14%. Thus, there is evidence that risk taking increased when risks were correlated. Regarding the gender effect, the mean WTP for women amounted to €3.86 (SD €0.57) for uncorrelated risks and €3.93 (SD €0.49) for correlated risks. However, for men, it increased from €3.86 (SD €0.61) for uncorrelated risks to €4.34 (SD €0.84) for correlated risks. Men were, on average, willing to pay €0.48 (almost 10% of the lottery's expected value) more for the lottery when risks were correlated. In their regression analysis, the correlated treatment effect was statistically highly significant for male subjects. The significant interaction term (interaction between correlated treatment and being male) indicated that male subjects drove the differences between the two treatments. This suggests that, according to their theory, men are more concerned with their relative position, while women are more concerned with their absolute payoff than their relative position.

Moreover, Friedl et al. (2014) examined how the correlation of risks among subjects

influences insurance decisions. Their model claims that the presence of a social reference point makes insurance less attractive for correlated than idiosyncratic risks. They used a between-subject design to compare the willingness to pay of participants in treatments with both correlated and uncorrelated risks. Subjects were endowed with €10. There was a 50% chance of losing the endowment and buying full insurance at different premiums for this potential loss was possible. In the first treatment, the individual risk to lose the endowment was independent from that of the others (idiosyncratic risks). In the second treatment, the risk to lose the endowment was correlated among the group (correlated risks) which means that either all subjects lost or no one. Subjects indicated for ten different prices whether they would buy an insurance. Only one of the ten prices was relevant for payment and was determined by a random draw of a ball from an urn. The WTP reflected that premium which made a subject indifferent between taking up full insurance and not to do so. The higher the degree of risk aversion the higher the WTP. The price ranged from €4.00 to €6.25. Thus, buying an insurance would result, depending on the relevant price, in a sure payoff between €6.00 and €3.75, while not buying insurance led to either keeping the €10 or losing them. They found that 73% of the subjects took up insurance at the fair premium (€5) in the treatment where risks were idiosyncratic, while only 56% did so in the treatment where risks were correlated. There was then a difference of 17 percentage points in insurance take-up between both treatments. Thus, the average willingness to pay for insurance was significantly higher for idiosyncratic than for correlated risks. This result is similar to that of [Schmidt et al. \(2015\)](#) who found that risk aversion increases when risks are uncorrelated.

Contrary to the previous findings, [Rohde and Rohde \(2011\)](#) found only a limited impact of social comparison on risk taking when analyzing whether people would change their individually chosen lottery if a social context is introduced. They used a within-subject design which consisted of 28 individual risk questions and 12 peer risk questions. Subjects had to make choices between allocation lotteries². In individual risk questions, each subject had to choose between two lotteries while fixing the lotteries that the others in the group received. In peer risk questions, subject had to choose between allocation lotteries for the other subjects in the group while the lottery that

²An allocation lottery is a lottery over allocations of money over a group of subjects.

a subject received was fixed. For example, a subject had to choose between a lottery where each other subject received an independent lottery yielding €20 with 30% probability and €10 otherwise, and a *corresponding allocation* yielding €20 to 30% of the other subjects and €10 to the rest of the other subjects. The expected value and the outcomes were the same in both options. They found that subjects preferred the lottery, where risks were independent rather than the corresponding allocation, where risks were correlated. Subjects then have a preference for uncorrelated risks over correlated risks.

Some studies explore whether people take risks to obtain an outcome as high as their peer. [Gamba et al. \(2014\)](#) also analyzed the effect of social comparison on risk taking behavior by using a between-subject design to reproduce in the lab a workplace environment. Each subject, after being paired with a co-worker, performed an effort task and a bonus task. Subjects received a wage from the effort task and a bonus on top of their wage when facing a risky decision. Bonuses were evaluated by subjects as positive variations with respect to their individual reference point. Both workers received the wage, but only one of the paired subjects, randomly determined, received the bonus. Hence, from the subjects perspective, their wage represented his individual reference point, while the co-worker's wage represented his social reference point. The risky decision that the worker faced had only positive outcomes, so that it was framed as individual gains domain. The subjects final earnings could fall either above (social gains) or below (social losses) their co-worker's final earnings. They found that subjects on average were more risk averse in a situation of small social gains than when facing social losses or large social gains. Subjects in social loss situation took more risk because they wanted to reduce the social distance from their peer. Moreover, subjects in large social gain situation did so because of the relative wealth effect.

[Lahno and Serra-Garcia \(2015\)](#) explored peer effects in risk taking. In the first part of the experiment (Part I), subjects made binary risky choices between a risky option A and a safe option B individually. In the second part (Part II), they made the same choices but in groups of two in such a way that one subject was the first mover (the peer) and the other second mover (the decision maker). Risks were perfectly correlated across group meaning that a single draw determined the payoff of both members. In

the one treatment, peers did not make decision in Part II, instead they were randomly allocated lottery A or B. In the another treatment, peers chose lottery A or B. There were four potential strategies of decision makers: i) Imitate the peer, ii) Deviate from the peer, iii) Revise own choice: make a different choice than in Part I, independent of the peer, iv) No change: make the same choice as in Part I (Absence of a peer effect). [Lahno and Serra-Garcia \(2015\)](#) found that in Part I, peer effects increased significantly when lotteries were chosen by peers than when they were randomly allocated a lottery. Imitation of the peer was the most frequent strategy particularly when peer made a risk averse choice. Those results suggest that peer effects are explained by both relative payoff concerns and a direct preference over peer choices.

[Linde and Sonnemans \(2012\)](#) used a within-subjects design to study the effect of different social conditions on risk attitudes. Subjects made a total of 42 binary risky choices while comparing one's own payoffs to the fixed payoff of one social referent. The safe and risky lottery in each choice situation had the same probabilities but with a larger variance of the outcomes in the risky lottery. Three kinds of social reference points were used: in loss situations maximum decision makers could earn was as much as their referents; in gain situation the minimum decision makers could earn was as much as their referents and in neutral situation decision makers and their referents had equal payoffs regardless the choice and outcome of the lottery. Subjects' choices affected only their own earnings and couldn't observe choices of others. They found that risk aversion decreased moving from social losses to a neutral setting, and decreased even more in presence of social gains. Thus, subjects were more risk averse in loss situation than in gain situation. The finding that the social reference point influences the behavior in another direction than the standard reference point is similar to that of [Bault et al. \(2008\)](#).

[Bault et al. \(2008\)](#) cast doubt on the presene of loss aversion around a social reference point when people make decisions that affect their own earnings. They used a within-subject design to compare how individuals evaluate the outcome of their decision in private versus social contexts. In single player game, subjects faced 40 binary lottery choices. Once subjects had made their choices, the outcome of both lotteries was

shown. They were then asked to rate how they felt about the outcome on a fixed scale from -50 to 50. Regret was when the outcome of the chosen lottery was less than that of the other lottery and relief was when the opposite happened. The two-player game is similar except that after his choice, the subject observed the choice that another subject had made in the same situation. If they chose different lotteries, then subject might experience envy (if his outcome was lower than that of the other) or gloating (if the opposite happened). [Bault et al. \(2008\)](#) found that in the private domain, loss aversion (regret) dominated. However, in the social domain, love of gain (gloating) dominated which was the opposite of loss aversion in the presence of social reference points.

[Fafchamps et al. \(2015\)](#) complements the previous experimental evidence by [Bault et al. \(2008\)](#) and [Linde and Sonnemans \(2012\)](#). They explored the effect of social comparison on risk taking by testing a “Keeping up with the Joneses” hypothesis³. They ran a multi-round experiment in Ethiopia in four rural villages, mainly with farmers, and with university students in the capital city Addis Ababa. As robustness check, the experiment was replicated in the UK. At the start of each round players were randomly given either a high (15 Ethiopian Birr) or a low (7 Ethiopian Birr) endowment. Then, they were asked to make a risky choice. The risky choice was an investment decision of a share of their endowment in a lottery with a 50% chance of winning thrice the amount invested. At the end each round, lottery winnings were determined, players were informed of their outcome as well as that of the others. The authors observed that subjects wanted to keep up with the winners. They risked more when others have higher past winnings, which means that the reference point that subjects used increased in the winnings of others.

[Schwerter \(2016\)](#) confirms the findings of [Fafchamps et al. \(2015\)](#). He analyzed in a between-subject design the role of social reference points and loss aversion on individual risk-taking. In this experiment, groups of two players were paired. A random draw determined the decision maker, who faced a risky lottery and the peer, who received an automatic payment that served as a natural comparison standard. The predetermined earnings of the peer was €8 in the “high” treatment and €2 in the “low” treatment in

³“Keeping up with the Joneses” is an effect proposed by [Duesenberry \(1949\)](#)’s relative income theory of consumption. Applied to risk taking, it predicts that people dislike being worse than their peers.

a way to induce social reference point for the decision maker. The decision-maker observed the predetermined earnings of his peer before making a risky choice then chose a binary lottery from a set of lotteries. Essentially, decision makers chose an upside payment between €3 and €16.5. The larger the decision maker chose this upside to be, the lower was the likelihood of receiving it. Choice involved a trade-off between the size of the upside and its likelihood. Subjects could choose larger upsides with lower likelihoods of receiving them (risky lottery) or lower upsides with higher upside likelihoods (less risky lottery). [Schwerter \(2016\)](#) found that decision makers chose more risky lotteries and lotteries with higher expected value in the high treatment than the low treatment. Thus, subjects were risk seeking in situations where their peers had higher earnings. The observed risk taking was consistent with an aversion against earning less than others.

[Vendrik and Woltjer \(2007\)](#) investigated whether the characteristics of [Kahneman and Tversky \(1979\)](#)'s value function like concavity of gains, convexity of losses and loss aversion apply to the dependence of life satisfaction on relative income. They examined the effect of the difference between a household's income and the average income of a likely reference group from the German Socio-Economic Panel⁴ on reported satisfaction. The estimation results indicate concavity of life satisfaction in positive relative income (gain domain) and in negative relative income as well (loss domain) which is not in line with the Prospect Theory where convexity is expected in the loss domain. One possible explanation is that when a person's income is considerably lower than the reference income, it becomes more than proportionally hard to raise the fund to participate in the social activities of the reference group. The diminishing marginal sensitivity of life satisfaction relative to income due to social comparison is counteracted by the rising marginal sensitivity of life satisfaction relative to income due to social participation deficits.

Decisions for others can differ from decisions for oneself. [Andersson et al. \(2013\)](#) studied experimentally risk-taking on behalf of others. The choices of a decision maker had consequences for two receivers. In one treatment, decision makers participated in a

⁴The GSOEP covers the years from 1984 -2001 for West Germany and 1991-2001 for East Germany. The sample included 16 000 individuals.

bonus-like incentive scheme where compensation was proportional to the total payoffs of the receivers. In another treatment, two decision makers were paired as i and j . The sum of receivers payoffs of i was compared to that of j . The decision maker with the higher sum for the receivers obtained a payoff equal to that sum, however, the other decision maker got nothing. In four decisions, payoffs of the two receivers were perfectly negatively correlated which created a hedging opportunity in the first treatment. In another four decisions, payoffs of the two receivers were perfectly positively correlated. When payoffs of the receivers were negatively correlated, decision makers took more risks when they had incentives to risk other people's money (in both treatments) than when they did not (baseline). However, when payoffs of the receivers were positively correlated, risk aversion decreased only in the second treatment.

[Andersson et al. \(2016\)](#) explored risk taking on behalf of others with and without loss using a large-scale incentivized experiment. They found that when losses were excluded, subjects chose about the same risk exposure for others as when they decided for themselves. However, when losses were included, they found that subjects were less loss averse when they also decided for someone else. One possible explanation is that loss aversion is generally viewed as a bias and being responsible for someone else's payoff may motivate people to move away from such biases. A similar de-biasing effect can be caused by group identity. [Sutter \(2009\)](#) has shown that when group identity is sufficiently strong, individual decisions that affect other group members become more risky compared to purely individual decisions. This finding is in line with that of [Andersson et al. \(2016\)](#) where the increase in risk taking is mainly driven by a decrease in loss aversion.

In summary, there is strong evidence that choice under risk is affected by social comparison. Some studies found that risk seeking increases when a subject is falling behind peers ([Fafchamps et al. \(2015\)](#); [Schwerter \(2016\)](#)), others found no effect of social context ([Rohde and Rohde \(2011\)](#)) or observe the opposite result ([Linde and Sonnemans \(2012\)](#); [Bault et al. \(2008\)](#)).

3.3 Hypotheses

Section 3.2 showed that several hypothesis can be set up.

Hypothesis 1: Social context has an impact on risk attitudes. Subjects are less risk averse in the social treatment.

The experiment tests this hypothesis in the following way. In the initial experiment, subjects face the same set of binary choices in individual and social treatments. Risks in both treatments are perfectly correlated. Hence, in social treatment, if relative payoff concerns matters, risk attitudes in the social treatment should be different from that in the individual treatment. In the individual treatment, risk attitudes stemming from relative payoff concerns are not expected. Subjects are expected to be less risk averse in the social treatment.

Hypothesis 2: Risk attitudes are different for gains and for losses. In the individual treatment, subjects are expected to be more risk averse in the gain domain than the loss domain. However, in the social treatment, subjects are expected to be more risk averse in the loss domain than in the gain domain.

The experiment tests the hypothesis in the following way. In the individual treatment, subjects face a set of binary choices where all outcomes are positive (gain domain) and another set of binary choices where all the outcomes are negative (loss domain). A choice situation is randomly selected to determine subject's potential earnings. In the initial experiment, the randomly selected choice situation is the same for all subjects, however, in the robustness experiment, the randomly selected choice situation can be different for each subject. A ball then is randomly drawn from the chosen urn to determine subject's potential earnings. In the social treatment, subjects face the same set of binary choice. A choice situation is randomly selected. Subjects who made the same choice then form groups of three and the lottery is played out for real. A ball is randomly drawn from the urn for each subject without replacement to determine their potential earnings.

In the gain domain, all outcomes have positive values, however, in the loss domain, all outcomes have negative values. The reflection effect predicts risk seeking choices in the loss domain and risk averse choices in the gain domain. This prediction should hold in the individual treatment. Nevertheless in the social treatment, the findings of [Bault et al. \(2008\)](#), [Linde and Sonnemans \(2012\)](#) and [Vendrik and Woltjer \(2007\)](#) predict that the social reference point influences the behavior in another direction than the standard reflection effect. [Bault et al. \(2008\)](#) find the opposite of loss aversion (i.e. gain seeking) in the presence of social reference points. They found that while losses loom larger than gains in individual decision making tasks, gains loom larger than losses in decision making tasks where social context is introduced. [Vendrik and Woltjer \(2007\)](#) examined the effect of social comparison on utility functions. They found that utility functions are concave in positive as well as negative relative income.

Hypothesis 3: Risk attitudes differ in mixed gambles where subjects are confronted by gains and losses in the same prospect.

The experiment tests this hypothesis in the following way. In the individual treatment, subjects face a set of binary choices where the outcomes can be positive or negative in the same choice situation (mixed domain). A choice situation is randomly selected and a ball then is drawn from the urn chosen by subjects to determine their potential earnings. In the social treatment, subjects face the same set of binary choice. A choice situation is randomly selected. Subjects who made the same choice then form groups of three and the lottery is played out for real. A ball is randomly drawn from the urn for each subject without replacement to determine their potential earnings.

Loss aversion in the mixed lotteries can be viewed as an aversion to a specific mean preserving spreads. Suppose we have a lottery that gives equal probability of worst and best outcomes which are, respectively, a loss and a gain of equal size. From this lottery a second one can be generated by subtracting from the worst outcome an amount that is added to the best outcome. Thus, in the second lottery the loss and the gain are increased by the same amount. Given a choice situation between these two lotteries, loss aversion is represented by a preference for the first lottery where the loss is small ([Brooks and Zank \(2005\)](#)).

Much of the existing empirical evidence on risk attitudes is concentrated on gains, where risk aversion is the main finding, and losses, where risk seeking is the main finding, separately. Behavior for mixed lotteries is different from that for gains and losses. What makes the mixed lotteries special is the influence of loss aversion on choice behavior. [Tversky and Kahneman \(1992\)](#) captures a sensitivity towards the sign of outcomes which was confirmed by other experimental studies ([Abdellaoui \(2000\)](#), [Abdellaoui et al. \(2007\)](#) and [Brooks and Zank \(2005\)](#)). [Brooks and Zank \(2005\)](#) found that risk attitudes vary depending on the domain of the outcomes, hence, a distinction of behavior over gain, loss and mixed domain is important. The latter study found that more of half of the subjects (25 out of 49) is classified as loss averse, roughly quarter as gain seeking while few subjects remain unclassified.

Thus, subjects are expected to be loss averse in the individual treatment and less loss averse in the social treatment. In the individual treatment, since loss resonates more than gains, subjects are expected to make safe choices. However, in the social treatment, since gain resonates more than losses, subjects are expected to make risky choices.

Hypothesis 4: Correlation of risks has an impact on risk attitudes. When risks are correlated, subjects are expected to be less risk averse.

I conducted a robustness experiment to test this hypothesis. In the initial experiment, to determine subjects potential earnings in the individual treatment, a choice situation is randomly selected. That choice situation is the same for all the subjects. Hence, risks are perfectly correlated. In the robustness experiment, the randomly selected choice situation for a subject can be different than that of other subjects. Hence, risks are not correlated in the individual treatment of the robustness experiment.

[Schmidt et al. \(2015\)](#) found that correlation of risks increases subjects risk taking. Moreover, when analyzing how the correlation of risks among subjects influences insurance decisions, [Friedl et al. \(2014\)](#) confirms experimentally the result of their theory where the presence of a social reference point makes insurance less attractive for correlated than for idiosyncratic risks. [Rohde and Rohde \(2011\)](#) found that subjects prefer

risks to be independent across members of the population rather than correlated. Subjects prefer everybody to undergo the same procedure, thereby avoiding the possibility to be held responsible for bad outcomes of others. Hence, when risks are uncorrelated, subjects are expected to be more risk averse.

3.4 Experimental Design

The experimental design is based on [Linde and Sonnemans \(2015\)](#). It is a within subject design that consists of two parts: individual treatment and social treatment. In the individual (control) treatment, subjects make series of choices between two lotteries. To determine subject's potential earnings, one choice situation is randomly selected for all subjects. The social treatment retains the same structure but introduces social context. One choice situation is randomly selected for all subjects. Subjects are then matched with two others who chose the same urn in that choice situation to create homogeneous groups. To determine each subject's potential earning, a ball is drawn randomly, without replacement, from the urn. Sometimes, it is possible that the number of subjects who chose the same urn is not a multiple of three. In that case, a subject is randomly selected to form a group with two others who did not choose the same urn as him. Participants were aware of this. In the social treatment, a lottery represents a distribution of earnings between a group of three subjects.

3.4.1 Individual treatment

Participants face 21 pair-wise choice situations in individually randomized order. In each situation, subjects choose between two urns, each urn contains three balls. Each ball has a color (white, grey or black) and a value in ECU (Experimenter Currency Unit). The value of a ball can be positive or negative. There are three types of situations that a subject faces in the experiment: gain, loss and mixed situations. There are 7 situations of each type. In gain (loss) situations, all balls in both urns have a positive (negative) value. In mixed situation, some balls have positive value and others that have negative

value. [Figure 4.4](#), [Table 42](#) and [Figure 4.6](#) present a screen shot of a choice situation in gain, loss and mixed domain respectively.

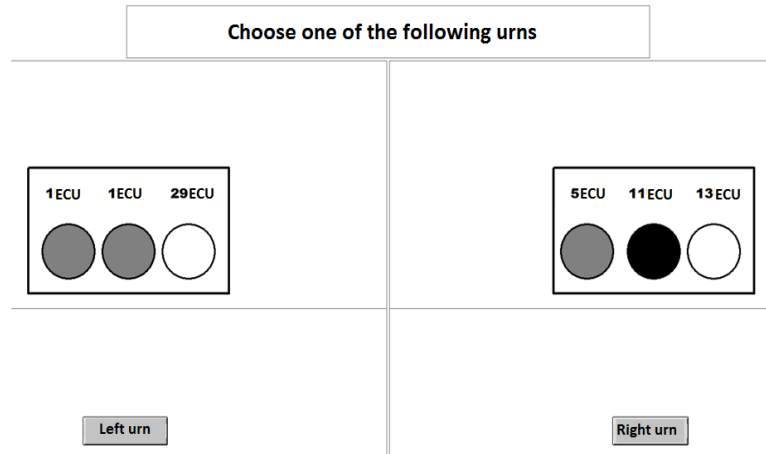


FIGURE 3.1: Gain Situation

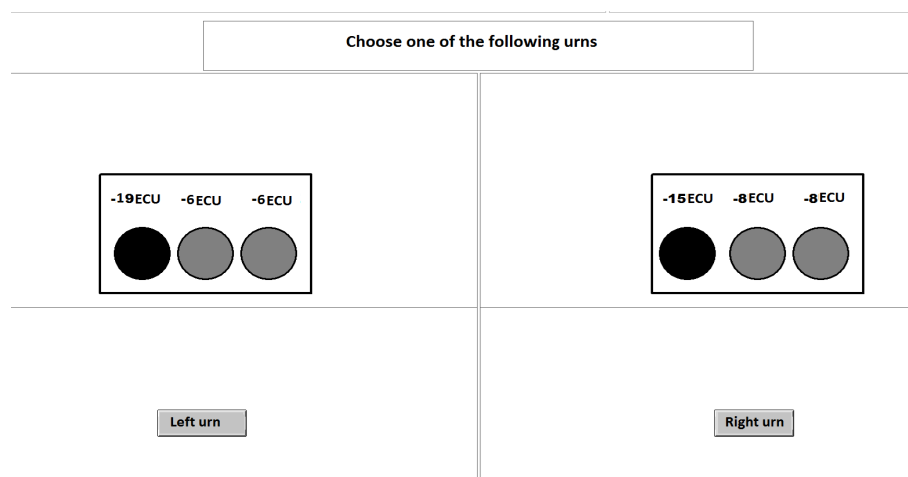


FIGURE 3.2: Loss Situation

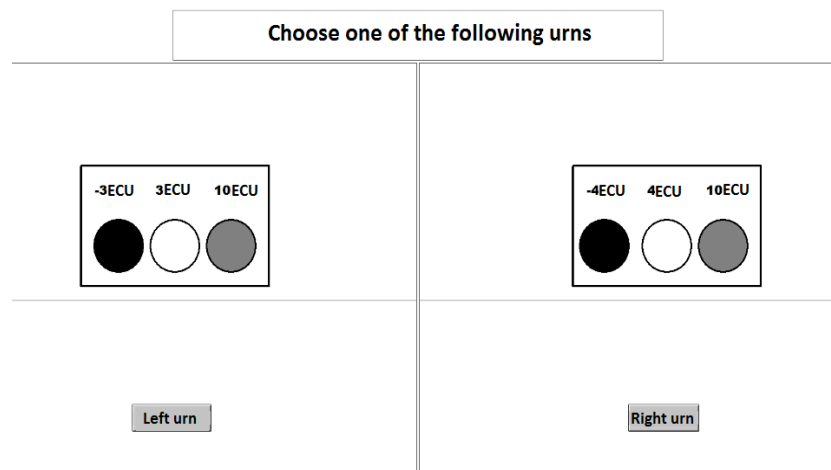


FIGURE 3.3: Mixed Situation

Before starting the individual treatment, subjects should indicate their preferences for the three colors (white, grey or black) to control for color preferences. They can either choose to rank the colors in order of preference or indicate no preferences. If a subject chooses to rank the colors in order of preference, the ball having the maximum value (in ECU) will be represented by the color they like the most (ranked 1). The ball having the minimum value (in ECU) will be represented by the color they like the least (ranked 3). The ball with the middle value (in ECU) will be represented by the color they have ranked 2. On the other hand, if a subject does not have a preference between the three colors, the computer will choose a random ranking for the three colors. At the end of the experiment, a choice situation is randomly selected for each subject. The randomly selected situation that determines subject's earnings is similar to that of other subjects. To determine their potential earnings, a ball is drawn from the urn the subject has chosen in this situation. The value of the drawn ball represents the earnings of the subject for this treatment.

3.4.2 Social treatment

In the social treatment, subjects face the same choice situations as in the individual treatment. One of the choice situations is randomly selected for all the subjects. Each

subject is matched with two others, who chose the same urn as him in the randomly selected choice situation. To determine the potential earnings of each subject, a ball is drawn, without replacement, from the urn. The order of the draw for each subject is random. The urn not only represents a lottery over the decision maker's own earnings, but also over his relative earnings. Sometimes it is impossible to make groups of three subjects who chose the same urn in the randomly selected situation. In this case, a subject, randomly selected, will form a group with two other subjects who have not made the same choice as him. In other words, a ball is randomly drawn from an urn that he did not choose.

Before starting the experiment, each subject draws an envelope out of 2. Each envelope contains a sheet a paper where is written a code that corresponds to one of the two treatments of the experiment. At the end of the experiment, the subject opens the envelope and enters the code of the envelope he chose to know his effective earnings, in other words, whether he will be paid for the individual or the social treatment. Additionally, after reading the instructions, subjects answer a questionnaire in order to make sure that they understood correctly the instructions. The experimenter then gives the right answers.

3.4.3 Procedures

All Experimental sessions were conducted at the CREM-CNRS (LABEX) institute of the University of Rennes 1, France. A total of 84 undergraduate students in business administration, economics, law and medicine have been recruited via the ORSEE software (Greiner (2004)). The majority (58%) were students of economics and business administration. Regarding gender 59.5% of participants are females. Average age is 19 years (S.D. 1.2 years). Participants earned on average €17.4, including a show-up fee of €5. During the experiment, all payments were expressed in experimental currency units (ECU), and are converted to Euros at a conversion rate of 1 Euro = 2 ECU. Each subject participated in only one session. The experiment lasted for 70 minutes on average including reading instructions and payment of participants. The experiment has

been programmed using the Z-tree software package (Fischbacher (2007)). Between 20 and 35 minutes were spent on reading the instructions. At the end of the instructions, there was a short questionnaire to test whether subjects understood the instructions. The experiment would continue only after all subjects understood the instructions. The instructions can be found in Appendix. At the end of the experiment subjects were asked to answer some socio-demographic questions.

3.5 Initial Experiment

3.5.1 Descriptive statistics and logistic regression

At the aggregate level, 55% of the subjects make risk averse choices. The aggregate proportions of risk averse choices across domains is reported in Table 3.1. In the gain domain, the share of risk averse choices in social treatment is higher than the individual treatment which is different from the literature. In contrast, in the mixed domain, the share of risk averse choices in individual treatment is higher than the social treatment which shows the importance of gains/losses asymmetry. According to Wilcoxon matched pairs signed-ranks test, the difference between the two treatments is statistically significant in gain (P-value= 0.0348) and mixed domain (P-value= 0.0094). However, in loss domain, there is no significant difference between the share of risk averse choices in individual and social treatment (P-value= 0.8897). Overall, based on subjects choices in all domain, there is no significant difference between the share of risk averse choices in individual and social treatment (P-value=0.810). There is a variation in the number of safer choices across tasks. In gain domain, there is a significant difference between the share of risk averse choices in individual treatment and social treatment in four tasks (tasks 3, 4, 6 and 7). In mixed treatment, the significance difference is found in tasks 17 and 20. In loss domain, only task 14 shows a significant difference (figures in Appendix). Table 3.2 presents the percentage of risk averse subjects across domains. Subjects are considered risk averse if more than 50% of their choices are safe choices. Similarly, according to Wilcoxon matched pairs signed-ranks test, there is a

significant difference between the share of risk averse subjects in the individual and social treatment in the gain domain at 10% significance level (P-value= 0.0533) and mixed domain P-value = 0.004). However, in loss domain, there is no significant difference between the share of risk averse subjects in individual and social treatment (P-value= 0.2994). Overall, based on subjects choices in all domains, there is a significant difference in the share of risk averse subjects between the individual and the social treatment (P-value=0).

TABLE 3.1: Aggregate proportions of risk averse choices across domains

Domain	Individual	Social
Overall	55.32%	54.99
Gain	58.2%	63.3%
Loss	52%	52.4%
Mixed	55.8%	49.3%

TABLE 3.2: Aggregate proportions of risk averse subjects across domains

Domain	Individual	Social
Overall	61.90%	54.76%
Gain	60.7%	65.5%
Loss	51.2%	48.9%
Mixed	54.8%	46.4%

I also investigate the factors that affect the probability of choosing a safe lottery over a risky one. Table 4.9 reports the logit regression results. Several variables have significant effect on choice in individual and social treatment. The increase in the difference in skewness between the safe and risky lottery made it less likely that a participant would choose the safe lottery in the individual and social treatment. This corresponds to prudence under Expected Utility theory by [Kimball \(1990\)](#). This is in line with the result of [Grossman and Eckel \(2015\)](#) who found that increased skewness in the payoff

TABLE 3.3: Logit regression with probability of choosing the safe lottery as dependent variable

	(1) Individual	(2) Social
Loss Domain	-0.434*** (0.144)	-0.615*** (0.155)
Mixed Domain	-0.250 (0.167)	-0.600*** (0.203)
Difference in variance between safe and risky lottery	0.00278 (0.003)	-0.00164 (0.003)
Difference of skewness between safe and risky lottery	-0.381*** (0.652)	-0.329*** (0.073)
<i>N</i>	1764	1764

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standards errors in parenthesis are clustered at the subject level.

structure entices 37.6% of their sample to take on greater risk in their choice of lotteries. Secondly, being in loss domain decreases the probability of choosing the safe lottery in both treatments. Additionally, being in mixed domain made less likely to choose the safe lottery only in social treatment, however it doesn't have an impact in individual treatment.

3.5.2 Structural Estimation: Expected Utility Theory by [Von Neumann and Morgenstern \(1947\)](#)

In this section, I estimate risk aversion parameters for subjects using the Expected Utility Theory specification by [Von Neumann and Morgenstern \(1947\)](#) (EUT). The EUT specification is defined over the final monetary prize that the subject would receive if the lottery were played out. The argument of the utility function is the prize plus the initial endowment.

Utility of an outcome is defined by:

$$U(s, x) = \frac{(s + x)^r}{r} \text{ if } x \geq 0 \quad (3.1)$$

$$U(s, x) = \frac{(s - x)^r}{r} \text{ if } x < 0 \quad (3.2)$$

where s is the fixed endowment provided at the beginning of the experiment, x is the value of a ball in the urn, r is the coefficient of Constant Relative Risk Aversion (CRRA), the parameter to be estimated. $r=1$ implies risk neutrality, $r < 1$ implies risk aversion, and $r > 1$ implies risk loving.

For k possible outcomes in an urn. The expected utility EU:

$$EU_i = \sum_{k=1, k} (P_k \cdot U_k) \quad (3.3)$$

Since there are 3 outcomes in each urn:

$$EU_i = \sum_{k=1,3} (P_k \cdot U_k) \quad (3.4)$$

The EU for each choice was calculated for a subject estimate of r , and the difference is:

$$\nabla EU = EU_R - EU_L \quad (3.5)$$

EU_R is the expected utility for the right urn and EU_L is that of the left urn.

The index ∇EU is used to define the cumulative probability of the observed choice using a logistic function:

$$\Phi(\nabla EU) = \frac{\exp(\nabla EU)}{[1 + (\nabla EU)]} \quad (3.6)$$

The likelihood, conditional of the EUT model being true, depends on the estimates of r given the observed choices. The conditional log-likelihood:

$$\ln L^{\text{EUT}}(r; y) = \sum_i [y_i \ln \Phi(\nabla EU) + (1 - y_i) \ln \Phi(1 - (\nabla EU))] \quad (3.7)$$

where $y_i=1(0)$ denotes the choice of the right(left) urn in task i .

3.5.2.1 All domains included

Pooling all the responses from each of the 84 subjects, the maximum likelihood estimates of the risk aversion parameter $r = 0.751$ with a standard error of 0.04 in the individual treatment. In the social treatment, the maximum likelihood estimates of the risk aversion parameter $r = 0.819$ with a standard error of 0.04. Subjects were risk averse in both treatments. Figure 3.4 shows the expected utility functions in the individual and social treatment.

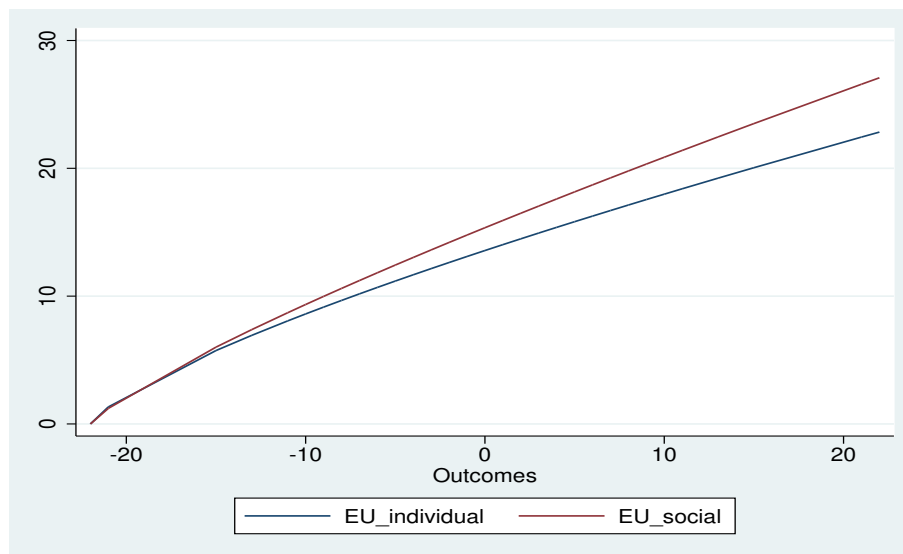


FIGURE 3.4: Expected Utility as a function of outcomes per treatment

Table 3.4 shows the classification of subjects according to their risk preferences represented by their CRRA coefficients. In the individual treatment, when estimating

the risk aversion parameter r for each subject based on his responses in 21 individual tasks, I find that 86% of the subjects (72 subjects) were considered as risk averse (their CRRA parameter $r < 1$). The rest of the subjects (12 subjects) were risk seeking (their CRRA parameter $r > 1$) and no subjects were risk neutral ($r = 1$).

On the other hand, in the social treatment, when estimating the risk aversion parameter r for each subject based on his responses in 21 social tasks, the percentage of risk averse subjects decreases. 71% subjects were risk averse (60 subjects). However, the rest of the subjects (21 subjects) were risk seeking and no subjects were risk neutral. This finding is in line with [Schmidt et al. \(2015\)](#) and [Friedl et al. \(2014\)](#) who found that risk aversion decreases when social comparison is introduced.

TABLE 3.4: Classification of subjects according to their CRRA coefficients

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	72	0	12	84
Social	60	0	24	84

Figure 3.5 displays a scatter plot of the CRRA coefficients for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak positive correlation between the CRRA coefficients in the individual and social treatment (Pearson correlation coefficient = 0.34, Spearman correlation coefficient = 0.33 and Kendall's tau coefficient = 0.23)

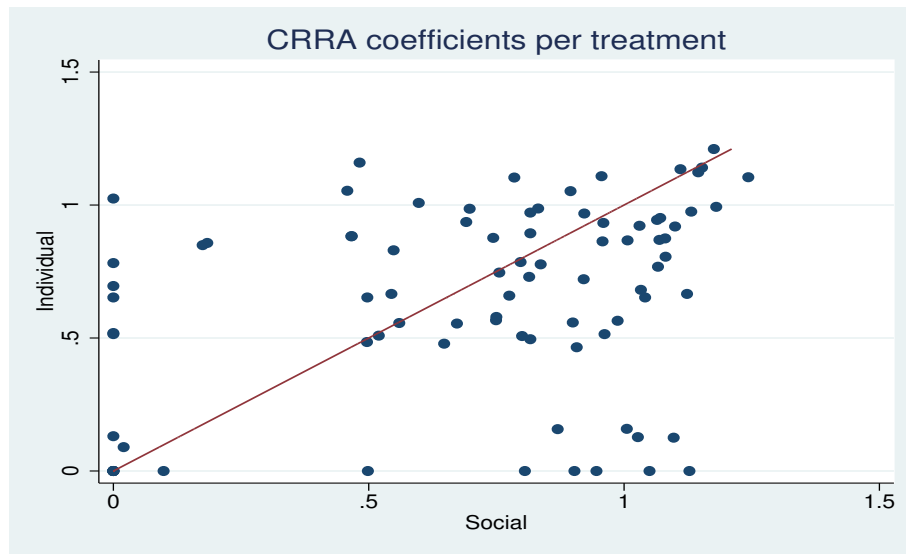


FIGURE 3.5: CRRA coefficients for each of 84 subjects per treatment

I run a Kolmogorov-Smirnov test to see whether there is a significant difference between the distributions functions of CRRA coefficients in both treatments. This test provides a criterion for deciding whether two samples are generated by the same probability distribution. The test result reports that CRRA coefficients do not have the same distribution in the individual and social treatment (P-value = 0). Cumulative density functions of CRRA coefficients in the individual and social treatment are presented in figure 3.6.

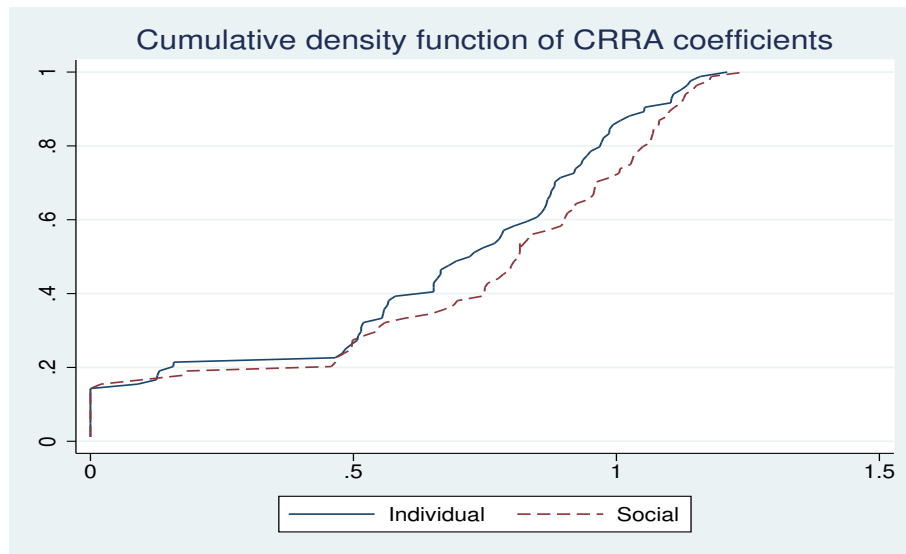


FIGURE 3.6: Cumulative density functions of CRRA coefficients

Table 3.5 presents the descriptive statistics of CRRA coefficients in both treatments. The measures of central tendency and variability of CRRA coefficients in the individual treatment are lower than those in the social treatment. In the individual treatment, CRRA coefficients have higher mean, standard deviation, maximum and minimum. A box plot of CRRA coefficients in the individual and social treatment is presented in figure 3.7. According to the variance comparison test, the hypothesis of the equality of the variances of CRRA coefficients in both treatments can not be rejected (P-value=0.67).

TABLE 3.5: Descriptive Statistics of CRRA coefficients

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1 - Q_3]
Individual	0.674	0.726	0.367	0	1.21	[0.490-0.935]
Social	0.709	0.815	0.385	0	1.24	[0.497-1.030]

Table 3.6 shows the classification of subjects according to their CRRA coefficients in both treatments. Fisher's exact test result suggest failing to reject the hypothesis of the equality of proportions of risk averse and risk seeking subjects in the both treatments (P-value=0.310). The majority of subjects (63%) are risk averse in both treatments. 23% of the subjects are risk averse in the individual treatment and risk seeking in the

social treatment. Only 8% of the subjects are risk seeking in both treatments. The rest 6% of the subjects are risk seeking in the individual treatment and risk averse in the social treatment. Nevertheless, when running a Fisher's exact test for CRRA coefficients estimated with $\epsilon = 0.05$, the hypothesis of the equality of proportions of risk averse, risk neutral and risk seeking subjects in both treatments is rejected (P-value = 0.021) which means that the introduction of social comparison has a significant effect on risk preferences. Table 68 shows the classification of subjects according to their CRRA coefficients estimated with $\epsilon = 0.05$ in both treatments.

TABLE 3.6: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0$ in both treatments

		Social		Total
		Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Individual	Risk averse ($r < 1$)	53	19	72
	Risk seeking ($r > 1$)	7	5	12
Total		60	24	84

TABLE 3.7: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0.05$ in both treatments

		Social			Total
		Risk averse ($r < 0.95$)	Risk neutral ($0.95 < r < 1.05$)	Risk seeking ($r > 1.05$)	
Individual	Risk averse ($r < 0.95$)	63	1	13	77
	Risk neutral ($0.95 < r < 1.05$)	3	1	2	6
	Risk seeking ($r > 1.05$)	0	0	1	1
Total		66	2	16	84

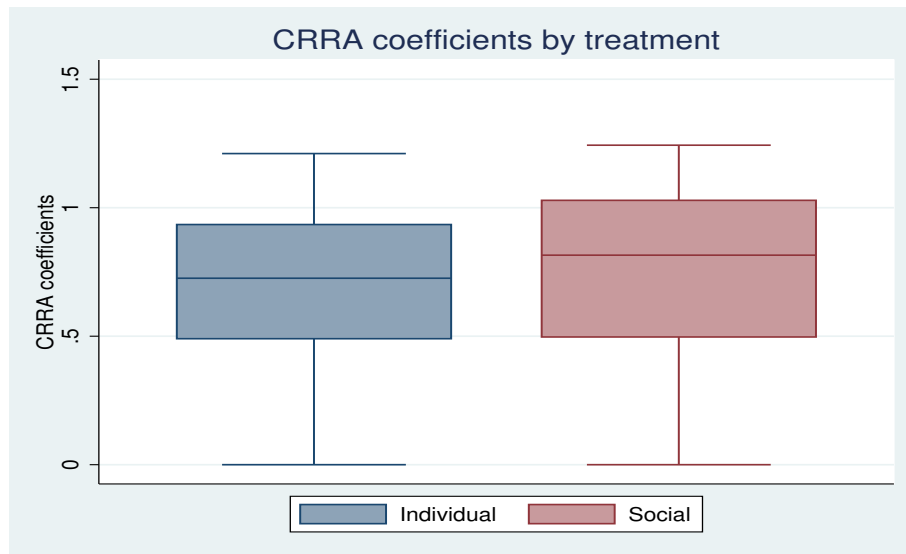


FIGURE 3.7: CRRA coefficients by treatment

3.5.2.2 Gain Domain

In this section, I limit the analysis to the 7 tasks of the Gain Domain. Pooling all responses from each of the 84 subjects in the gain domain, the maximum likelihood estimates of the risk aversion parameter $r = 0.721$ with a standard error of 0.005 in the individual treatment. In the social treatment, the maximum likelihood estimates of the risk aversion parameter $r = 0.715$ with a standard error of 0.001 in the social treatment. Table 3.8 reports the classification of subjects according to their risk preferences in the gain domain represented by their CRRA coefficients. When estimating CRRA coefficient for each subject based on his responses in the 7 tasks of the Gain Domain, I find that all the subjects are risk averse in the individual and social treatment. There is problem in the estimation of CRRA coefficient for each subject as around 40% of the subjects have CRRA coefficient which is equal to zero.

Figure 3.8 presents a scatter plot of CRRA coefficients for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak positive correlation between CRRA coefficients for each subject in the individual and

TABLE 3.8: Classification of subjects according to their CRRA coefficients in the Gain Domain

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	84	0	0	84
Social	84	0	0	84

social treatment (Pearson correlation= 0.32, Spearman correlation coefficient= 0.24 and Kendall's tau coefficient =0.17).

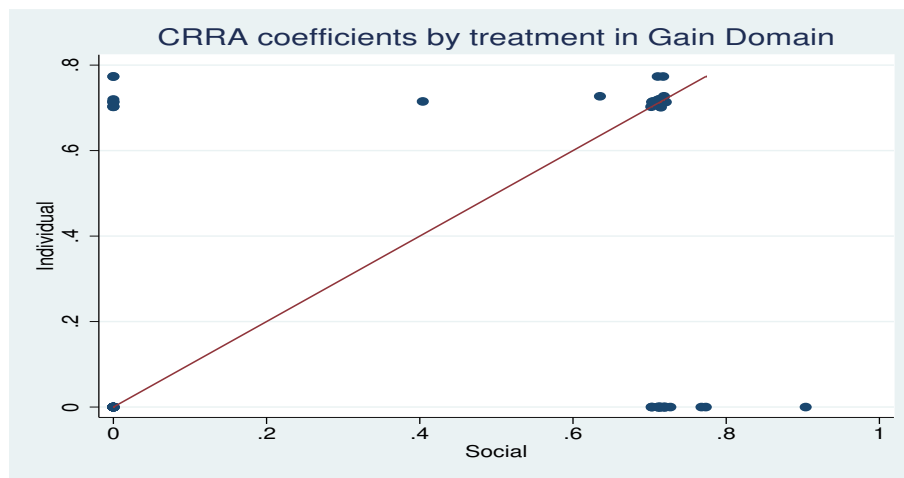


FIGURE 3.8: CRRA coefficients for subjects per treatment in Gain Domain

Kolmogrov-Smirnov test result rejects the hypothesis the equality of distribution functions of CRRA coefficients in the individual and social treatment (P-value=0). Cumulative density functions of CRRA coefficients in the individual and social treatment are presented in figure 3.9.

A box plot of CRRA coefficients in the individual and social treatment is presented in figure 3.10. Table 3.9 presents the descriptive statistics of CRRA coefficients in the gain domain. CRRA coefficients in the social treatment have higher mean, median and maximum than those in the individual treatment. However, the interquartile range (Q_1 - Q_3) is the same in both treatments. Regarding the variances of CRRA coefficients in the individual and social treatment, the hypothesis of the equality of variances is not rejected (P-value = 0.660).

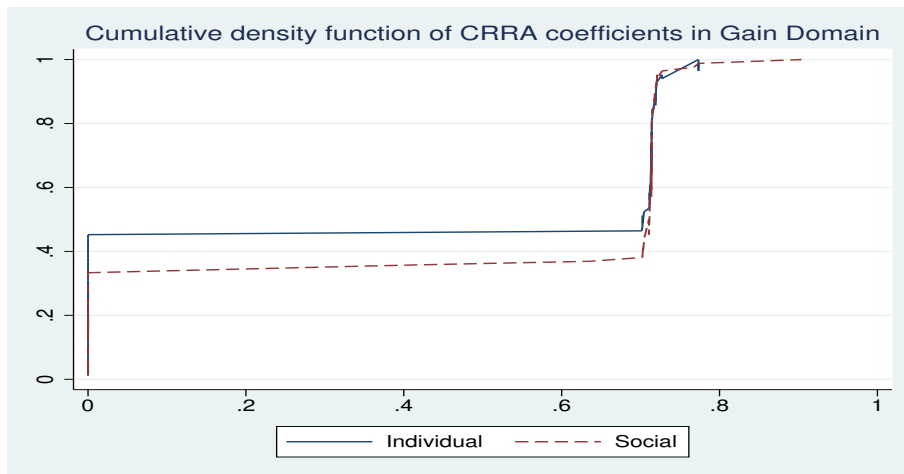


FIGURE 3.9: Cumulative density functions of CRRA coefficients in Gain Domain

TABLE 3.9: Descriptive Statistics of CRRA coefficients in the Gain Domain

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1 - Q_3]
Individual	0.394	0.703	0.360	0	0.773	[0-0.714]
Social	0.466	0.711	0.343	0	0.904	[0-0.714]

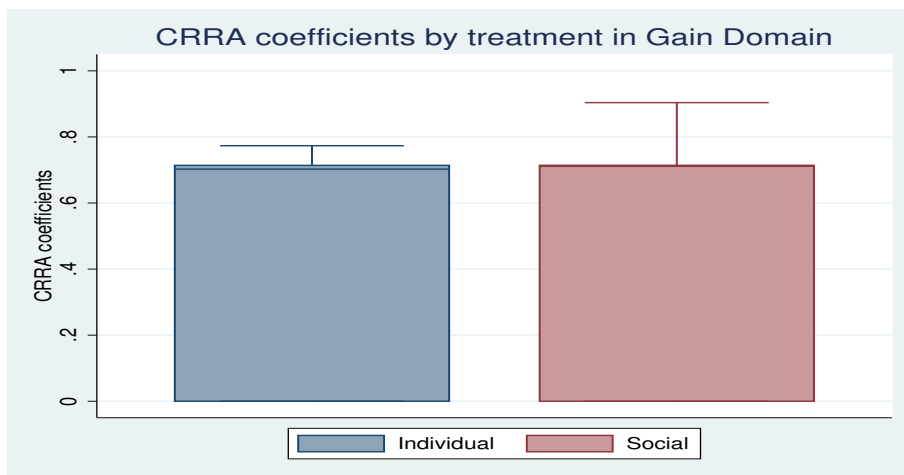


FIGURE 3.10: CRRA coefficients per treatment in the Gain Domain

3.5.2.3 Loss Domain

In this section, I limit the analysis to the 7 tasks of the loss domain. Pooling all the responses of the 84 subjects in the loss domain, the maximum likelihood estimates

of the risk aversion parameter $r = 0.978$ with a standard error of 0.02 in the individual treatment. In the social treatment, the maximum likelihood estimates of the risk aversion parameter $r = 0.986$ with a standard error of 0.03. Aggregate CRRA coefficient estimates in both treatments in the loss domain are higher than those in the gain domain (subsection 3.5.2.2) and in all domains (subsection 3.5.2.1).

CRRA coefficients for each subject in the Loss Domain are estimated for 82 subjects out of 84 in the individual treatment and 79 subjects out of 84 in the social treatment. It was not possible to estimate CRRA coefficients for subjects 16 and 27 in the individual treatment and subjects 2, 5, 64, 65 and 82 in the social treatment.

Table 3.10 shows the classification of subjects according to their risk preferences in the loss domain. When estimating CRRA coefficients for each subject based on his responses in the 7 tasks on the Loss Domain, around 57% of the subjects are risk averse in the individual treatment and 43% are risk seeking. In the social treatment, percentages are the same as in the individual treatment. In the gain domain (Subsection 3.5.2.2) and in the all domains (Subsection 3.5.2.1), the percentage of risk averse subjects is higher in both treatments. In the gain domain, all subjects are risk averse in both treatments. In the all domains, 86% are risk averse in the individual treatment and 71% in the social treatment. Thus, risk aversion decreases in the Loss domain in both treatments.

TABLE 3.10: Classification of subjects according to their CRRA coefficients in the Loss Domain

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	47	0	35	82
Social	45	0	34	79

Figure 3.11 presents a scatter plot of the CRRA coefficients in the individual and social treatment. Different correlation coefficients show that there is a weak positive correlation between the CRRA coefficients in the individual and social treatment (Pearson correlation coefficient = 0.26, Spearman correlation coefficient = 0.27 and Kendall's tau = 0.21)

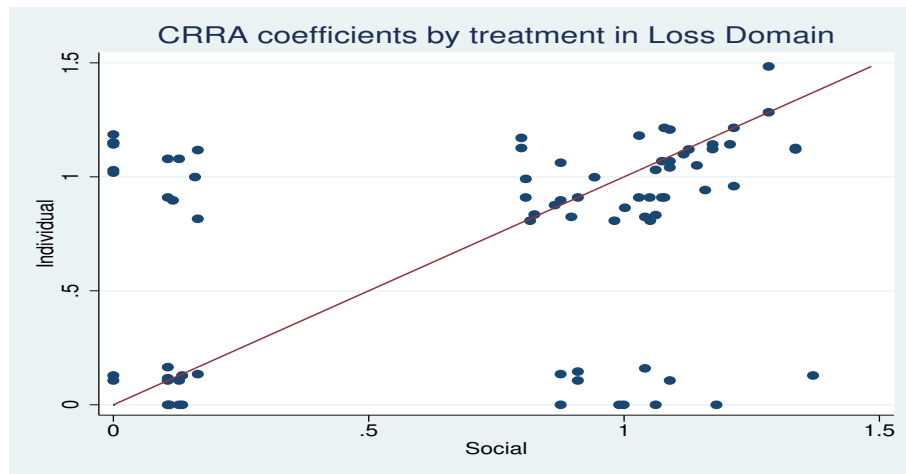


FIGURE 3.11: CRRA coefficients for subjects per treatment in Loss Domain

I run Kolmogorov-Smirnov test result shows that CRRA coefficients do not have the same distribution in the Loss Domain (P-value=0). Figure 3.12 presents the cumulative density functions of CRRA coefficients in the Loss Domain in both treatments.

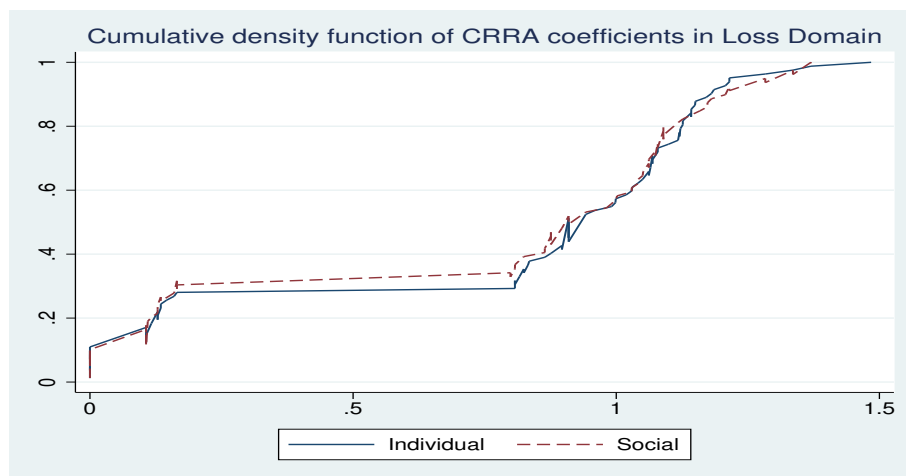


FIGURE 3.12: Cumulative density functions of CRRA coefficients in Loss Domain

Table 3.11 shows the descriptive statistics of CRRA coefficients in the individual and social treatment. CRRA coefficients in the individual treatment have higher mean, maximum and IQR than those in the social treatment. However, medians in both treatments are equal. Regarding the variances of CRRA coefficients in the individual and

social treatment, the hypothesis of the equality of variances is not rejected (P-value = 0.798). Figure 3.13 presents a box plot of CRRA coefficients in both treatments.

TABLE 3.11: Descriptive Statistics of CRRA coefficients in Loss Domain

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1 - Q_3]	Total
Individual	0.769	0.910	0.454	0	1.484	[0.146-1.117]	82
Social	0.742	0.910	0.468	0	1.370	[0.135-1.090]	79

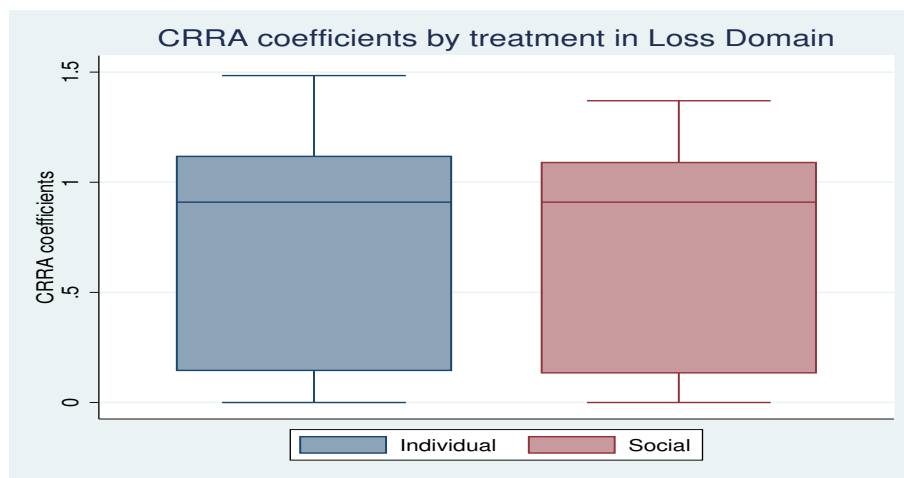


FIGURE 3.13: CRRA coefficients for subjects per treatment in the Loss Domain

Table 3.12 the classification of subjects according to their CRRA coefficients in both treatments in the Loss Domain. Fisher's exact test result suggests that there is a significant difference in the proportions of risk averse and risk seeking subjects in both treatments (P-value = 0). 38% subjects are risk averse in both treatments. 29% of the subjects are risk seeking in both treatments. 18% of subjects are risk averse in the individual treatment and risk seeking in the social treatment. 15% of the subjects are risk averse in the social treatment and risk seeking in the individual treatment.

This result is confirmed by Fisher's exact test for CRRA coefficients estimated with $\epsilon = 0.05$ in table 3.13 (P-value = 0).

TABLE 3.12: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0$ in both treatments in the Loss Domain

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	32	15	47
Risk seeking ($r > 1$)	13	24	37
Total	45	39	84

TABLE 3.13: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0.05$ in both treatments in the Loss Domain

	Social			Total
Individual	Risk averse ($r < 0.95$)	Risk neutral ($0.95 < r < 1.05$)	Risk seeking ($r > 1.05$)	
Risk averse ($r < 0.95$)	12	9	2	23
Risk neutral ($0.95 < r < 1.05$)	8	23	6	37
Risk seeking ($r > 1.05$)	5	6	13	24
Total	25	38	21	84

3.5.3 Structural Estimation: Reference Point Model

In this section, I estimate Reference Point Model parameters. The utility function of the model is defined over gains and losses separately. The arguments of the utility function are gains and losses relative to some reference point and losses loom larger than gain in the utility function. According to [Tversky and Kahneman \(1992\)](#), the utility function is defined separately over gains and losses:

$$U(x) = \frac{x^\alpha}{\alpha} \text{ if } x \geq 0 \quad (3.8)$$

$$U(x) = -\lambda \frac{-x^\beta}{\beta} \text{ if } x < 0 \quad (3.9)$$

α and β are the risk aversion parameters and λ is the coefficient of loss aversion.

Thus, the difference in reference point utilities is defined :

$$\nabla RPU = RPU_R - RPU_L \quad (3.10)$$

The likelihood, conditional of the Prospect Theory model being true, depends on the estimates of α , β and λ given the observed choices. The conditional log-likelihood:

$$\ln L^{\text{RP}}(\alpha, \beta, \lambda; y) = \sum_i [y_i \ln \Phi(\nabla RPU) + (1 - y_i) \ln \Phi(1 - (\nabla RPU))] \quad (3.11)$$

where $y_i=1(0)$ denotes the choice of the right(left) urn in task i .

Pooling all the responses from each of the 84 subjects, the maximum likelihood estimates of the risk aversion parameter $\alpha = 0.918$ with a standard error of 0.04, $\beta = 1.022$ with a standard error of 0.02 and $\lambda = 1.257$ with a standard error of 0.229 in the individual treatment. The estimated loss aversion coefficient is significantly different from 1 at 5% significance level, since the p-value of the test is $\neq 0$. The risk aversion parameters α and β are not significantly different from each other since at 5% significance level, since the p-value of the test = 0.522. Thus, subjects are risk averse over gains and risk seeking over losses.

In the social treatment, the maximum likelihood estimates of the risk aversion parameter $\alpha = 0.715$, $\beta = 1.036$ and $\lambda = 1.054$. The estimated loss aversion coefficient is significantly different from 10% at 5% significance level, since the p-value of the test is $\neq 0.018$. The risk aversion parameters α and β are not significantly different from each other since at 5% significance level, since the p-value of the test = 0.144. The model parameters α , β and λ for each subject are estimated for 48 subjects out of 84 in the individual treatment and 42 subjects out of 84 in the social treatment. Tables ?? and 3.15 present the descriptive statistics of the model parameters in the individual and social treatment.

TABLE 3.15: Descriptive Statistics of the model parameters in the social treatment

Parameters	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1-Q_3]
α	0.492	0.485	0.441	0	1.265	[0-0.850]
β	2.897	1.454	0.416	0	22.134	[1.111-2.249]
λ	∞	1.181	∞	0	∞	[0.999-7.208]

Table 3.16 reports the classification of subjects according to their risk preferences in the gain domain represented by their α coefficients. When estimating α coefficients for subjects, I find that around 79% of the subjects are risk averse in the individual and 21% are risk seeking. In the social treatment, percentages stays almost the same. The percentage of risk averse subjects is 78.6% and that of risk seeking subjects is 21.4% . No subjects are classified as risk neutral.

TABLE 3.16: Classification of subjects according to risk aversion coefficients α

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	38	0	10	48
Social	33	0	9	42

Figure 3.14 presents a scatter plot of risk aversion coefficients α for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak positive correlation between risk aversion coefficients α for each subject in the individual and social treatment (Pearson correlation= 0.35, Spearman correlation coefficient= 0.40 and Kendall's tau coefficient =0.34).

Figure 3.15 displays a box plot of risk aversion coefficients α in the individual and social treatment. Regarding their variances, the hypothesis of the equality of variances is not rejected (P-value = 0.839).

Kolmogorov-Smirnov test result shows that α coefficients do not have the same distribution in both treatments (P-value=0). Figure 3.16 presents the cumulative density functions of α coefficients in both treatments.

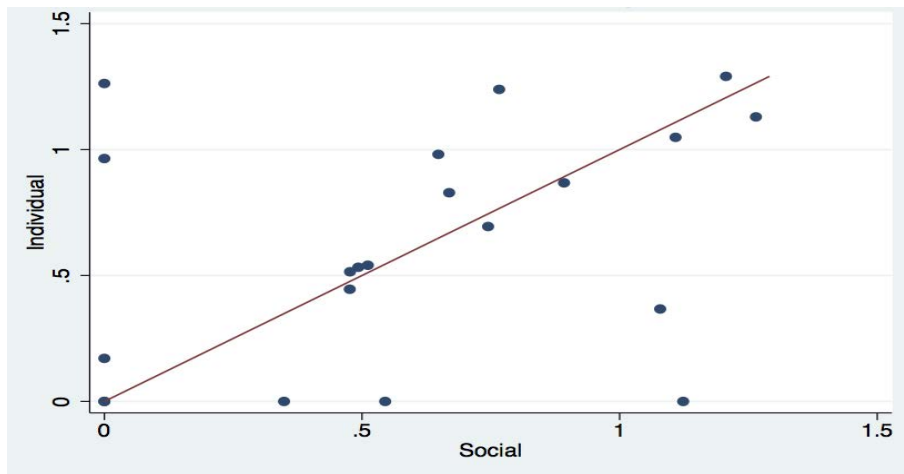
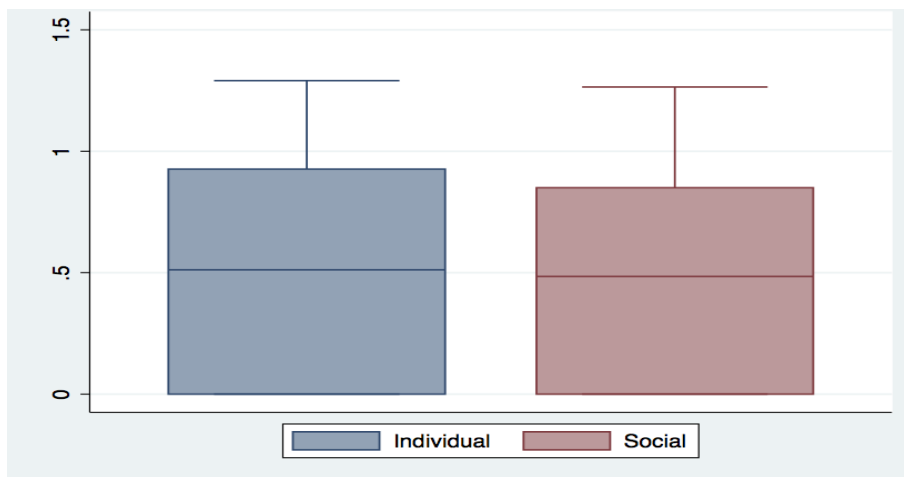
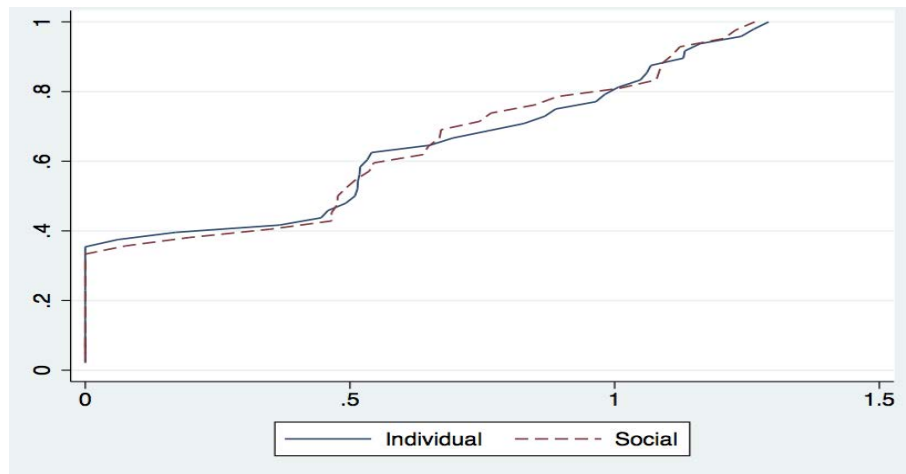
FIGURE 3.14: Risk aversion coefficients α for subjects per treatmentFIGURE 3.15: Risk aversion coefficients α for subjects per treatment

Table 3.17 presents the classification of subjects according to their α coefficients to compare risk preferences over gains by treatment. The total number of subjects in this table is 21 for whom the estimation of α coefficients in both treatments was possible. Fisher's exact test result suggests that there is a significant difference in the proportions of risk averse and risk seeking subjects in both treatments at 10% significance level (P-value = 0.06).

Table 3.18 reports the classification of subjects according to their risk preferences for negative outcomes represented by their β coefficients. The total number of subjects

FIGURE 3.16: Risk aversion coefficients α for subjects per treatmentTABLE 3.17: Classification of subjects according to their α coefficients estimated in both treatments^a

	Social		Total
	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Individual			
Risk averse ($r < 1$)	14	3	16
Risk seeking ($r > 1$)	2	3	5
Total	16	5	21

^a The table includes 21 subjects for whom the estimation of α coefficients in both treatments were possible

in this table is 21 for whom the estimation of β coefficients in both treatments was possible. When estimating β coefficients for subjects, I find that around 25% of the subjects are risk averse in the individual and 75% are risk seeking. In the social treatment, the percentage of risk averse subjects decreases to 14% and that of risk seeking subjects is 86%. No subjects are classified as risk neutral.

Figure 3.17 presents a scatter plot of risk aversion coefficients β for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak negative correlation between risk aversion coefficients β for each subject in

TABLE 3.18: Classification of subjects according to risk aversion coefficients β

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	12	0	36	48
Social	6	0	36	42

the individual and social treatment (Pearson correlation= 0.26, Spearman correlation coefficient= 0.29 and Kendall's tau coefficient =0.21).

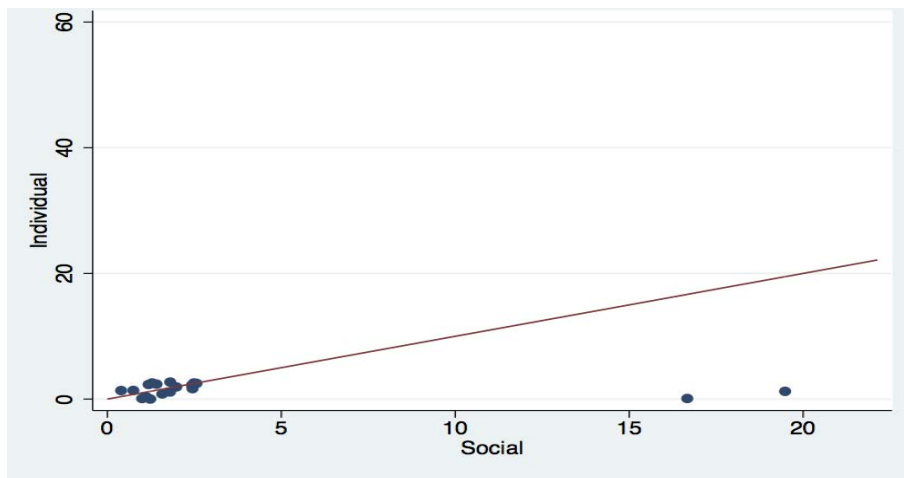
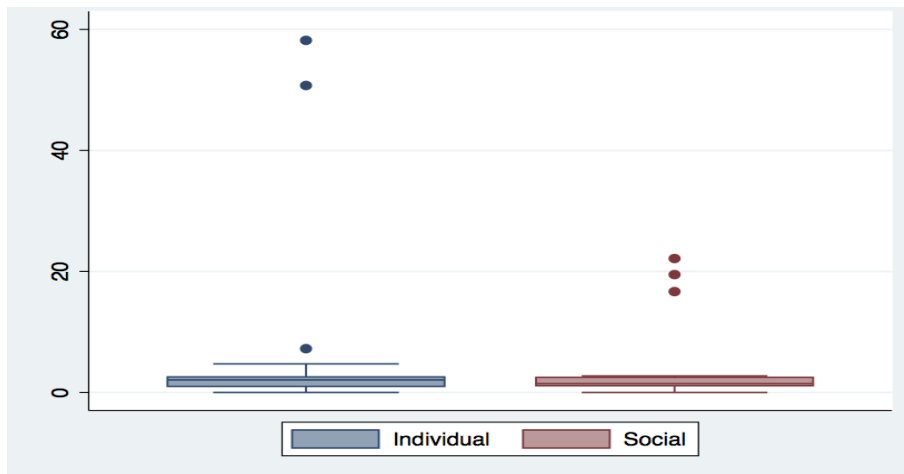
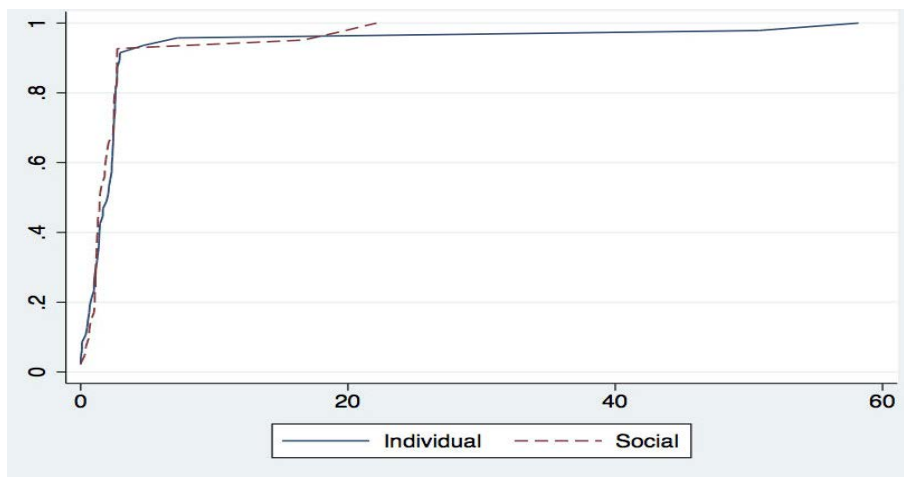
FIGURE 3.17: Risk aversion coefficients β for subjects per treatment

Figure 3.18 displays a box plot of risk aversion coefficients β in the individual and social treatment. Regarding their variances, the hypothesis of the equality of variances is rejected (P-value = 0).

Kolmogorov-Smirnov test result shows that β coefficients do not have the same distribution in both treatments (P-value=0). Figure 3.19 presents the cumulative density functions of β coefficients in both treatments.

Table 3.19 presents the classification of subjects according to their β coefficients to compare risk preferences over losses by treatment. Fisher's exact test result suggests not rejecting the hypothesis of the equality of proportions of risk averse and risk seeking subjects in both treatments (P-value=0.553).

FIGURE 3.18: Risk aversion coefficients β for subjects per treatmentFIGURE 3.19: Risk aversion coefficients β for subjects per treatment

Regarding loss aversion measured by λ , a subject is classified as loss averse if λ exceeded 1, as loss neutral if $\lambda = 1$, and as gain seeking if λ were less than 1. In the individual treatment, 67% of the subjects are loss averse and 33% of the subjects are gain seeking. No subjects are considered as loss neutral. However, in the social treatment, 58% of the subjects are loss averse, 2% are loss neutral and 40% are gain seeking. Thus, The introduction of the social context increases loss aversion.

Table 3.21 presents the classification of subjects according to their λ coefficients. The total number of subjects in this table is 21 for whom the estimation of λ coefficients

TABLE 3.19: Classification of subjects according to their β coefficients^a

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	0	5	5
Risk seeking ($r > 1$)	2	14	16
Total	2	19	21

^a The table includes 21 subjects for whom the estimation of β coefficients in both treatments was possible.

TABLE 3.20: Classification of subjects according to loss aversion coefficients λ

Treatment	Loss averse ($\lambda > 1$)	Loss neutral ($\lambda = 1$)	Gain seeking ($\lambda < 1$)	Total
Individual	32	0	16	48
Social	23	1	16	40

in both treatments was possible. Fisher's exact test result suggests not rejecting the hypothesis of the equality of proportions of loss averse and loss neutral and gain seeking subjects in both treatments (P-value=0.67). 57% of the subjects are loss averse in both treatments.

TABLE 3.21: Classification of subjects according to their λ coefficients^a

	Social			Total
Individual	Loss averse ($\lambda > 1$)	Loss neutral ($\lambda = 1$)	Gain seeking ($\lambda < 1$)	
Loss averse ($\lambda > 1$)	12	1	3	16
Loss neutral ($\lambda = 1$)	0	0	0	0
Gain seeking ($\lambda < 1$)	3	0	2	5
Total	15	1	5	21

^a The table includes 21 subjects for whom the estimation of λ coefficients in both treatments was possible

3.6 Robustness Experiment- Non correlation

In this section, I analyze the data of the robustness experiment where in the individual treatments, risks are independent.

3.6.1 Descriptive statistics and logistic regression

I ran the same experiment with one difference in the individual treatment. The randomly selected situation that determines subject's earnings can be different of that of other subjects. So, in that case, subjects earnings are not correlated in the individual treatment, however, they correlated in the social treatment. Previously, subjects earnings were correlated in both treatment. The aggregate proportions of risk averse choices across domains is reported in Table 3.22. I find no significance difference between the share of risk averse choices in individual and social treatment across domains. According to Wilcoxon matched pairs signed-ranks test, the difference of the share of risk averse choices between the individual and social treatment is not statistically significant (P-value= 0.2441, 0.1692 and 0.4751 in gain, loss and mixed domain respectively). The percentage of risk averse subjects across domains is reported in Table 3.23. Subjects are less risk averse in mixed and loss domain than gain domain. Subjects are considered risk averse if more than 50% of their choices are safe choices. According to Wilcoxon matched pairs signed-ranks test, there is no significant difference between the share of risk averse subjects in the individual and social treatment in the gain domain (P-value= 1). However, in the loss and mixed domain, there is a significant difference between the share of risk averse subjects in individual and social treatment (P-values = 0.006 and 0.013 respectively).

I also investigate the factors that affect the probability of choosing a safe lottery over a risky one. Table 3.24 reports the logit regression results. Several variables have significant effect on choice in individual and social treatment. The increase in the difference in skewness between the safe and risky lottery made it less likely that a participant would choose the safe lottery in the individual and social treatment. Secondly, being

TABLE 3.22: Aggregate proportions of risk averse choices across domains

Domain	Individual	Social
Overall	48.7%	50.1%
Gain	56.7%	59.3%
Loss	49.8%	52.7%
Mixed	39.8%	38.2%

TABLE 3.23: Aggregate proportions of risk averse subjects across domains

Domain	Individual	Social
Overall	43%	46.2%
Gain	64.5%	64.5%
Loss	49.5%	54.8%
Mixed	40.9%	36.6%

in loss and mixed domain decreases the probability of choosing the safe lottery in both treatments.

3.6.2 Structural Estimation: Expected Utility Theory by [Von Neumann and Morgenstern \(1947\)](#)

3.6.2.1 All domains

Pooling all the responses from each of the 93 subjects, the maximum likelihood estimates of the risk aversion parameter $r = 0.863$ with a standard error of 0.03 in the individual treatment. In the social treatment, the maximum likelihood estimates of the risk aversion parameter $r = 0.897$ with a standard error of 0.03. Subjects are risk averse

TABLE 3.24: Logit regression with probability of choosing the safe lottery as dependent variable

	(1) Individual	(2) Social
Loss Domain	-0.525*** (0.149)	-0.508*** (0.164)
Mixed Domain	-0.830*** (0.170)	-1.023*** (0.196)
Difference in variance between safe and risky lottery	0.00165 (0.002)	0.00230 (0.002)
Difference of skewness between safe and risky lottery	-0.487*** (0.064)	-0.478*** (0.078)
<i>N</i>	1953	1953

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standards errors in parenthesis are clustered at the subject level.

in both treatments. Figure 3.20 shows the expected utility functions in the individual and social treatment.

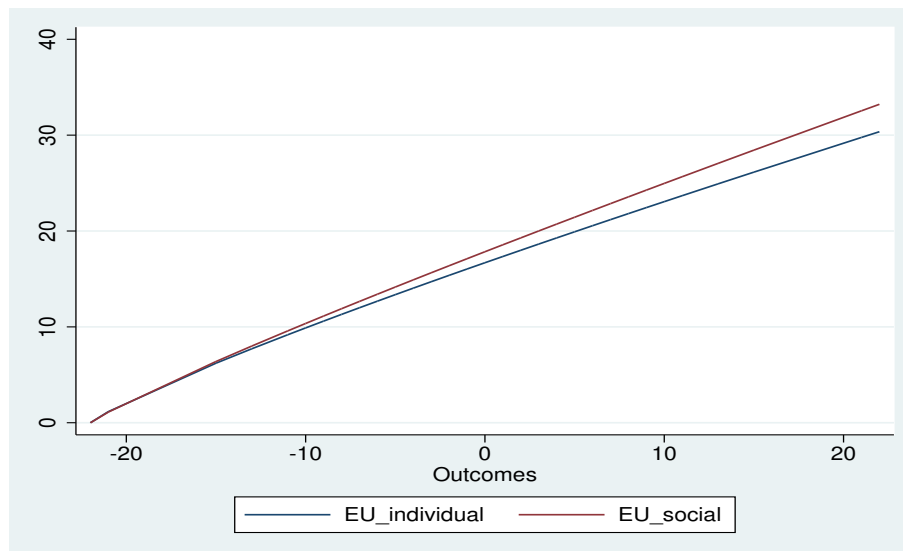


FIGURE 3.20: Expected Utility as a function of outcomes per treatment

Table 3.25 shows the classification of subjects according to their risk preferences represented by their CRRA coefficients. In the individual treatment, when estimating the risk aversion parameter r for each subject based on his responses in 21 individual tasks of the three domains, I find that 75% of the subjects (70 out of 93 subjects) are considered as risk averse (their CRRA parameter $r < 1$). 25% of the subjects (23 out of 93 subjects) are risk seeking (their CRRA parameter $r > 1$) and no subjects are risk neutral ($r = 1$).

On the other hand, in the social treatment, when estimating the risk aversion parameter r for each subject based on his responses in 21 social tasks of the three domains, the percentage of risk averse subjects decreases. 69% subjects are risk averse (64 out of 93 subjects). However, the rest of the subjects (29 out of 93 subjects) are risk seeking and no subjects are risk neutral.

TABLE 3.25: Classification of subjects according to their CRRA coefficients

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	70	0	23	93
Social	64	0	29	93

Figure 3.21 displays a scatter plot of the CRRA coefficients for each subject in the individual and social treatments. Different correlation coefficients show that there is a weak positive correlation between the CRRA coefficients in the individual and social treatment (Pearson correlation coefficient = 0.44, Spearman correlation coefficient = 0.38 and Kendall's tau coefficient = 0.27)

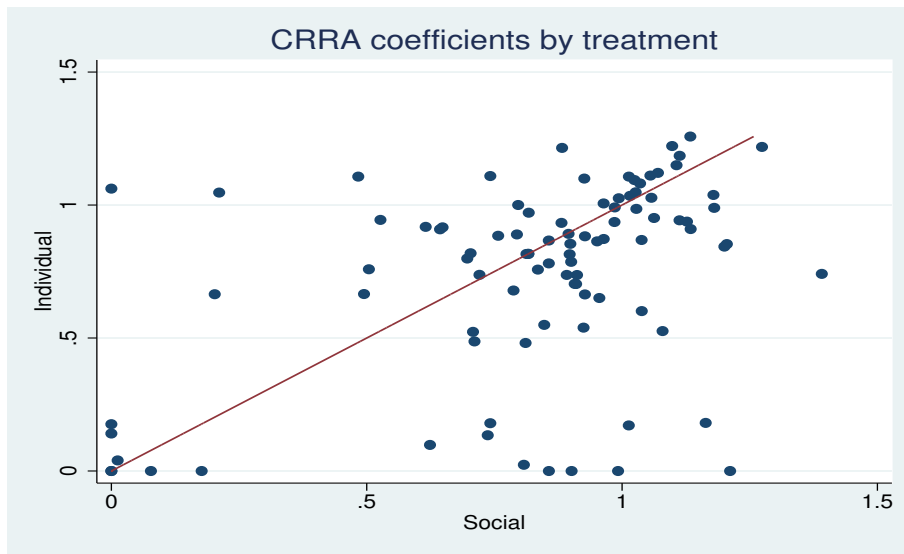


FIGURE 3.21: CRRA coefficients for each of 93 subjects per treatment

I run a Kolmogorov-Smirnov test to see whether there is a significant difference between the distributions functions of CRRA coefficients in both treatments. The test result reports that CRRA coefficients do not have the same distribution in the individual and social treatment (P-value = 0). Cumulative density functions of CRRA coefficients in the individual and social treatment are presented in figure 3.22.

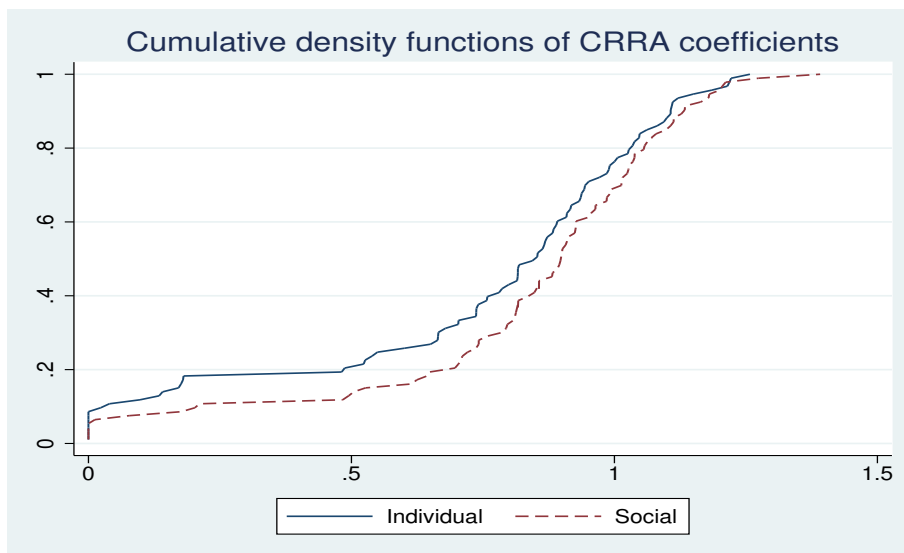


FIGURE 3.22: Cumulative density functions of CRRA coefficients

Table 3.26 presents the descriptive statistics of CRRA coefficients in both treatments. The measures of central tendency and variability of CRRA coefficients in the individual treatment are lower than those in the social treatment. A box plot of CRRA coefficients in the individual and social treatments is presented in figure 3.23. According to the variance comparison test, the hypothesis of the equality of the variances of CRRA coefficients in both treatments can not be rejected (P-value=0.22).

TABLE 3.26: Descriptive Statistics of CRRA coefficients

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1-Q_3]
Individual	0.738	0.853	0.363	0	1.26	[0.601-0.991]
Social	0.826	0.899	0.316	0	1.39	[0.737-1.03]

Table 3.27 shows the classification of subjects according to their CRRA coefficients in both treatments to compare risk preferences by treatment. Fisher's exact test result suggests rejecting the hypothesis of the equality of proportions of risk averse and risk seeking subjects in both treatments (P-value=0). Nevertheless, when running a Fisher's exact test for CRRA coefficients estimated with $\epsilon = 0.05$ in table 3.28, the hypothesis of the equality of proportions in both treatments is also rejected (P-value = 0) which means that the introduction of social comparison has a significant effect on risk preferences. CRRA coefficients with $\epsilon = 0.05$ couldn't be estimated for two subjects.

TABLE 3.27: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0$ in both treatments

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	55	15	70
Risk seeking ($r > 1$)	9	14	23
Total	64	29	93

TABLE 3.28: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0.05$ in both treatments

Individual \ Social	Risk averse ($r < 0.95$)	Risk neutral ($0.95 < r < 1.05$)	Risk seeking ($r > 1.05$)	Total
	Risk averse ($r < 0.95$)	66	10	2
Risk neutral ($0.95 < r < 1.05$)	4	5	0	9
Risk seeking ($r > 1.05$)	3	0	1	4
Total	73	15	3	91

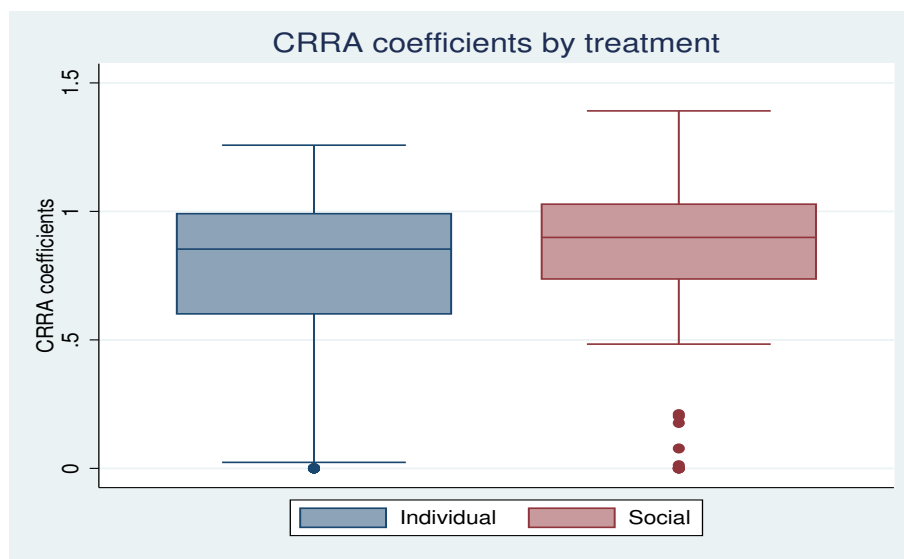


FIGURE 3.23: CRRA coefficients by treatment

3.6.3 Structural Estimation: Reference Point Model

Pooling all the responses from each of the 84 subjects, the maximum likelihood estimates of the risk aversion parameter $\alpha = 0.744$ with a standard error of 0.03, $\beta = 0.868$ with a standard error of 0.01 and $\lambda = 1.623$ in the individual treatment. The estimated loss aversion coefficient is significantly different from 1 at 10% significance level, since the p-value of the test is =0.0961. The risk aversion parameters α and β are not significantly different from each other since at 5% significance level, since the p-value of the test = 0.363.

In the social treatment, the maximum likelihood estimates of the risk aversion parameter $\alpha = 0.723$ with a standard error of 0.006, $\beta = 0.955$ with a standard error of 0.05 and $\lambda = 1.758$. The estimated loss aversion coefficient is not significantly different from 1 at 5% significance level, since the p-value of the test is = 0.187. The risk aversion parameters α and β are significantly different from each other since at 5% significance level, since the p-value of the test = 0.

PT model parameters for each subject are estimated for 51 subjects out of 93 in the individual treatment and 50 subjects out of 93 in the social treatment. Tables 3.29 and 3.30 present the descriptive statistics of PT model parameters in the individual and social treatment.

TABLE 3.29: Descriptive Statistics of PT model parameters in the individual treatment

Parameters	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1-Q_3]
α	0.773	0.727	0.422	0	1.59	[0.620-1.030]
β	0.863	0.874	0.925	0	4.280	[0.034-0.999]
λ	∞	1.132	∞	0	∞	[0.790-2.102]

TABLE 3.30: Descriptive Statistics of PT model parameters in the social treatment

Parameters	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1-Q_3]
α	0.802	0.882	0.999	0	1.592	[0.719-1.150]
β	1.373	0.952	1.651	0	7.785	[0.650-1.539]
λ	∞	1.113	∞	0	∞	[0.790-10.527]

Table 3.31 reports the classification of subjects according to their risk preferences in the gain domain represented by their α coefficients. When estimating α coefficients for subjects, I find that around 67% of the subjects are risk averse in the individual and 33% are risk seeking. In the social treatment the percentage of risk averse subjects decreases and becomes 54% and that of risk seeking subjects is 46% . No subjects are classified as risk neutral.

Figure 3.24 presents a scatter plot of risk aversion coefficients α for each subject in the individual and social treatment. Different correlation coefficients show that there

TABLE 3.31: Classification of subjects according to risk aversion coefficients α

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	34	0	17	51
Social	27	0	23	50

is a weak positive correlation between risk aversion coefficients α for each subject in the individual and social treatment (Pearson correlation = 0.35, Spearman correlation coefficient = 0.35 and Kendall's tau coefficient = 0.22).

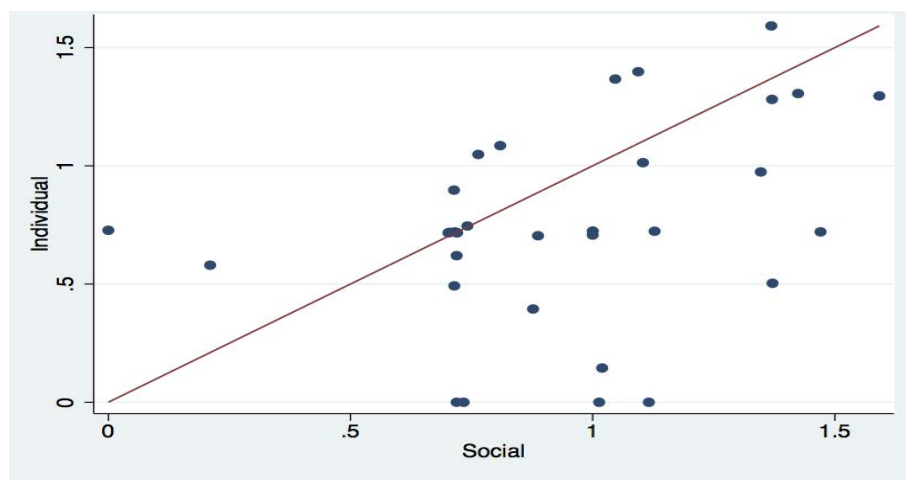
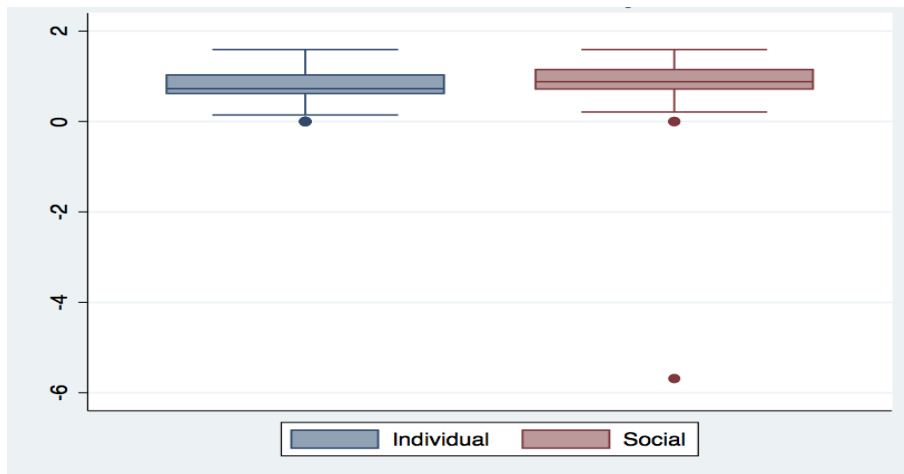
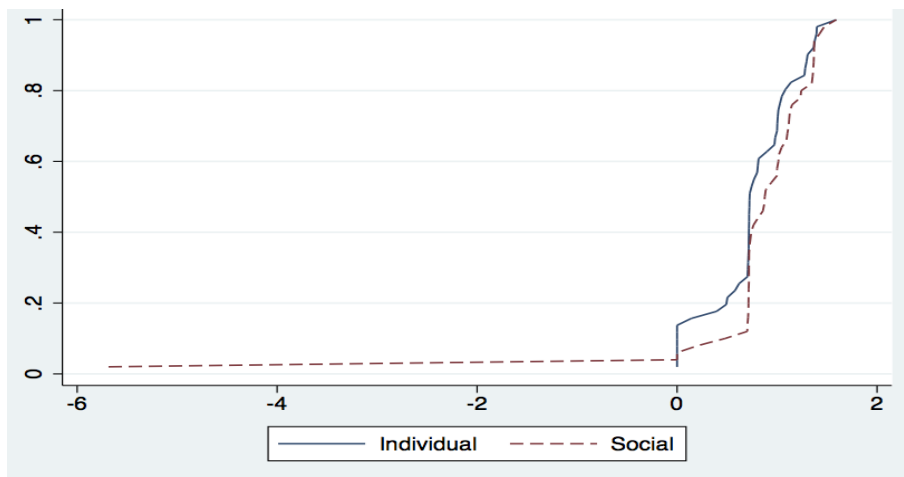
FIGURE 3.24: Risk aversion coefficients α for subjects per treatment

Figure 3.25 displays a box plot of risk aversion coefficients α in the individual and social treatment. Regarding their variances, the hypothesis of the equality of variances is rejected (P-value = 0).

Kolmogorov-Smirnov test result shows that α coefficients do not have the same distribution in both treatments (P-value = 0). Figure 3.26 presents the cumulative density functions of α coefficients in both treatments.

Table 3.32 presents the classification of subjects according to their α coefficients estimated in both treatments. The total number of subjects in this table is 33 for whom the estimation of α coefficients in both treatments was possible. Fisher's exact test for α coefficients result suggests that there is a significant difference in the proportions of risk

FIGURE 3.25: Risk aversion coefficients α for subjects per treatmentFIGURE 3.26: Risk aversion coefficients α for subjects per treatment

averse and risk seeking subjects in both treatments at 10% significance level (P-value = 0.046).

Table 3.33 reports the classification of subjects according to their risk preferences for negative outcomes represented by their β coefficients. When estimating β coefficients for subjects, I find that around 78% of the subjects are risk averse in the individual and 22% are risk seeking. In the social treatment, risk aversion increases, the percentage of risk averse subjects is 62% and that of risk seeking subjects is 38%. No subjects are classified as risk neutral.

TABLE 3.32: Classification of subjects according to their α coefficients estimated in both treatments^a

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse	15	9	24
Risk seeking	2	7	9
Total	17	16	33

^a The table includes 33 subjects for whom the estimation of α coefficients in both treatments was possible.

TABLE 3.33: Classification of subjects according to risk aversion coefficients β

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	40	0	11	51
Social	31	0	19	50

Figure 3.27 presents a scatter plot of risk aversion coefficients β for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak positive correlation between risk aversion coefficients β for each subject in the individual and social treatment (Pearson correlation = 0.12, Spearman correlation coefficient = 0.22 and Kendall's tau coefficient = 0.19).

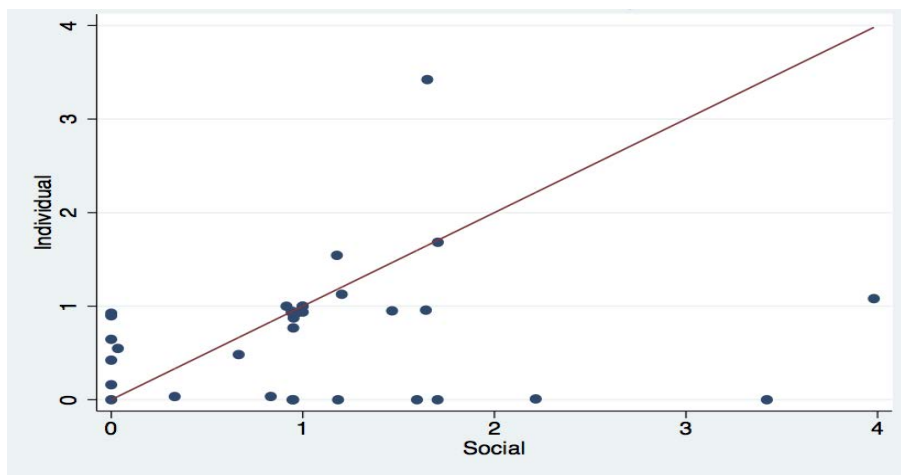
FIGURE 3.27: Risk aversion coefficients β for subjects per treatment

Figure 3.28 displays a box plot of risk aversion coefficients β in the individual and social treatment. Regarding their variances, the hypothesis of the equality of variances is rejected (P-value = 0).

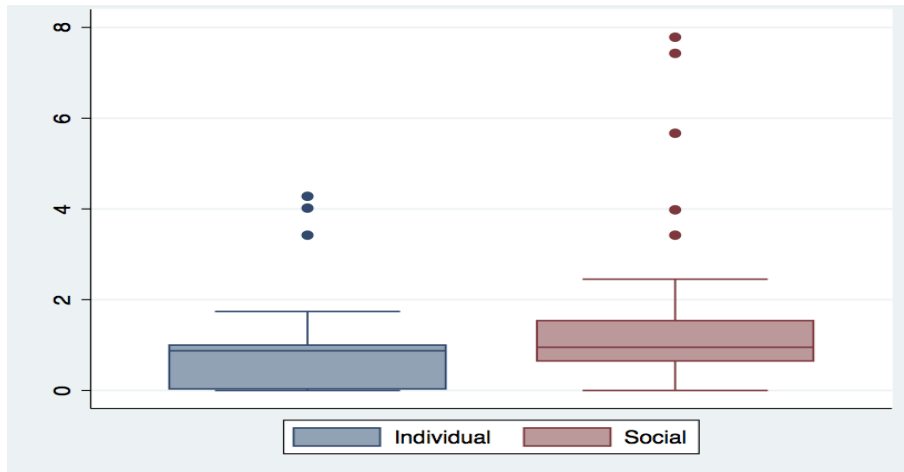


FIGURE 3.28: Risk aversion coefficients β for subjects per treatment

Kolmogorov-Smirnov test result shows that β coefficients do not have the same distribution in both treatments (P-value=0). Figure 3.29 presents the cumulative density functions of β coefficients in both treatments.

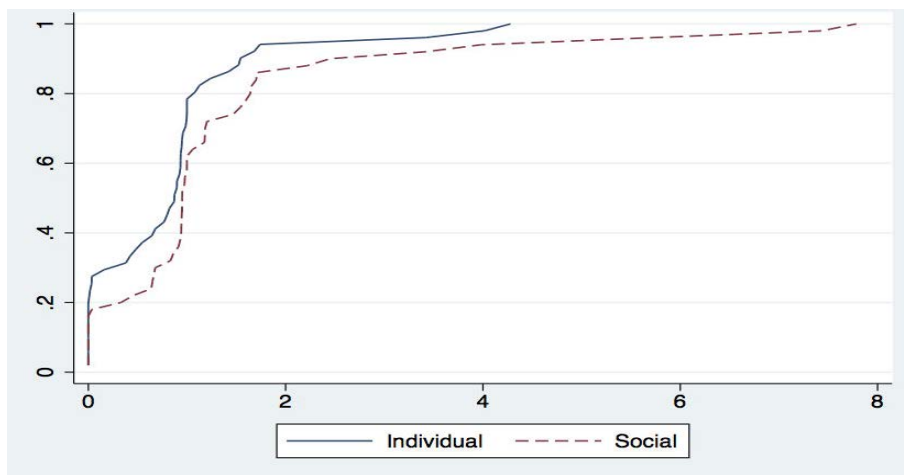


FIGURE 3.29: Risk aversion coefficients β for subjects per treatment

Table 3.34 presents the classification of subjects according to their β coefficients to compare risk preferences over losses by treatment. The total number of subjects in this

table is 33 for whom the estimation of β coefficients in both treatments was possible. Fisher's exact test result suggests rejecting the hypothesis of the equality of proportions of risk averse and risk seeking subjects in both treatments (P-value=0).

TABLE 3.34: Classification of subjects according to their β coefficients^a

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	21	7	28
Risk seeking ($r > 1$)	0	5	5
Total	21	12	33

^a The table includes 33 subjects for whom the estimation of β coefficients in both treatments was possible.

Regarding loss aversion measured by λ , a subject is classified as loss averse if λ exceeded 1, as loss neutral if $\lambda = 1$, and as gain seeking if λ were less than 1. In the individual treatment, 61% of the subjects are loss averse and 39% of the subjects are gain seeking. No subjects are considered as loss neutral. However, in the social treatment, 69% of the subjects are loss averse, 4% are loss neutral and 27% are gain seeking. Thus, The introduction of the social context increases loss aversion.

TABLE 3.35: Classification of subjects according to loss aversion coefficients λ

Treatment	Loss averse ($\lambda > 1$)	Loss neutral ($\lambda = 1$)	Gain seeking ($\lambda < 1$)	Total
Individual	30	0	19	49
Social	32	2	13	48

Table 3.35 presents the classification of subjects according to their λ coefficients. The total number of subjects in this table is 30 for whom the estimation of λ coefficients in both treatments was possible. Fisher's exact test result suggests rejecting the hypothesis of the equality of proportions of loss averse and loss neutral and gain seeking subjects in both treatments (P-value=0). 47% of the subjects are loss averse in both treatments.

TABLE 3.36: Classification of subjects according to their λ coefficients^a

	Social		Total
Individual	Loss averse ($\lambda > 1$)	Gain seeking ($\lambda < 1$)	
Loss averse ($\lambda > 1$)	14	1	15
Gain seeking ($\lambda < 1$)	7	8	15
Total	21	9	30

^a The table includes 30 subjects for whom the estimation of λ coefficients in both treatments was possible

3.7 Discussion

Hypothesis 1: Social context has an impact on risk attitudes. Subjects are less risk averse in the social treatment.

This hypothesis is verified. In the initial experiment, according to Wilcoxon matched pairs signed-ranks test, the share of risk averse subjects in the individual treatment (61.9%) is significantly higher than that in the social treatment (54.76%) (P-value=0).

When using the Expected Utility Theory specification to estimate risk aversion parameters for each subject based on his choices in all domains, the introduction of the social context decreases the share of risk averse subjects having a CRRA coefficient less than 1 ($r < 1$). In the individual treatment, the share of risk averse subjects is 86%. However, in the social treatment this share is 71%. This difference between the share of risk averse subjects in the individual treatment and that in the social treatment is significant. The hypothesis of the equality of this share in both treatment is rejected at 5% significance level (P-value=0.012). Hence, the introduction of the social context has a significant effect on subjects risk attitudes.

Hypothesis 2: Risk attitudes are different for gains and for losses. In the individual treatment, subjects are expected to be more risk averse in the gain domain than in the loss domain. However, in the social treatment, subjects are expected to be more risk averse in the loss domain than in the gain domain.

This hypothesis is not verified. In both treatments, the share of risk averse subjects for gains is significantly higher than that for losses. In the individual treatment, the share of risk averse subjects in the gain domain (60.7%) is significantly higher than that in the loss domain (51.2%) at 5% significance level (P-value=0.003) which is in line with the Prospect Theory. Similarly, in the social treatment, the share of risk averse subjects in the gain domain (65.5%) is significantly higher than that in the loss domain (48.9%) at 5% significance level (P-value=0.002). This finding is not in line with [Linde and Sonnemans \(2012\)](#), [Bault et al. \(2008\)](#) and [Vendrik and Woltjer \(2007\)](#) who found the opposite of the prediction of the Prospect theory with a social reference point.

I use the Expected Utility Theory specification to estimate risk aversion parameters for each subject based on his choices on the gain domain and the loss domain separately. There is a significant difference between the share of risk averse subjects in the gain domain and that in the loss domain per treatment. The share of risk averse subjects in the gain domain is significantly higher than that in the loss domain in both treatments (P-value=0 in both treatments).

Hypothesis 3: Subjects are expected to be loss averse in the individual treatment and less loss averse in the social treatment.

This hypothesis is verified. In the mixed domain, the introduction of the social context decreased significantly the share of risk averse subjects from 54.8% to 46.4% (P-value=0). Since safe lotteries have smaller loss, then subjects are loss averse in the individual treatment, and less loss averse in the social treatment. In the mixed domain, loss resonates more than gains in the individual treatment. However, in the social treatment gain resonates more than losses.

However, according to the Reference Point model, this hypothesis is not verified. When estimating the loss aversion parameter λ and risk aversion parameters α for gains and β for losses, I find that the introduction of the social context has no significant effect on risk attitudes and loss aversion. When estimating λ the loss aversion parameter, the share of loss averse subjects ($\lambda > 1$) is 67% in the individual treatment and amounts to 58% in the social treatment. The difference between the share of loss averse subjects

in both treatments is not significant, the hypothesis of the equality of this share in both treatments is not rejected (P-value= 0.382). This result can be due to the limited sample size since the estimation of λ the loss aversion parameter in both treatments was only possible for 21 out of 84 subjects.

Hypothesis 4: Correlation of risks has an impact on risk attitudes. When risks are correlated, subjects are expected to be less risk averse.

I study the effect of correlating risks on risk attitudes by comparing the results of the initial experiment with those of the robustness experiment in the individual treatment.

To test this hypothesis, I compare individual choices in the initial experiment (where risks are correlated) and the robust (where risks are uncorrelated) experiment.

Hypothesis 4 is not verified. Overall, the share of risk averse subjects in the initial experiment (where risks are correlated) (61.9%) is significantly higher than that in the robustness experiment (where risks are uncorrelated) (43%) (P-value=0). Hence, when risks are correlated, subjects are risk averse.

For gains and losses, correlation does not have a significant impact on risk attitudes. In the gain domain, the share of risk averse subjects in the initial experiment (60.7%) is not significantly different that in the robustness experiment (64.5%) (P-value=0.296). Similarly, in loss domain, the share of risk averse subjects in the initial experiment (51.2%) is not significantly different that in the robustness experiment (49.5%) (P-value=0.397).

However, in the mixed domain, the share of risk averse subjects in the initial experiment (54.8%) is significantly higher than that in the robustness experiment (40.9%) at 5% significance level (P-value=0). Hence, when risks are correlated, subjects are more risk averse in mixed domain.

When estimating risk aversion parameters for each subject using the Expected Utility Theory specification (Section 3.5.2 and subsection 3.6.2), I find that in the individual treatment, the share of risk averse subjects, based on their responses in all domains, in the initial experiment is 86% and in the robustness experiment is 75%. The difference

is significant, the hypothesis of the equality of the shares in both experiments is rejected at 5% level (P-value= 0.041). Hence, when risks are correlated, the share of risk averse subjects increases.

Furthermore, when estimating risk aversion parameters for each subject based on his choices in the gain domain, in the individual treatment, the share of risk averse subjects, in the initial experiment is 100% and in the robustness experiment is 44%. Thus, when risks are correlated, the share of risk averse subjects increases. (P-value=0).

However, in the loss domain, in the individual treatment, the share of risk averse subjects, based on their responses in the loss domain, in the initial experiment is 57% and in the robustness experiment is 60%. The difference is not significant, the hypothesis of the equality of the shares in both experiments is not rejected (P-value=0.652).

When using a Reference Point model to estimate loss aversion parameter λ and risk aversion parameters α and β (Section 3.5.3 and section 3.6.3), I find that the correlation of risks has a significant effect on risk attitudes but no significant effect on loss aversion. The share of risk averse subjects over gains (measured by α) is 79% in the initial experiment in the individual and social treatment. In the robustness experiment, this share amounts to 67% in the individual treatment. There is a significant difference between the share of risk averse subjects in gains in both experiment at 10% level (P-value= 0.083). Hence, when risks are correlated, the share of risk averse subjects increases.

The share of risk averse subjects over losses (measured by β) in the individual treatment is 75% in the initial experiment. This share amounts to 25% in the robustness experiment. There is a significance difference between both experiments (P-value=0). Thus, when risks are correlated, the share of risk averse subjects increases.

Regarding λ the loss aversion parameter, the share of loss averse subjects is 67% in the initial experiment in the individual treatment. In the robustness experiment, this share decreases to 61%. However, there is no significant difference between both shares (P-value=0.291).

3.8 Conclusion

The aim of this chapter is to explore experimentally the effect of social context on individual risk attitudes in gain, loss and mixed domain and to investigate the impact of correlation of risks among subjects in these three domains. The experiment consists of two treatments. In the first treatment, subjects made binary choices of three outcomes each individually. In the second treatment, social comparison was introduced. The first finding of this chapter is that social context matters for individual risk attitudes. When aggregating choices of all domains, the introduction of social context decreases risk aversion.

Regarding each domain separately, risk aversion for gains is significantly higher than that for losses as predicted by the Prospect Theory. When introducing social context, risk aversion for gains remains higher than that for losses. This result is not in line with [Linde and Sonnemans \(2012\)](#) and [Vendrik and Woltjer \(2007\)](#). [Linde and Sonnemans \(2012\)](#) found that participants were more risk averse when they can earn at most as much as their peer (loss situation) than when they were ensured they would earn at least as much as the social referent (gain situation). [Vendrik and Woltjer \(2007\)](#) established that both below and above the social reference point utility functions are concave, while other reference points lead to a convex utility function for losses. As the utility function is also steeper for losses, this implies fewer risk seeking choices in the loss domain.

Previous research has explored the effect of social comparison as well as the correlation of risks on individual risk attitudes for gains and losses separately. The contribution of this chapter is to add a mixed domain. What makes the mixed domain special is the influence of loss aversion on choice behavior. Loss aversion can be viewed as the component of risk attitude that relates risk behavior in the separate domains of gains and losses ([Brooks and Zank, 2005](#)). This highlights the importance of mixed lotteries for a complete description of risk attitudes. Loss aversion implies trading off a potential marginal gain against an equally likely marginal loss of the same amount. Loss aversion has been linked to many empirical findings in economics and finance including

financial market puzzles ([Benartzi and Thaler, 1995](#)), endowment effect ([Kahneman et al., 1991](#)) and health outcomes ([Bleichrodt and Pinto, 2000](#)).

Another contribution of this chapter is to fit a structural model of choice to experimental data set from a mixed domain. This approach provides a joint estimation of parameters for risk aversion and loss aversion for individual decisions in isolation and when social context is introduced. To date, [Andersson et al. \(2016\)](#) were the first to fit a structural model of choice to experimental data set from a mixed domain to study decisions on behalf of others. They found that making decisions on behalf of others reduces loss aversion.

In this chapter, the introduction of the social context decreases significantly loss aversion in the mixed domain. Subjects chose more lotteries with potential higher loss in order to have potential higher gain. This result implies that contrary to the individual setting, gains resonate more than losses in social setting. Hence, favorable social comparisons resonate more than unfavorable social comparisons. This result in the mixed domain is in line with [Bault et al. \(2008\)](#). Contrary to the previous finding, [Schwerter \(2016\)](#) found evidence of loss aversion around social reference points. This translates to the idea that unfavorable social comparisons resonate more than favorable social comparisons. In his experiment, subjects made risky choices after observing the earnings of their peers. He finds that subjects made riskier choices when their peers earnings are larger.

The correlation of risks is an experimental feature that influences risk taking behavior ([Schmidt et al., 2015](#)). The correlation of risks has no effect on risk attitudes in the gain and loss domain. However, it generates an increase in risk aversion only in mixed domain. [Schmidt et al. \(2015\)](#) explored the effect of the correlation of risks for gains. They used the willingness to pay (WTP) for a lottery where subjects could either win 10 euros or receive nothing to elicit risk attitudes and showed that risk aversion decreases when risks are correlated. Hence, the correlation of risks affects differently risk attitudes depending on the domain.

To conclude, social context matters for risk attitudes. When social context is introduced, risk attitudes in gains and losses are as predicted by the Prospect Theory, risk aversion is higher for gains than that for losses. However, in the mixed domain, the introduction of social context decreases loss aversion. This result implies that social gains loom more than social losses.

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Chapter 4

Ambiguity attitudes in gain, loss and mixed domain

4.1 Introduction

In many decisions under uncertainty, people have been found to prefer situations with objectively known probabilities (risk) to situations with unknown or uncertain probabilities (ambiguity) even if they are equivalent under Subjective Expected Utility (Savage (1954)). This phenomenon is called ambiguity aversion (Ellsberg (1961)). Ellsberg (1961)'s conjecture has initiated a large empirical literature studying the prevalence and the causes of ambiguity aversion. The literature has shown that attitudes toward ambiguity depends on the likelihood of the uncertain events, the domain of the outcome and the source that generates uncertainty (Trautmann and Van De Kuilen (2015)).

On the other hand, behavioral economics literature has shown that social comparison is a fundamental psychological mechanism influencing people's behavior. Studying the impact of social context on individual decisions is therefore important. Few studies explored the impact of social context and group environment on ambiguity attitudes (Brunette et al. (2015) and Charness et al. (2013)). Groups have been found to attenuate, amplify, or replicate the biases found for individual decisions (Kerr et al. (1996)). Sutter

(2009) has shown that group identity can have a de-biasing effect. When group identity is sufficiently strong, individual decisions that affect other group members become more risky compared to purely individual decisions. Similarly, [Andersson et al. \(2016\)](#) found that a decrease in loss aversion when subjects took risks on behalf of others. Loss aversion is regarded as a bias and being responsible for someone else's payoff may motivate people to move from such biases, hence decreases loss aversion. The purpose of this chapter is to complement prior economic research on the impact of social context on individual decisions under ambiguity. I do so by correlating payments across subjects. This chapter aims to answer the following questions: Do ambiguity attitudes vary across domains (whether it is gain, loss or mixed domain). Does correlating payments have an impact on ambiguity attitudes? Do ambiguity attitudes vary with the size of the group of subjects for which payments are correlated? To answer the first question, I conduct an experiment where subjects are asked to choose between betting on unambiguous event and ambiguous events of their choice in a three-color version of [Ellsberg \(1961\)](#) experiment in a between-subjects design in three types of prospects: gain, loss and mixed prospects in accordance with the previous chapter. To answer the second and the third question, I correlate payments across subjects to see if correlation of payments has an impact on ambiguity attitudes.

The main findings of this chapter are that correlating payments decreases significantly ambiguity aversion. Regarding ambiguity aversion in gains and losses, a switch from gains to losses leads to a decrease in ambiguity neutrality which is in line with the findings of [Voorhoeve et al. \(2016\)](#). However, a switch from gain to mixed domain decreases ambiguity seeking when payments are correlated across all subjects. Lastly, the size of the group for which payments are correlated does not have a significant effect on ambiguity attitudes.

The remainder of the chapter is structured as follows. Section [4.2](#) presents a literature review. Section [4.3](#) presents the hypotheses. Section [4.4](#) explains the experimental design. Sections [4.5](#) discusses the results and section [4.6](#) concludes.

4.2 Related research

Ellsberg (1961) presented a thought-experiment to show that missing information about objective probabilities can affect people's decision making in a way that is inconsistent with Savage (1954). Ellsberg (1961)'s simplest example, known as the "two-color" problem, involved two urns each containing 100 balls that are either red or black. Urn A contained 50 red balls and 50 black ones (risky urn), whereas the composition of urn B was unknown (ambiguous urn). Suppose that a ball is drawn at random from an urn and one received 100\$ or nothing depending on the outcome. Most people would be indifferent between betting on red or on black for either urn, while they would prefer to bet on the urn with the known composition rather than on the urn with the unknown composition. This pattern of preferences is inconsistent with subjective probability assessments and Expected Utility Theory because it implies that the subjective probabilities of red and of black in the 50-50 urn are greater than in the unknown urn, and thus the total probability in the unknown urn would be less than 1. To see this, suppose $p(r_A)$ ($p(r_B)$) and $p(b_A)$ ($p(b_B)$) are the subjective probabilities of drawing red and black ball respectively from Urn A (B). This pattern of preferences implies that $p(r_A) > p(r_B)$ and $p(b_A) > p(b_B)$ whereas $p(r_A) = p(b_A) = 1/2$. Hence, $p(r_B) + p(b_B)$ would be less than 1. The paradoxical results of Ellsberg's thought experiment were confirmed experimentally by Becker and Brownson (1964) and Slovic and Tversky (1974).

Ellsberg also proposed a three-color choice problem. The urn contained 90 balls, 30 of which were red and 60 are somehow divided between black and yellow balls without any information on the composition. Subjects faced two choice problems. In the first choice problem, subjects were asked to choose between the bet yielding 100\$ if the ball drawn was red and 0\$ otherwise; and the bet yielding 100\$ if the ball drawn was black and 0\$ otherwise. The second choice was between the bet paying 100\$ if the drawn ball was not-black (either red or yellow) and 0\$ otherwise; and the bet that paying 100\$ if the drawn ball was not-red (either black or yellow) and 0\$ otherwise. After choices were made, two independent draws with replacements were conducted to determine subjects earnings. In the first choice problem, subjects preferred to bet on red where they knew

that they have $1/3$ chance of winning in this case. In the second choice problem, subjects preferred to bet on the not-red color (either black or yellow) because that they knew that they have $2/3$ chance of winning. The beliefs of the individual exhibiting such preferences cannot be represented through an additive probability distribution. To see this, suppose $p(r)$, $p(b)$ and $p(y)$ are the subjective probabilities of drawing red, black and yellow ball respectively. Given subjects first choice and setting $U(0)=0$, Savage's subjective expected utility implies that $p(r)U(1) > p(b)U(1)$, hence $p(r) > p(b)$. Hence, $p(r) + p(y) > p(b) + p(y)$ which conflicts with subjects second choice. As a result, these preferences contradict Expected Utility Theory and theories of rational behavior under uncertainty that assumes a unique additive probability measure underlying choices.

Several studies were surveyed in [Camerer and Weber \(1992\)](#) and [Trautmann and Van De Kuilen \(2015\)](#). Basics of ambiguity attitudes has been extensively studied. [Becker and Brownson \(1964\)](#) conducted an experiment where they screened subjects for ambiguity aversion before participating using a two-color Ellsberg problem. About half of the subjects participated in the experiment. Subjects faced pairs of urns. In each pair, there were a risky urn containing 50 red balls out of 100 and an ambiguous urn where the number of red balls varied. Subjects were asked to choose one urn from each pair and bet on the color from that urn. Subjects were willing to pay high premia to avoid an ambiguous urn. They were willing to pay on average 72% of the expected value to avoid an ambiguous urn when ambiguous urn had from 0 to 100 red balls and 28% when the ambiguous urn had 40 to 60 red balls. [MacCrimmon and Larsson \(1979\)](#) used a three-color Ellsberg urn to elicit ambiguity preferences. They found that 15 out of 19 subjects committed the paradox and displayed ambiguity aversion. They lowered the probability of the red ball from $1/3$ to $1/4$ to measure the probability premium subjects were willing to pay to avoid ambiguity. The number of subjects that committed the paradox decreases to 6 out of 19 subjects. More recently, [Chew et al. \(2012\)](#) conducted an experiment where subjects had to choose between betting a color of a card pulled from a deck containing the same number of red and black cards and betting on a color from a deck of unknown composition. 49.4% of the subjects preferred the risky option to the ambiguous one even if the latter option paid 20% more than the former.

Lastly, [Ahn et al. \(2014\)](#) conducted a portfolio-choice experiment to estimate parametric models of ambiguity aversion at the level of the individual subject. Subjects were endowed with a budget and were asked to choose among three Arrow securities, corresponding to three states of nature $s = 1, 2, 3$ where the second state was risky with known probability $\pi(s_2) = 1/3$ and two states were ambiguous with unknown probabilities. Prices of the three Arrow securities were given. Ambiguity can be avoided by choosing $x_1 = x_3$ where x_s denotes the quantity of Arrow securities of type s . They estimated the parameters of four models of choice under uncertainty (Subjective Expected Utility, Maxmin Expected Utility, Recursive Expected Utility and α -maxmin). Their estimates of preference parameters confirm the heterogeneity of individual attitudes to uncertainty. Despite this heterogeneity, SEU preference was not rejected for over 60% of the subjects.

Other studies focused on ambiguity attitudes for gains and losses. The literature found that ambiguity aversion is not robust to changes in framing, with subjects being more ambiguity loving when faced with losses ([Trautmann and Van De Kuilen \(2015\)](#)). [Hogarth and Einhorn \(1990\)](#) explored risk and ambiguity preferences for gains and losses. In their experiment, subjects were asked to rank 2 possible options: choosing a certain sum, an urn where the probabilities were known and an urn where the probabilities were unknown. In the last option, subjects were told that they had been allowed to look into the urn and estimate its composition. There were 2 levels of payoffs : small 1\$ and large 10,000\$; 3 probability levels : 0.10, 0.50 and 0.90 and versions involving gains and losses. [Hogarth and Einhorn \(1990\)](#) found that subjects were generally ambiguity averse. Ambiguity aversion was weaker for losses than for gains and was slightly weaker for small payoffs than large payoffs. Regarding risk, they assume that risk preferences depend on the probabilities used and whether the payoff is large or small. They found an increasing risk aversion with increasing payoffs/probabilities for gains and decreasing risk aversion with increasing absolute payoff/probability for losses. Cumulative Prospect Theory ([Tversky and Kahneman, 1992](#)) predicts risk aversion for gains/risk seeking for losses for moderate and high probabilities, but risk seeking for gains/risk aversion for losses for low probabilities.

However, [Voorhoeve et al. \(2016\)](#) examined whether ambiguity attitudes are sensitive to changes from a gain to a loss frame by reframing one Ellsberg's experiments in terms of losses rather than gains. They found that ambiguity attitudes are little affected by gain/loss framing but correlates markedly with subjects consistency of choice.

[Kocher et al. \(2015\)](#) provide a systematic experimental assessment of ambiguity attitudes in different likelihood ranges and in the gain, the loss domain and with mixed outcomes. They found that ambiguity attitudes are domain-specific and depend on likelihood ranges. In all domains, the majority of the subjects were classified as ambiguity neutral. For subjects who deviated from ambiguity neutrality, a fourfold pattern of ambiguity attitudes was found: Ambiguity aversion was found for modest likelihood gain (as in the classic Ellsberg paradox) and low likelihood loss prospects. Ambiguity seeking was found for low likelihood gain prospects and modest likelihood loss prospects.

[Dimmock et al. \(2016\)](#) explored ambiguity attitudes in large representative surveys of the Dutch population in which subjects were asked about their preferences as well as about their portfolio holdings. They found a weak negative correlation between ambiguity aversion and stock market participation but only for subjects who perceive stock returns as highly ambiguous. The weak effect of ambiguity aversion might be explained by reference dependence, distinguishing between gains and losses and implying a reflection effect. Stock market participation involves gains and losses, hence, reference dependence is relevant. Reference dependence and its implied reflections of loss attitudes relative to gain attitudes reverse the effects of ambiguity aversion in the same way as it is known to reverse risk aversion. Thus, it weakens the effect of ambiguity aversion. Beside aversion to ambiguity, they found significant results for another relevant component of ambiguity attitudes: a-insensitivity (ambiguity-generated likelihood insensitivity). A-insensitivity implies that people do not sufficiently distinguish between different levels of ambiguity, transforming subjective likelihood towards 50-50. This leads to ambiguity seeking for low likelihoods and ambiguity aversion for high likelihoods. A-insensitivity is not different for losses than for gains because reflecting the overweighting of extreme gains leads to the same overweighting of extreme losses. However, reflecting ambiguity aversion leads to ambiguity seeking. For a-insensitive

individuals, loss aversion aggravates the overweighting of extreme losses relative to the overweighting of extreme gains. Hence, a-insensitivity generates a negative relation with stock market participation.

Abdellaoui et al. (2016) and Baillon and Bleichrodt (2015) provide more details measurements. Abdellaoui et al. (2016) provides for the first time a method to measure loss aversion under ambiguity without making simplifying assumptions about Prospect Theory's parameters. They tested whether both utility and loss aversion are the same under risk and ambiguity as assumed by the Prospect Theory. Their procedure has three main steps. The first elicited the loss L in a mixed prospect that would make the subject indifferent between the prospect and the reference point. The second elicited the prespecified gain G that would make the subject indifferent between the prespecified gain and a gain prospect. The third elicited the prespecified loss X that would make the subject indifferent between the prespecified loss and a loss prospect (that involved a loss $\in L$ or 0). The ratio $\lambda = G/X$ measures the loss aversion of the subject. Subjects were considered loss averse if the estimate was greater than 1, loss neutral if it was equal to 1 and gain seeking if it was less than 1. Abdellaoui et al. (2016)'s experimental data was consistent with the Prospect theory and supported that both utility and loss aversion are the same for risk and ambiguity.

Baillon and Bleichrodt (2015) measured matching probabilities for gains and losses in two experiments. They use elementary choices involving one non-zero money amount and naturally occurring ambiguous events based on the performances of stock markets. They found clear violations of probabilistic sophistication: matching probabilities were not additive and sign dependent and the violations of additivity differed between gains and losses. These findings imply a fourfold pattern of ambiguity attitudes: ambiguity aversion for likely gains and unlikely losses and ambiguity seeking for unlikely gains and likely losses. Thus, ambiguity attitudes are richer than uniform ambiguity aversion or ambiguity seeking. Nevertheless, Prospect Theory takes this pattern into consideration.

Trautmann and Van De Kuilen (2015) reviewed the empirical literature on ambiguity and found evidence for a more complex pattern of attitudes: While ambiguity aversion is

the predominant finding in the domain of moderate likelihood gains and low likelihood losses, for moderate likelihood gains and low likelihood losses ambiguity seeking was often reported.

In comparison with this vast literature on individual decision making, few studies explored individual ambiguity attitudes in a social setting and distinguished the differences between individuals and groups in their attitude towards ambiguity. [Keck et al. \(2014\)](#) explored the effect of the exposure of other individuals opinions and attitudes on subsequent individual decisions. They conducted an experiment to compare individual and group decisions under risk and ambiguity. Subjects made binary choices between sure amounts of money and different risky and ambiguous gambles. In one treatment, the experiment consisted of two stages: individual and group decision making. In the other treatment, it consisted of three stages: individual decisions, group decisions and second round of individual decisions. They found that for all levels of probabilities and all level of ambiguity, groups made ambiguity-neutral choices more often than individuals and that choices made after group discussions with other subjects were more ambiguity neutral than decisions before the interaction. Hence, groups were closer to Expected Utility than individuals.

[Brunette et al. \(2015\)](#) conducted an experiment to test the effect of two variables on individuals decisions: the source of uncertainty (risk vs. ambiguity) and the type of decision rule (majority vs. unanimity). Subjects faced a series of binary choice decisions (under risk and ambiguity) and had to make choices alone and a part of a group of three subjects. In risk, they used multiple price list (MPL) procedure of [Holt et al. \(2002\)](#) to elicit attitudes toward risk. In ambiguity, they used [Chakravarty and Roy \(2009\)](#) procedure which mimics the MPL. Subjects were asked to make a series of 10 choices between a non-ambiguous prospect and an ambiguous prospect to elicit ambiguity attitudes. There were two decision rules: majority and unanimity. In the majority treatment, choices of the three group members were combined in order to compute group choice. In the unanimity group treatment, not all configurations of individual preferences allows to implement the decision rule successfully. Group members could play up to 5 trials till they reach an unanimous decision. The main difference between the two

decision rules: individuals assigned to a group implementing a unanimity rule have no guarantee that an unanimous decision will be reached whereas the majority decision can always be reached. They found that, first, a group environment decreased risk aversion. Second, concerning ambiguity, individuals in a group environment tended to be more ambiguity averse than individuals who were not part of a group. Decision rule matters in ambiguity attitudes. Individuals who belonged to a group implementing a majority decision rule were significantly averse to ambiguity, however, individuals who belonged to a group implementing a unanimity decision rule were ambiguity neutral. Hence, the unanimity rule leads to more rationality which is line with [Keck et al. \(2014\)](#) who found that groups are closer to Expected Utility (ambiguity neutrality) than individuals.

[Charness et al. \(2013\)](#) is the closest paper to this chapter. [Charness et al. \(2013\)](#) conducted an experiment with three-color [Ellsberg \(1961\)](#) urn to explore how prevalent are non-neutral ambiguity attitudes and how resistant are ambiguity attitudes in the context of interpersonal interactions. Based on their choices, subjects were classified as ambiguity averse, neutral, seeking and incoherent. They found that 60.3% of the subjects displayed ambiguity neutral attitudes, 8.1% displayed ambiguity aversion, 11.8% displayed ambiguity seeking and 19.9% displayed choice behavior that was incoherent. To address the question of the impact of interactions on ambiguity attitudes, [Charness et al. \(2013\)](#) ran experiments in which subjects were allowed to interact and discuss their choice before proceeding to place their individual bets on the colors of their choice. They found that ambiguity neutrality became more prevalent following social interactions.

Another close study to this chapter is [Friedl et al. \(2017\)](#) which analyzes the effect of outcome correlation structures on gender differences in ambiguity aversion. They measure subjects willingness to pay (WTP) for an investment game. The participants faced a risky lottery first and an ambiguous lottery afterwards. The difference between the WTP for the risky lottery and the ambiguous lottery is used as an indicator for subjects ambiguity attitudes. Positive values indicate ambiguity aversion, negative values indicate ambiguity seeking, and zero indicates ambiguity neutrality. To study the effect of different outcome correlation structures on gender differences in ambiguity aversion, they

created two treatments. In the uncorrelated treatment, the outcomes of the investment game were determined individually. In the correlated treatment, the outcomes of the investment game were determined collectively within a reference group. They observed significant levels of ambiguity aversion in the aggregate data set and also in both treatments individually. Regarding gender differences in ambiguity aversion, they found that men showed significant levels of ambiguity aversion in the correlated treatment, but not in the uncorrelated treatment. Hence, men were less ambiguity averse in the uncorrelated treatment. Additionally, women's choices were not significantly different between the two treatments.

4.3 Hypotheses

Section 4.2 showed that several hypothesis can be set up based on existing empirical evidence.

Hypothesis 1: Ambiguity attitudes are different for gains and losses. Subjects are expected to be ambiguity averse for gains and ambiguity seeking in losses.

The experiment test this hypothesis in the following way. Subjects are asked to choose between betting on an unambiguous event and ambiguous events of their choice in a three-color version of [Ellsberg \(1961\)](#) experiment. Subjects faces 6 urns (in each domain) containing 36 balls each. The balls in the urn can be either red, blue or green. Subjects are only informed of the total number of balls and the number of red balls in the urn. However, they are not informed of the number of blue and green balls. Then, they are asked to indicate a color they would like to bet on: red, blue or green. The urns differ in the number of red balls. In the first urn, there are 9 red balls and the remaining 27 are either blue or green. In the second urn, there are 10 red balls and the remaining 26 are either blue or green and so on.

Subjects face 6 urns in the gain and loss domain. In the gain domain, subjects could win €5 (positive outcome) if they won the bet, and €0 otherwise. In the loss domain, subjects could win €0 if they won the bet and lose €5 (negative outcome) otherwise.

Hypothesis 2: Ambiguity attitudes differ in mixed domain where subjects are confronted by gains and losses in the same situation.

[Abdellaoui et al. \(2016\)](#) found that both utility and loss aversion are the same under risk and ambiguity as assumed by the Prospect Theory. Utility functions are consistent with the typical finding of convex utility for losses and concave utility for gains. Furthermore, the utility functions were steeper for losses than for gains, indicating loss aversion.

To test this hypothesis, I add mixed prospects in the experiment where subjects could win €5 if they won the bet or lose €5 otherwise.

Hypothesis 3: Correlating payments has an impact on ambiguity attitudes. Subjects are expected to be less ambiguity averse when payments are correlated.

The experiment tests this hypothesis with an in between-subject design. Subjects were asked to choose between betting on unambiguous event and ambiguous events of their choice in a three-color version of [Ellsberg \(1961\)](#). To see if correlation of payments has an impact on ambiguity attitudes, in one treatment payments are perfectly correlated and in another treatment, payments are not correlated. In one treatment (treatment ZERO), after subjects made their choices, to determine subjects earnings, a choice situation (an urn in that case) is randomly selected by the program and a ball is randomly drawn of that urn. The randomly selected urn for a subject may be different or similar to that of the other subjects. In another treatment (treatment ALL), to determine subjects earnings, a choice situation (an urn in that case) is randomly selected by the program and a ball is randomly drawn of that urn. The randomly selected choice situation is the same for all subjects of the session.

Hypothesis 4: The size of the group for which payments are correlated matters.

After subjects made their choices, each subject form a random group with other subjects. To determine subjects earnings, a choice situation (an urn in that case) is randomly selected by the program and a ball is randomly drawn of that urn. The randomly selected urn is the same for all the participants of the same group and may vary from

one group to another. The size of the group differs between sessions. The size of the group for which payments are correlated can be : 4 subjects (treatment FOUR) and 6 subjects (treatment SIX).

4.4 The experiment

4.4.1 Experimental Design

The experimental design is based on [Charness et al. \(2013\)](#) who found that the majority (60.3%) of subjects displayed ambiguity neutral attitudes. Hence, I conduct the following experiment to see if the prevalence of ambiguity neutrality in [Charness et al. \(2013\)](#) is affected by a switch from gains to a loss or mixed domain as well as correlating payments among a group of subjects.

In this experiment, subjects were asked to choose between betting on unambiguous event and ambiguous events of their choice in a three-color version of [Ellsberg \(1961\)](#) experiment in a between-subjects design. Subjects faced 6 urns (in each domain) containing 36 balls each. The balls in the urn can be either red, blue or green. Subjects are only informed of the total number of balls and the number of red balls in the urn. However, they are not informed of the number of blue and green balls. Then, they are asked to indicate a color they would like to bet on: red, blue or green. The urns differ in the number of red balls. In the first urn, there are 9 red balls and the remaining 27 are either blue or green. In the second urn, there are 10 red balls and the remaining 26 are either blue or green. In the third, there are 11 red balls and the remaining 25 are either blue or green. The number of red balls increases and that of the remaining balls decreases till the sixth urn where the number of red balls is 14 and that of the remaining balls is 22. The number of red balls is known for the subject in each urn.

After the subjects made their choices, each subject form a random group with other participants. To determine subjects earnings, an urn is randomly selected and a ball is randomly drawn from that urn. The randomly selected urn is the same for all the

participants of the same group and may vary from one group to another. The size of the group differs between sessions. The size of the group can be :

- Treatment FOUR: 4 participants (3 sessions = 20 participants each)
- Treatment SIX: 6 participants (3 sessions= 18 participants each)
- Treatment ALL: All participants of the session form a group. Then, an urn is randomly selected for all the participants of the session. (3 sessions: 18, 22 and 21 participants)
- Treatment ZERO (Baseline): No groups. An urn is randomly selected for each participant. (2 sessions of 13 participants each).

There are three domains in the experiment: Gain, Loss and Mixed domain. The gain domain is presented in the first 6 urns where subjects can win €5 if they win the bet (if the color they bet on is similar to that of the randomly drawn ball from the urn) or €0 if they lose the bet (if the color they bet on is different from that of the randomly drawn ball from the urn). The loss domain is presented from the seventh to the twelfth urn where subjects can win €0 if they win the bet (if the color they bet on is similar to that of the randomly drawn ball from the urn) or lose €5 if they lose the bet (if the color they bet on is different from that of the randomly drawn ball from the urn). The mixed domain is presented from the twelfth to eighteenth urn, subjects can win €5 if they win the bet (if the color they bet on is similar to that of the randomly drawn ball from the urn) or lose €5 if they lose the bet (if the color they bet on is different from that of the randomly drawn ball from the urn). Hence, subjects face overall 18 urns (6 in each domain). Figure [4.1](#), [4.2](#) and [4.3](#) present a screen shot of the experiment in treatment ZERO.

You will face 3 tables, containing 3 tables of 6 rows each. Each row represents an urn. For each urn, you have to choose a color to bet on (red, green or blue). After all participants made their choices, one of the 18 following urns will be randomly selected to determine your earnings.

Tableau A1 : Your potential gain is equal to **5 euros** if the randomly drawn ball has the color you placed a bet on and **zero euro** if the randomly drawn ball does not have the color you placed a bet on

Urn number	Numbers of red balls in the urn	Number of blue or green balls in the urn	Which color would you like to bet on		
1	9	27	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
2	10	26	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
3	11	25	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
4	12	24	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
5	13	23	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
6	14	22	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue

FIGURE 4.1: Screenshot of the gain domain

Tableau A2 : Your potential gain is equal to **zero euro** if the randomly drawn ball has the color you placed a bet on and **a loss of 5 euros** if the randomly drawn ball does not have the color you placed a bet on

Urn Number	Numbers of red balls in the urn	Number of blue or green balls in the urn	Which color would you like to bet on		
7	9	27	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
8	10	26	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
9	11	25	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
10	12	24	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
11	13	23	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
12	14	22	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue

FIGURE 4.2: Screenshot of the loss domain

Tableau A3 : Your potential gain (or loss) is equal to **5 euros** if the randomly drawn ball has the color you placed a bet on and **a loss of 5 euros** if the randomly drawn ball does not have the color you placed a bet on

Urn Number	Numbers of red balls in the urn	Number of blue or green balls in the urn	Which color would you like to bet on		
13	9	27	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
14	10	26	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
15	11	25	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
16	12	24	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
17	13	23	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue
18	14	22	<input type="radio"/> Red	<input type="radio"/> Green	<input type="radio"/> Blue

FIGURE 4.3: Screenshot of the mixed domain

Based on their choice, subjects can be classified as ambiguity averse, neutral, seeking or incoherent. Subjects who choose to bet on red when the number of red balls in the

urn is 9 and continue to bet on red all the way to 14 are classified as ambiguity averse. Subjects who always choose another color when the number of red balls is lower than 12 and chose to bet on red when the number of red balls is 13 and 14 are classified as ambiguity neutral. Subjects who chose to bet on another color when there are from 9 to 13 or more red balls in the urn are classified as ambiguity seeking. Finally, subjects that display another pattern of choice are classified as ambiguity incoherent.

All Experimental sessions were conducted at the CREM-CNRS (LABEX) institute of the University of Rennes 1, France. A total of 201 undergraduate students in business administration, economics, law and medicine have been recruited via the ORSEE software ([Greiner \(2004\)](#)). Subjects were given a participation fees of 5 euros and an initial endowment of 5 euros before starting the experiment.

4.5 Results

4.5.1 Difference across treatments

Table [4.1](#), [4.2](#), [4.3](#) and [4.4](#) present the percentages of ambiguity averse, neutral, seeking and incoherent subjects respectively per treatment and domain.

TABLE 4.1: Percentages of ambiguity averse subjects per treatment and domain

	Gain	Loss	Mixed
ZERO	15.38%	11.54%	15.38%
FOUR	1.67%	5%	3.33%
SIX	7.41%	7.41%	11.11%
ALL	1.64%	1.64%	3.28%

Overall, the majority of subjects are ambiguity neutral in all treatments and domains. Their share varies from 50% to 73.33%. This finding is in line with [Voorhoeve et al. \(2016\)](#), [Charness et al. \(2013\)](#) and [Stahl \(2014\)](#) who found that ambiguity neutrality is dominant. The share of ambiguity incoherent subjects ranges from 20% to 33% in all treatments and domains. The share of ambiguity averse subjects ranges from 1.64%

TABLE 4.2: Percentages of ambiguity neutral subjects per treatment and domain

	Gain	Loss	Mixed
ZERO	61.54%	50%	57.69%
FOUR	73.33%	61.67%	61.67%
SIX	68.52%	51.85%	61.11%
ALL	67.21%	60.66%	70.49%

TABLE 4.3: Percentages of ambiguity seeking subjects per treatment and domain

	Gain	Loss	Mixed
ZERO	0%	0%	0%
FOUR	5%	6.67%	1.67%
SIX	1.85%	5.56%	1.85%
ALL	3.28%	4.92%	0%

TABLE 4.4: Percentages of ambiguity incoherent subjects per treatment and domain

	Gain	Loss	Mixed
ZERO	23.8%	38.46%	26.92%
FOUR	20%	26.67%	33.33%
SIX	22.22%	35.19%	25.93%
ALL	27.87%	32.79%	26.23%

and 15.58% in all treatments and domains. Few subjects are ambiguity seeking, their share ranges from 0% to 6.67%. The prevalence of ambiguity neutrality is due to the task. [Trautmann et al. \(2011\)](#) bring evidence that choice tasks elicit lower ambiguity aversion than valuation tasks. Hence, the type of elicitation tasks used has an important influence in measuring ambiguity attitudes. The share of ambiguity averse subjects is not sufficient to have a reliable conclusion regarding the effect of the treatments on ambiguity aversion.

To see if there is a significant difference in ambiguity attitudes across treatments, I compare the share of ambiguity averse subjects in treatment ZERO (baseline) to that in the other treatments (FOUR, SIX and ALL) in each domain. In the gain domain, Fisher's exact test result shows that the share of ambiguity averse subjects in ZERO treatment is significantly higher than that in FOUR and ALL treatments at 5% level (P-value=0.026 and 0.028 respectively). This results suggest that when payments are correlated (in

treatments FOUR and ALL), subjects tend to be significantly less ambiguity averse than when payments are not correlated (in treatment ZERO). Hence, correlation of payments decreases ambiguity aversion and hypothesis 3 is verified in the gain domain. However, there is no significant difference in share of ambiguity averse subjects in ZERO and SIX treatment.

Similarly, in the loss domain, Fisher's exact test result shows that the share of ambiguity averse subjects in ZERO treatment is significantly higher than that of the treatment ALL at 10% level (P-value=0.078). Hence, the share of ambiguity averse subjects decreased significantly when payments are correlated. Therefore, hypothesis 3 is also verified in the loss domain. However, there is no significant difference in the share of ambiguity averse subjects in ZERO treatment and that in treatments FOUR and SIX.

In the mixed domain, Fisher's exact test result shows that the share of ambiguity averse subjects in ZERO treatment is significantly higher than that of the treatment FOUR and ALL at 10% level (P-value=0.063 and 0.065 respectively). Therefore, hypothesis 3 is verified in the mixed domain. However, there is no significant difference of that share in ZERO and SIX treatment.

Regarding the rest of ambiguity attitudes, in all domains, there is no significant difference in the share of ambiguity neutral, ambiguity incoherent and ambiguity seeking subjects across treatments.

Thus, in all domain, the correlation of payments decreases significantly ambiguity aversion.

To see if the size of the group for which payments are correlated has an impact on ambiguity attitudes, I compare ambiguity aversion in treatment SIX and FOUR across domains. In the gain, loss and mixed domains, Fisher's exact test result shows that there is no significant difference in the share of ambiguity averse subjects between FOUR and SIX treatments (P-value=0.188, 0.706 and 0.147 respectively). Similarly, there is no significant difference in ambiguity seeking, neutrality and incoherence across domains. This results suggest that the increase in the size of the group for which payments are correlated does not have a significant impact on ambiguity attitudes. Hence, Hypothesis

4 is not verified. However, this result might be due to the minor difference in group size between treatment FOUR and SIX.

4.5.2 Difference across domain

Table 4.5, 4.6 and 4.7 present the classification of subjects according to their ambiguity attitudes in the gain, loss and mixed domain respectively.

TABLE 4.5: Classification of subjects in the gain domain

	Ambiguity Averse	Ambiguity Neutral	Ambiguity Seeking	Ambiguity Incoherent
ZERO	15.58%	61.54%	0%	23.08%
FOUR	1.67%	73.33%	5%	20%
SIX	7.41%	68.52%	1.85%	22.22%
ALL	1.64%	67.21%	3.28%	27.87%

TABLE 4.6: Classification of subjects in the loss domain

	Ambiguity Averse	Ambiguity Neutral	Ambiguity Seeking	Ambiguity Incoherent
ZERO	11.54%	50%	0%	38.46%
FOUR	5%	61.67%	6.67%	26.67%
SIX	7.41%	51.85%	5.56%	35.19%
ALL	1.64%	60.66%	4.92%	32.79%

TABLE 4.7: Classification of subjects in the mixed domain

	Ambiguity Averse	Ambiguity Neutral	Ambiguity Seeking	Ambiguity Incoherent
ZERO	15.38%	57.69%	0%	26.92%
FOUR	3.33%	61.67%	1.67%	33.33%
SIX	11.11%	61.11%	1.85%	25.93%
ALL	3.28%	70.49%	0%	26.23%

To see if there is a significant difference in ambiguity attitudes across domain, I compare the share of ambiguity neutral, ambiguity averse, ambiguity seeking and ambiguity incoherent subjects in the gain domain to that in the loss and mixed domain in each

treatment. In the treatment of FOUR, there is only a significant difference in ambiguity neutrality between the gain and loss domain. The share of ambiguity neutral subjects in the gain domain is significantly higher than that in the loss domain at 10% significance level (P-value=0.0862). There is no significant difference in ambiguity aversion, seeking and incoherence. Hence, in treatment FOUR, hypothesis 1 is not verified, which states that changings from gains to loses leads to a readuction in ambiguity aversion and an increase in ambiguity seeking. That decrease in ambiguity neutral subjects in the loss domain is in line with [Voorhoeve et al. \(2016\)](#)'s findings.

In the treatment of SIX, there is a significant difference in ambiguity neutrality and ambiguity incoherence between the gain and loss domain. The share of ambiguity neutral subjects in the gain domain is significantly higher than that in the loss domain at 5% significance level (P-value=0.0384). However, The share of ambiguity incoherent subjects in the gain domain is significantly lower than that in the loss domain at 10% significance level (P-value=0.0682). There is no significant difference in ambiguity aversion and ambiguity seeking between the gain and loss domain. Hence, Hypothesis 2 is not verified in treatment SIX.

In the treatment of ZERO, there is no significance difference in ambiguity attitudes across domains. Similarly, in the treatment ALL, there is no a significant difference in ambiguity attitudes across domains. Hence, hypothesis 1 is not verified in treatment ZERO and ALL.

To see the effect of the mixed domain on ambiguity attitudes, I compare ambiguity attitudes in the gain domain to that in mixed domain. In the treatment of FOUR, there is significant difference in ambiguity neutrality and ambiguity incoherence between the gain and mixed domain. The share of ambiguity neutral subjects in the gain domain is significantly higher than that in the mixed domain at 10% significance level (P-value=0.0862). The share of ambiguity incoherent subjects in the gain domain is significantly lower than that in mixed domain at 5% significance level (P-value=0.0493). There is no significant difference in ambiguity aversion and ambiguity seeking between the gain and mixed domain. Hence, Hypothesis 3 is not verified in treatment FOUR.

In the treatment of ALL, there is a significant difference only in ambiguity seeking between the gain and mixed domain. The share of ambiguity seeking subject is significantly higher in the gain domain than that in the mixed domain at 10% significance level (P-value=0.0769). Hence, Hypothesis 3 is verified in treatment ALL.

In the treatment of SIX and ZERO there is no significance difference in ambiguity attitudes between the gain and mixed domain. Hence, Hypothesis 3 is not verified in treatments SIX and ZERO.

There is a significant difference across domains in ambiguity neutrality and ambiguity incoherence. The decrease within [Charness et al. \(2013\)](#)'s ambiguity task in ambiguity neutrality between the gain and loss and mixed domain is translated into an increase in ambiguity incoherence.

4.5.3 Individual switches

Table 4.8 shows the percentage of subjects who switch their ambiguity attitudes across domain. For example, in ambiguity aversion, a subject does "not switch", if they are ambiguity averse in the three domains. However, a subject "switches" if they express ambiguity aversion in at most two (one or two) of the three domains. Subjects who does not express ambiguity aversion in any domain are excluded. Out of all the subjects who express ambiguity aversion at least in one domain, 66.67% are ambiguity averse in the three domains, hence, they do not switch. However, 33% switch their ambiguity aversion across domain.

In ambiguity neutrality, out of all the subjects who express ambiguity neutrality at least in one domain, 67.12% are ambiguity neutral in the three domains, hence, they do not switch. However, 32.88% switch their ambiguity neutrality across domain.

In ambiguity seeking, out of all the subjects who express ambiguity seeking at least in one domain, 8.33% are ambiguity seeking in the three domains, hence, they do not switch. However, 91.67% switch their ambiguity seeking across domain.

In ambiguity incoherence, out of all the subjects who express ambiguity incoherence at least in one domain, 44.44% are ambiguity incoherent in the three domains, hence, they do not switch. However, 55.56% switch their ambiguity ambiguity incoherence across domain.

The percentages of subjects who switch vary between 32.88% and 91.67%. This might be due to the design where the difference between domains is not salient enough for subjects to change their ambiguity attitudes.

TABLE 4.8: Individual switches across domains

	Percentage
Ambiguity aversion	33.33%
Ambiguity neutral	32.88%
Ambiguity seeking	91.67%
Ambiguity incoherent	55.56%

4.5.4 Logit regression results

I also investigate the factors that affect the probability of a subject being ambiguity averse. Table 4.9 reports the logit regression results. Treatment ZERO has a significant positive effect on the probability of a subject to be ambiguity averse in gain and mixed domain. However, in the loss domain, treatment ZERO is not significant. Hence, when payments are not correlated, the probability of a subject to be ambiguity averse increases in gain and mixed domain. Hence, the logit regression results show that hypothesis 3 is verified in gain and mixed domain.

Furthermore, correlating payments has an effect on ambiguity aversion. Treatment ALL has a negative significant effect on the probability of being ambiguity averse in gain, loss and mixed domain. Hence, correlating payments for all subjects decreases the probability of being ambiguity averse in all domains. Therefore, hypothesis 3 is verified. However, treatment FOUR has only a significant effect in gain and mixed domain. Treatment FOUR decreases the probability for a subject to be ambiguity averse

in gain and mixed domain. Treatment SIX has negative and non significant effect on the probability of being ambiguity averse in all domains.

To see if hypothesis 1 is verified, I test the equality of estimated coefficients between the logit regressions of ambiguity aversion in gain and loss domain. The test results show that there is no significant difference in estimated coefficients of ambiguity aversion in gain and loss domain (P-value= 0.311 for Treatment SIX, P-value= 0.102 for Treatment FOUR and P-value=0.393 for Treatment ALL). Hence, hypothesis 1 is not verified because ambiguity aversion does not differ between gains and losses.

Similarly, I test the equality of estimated coefficients between the logit regressions of ambiguity aversion in gain and mixed domain. I also find that there is no significant difference in estimated coefficients of ambiguity aversion in gain and mixed domain (P-value= 0.393 for Treatment SIX, P-value= 0.394 for Treatment FOUR and P-value=0.394 for Treatment ALL). Hence, in ambiguity aversion, Hypothesis 2 is not verified.

TABLE 4.9: Logit regression with probability of being Ambiguity Averse across domains as dependent variable

	(1) Gain	(2) Loss	(3) Mixed	(4) Gain	(5) Loss	(6) Mixed
ZERO	1.633*** (0.686)	1.002 (0.714)	1.099* (0.635)			
SIX				-0.821 (0.754)	-0.489 (0.806)	-0.375 (0.697)
FOUR				-2.373** (1.148)	-0.908 (0.855)	-1.663* (0.904)
ALL				-2.390** (1.148)	-2.057* (1.183)	-1.680* (0.904)
Number of observations	201	201	201	201	201	201

***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Standards errors in parenthesis are clustered at the subject level.

Figure 4.4, 4.2, 4.6 present the proportion of subjects choosing to bet on the Red ball (the ambiguity averse option) per treatment in the gain, loss and mixed domain respectively. In figure 4.4, choices vary from 1 to 6, where 1 is the choice where the number of Red balls is 9 and 6 is the choice where the number of Red balls is 14. The share of ambiguity averse subjects per treatment increases with the increase in the number of the Red balls in the urn. In figure 4.2, choices vary from 7 to 12, where 7 is the choice where the number of Red balls is 9 and 12 is the choice where the number of Red balls is 14. In figure 4.6, choices vary from 12 to 18, where 12 is the choice where the number of Red balls is 9 and 18 is the choice where the number of Red balls is 14.

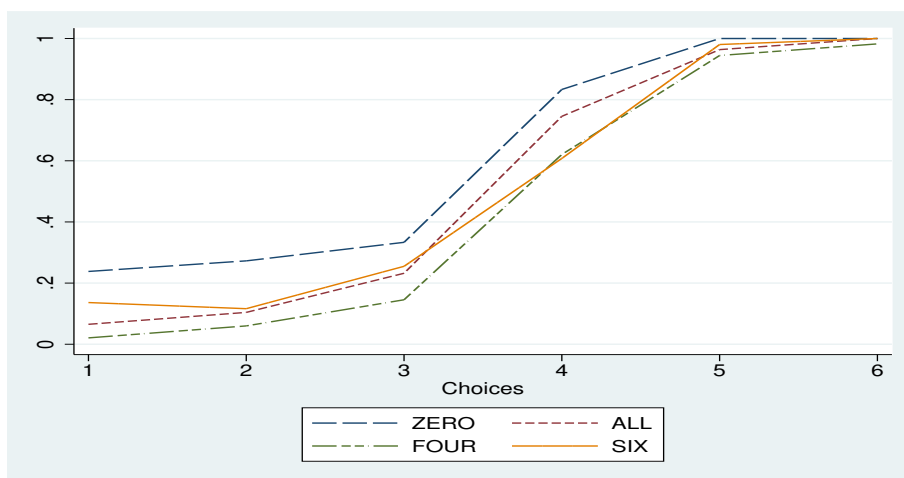


FIGURE 4.4: Proportion of subjects choosing to bet on the Red ball per treatment in the gain domain

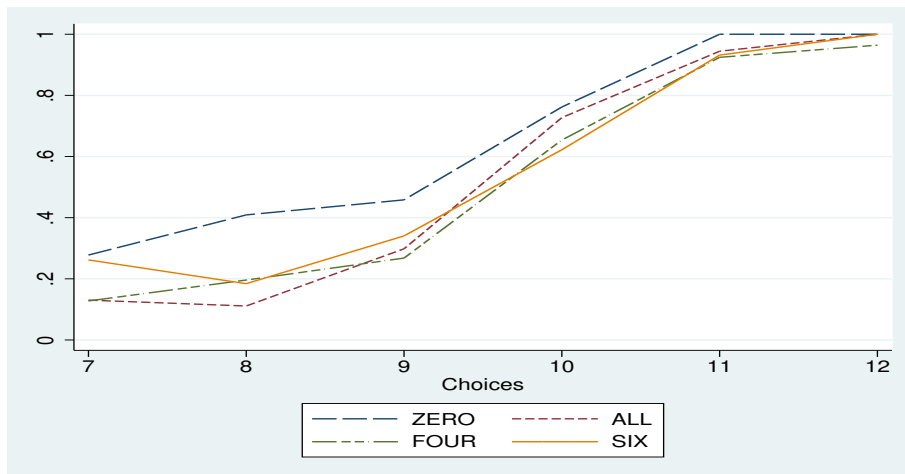


FIGURE 4.5: Proportion of subjects choosing to bet on the Red ball per treatment in the loss domain

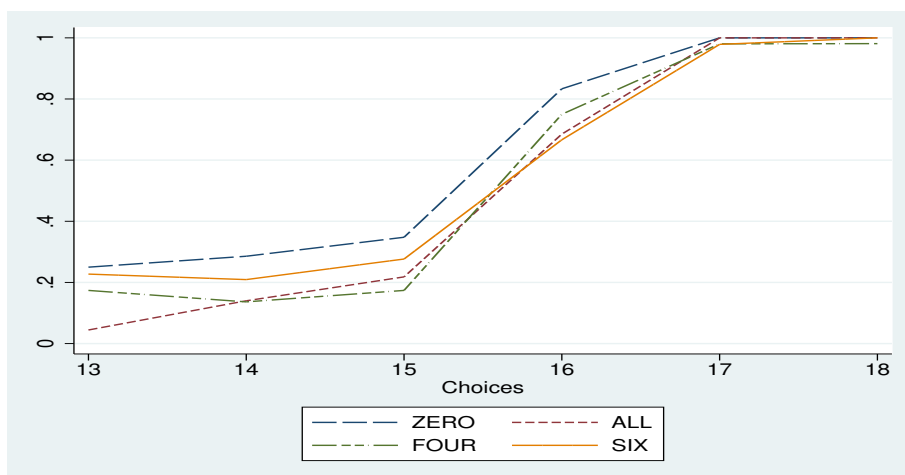


FIGURE 4.6: Proportion of subjects choosing to bet on the Red ball per treatment in the mixed domain

4.6 Discussion

4.6.1 Discussion of the findings

This chapter contributes to the literature on social influence on individual decision making in two ways. First, the impact of domain outcomes is considered (whether gain, loss or mixed domain) and the impact of correlation of payments and the size of the group of the subjects for which payments are correlated.

Hypothesis 1: Ambiguity attitudes are different for gains and losses. Subjects are expected to prefer less ambiguous events for gains and more ambiguous events for losses.

This hypothesis is not verified. I find no significance difference in ambiguity aversion and ambiguity seeking between gains and losses. However, in treatment FOUR, ambiguity neutrality in gains is significantly higher than in losses. Moreover, in treatment SIX, ambiguity neutrality is significantly higher in gains than in losses, and ambiguity incoherence is significantly lower in gains than in losses. This result is in line with [Voorhoeve et al. \(2016\)](#) who found that the prevalence of ambiguity aversion does not depend on framing. When comparing the aggregates of gain and loss frames, the only significant finding (at 10% level) is an unpredicted decrease in ambiguity neutral behavior.

Hypothesis 2: Ambiguity attitudes differ in mixed domain where subjects are confronted by gains and losses in the same situation.

This hypothesis is only verified in treatment ALL where ambiguity seeking in gains is significantly higher than in mixed domain which is in line with [Abdellaoui et al. \(2016\)](#). In treatment FOUR, ambiguity neutrality in gains is significantly higher than in mixed domain and ambiguity incoherence is significantly lower in gains than in mixed domain.

Hypothesis 3: Correlating payments has an impact on ambiguity attitudes. Subjects are expected to be less ambiguity averse when payments are correlated.

This hypothesis is verified in gain, loss and mixed domains. The share of ambiguity averse subjects in ZERO treatment is significantly higher than that in ALL treatment. Hence, correlating payments decreases significantly ambiguity aversion.

Friedl et al. (2017) found that men showed significant levels of ambiguity aversion in the correlated treatment, but not in the uncorrelated treatment. Hence, men were less ambiguity averse in the uncorrelated treatment. Additionally, women's choices were not significantly different between the two treatments. However, I find that subjects were less ambiguity averse when payments are correlated.

Hypothesis 4: The size of the group for which payments are correlated matters.

This hypothesis is not verified. There is no significant difference in ambiguity attitudes in treatment SIX and FOUR. This result might be due to the minor difference in group size between both treatments.

4.6.2 Discussion of the task

One question on which there is disagreement in the literature is the prevalence of ambiguity aversion. While there is a number of studies showing that subjects are typically ambiguity averse (Trautmann and Van De Kuilen (2015)), some recent papers (Binmore et al. (2012), Charness et al. (2013), Stahl (2014)) report very small fractions of ambiguity averse subjects. A possible conclusion from these studies is that the measured degree of ambiguity aversion may depend on the elicitation method. Trautmann et al. (2011) bring evidence that choice tasks elicit lower ambiguity aversion than valuation tasks. In Charness et al. (2013)'s design a combination of the three-color task with choice based elicitation procedures leads to low levels of ambiguity aversion. Hence, other elicitation methods could have been more convenient. First, Halevy (2007)'s version of Ellsberg's measure of ambiguity aversion using the Becker et al. (1964) mechanism to elicit subjects reservation prices for a risky urn and an ambiguous urn could have been used to

elicit ambiguity attitudes. However, this method entails a uniform overestimation of ambiguity aversion. Second, [Dimmock et al. \(2016\)](#) showed that matching probabilities are convenient for measuring ambiguity attitudes. Matching probability is defined as the objective probability of the risky urn for which the participant is indifferent between betting on the risky versus the ambiguous urn. In this context, matching probabilities could have been used to elicit subjects ambiguity aversion.

4.6.3 Impact of the findings

The existing literature on how social aspects influence ambiguity attitudes is related to this chapter because different outcome correlation structures are expected to have an impact on choices only under social comparison. Another line of research studies the impact of joint group decisions under ambiguity. Making a joint group decision or at least having the possibility of interacting with others before decision reduces the fear of negative evaluation which has been proposed in the literature as a cause of ambiguity aversion ([Trautmann et al. \(2008\)](#), [Curley et al. \(1986\)](#)). People shy away from processes about which they think they have insufficient information because of the expectation that one's actions may be difficult to justify in front of others ([Frisch and Baron, 1988](#)). Thus, a risky prospect is perceived as more justifiable than the ambiguous one because probabilistic information is missing from the ambiguous urn. In group decisions, payments are correlated in such a way that they are determined according to one, randomly selected, choice the group made. However, in this experiment, decisions were made individually and payments are correlated such that one urn is randomly chosen to determine all subjects earnings. Thus, all subjects are hit by the same "fate" and social comparison is possible. I find that the correlation of payments decreases significantly ambiguity aversion in all domains although decisions are made individually. Hence, the convergence towards ambiguity neutrality in group decision can be explained by the correlation of payments.

4.6.4 Practical Implications

It has been found that risk-taking behavior is influenced by the correlation of outcomes and I test whether this also holds for ambiguity attitudes. To extend this field to ambiguity appears relevant, because most decisions in the real world are characterized by ambiguity where objective probabilities do not exist or are unknown rather than risk (Heath and Tversky (1991)). The most familiar domain is insurance that requires the estimation of various risks and potential losses such as insurance against unintended side-effects of newly developed technologies that can affect a person and their peers. Insurance is less attractive when outcomes are correlated.

4.6.5 Conclusion

In this chapter, I used the design of Charness et al. (2013) to see whether ambiguity attitudes vary across domain (gain, loss and mixed domain) and with the correlation of payments. The mixed domain is important since it relates to the type of prospects experienced by decision makers in financial markets, medical decisions, or legal decisions, for example.

Correlating payments has an impact on ambiguity attitudes. The design of Charness et al. (2013) predicts the prevalence of ambiguity neutrality, thus a small share of subjects are ambiguity averse. When correlating payments, the share of ambiguity aversion decreases even more. However, the share of ambiguity averse subjects is not sufficient to have a reliable conclusion regarding the effect of the treatments on ambiguity aversion. Regarding the difference across domains, a switch from gains to losses does not change ambiguity aversion and ambiguity seeking behavior, however, it leads to a decrease in ambiguity neutrality. A switch from gains to mixed domain also leads to a decrease in ambiguity neutrality.

Finally, the size of the group for which payments are correlated does not affect ambiguity attitudes. This result might be due to the minor difference in group size

between treatment FOUR (where payments are correlated for groups of four subjects) and SIX (where payments are correlated for groups of six subjects).

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General Conclusion

Within the chapters of this thesis, I contributed with three essays on decision making under risk and ambiguity. Some questions have been answered and discussed in this thesis. Chapter 1 raises the question about the representativeness of the experimental results based on samples of students drawn from Western, Educated, Industrialized, Rich, and Democratic (WEIRD) societies based on the criticism of [Henrich et al. \(2010\)](#) and whether these results are generalizable. To answer this question, this chapter provided an overview of the experimental literature on individual preferences and compared between experimental results across countries as well as within country. The analysis of the experimental results on individual preferences included social preferences, risk and time preferences.

Regarding social preferences, first, this chapter assessed the external validity of experimental results on prosocial behavior in prisoner's dilemma and public good games. Previous studies showed a heterogeneity in cooperation levels across countries as well as within country. There is a negative relation between norms of cooperation and development level of a country. At the aggregate level, the results showed that students and WEIRD populations cooperate significantly less than non-students and non-WEIRD populations. Second, the results of experiments on trust games were used to assess the levels of trust and reciprocity. There is a monotonic positive correlation between trust and reciprocity for student and WEIRD populations. However, this correlation does not exist for non-student as well as non-WEIRD populations. Third, the results of experiments on ultimatum and dictator games were used to assess norms of fairness and altruism. The difference between the average offer of the ultimatum and the dictator game

in developing countries is much lower than that of the student populations. Hence, the behavior of subjects in developing countries are influenced by the norms. Regarding risk and time preferences, experimental results on risk preferences showed that there is indeed a variability across countries as well as within country. The experimental literature is heterogeneous in terms of methodology, design and context. Therefore, it is difficult to have a conclusion for students or any other particular population regarding these preferences.

The following chapters focused on decision making under risk and ambiguity. The main research question in Chapter 2 is how risk and ambiguity impact job search behavior. To answer this question, we conducted an experiment that aims at eliciting both search durations and reservation wages under risk and ambiguity. The two treatments of risk and ambiguity differ in the information about the probability of receiving an offer. Under risk, this probability was known, however, under ambiguity this probability was unknown. We found that observed reservation wages are overall lower than the theoretical reservation wages and are decreasing over time under risk and ambiguity. The decrease in reservation wage under risk in an infinite search horizon is line in with [Braunstein and Schotter \(1981, 1982\)](#). By comparing reservation wages under risk and ambiguity, we found that subjects behave as ambiguity neutral agents suggesting that ambiguity does not have a strong impact on job search decisions. To our knowledge, the effect of ambiguity on search behavior in an infinite horizon has not been studied before. However, [Asano et al. \(2015\)](#) studied the effect of ambiguity on search behavior in a finite horizon and found that ambiguity decreases significantly the reservation points. Ambiguity in their study was presented by an unknown offer distribution. In our experiment, ambiguity was presented over the probability of receiving an offer in a search spell.

Research in economics and other disciplines has acknowledged that social comparison is an important determinant of human behavior, since agents care not only about their own absolute income and consumption levels, but also their relative position with respect to others. In order to provide a good understanding of the relevance of social

comparison, Chapter 3 explored the effect of social comparison as well as the correlation of risks on risk attitudes in the gain, loss and mixed domain. The contribution of this chapter is to add a mixed domain. What makes the mixed domain special is the influence of loss aversion on choice behavior. Loss aversion can be viewed as the component of risk attitude that relates risk behavior in the separate domains of gains and losses (Brooks and Zank, 2005). To do so, I conducted an experiment (Initial Experiment) based on Linde and Sonnemans (2015) to elicit risk attitudes in three types of domains: gains (all outcomes are positive), losses (all outcomes are negative), and mixed domain (where outcomes can be gains or losses). In the first part of the experiment, subjects faced a set of binary risky choices individually. In the second part, social comparison was introduced. In this experiment, risks were correlated in the first part (Individual treatment) as well as the second part (Social treatment). To see if correlation of risks has an effect on risk attitudes, I conducted another experiment (Robustness experiment) that has the same design as the initial experiment except that risks are not correlated in the first part of the experiment (Individual treatment). In this chapter, I find that when introducing social context, risk aversion for gains remains significantly higher than that for losses as predicted by the Prospect Theory. This result is not in line with Linde and Sonnemans (2012) who found that when social comparison is present subjects are more risk averse in loss situation than in gain which is the opposite of the Prospect Theory. Additionally, the introduction of social context in the mixed domain decreases significantly loss aversion. This result implies that contrary to the individual setting, gains resonate more than losses in social setting. Hence, favorable social comparisons resonate more than unfavorable social comparisons. This result in the mixed domain is in line with Bault et al. (2008).

The correlation of risks is an experimental feature that influences risk taking behavior (Schmidt et al., 2015). I find that the correlation of risks generates an increase in risk aversion only in mixed domain. However, Schmidt et al. (2015) explored the effect of the correlation of risks in the gain domain. They used the willingness to pay (WTP) for a lottery where subjects could either win 10 euros or receive nothing to elicit risk attitudes and showed that risk aversion decreases when risks are correlated. Hence, the correlation of risks affects differently risk attitudes depending on the domain.

In accordance with the previous chapter, Chapter 4 aims to answer the following questions: Do ambiguity attitudes vary across domains? Does correlating payments have an impact on ambiguity attitudes? Do ambiguity attitudes vary with the size of the group of subjects for which payments are correlated? To answer the first question, I conduct an experiment where subjects were asked to choose between betting on unambiguous event and ambiguous events of their choice in a three-color version of [Ellsberg \(1961\)](#) experiment in a between-subjects design in three types of prospects: gain, loss and mixed prospects. To answer the second and the third question, I correlate payments across subjects to see if correlation of payments has an impact on ambiguity attitudes. I find that overall the majority of subjects are ambiguity neutral and that correlating payments decreases significantly ambiguity aversion. The prevalence of ambiguity neutrality is due to the task. One limitation of this chapter is the method used to elicit ambiguity attitudes. I used the design of [Charness et al. \(2013\)](#) where they found that the majority of subjects are ambiguity neutral. [Trautmann et al. \(2011\)](#) bring evidence that choice tasks, which is used in this chapter, elicit lower ambiguity aversion than valuation tasks. Hence, the type of elicitation tasks used has an important influence in measuring ambiguity attitudes. Thus, the share of ambiguity averse subjects is not sufficient to have reliable conclusions regarding the effect of the treatments on ambiguity aversion. Matching probabilities could have been used to elicit ambiguity attitudes providing more reliable results.

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Appendix A

.1 Mesures Comportementales de l'équité, de la confiance et de l'altruisme

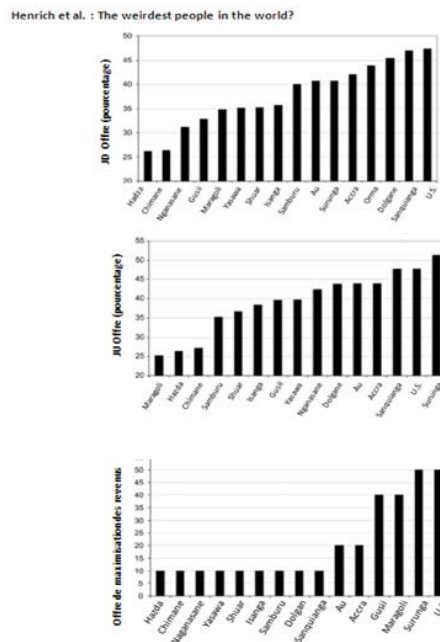


FIGURE 7: Mesures Comportementales de l'équité et de la punition des jeux de dictateur et de l'ultimatum pour 15 sociétés

Source: Henrich, et al. (2010). The weirdest people in the world?. Behavioral and brain sciences, 33(2-3), 61-83.

Etude	Pays	Etudiants	Fraction envoyée	Fraction reçue	Proportion de retour
Ashraf et al. (2005)	Russie	Oui	0.49	0.29	0.80
	Afrique de Sud	Oui	0.43	0.27	0.73
Berg et al. (1995)	Etats-Unis	Oui	0.52	0.32	0.90
Burks et al. (2003)	Etats-Unis	Oui	0.65	0.40	1.31
	Etats-Unis	Oui	0.41	0.23	0.58
Barr (2003)	Zimbabwe	Non	0.43	0.43	1.28
Buchan et al. (2003)	Etats-Unis	Oui	0.65	0.45	1.35
	Chine	Oui	0.73	0.50	1.51
	Japon	Oui	0.68	0.50	1.51
	Corée du Sud	Oui	0.64	0.49	1.47
Burns (2004)	Afrique du Sud	Oui	0.33	0.23	0.70
Cardenas (2003)	Colombie	Oui	0.50	0.41	1.22
Carter et Castillo (2002)	Afrique du Sud	Non	0.53	0.38	1.14
Castillo et Carter (2003)	Honduras	Non	0.49	0.42	1.26
Holm et Danielson (2005)	Tanzanie	Oui	0.53	0.37	1.17
	Suède	Oui	0.51	0.35	1.05
Danielson et Holm (2003)	Tanzanie	Non	0.56	0.46	1.40
Ensminger (2000)	Kenya	Non	0.44	0.18	0.54
Fehr et List (2004)		Oui	0.40	0.32	0.96
	Costa Rica	Non	0.59	0.44	1.32
Greig et Bohnet (2005)	Kenya	Non	0.30	0.41	0.82
Johansson-Stenman et al. (2013)	Bangladesh	Non	0.46	0.48	1.45
Karlan (2005)	Pérou	Non	0.46	0.43	1.12
Koford (2001)	Bulgarie	Oui	0.63	0.46	1.34
Lazzarini et al. (2004)	Brésil	Oui	0.56	0.34	0.80
Mosley et Verschoor (2003)	Ouganda	Non	0.49	0.33	0.99
Schechter (2004)	Paraguay	Non	0.47	0.44	1.31
Wilson et Bahry (2002)	Russie	Non	0.51	0.38	1.51

TABLE 10: Confiance dans les pays développés et en voie de développement

Source: Cardenas et al. (2008). Behavioural development economics: Lessons from field labs in the developing world. *Journal of Development Studies* 44(3):311–38.

Etudes	Lieu	Etudiants	Offre moyenne	Taux de rejet	
Carpenter et al. (2005)	Etats-Unis	Oui	0,41	0,05	
		Non	0,45	0,07	
Cameron (1999)	Indonésie	Oui	0,42	0,10	
Gowdy et al. (2003)	Nigéria	Non	0,43	0,01	
	Pérou – Matsigenka	Non	0,26	0,05	
	Tanzanie – Hadza	Non	0,40 ; 0,27	0,19 ; 0,28	
	Bolivie – Chimane	Non	0,37	0,00	
	Equateur – Quichua	Non	0,27	0,15	
	Mongolie – Torgut	Non	0,35 ; 0,36	0,05	
	Chili – Mapuche	Non	0,34	0,07	
	PNG – Au	Non	0,43 ; 0,38	0,27 ; 0,40	
	Tanzanie – Sangu	Non	0,41 ; 0,42	0,25 ; 0,05	
	Zimbabwe	Non	0,41 ; 0,45	0,10 ; 0,07	
	Equateur – Achuar	Non	0,42	0,00	
	Kenya – Orma	Non	0,44	0,04	
	Paraguay – Aché	Non	0,51	0,00	
	Indonésie – Lamelera	Non	0,58	0,00	
	Henrich et al. (2006)	Etats-Unis	Oui	0,41	0,42
		Etats-Unis	Non	0,48	0,71
Kenya – Maragoli		Non	0,25	0,96	
Kenya – Samburu		Non	0,35	0,10	
Kenya – Gusii		Non	0,40		
Ghana – Accra		Non	0,44	0,33	
Tanzanie – Hadza		Non	0,26	0,42	
Tanzanie – Isanga		Non	0,38	0,10	
Sibérie – Dolgan		Non	0,43	0,35	
La Papouasie-Nouvelle-Guinée – Au		Non	0,44	0,43	
La Papouasie-Nouvelle-Guinée – Surunga		Non	0,51	0,69	
Fiji – Yawasa		Non	0,40	0,15	
Bolivie – Chimane		Non	0,27	0,03	
Colombie Sanquianga		Non	0,48	0,30	
Equateur – Shuar		Non	0,37	0,10	

TABLE 11: Confiance dans les pays développés et en voie de développement (Etudes du Jeu de l'Ultimatum)

Source: Cardenas et al. (2008). Behavioural development economics: Lessons from field labs in the developing world. *Journal of Development Studies* 44(3):311–38.

Etudes	Lieu	Etudiants	Allocation moyenne
Carpenter et al. (2005)	Etats-Unis	Oui	0,25
		Non	0,45
Ashraf et al. (2005)	Etats-Unis	Oui	0,24
	Russie	Oui	0,26
	Afrique du Sud	Oui	0,25
Burns (2004)	Afrique du Sud	Oui	0,26
Cardenas et Carpenter (2004)	Etats-Unis	Oui	0,27
	Colombie	Oui	0,19
Carter et Castillo (2002)	Afrique du Sud	Non	0,42
Castillo et Carter (2003)	Honduras	Non	0,42
Holm et Danielson (2005)	Tanzanie	Oui	0,24
	Suède	Oui	0,28
Ensminger (2000)	Kenya	Non	0,31
Gowdy et al. (2003)	Nigéria	Non	0,42
Henrich et al. (2006)	Etats-Unis	Oui	0,32
	Etats-Unis	Non	0,47
	Kenya – Maragoli	Non	0,35
	Kenya – Samburu	Non	0,40
	Kenya – Gusii	Non	0,33
	Ghana – Accra	Non	0,42
	Kenya – Samburu	Non	0,35
	Kenya – Gusii	Non	0,40
	Ghana – Accra	Non	0,44
	Tanzanie – Hadza	Non	0,26
	Tanzanie – Isanga	Non	0,36
	Sibérie – Dolgan	Non	0,37
	La Papouasie-Nouvelle-Guinée – Au	Non	0,41
	La Papouasie-Nouvelle-Guinée – Surunga	Non	0,41
	Fiji – Yawasa	Non	0,35
	Bolivie – Chimane	Non	0,26
Colombie – Sanquianga	Non	0,44	
Equateur – Shuar	Non	0,35	

TABLE 12: Altruisme dans les pays en développement (Etudes du Jeu de l'Ultimatum)

Source: Cardenas et al. (2008). Behavioural development economics: Lessons from field labs in the developing world. *Journal of Development Studies* 44(3):311–38

Appendix B

From table 13 to 17, the reservation wage in period t is denoted with *, ** and *** if it is significantly lower than that of period 1 at 1%, 5% and 10% significance level respectively. Additionally, the reservation wage in period t is highlighted if it is significantly lower than that of period $t - 1$.

From table 28 to 34, the reservation wage in period t is denoted with *, ** and *** if it is significantly lower than that of period $t - 1$ at 1%, 5% and 10% significance level respectively.

From table 35 to 40, the reservation wage in period t is denoted with *, ** and *** if it is significantly lower than that of period $t - 1$ at 1%, 5% and 10% significance level respectively.

.2 Tables

TABLE 13: Average reservation wage per period for the urn K_1

Period \ Subjects	114	107	100	88	81	72	67	64	56	53
1	6.72	6.76	6.67	6.78	7.09	7.37	7.57	7.73	7.41	7.57
2		5.99**	6.09**	6.09**	6.33**	6.35***	6.46***	6.58***	6.7**	6.87**
3			6.11**	6.15**	6.39**	6.51***	6.6***	6.67***	6.48***	6.62***
4				5.92***	6.14***	6.25***	6.31***	6.39***	6.29***	6.38**
5					5.85***	6.04***	6.15***	6.2***	6.11***	6.13***
6						6.07***	6.18***	6.23***	6.16***	6.21***
7							5.78***	6***	5.8***	5.74***
8								6.14***	5.95***	5.91***
9									6.16***	6.06***
10										5.77***

TABLE 14: Average reservation wage per period for the urn K_3

Period \ Subjects	114	90	72	57	47	38
1	8.54	8.54	8.64	9.53	10.17	9.95
2		8.21**	8.42	9.19**	9.68***	9.47***
3			7.86***	8.54***	9.25***	9***
4				8.3***	9.02***	8.68***
5					8.64*	8.42***
6						8.05***

TABLE 15: Average reservation wage per period for the urn K_5

Period \ Subjects	114	70	48	38
1	11.17	11.71	12.15	12.24
2		11.26***	11.75*	11.82*
3			11.27***	11.18***
4				10.5**

TABLE 16: Average reservation wage per period for the urn K_7

Period \ Subjects	114	82	52	33
1	13.35	14.76	15.63	16.3
2		13.95***	14.5***	15.97*
3			14.08***	15.3**
4				13.91***
5				

TABLE 17: Average reservation wage per period for the urn K_9

Period \ Subjects	114	64	40
1	14.39	16.37	16.65
2		15.75**	15.95***
3			15.15***

TABLE 18: Difference between urn K_1 and K_3

Period \ Subjects	114	85	63
1 K_1	6.72	6.51	6.41
1 K_3	8.54	8.51	8.56
2 K_1		5.84	6.05
2 K_3		8.18	8.33
3 K_1			6.21
3 K_3			7.68

TABLE 19: Difference between urn K_1 and K_5

Period \ Subjects	114	65	41
1 K_1	6.72	6.8	7.29
1 K_5	11.18	11.88	12.12
2 K_1		5.47	6.34
2 K_5		11.43	11.93
3 K_1			6.61
3 K_5			11.24

TABLE 20: Difference between urn K_1 and K_7

Period \ Subjects	114	77	47
1 K_1	6.72	7.17	7.28
1 K_7	12.35	14.79	15.51
2 K_1		6.17	6.15
2 K_7		14.1	14.51
3 K_1			6.57
3 K_7			13.98

TABLE 21: Difference between urn K_1 and K_9

Period \ Subjects	114	57	34
1 K_1	6.72	7	6.79
1 K_9	14.39	16.44	16.59
2 K_1		6.3	6.26
2 K_9		15.86	16.32
3 K_1			6.59
3 K_9			15.62

TABLE 22: Difference between urn K_3 and K_5

Period \ Subjects	114	58	30
1 K_3	8.54	8.69	10.07
1 K_5	11.18	12.07	12.7
2 K_3		8.33	9.67
2 K_5		11.66	12.43
3 K_3			9.03
3 K_5			11.97

TABLE 23: Difference between urn K_3 and K_7

Period \ Subjects	114	63	30
1 K_3	8.54	9.54	10.37
1 K_7	13.35	15.2	16.33
2 K_3		8.9	9.7
2 K_7		14.5	15.33
3 K_3			9.4
3 K_7			15.07

TABLE 24: Difference between urn K_3 and K_9

Period \ Subjects	114	53
1 K_3	8.54	9.4
1 K_9	14.39	17.11
2 K_3		8.98
2 K_9		16.43

TABLE 29: Average reservation wage over periods for the urn U_5

Period \ Subjects	114	82	52	37	28
1	10.57	11.28	12.08	12.38	13.18
2		10.73**	11.58*	12.03	12.79
3			11	11.22***	11.75***
4				10.62***	11.18***
5					10.96***

TABLE 30: Average reservation wage over periods for the urn U_9

Period \ Subjects	114	52	22
1	10.19	12.6	13.77
2		11.65***	13.41**
3			12.72***

TABLE 31: Average reservation wage over periods for the urn U_1^L

Period \ Subjects	114	105	97	89	83	73	70	66	60	56
1	8.92	8.98	9.11	9.27	9.46	9.62	9.63	9.42	9.48	9.57
2		8.73**	8.82***	8.97***	9.24**	9.32**	9.37***	9.17**	9.18***	9.27**
3			8.72**	8.83**	9.12**	9.22**	9.26**	9.06*	9.13*	9.16**
4				8.42***	8.76***	8.74***	8.8***	8.65**	8.87***	9**
5					8.17***	8.16***	8.2***	8.08***	8.47**	8.59***
6						8.26***	8.33***	8.2***	8.6**	8.7**
7							8.09***	7.93***	8.32***	8.32***
8								7.74***	8.13***	8.2***
9									7.32***	7.46***
10										7.63***

TABLE 32: Average reservation wage over periods for the urn U_5^L

Period \ Subjects	114	70	34	25
1	8.91	9.01	10.68	10.6
2		8.69**	10.5	10.36
3			10.03**	10
4				9.48***

TABLE 33: Average reservation wage over periods for the urn U_5^H

Period \ Subjects	114	84	67	53	39	23
1	12.27	13.48	14.09	14.19	14.77	15.48
2		13.26	13.94	14.04	14.62	14.78**
3			13.37***	13.55**	13.97**	14.22***
4				12.57***	12.92***	13.35***
5					11.59***	12.04***
6						12.87***

TABLE 34: Average reservation wage over periods for the urn U_9^H

Period \ Subjects	114	63	44	24
1	12.61	13.87	14.55	15.46
2		13.3*	14.2	15.46
3			13.11***	13.83***
4				13.08***

TABLE 35: Average reservation wage over periods for the urn U_1

Period \ Subjects	114	107	100	89	82	74	70	64	60	58
1	10.73	10.79	10.66	10.82	10.78	10.91	10.21	11.09	11.37	11.29
2		9.96***	9.84***	10***	9.96***	10.19***	10.21***	10.34***	10.72***	10.62***
3			9.52	9.75	9.71	9.905	9.94	10.13	10.53	10.48
4				9.1***	8.92***	9.3***	9.3**	9.48**	9.72***	9.81**
5					8.12***	8.39***	8.41**	8.5***	8.72***	8.86**
6						8.24	8.27	8.36	8.42	8.55
7							7.91	8.02	8.07	8.19
8								7.83*	7.92	8.03
9									7.53	7.67
10										7.64

TABLE 36: Average reservation wage over periods for the urn U_5

Period \ Subjects	114	82	52	37	28
1	10.57	11.28	12.08	12.38	13.18
2		10.73**	11.58*	12.03	12.79
3			11***	11.22***	11.75***
4				10.62***	11.18***
5					10.96

TABLE 37: Average reservation wage over periods for the urn U_9

Period \ Subjects	114	52	22
1	10.19	12.6	13.77
2		11.65***	13.41**
3			12.72***

TABLE 38: Average reservation wage over periods for the urn U_1^L

Period \ Subjects	114	105	97	89	83	73	70	66	60	56
1	8.92	8.98	9.11	9.27	9.46	9.62	9.63	9.42	9.48	9.57
2		8.73**	8.82***	8.97***	9.24**	9.32**	9.37***	9.17**	9.18***	9.27**
3			8.72	8.83	9.12	9.22	9.26	9.06	9.13	9.16
4				8.42***	8.76**	8.74***	8.8***	8.65**	8.87*	9
5					8.17***	8.16***	8.2***	8.08***	8.47**	8.59**
6						8.26	8.33	8.2	8.6	8.7
7							8.09	7.93	8.32	8.32
8								7.74	8.13	8.2
9									7.32***	7.46***
10										7.63

TABLE 39: Average reservation wage over periods for the urn U_5^L

Period \ Subjects	114	70	34	25
1	8.91	9.01	10.68	10.6
2		8.69**	10.5	10.36
3			10.03**	10
4				9.48*

TABLE 40: Average reservation wage over periods for the urn U_9^H

Period \ Subjects	114	63	44	24
1	12.61	13.87	14.55	15.46
2		13.3*	14.2	15.46
3			13.11**	13.83*
4				13.08***

TABLE 41: Difference in average reservation wage between urns U_5^H and U_9^H

Period	Subjects		
	114	45	30
1 U_5^H	12.27	14.44	14.53
1 U_9^H	12.61	15.16	15.3
2 U_5^H		14.11	14.4
2 U_9^H		14.2	14.53
3 U_5^H			13.47
3 U_9^H			13.83

TABLE 42: Difference in average reservation wage between urns U_1^L and U_5^L

Period	Subjects	
	114	64
1 U_1^L	8.92	8.88
1 U_5^L	8.91	8.91
2 U_1^L		8.73
2 U_5^L		8.55

TABLE 43: Difference in average reservation wage between urns U_1 and U_9

Period	Subjects	
	114	49
1 U_1	10.73	12.08
1 U_9	10.19*	12.47
2 U_1		11.08
2 U_9		11.59

TABLE 44: Difference in average reservation wage between urns U_5 and U_9

Period	Subjects	
	114	34
1 U_5	10.57	12.47
1 U_9	10.19	13.68
2 U_5		12.42
2 U_9		13

TABLE 45: Difference in average reservation wage between urns U_9^H and K_9

Period \ Subjects	Subjects	
	114	39
1 Risk	14.39	16.59
1 Ambiguity	12.61***	14.69***
2 Risk		15.72
2 Ambiguity		14***

TABLE 46: Difference in average reservation wage between urns U_9^H and K_5

Period \ Subjects	Subjects	
	114	40
1 Risk	11.18	12.5
1 Ambiguity	12.61***	14.08***
2 Risk		12.5
2 Ambiguity		13.1

TABLE 47: Difference in average reservation wage between urns U_9^H and K_7

Period \ Subjects	Subjects	
	114	44
1 Risk	13.35	15.2
1 Ambiguity	12.61**	14.73
2 Risk		14.48
2 Ambiguity		14.48

TABLE 48: Difference in average reservation wage between urns U_5^H and K_5

Period \ Subjects	Subjects		
	114	55	30
1 Risk	11.18	12.25	13
1 Ambiguity	12.27***	13.49**	14.57*
2 Risk		11.87	13
2 Ambiguity		13.14**	14.27*
3 Risk			12.33
3 Ambiguity			13.8**

TABLE 49: Difference in average reservation wage between urns U_5^H and K_7

Period \ Subjects	114	64	39
1 Risk	13.35	15.31	16.15
1 Ambiguity	12.27***	13.95***	14.44***
2 Risk		14.42	14.94
2 Ambiguity		13.8	14.31
3 Risk			14.67
3 Ambiguity			13.77

TABLE 50: Difference in average reservation wage between urns U_5^H and K_9

Period \ Subjects	114	49	26
1 Risk	14.39	16.47	17.81
1 Ambiguity	12.27***	14.16***	14.35***
2 Risk		16.16	17.54
2 Ambiguity		14.14***	14.58***
3 Risk			16.77
3 Ambiguity			14***

TABLE 51: Difference in average reservation wage between urns U_5^L and K_1

Period \ Subjects	114	64	27
1 Risk	6.72	6.67	6.89
1 Ambiguity	8.91***	8.89***	10.41***
2 Risk		6.2	6.89
2 Ambiguity		8.56***	10.22***
3 Risk			6.48
3 Ambiguity			9.67***

TABLE 52: Difference in average reservation wage between urns U_5^L and K_3

Period	114	51
1 Risk	8.54	8.35
1 Ambiguity	8.91	9.45**
2 Risk		8.02
2 Ambiguity		9.16**

TABLE 55: Difference in average reservation wage between urns U_1^L and K_3

Period \ Subjects	114	83	61	46	35
1 Risk	8.54	8.58	8.46	9.48	10.29
1 Ambiguity	8.92	9.14	9.02	9.67	10.6
2 Risk		8.2	8.21	9.09	9.74
2 Ambiguity		8.83*	8.77	9.45	10.34
3 Risk			7.63	8.41	9.34
3 Ambiguity			8.66**	9.24*	10.09
4 Risk				8.2	9.11
4 Ambiguity				8.8	9.4
5 Risk					8.6
5 Ambiguity					8.69

TABLE 56: Difference in average reservation wage between urns U_1^L and K_5

Period \ Subjects	114	66	37	30
1 Risk	11.18	11.86	12.51	12.53
1 Ambiguity	8.92***	9.17***	10.32***	9.9***
2 Risk			12.21	12.2
2 Ambiguity			9.89***	9.53***
3 Risk			11.65	11.47
3 Ambiguity			9.78**	9.47**
4 Risk				10.37
4 Ambiguity				8.97

TABLE 57: Difference in average reservation wage between urns U_1 and K_1

Subjects Period	114	100	89	68	56	42	36	32
1 Risk	6.72	6.8	6.54	6.97	7.36	7.86	7.92	7.88
1 Ambiguity	10.73***	10.73***	10.55***	11***	10.89***	11.57***	11.96***	11.72***
2 Risk		6.15	6.34	6.71	7.04	7.17	7.08	7
2 Ambiguity		9.92***	9.79***	10.21***	10.09***	18.83***	10.94***	10.97***
3 Risk			6.13	5.57	6.82	7.12	6.97	6.81
3 Ambiguity			9.25***	9.71***	9.66***	10.17***	10.11***	10.19***
4 Risk				6.34	6.57	6.69	6.75	6.53
4 Ambiguity				9.29***	9.11***	5.57***	9.44***	9.56***
5 Risk					6.07	6.24	6.33	6.03
5 Ambiguity					8.55***	8.9***	8.75***	8.78***
6 Risk						6.33	6.53	6.31
6 Ambiguity						8.79***	8.56***	8.6***
7 Risk							6.44	6.22
7 Ambiguity							8.42***	8.5***
8 Risk								6.09
8 Ambiguity								8.28***

TABLE 58: Difference in average reservation wage between urns U_1 and K_5

Subjects Period	114	65	41	29
1 Risk	11.16	11.68	12	12.69
1 Ambiguity	10.73	11.38	11.93	12.66
2 Risk		11.25	11.56	12.21
2 Ambiguity		10.32**	10.59*	11.52
3 Risk			11.073	11.48
3 Ambiguity			10.1*	10.35*
4 Risk				10.62
4 Ambiguity				9.28

TABLE 59: Difference in average reservation wage between urns U_5 and K_1

Period \ Subjects	114	75	45	30
1 Risk	6.79	6.79	7.33	7.5
1 Ambiguity	10.57***	11.12***	12.16***	12.47***
2 Risk		6.45	7.36	7.5
2 Ambiguity		10.72***	11.42***	11.87***
3 Risk			6.96	7.33
3 Ambiguity			10.98***	11.27***
4 Risk				7.2
4 Ambiguity				10.7***

TABLE 60: Difference in average reservation wage between urns U_5 and K_5

Period \ Subjects	114	48
1 Risk	11.16	12.29
1 Ambiguity	10.57**	11.79
2 Risk		11.81
2 Ambiguity		11.1

TABLE 61: Difference in average reservation wage between urns U_5 and K_9

Period \ Subjects	114	63	38
1 Risk	14.39	16.32	16.44
1 Ambiguity	10.73***	12.13***	12.55***
2 Risk		15.68	15.74
2 Ambiguity		12.13***	11.45***
3 Risk			15
3 Ambiguity			11.45***

TABLE 62: Difference in average reservation wage between urns U_9 and K_1

Period \ Subjects	114	50
1 Risk	6.72	6.82
1 Ambiguity	10.19***	12.44***
2 Risk		6.14
2 Ambiguity		11.6***

TABLE 63: Difference in average reservation wage between urns U_9 and K_5

Period \ Subjects	Subjects	
	114	33
1 Risk	11.16	13
1 Ambiguity	10.19***	12.79
2 Risk		12.52
2 Ambiguity		12.09

TABLE 64: Difference in average reservation wage between urns U_9 and K_9

Period \ Subjects	Subjects	
	114	28
1 Risk	14.39	17.96
1 Ambiguity	10.19***	13.32***
2 Risk		16.68
2 Ambiguity		12.89***

.3 Instructions

You are participating in an experiment organized by CREM laboratory. During this experiment, you can earn money including a show-up fee for participating in the experiment and your earnings in the experiment. Your score and your final earning in the experiment are expressed in points. At the end of the experiment, your final earning in points will be converted according to the following rate:

$$10 \text{ points} = 1 \text{ euro}$$

Take carefully your decisions. Pay attention to the chances that each possibility is realized as well as the results associated with each possibility before making a decision. These decisions are individual: you will never interact with other participants.

During this experience, you will receive offers that you can accept or reject in successive periods. Your monetary earnings depend on the offers that you have accepted. Obviously, the lower the offers you accept are, the lower your earnings will be.

The experience includes 14 independent markets. Each market is divided in periods that take place in the same way.

.3.1 A market in detail

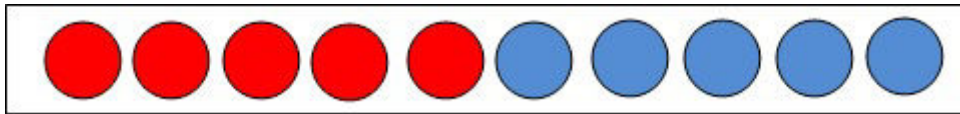
At the beginning of each market, you will learn about the conditions in which the offers will be proposed to you. These conditions are similar for all periods in a market. However, they may vary from one market to another.

In each period, you can receive an offer or not. An offer is proposed to you if a random draw is favorable. This random draw is performed in an urn including 10 balls that are either red or blue. If the drawn ball is red, you will receive an offer. If it is

blue, you will not receive any offer. The content of the urn will remain the same for all periods in a market. However, it may vary from one market to another.

.3.1.1 The content of urns

During the first six markets of the experiment, the content of the urn is completely revealed to you. For example, the following urn will be displayed on your screen:



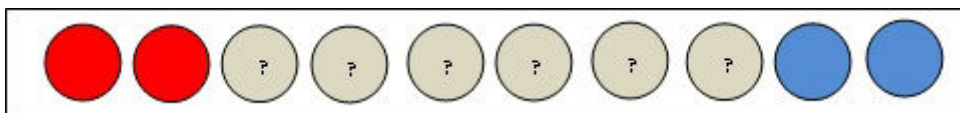
In this example, you know the color of all balls in the urn. It contains 5 red balls and 5 blue balls. So you have 5 chances out of 10 to receive an offer.

Another example of urn is as follows:



In this example, you still know the color of all balls in the urn. It contains 1 red ball and 9 blue balls. In this example, you also know the color of all balls containing the urn. The urn contains this time one red ball and 9 blue balls. So you have 1 chance out of 10 to receive an offer.

On the other hand, during the last eight markets of the experiment, the content of the urn is only partially revealed to you. For example, the following urn will be displayed on your screen:



In this example, you do not know the color of all balls in the urn. It contains 2 red balls, 2 blue balls and 6 balls of indeterminate color that are either red or blue. So you have between 2 chances out of 10 and 8 chances out of 10 to receive an offer.

The content of urns was determined before your arrival in the laboratory. To make sure that the content of the urn has not be chosen to your disadvantage, you could choose, at the beginning of the experiment, if you want either the red balls to be the winning balls or the blue balls to be the winning balls. If you choose

- RED: you will receive an offer when the drawn ball is red but not when it is blue.
- BLUE: you will receive an offer when the drawn ball is blue but not when it is red.

.3.1.2 Your decision

In each market, you make a decision in each period. At each period, your decision consists in indicating for each possible offer if you reject or accept the offer. The possible offers are all integers ranging from 1 to 25 (1, 2, 3, ..., 25). So you have to make 25 decisions.

To make your decisions, you have to complete the following table:

Offer	I reject	I accept
1	<input type="checkbox"/>	<input type="checkbox"/>
2	<input type="checkbox"/>	<input type="checkbox"/>
3	<input type="checkbox"/>	<input type="checkbox"/>
4	<input type="checkbox"/>	<input type="checkbox"/>
5	<input type="checkbox"/>	<input type="checkbox"/>
6	<input type="checkbox"/>	<input type="checkbox"/>
7	<input type="checkbox"/>	<input type="checkbox"/>
8	<input type="checkbox"/>	<input type="checkbox"/>
9	<input type="checkbox"/>	<input type="checkbox"/>
10	<input type="checkbox"/>	<input type="checkbox"/>
11	<input type="checkbox"/>	<input type="checkbox"/>
12	<input type="checkbox"/>	<input type="checkbox"/>
13	<input type="checkbox"/>	<input type="checkbox"/>
14	<input type="checkbox"/>	<input type="checkbox"/>
15	<input type="checkbox"/>	<input type="checkbox"/>
16	<input type="checkbox"/>	<input type="checkbox"/>
17	<input type="checkbox"/>	<input type="checkbox"/>
18	<input type="checkbox"/>	<input type="checkbox"/>
19	<input type="checkbox"/>	<input type="checkbox"/>
20	<input type="checkbox"/>	<input type="checkbox"/>
21	<input type="checkbox"/>	<input type="checkbox"/>
22	<input type="checkbox"/>	<input type="checkbox"/>
23	<input type="checkbox"/>	<input type="checkbox"/>
24	<input type="checkbox"/>	<input type="checkbox"/>
25	<input type="checkbox"/>	<input type="checkbox"/>

In each market, you make a decision in each period. At each period, your decision consists in indicating for each possible offer if you reject or accept the offer. The possible offers are all integers ranging from 1 to 25 (1, 2, 3, ..., 25). So you have to make 25 decisions. To make your decisions, you have to complete the following table. For each possible offer, you have to check:

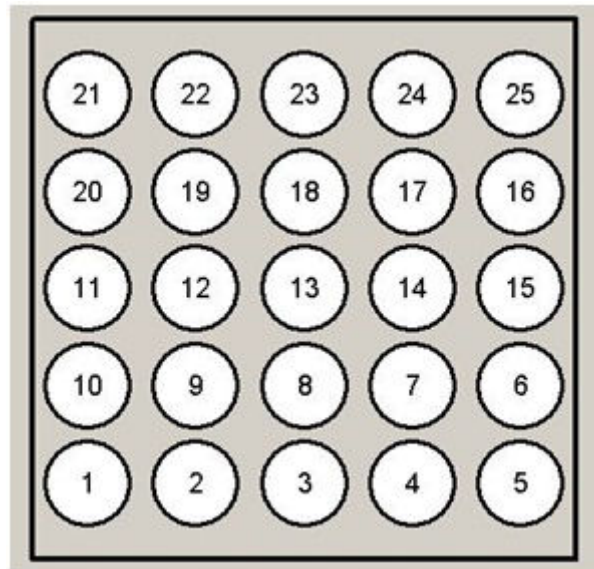
- either the box "I reject"
- or the box "I accept"

To help you to complete the table, when you check a box "I reject", the box "I reject" is automatically checked for all lower offers. By contrast, when you check a box "I accept", the box "I accept" is automatically checked for all higher offers. As long as you do not validate your answers, you can modify them.

.3.1.3 The arrival of an offer and acceptance / rejection

After making and validating your decisions, the random draw performed in the urn determines if you receive an offer (favorable color ball) or not.

- If you do not receive an offer, you start the next period that takes place in the same way.
- If you receive an offer, its value will be randomly drawn between 1 and 25. Each offer has exactly the same chance of being drawn.



- If you committed to reject such offer, it is rejected and you start the next period that takes place in the same way. You have not completed this market and you will have the opportunity to receive other offers in the next periods.
- If you committed to accept such offer, it is accepted and this market is closed. You will not have the opportunity to receive other offers and your score in this market is equal to the present value associated with the offer you have accepted.

.3.1.4 What is your score in this market?

Your score in each market corresponds to the present value of the offer you have accepted . The current value of an offer varies with the offer amount as well as the period in which you accept this offer.

- The current value increases with the offer amount. So the higher the offer you accept is, the higher your score is. For example, in period 3:

Offer	Present value
5	45
10	91
15	136

In period 3, an offer of 5 has a present value equal to 45 points, an offer of 10 has a present value equal to 91 points and an offer of 15 has a present value equal to 136 points.

- The present value decreases over periods. So the later you accept an offer in a market, the lower your score is. For example, an offer of 15:

Period	Present value
1	165
5	113
10	70

An offer of 15 has a present value equal to 165 points at period 1, a present value equal to 113 points at period 5 and a present value equal 70 points at period 10.

During the experiment, you do not need to use a calculator to know the present value of each offer. Throughout the experience, you can refer to a table that shows you the present value of the 25 possible offers in the current period and in a period of your

Offer	Present value in period 3	Present value in period 10
1	9	5
2	18	9
3	27	14
4	36	19
5	45	23
6	55	28
7	64	33
8	73	37
9	82	42
10	91	47
11	100	51
12	109	56
13	118	61
14	127	65
15	136	70
16	145	75
17	155	79
18	164	84
19	173	89
20	182	93
21	191	98
22	200	103
23	209	107
24	218	112
25	227	117

choice, if you want. For example, if you are in period 3 and you also want to know the present value of offers in period 10, you can see the table below:

To display this table on your screen you have to click on the button "PRESENT VALUES", which is at the top right-hand corner of your screen throughout the experiment.

Throughout the experience, you can also refer to a summary table that shows you what happened in previous periods of the market. This table is as follows:

Period	Minimum offer you decided to accept	Offer	Offer amount	Present value
1	17	Yes	10	110
2	19	No		
3	18	Yes	5	45
4	18	No		

In this example, the current period is the period 5 and so the summary table shows what happened in the periods from 1 to 4. The first column displays the period's number. The second column corresponds to your decisions. It indicates the minimum offer you are willing to accept in this period. In this example, at the first period the subject chose to reject all offers ranged from 1 to 17 and to accept all offers ranged from 18 to 25. The third column indicates if you received an offer in this period or not that depends on the color of the randomly drawn ball in the urn. If you received an offer, the fourth column shows the value of the randomly draw offer among the 25 possible offers and the fifth column indicates the current value of this offer. For example, the subject received an offer equals to 5 at the period 3 and the present value of this offer was 45 points. When you do not receive an offer the last two columns remain empty.

During all the experiment, you can display this table by clicking on the button "SUMMARY TABLE" that is at the top right-hand corner of your screen as the button "PRESENT VALUES".

When you accept an offer, the market is closed and the summary table is cleared.

To make clearer what happens in a market, let's take some examples.

Example 1

Example 1 is described in the following table:

Period	Minimum offer you decided to accept	Offer	Offer amount	Present value
1	9	No		
2	11	No		
3	11	Yes	16	145

The subject does not receive any offers during the two first periods. Then he receives an offer of 16 in period 3. In period 3, the subject has chosen to reject offers less than 11 and to accept offers greater than or equal to 11, so the offer of 16 is accepted. The current value of this offer is 145 points. The subject finished this market and his score in this market is 145 points.

Example 2

Example 2 is described in the following table:

Period	Minimum offer you decided to accept	Offer	Offer amount	Present value
1	11	No		
2	11	Yes	7	70
3	11	No		
4	11	Yes	15	124

The subject receives no offer in the first period. Then he receives an offer of 7 at period 2. In period 2, the subject has chosen to reject offers less than 11 and to accept offers greater than or equal to 11, the offer of 7 is rejected and the subject continues this market. In period 3, no offer is made. An offer of 15 is made at period 4. In this period, the subject has chosen to reject offers less than 11 and to accept offers greater than or equal to 11, the offer of 15 is accepted. The present value of this offer is 124 points. The

Period	Minimum offer you decided to accept	Offer	Offer amount	Present value
1	12	Yes	2	22
2	12	No		
3	13	No		
4	13	No		
5	13	No		
6	11	No		
7	11	Yes	9	56
8	11	No		
9	11	No		
10	11	No		
11	11	No		
12	12	No		
13	12	No		
14	12	No		
15	11	No		
16	11	No		
17	11	No		
18	11	No		
19	10	No		
20	10	No		
21	10	Yes	16	26

subject finished this market and his score in this market is 124 points. In the summary table, you can observe the subject would get a lower score by accepting the offer of 7 at period 2 because its presentvalue of 70 points was lower than the 124 points he got.

Example 3

Example 3 is described in the following table:

The subject receives an offer of 2 in period 1. In period 1, the subject has chosen to reject offers less than 12 and to accept offers greater than or equal to 12, the offer of 12 is rejected and the subject continues this market. In periods 2, 3, 4, 5 and 6, the subject does not receive any offer. Then an offer of 9 is made in period 7. In this period, the subject has chosen to reject offers less than 11 and to accept offers greater than or equal to 11, the offer rejected and the subject continues this market. In periods from 8 to 20, the subject receives no offer. Then an offer of 16 is made in period 21. In this period,

the subject has chosen to reject offers less than 11 and to accept offers greater than or equal to 10, the offer of 16 is accepted. The current value of this offer is 26 points. The subject finished this market and his score in this market is 26 points. In the summary table, you can observe the subject would get a higher score by accepting the offer of 9 at period 7 because its present value of 56 points was greater than the 26 points he got.

.3.2 Your final earning in the experiment

Your final earning consists of three parts. The first part is a 4 euros show-up fee for your participation. You also have the opportunity to earn 3 euros if your answers to a simple quiz performed at the beginning of the experiment are correct. The third part of the payment is the most important and it depends on your choices during the experiment. The detail of this part is as follows.

Before starting the experiment, you are going to randomly draw an envelope among 50 envelopes. **YOU MUST NOT OPEN YOUR ENVELOPE AT RISK OF BEING EXCLUDED FROM THE PAYOFF.** Your envelope will be opened by the experimentalist at the end of the experiment. This envelope contains an urn corresponding to one out of 14 markets you completed during the experiment. The order of markets has been randomly drawn before the experiment and neither you, nor the computer program, nor the organizers can change it. For your final earning, we use your score in the market corresponding to the content of your envelope. Your final earning corresponds to the present value of the offer that you accepted in this market. Your scores in the 13 other markets will not be taken into account in the calculation of your payment. **THERE IS ONLY ONE MARKET THAT IS PAID.** It is therefore important that you take your decisions very carefully in each market.

After the experimentalist opened your envelope, to know your score in this market, you have to insert a code that is written on a paper in your envelope into the computer. At the end of the experiment, your earning will be converted into Euros according to the following rate:

10 points = 1 Euro

Your final earnings will be privately paid to you before you leave the laboratory.

In order to become familiar with the game before starting the experiment, you are going to participate in 8 trial markets. These markets are not taken into account for your final earning. When you have completed the 8 trial markets, you have to wait that all the participants finish trial markets before starting the experiment.

You have time to read again those instructions. If you have any question, please raise your hand and we will come to answer you.

Communication between participants is forbidden throughout the session.

Finally, the whole experiment is fair. Neither the choice of envelopes, nor the random draws, nor the offers which will be proposed to you are to be in your favor or in your disadvantage. The organizers are at your disposal for more information about this point.

Appendix C

.4 Initial Experiment: Structural Estimation: Expected Utility Theory by Von Neumann and Morgenstern (1947) in the Loss Domain

In this Appendix, I limit the analysis of CRRA coefficients in the Loss Domain to 58 subjects out of 84 in the individual treatment and 54 in the social treatment for those the CRRA coefficients estimation is significant. Table 65 shows the classification of subjects according to their risk preferences in the loss domain.

TABLE 65: Classification of subjects according to their CRRA coefficients in the Loss Domain

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	24	0	34	58
Social	20	0	34	54

In the individual treatment, around 59% of the subjects are risk seeking and 41% are risk averse. However, in the social treatment, the percentage of risk averse subject decreases. 37% of the subjects are risk averse, and 63% of the subjects are risk seeking. When estimating CRRA coefficients in all domains for each subject, I found that the percentage of risk averse subjects is higher in both treatments. However, when limiting the analysis to the loss domain, the percentage of risk seeking subjects is higher in both treatments.

Figure 8 presents a scatter plot the CRRA coefficients for each subject in the individual and social treatment. Different correlation coefficients show that there is a positive correlation between the CRRA coefficients in the individual and social treatment (Pearson correlation coefficient= 0.51, Spearman correlation coefficient = 0.53 and Kendall's tau coefficient = 0.40).

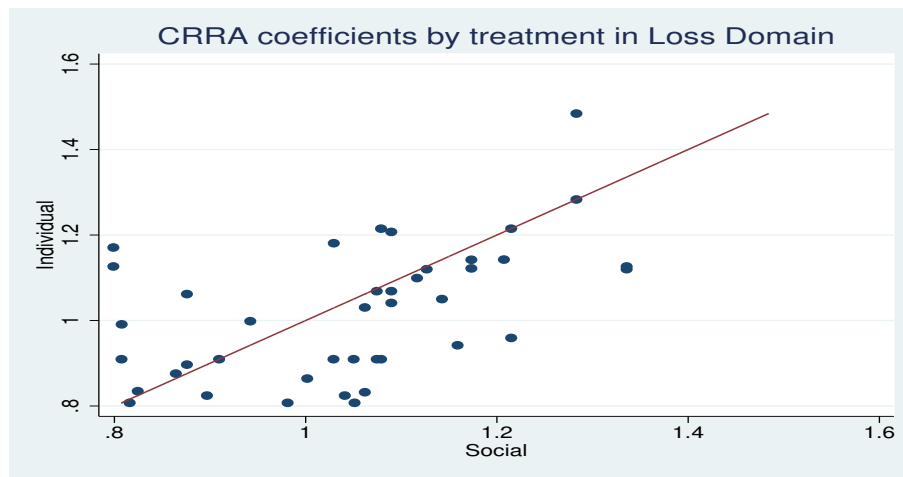


FIGURE 8: CRRA coefficients for subjects per treatment in Loss Domain

I run Kolmogorov-Smirnov test to test for equality of distribution functions of CRRA coefficients in both treatments in the Loss Domain. The test results show that CRRA coefficients do not have the same distribution (P-value=0). Figure 9 presents the cumulative density functions of CRRA coefficients in the Loss Domain in both treatments.

TABLE 66: Descriptive Statistics of CRRA coefficients

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1 - Q_3]	Total
Individual	1.040	1.062	0.153	0.807	1.484	[0.909-1.142]	58
Social	1.045	1.057	0.156	0.799	1.370	[1.057-1.143]	54

A box plot of CRRA coefficients in the individual and social treatment is presented in figure 10. CRRA coefficients in the individual treatment have higher median, minimum, maximum but lower mean, standard deviation and interquartile range (Q_1 - Q_3) than those in the social treatment. Moreover, Table 66 presents the descriptive statistics of CRRA coefficients in both treatments. Regarding the comparison of variances

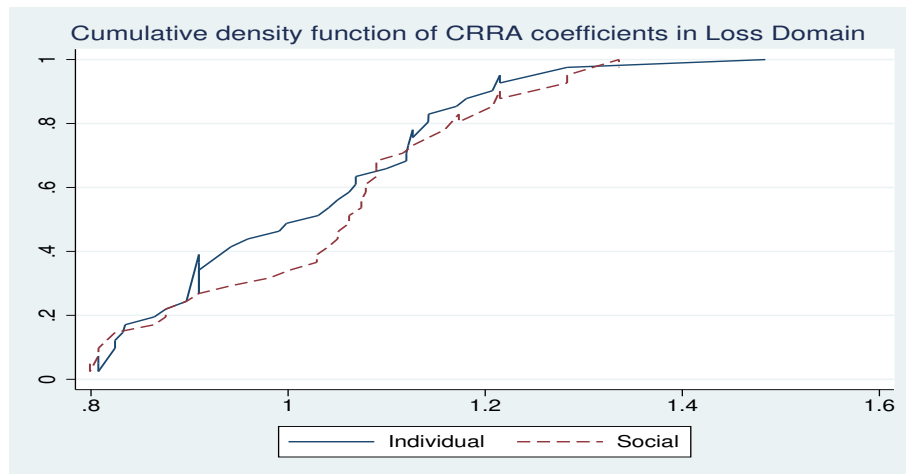


FIGURE 9: Cumulative density functions of CRRA coefficients in Loss Domain

of CRRA coefficients in both treatments, the hypothesis of the equality of variances in both treatments is not rejected (P-value= 0.890).

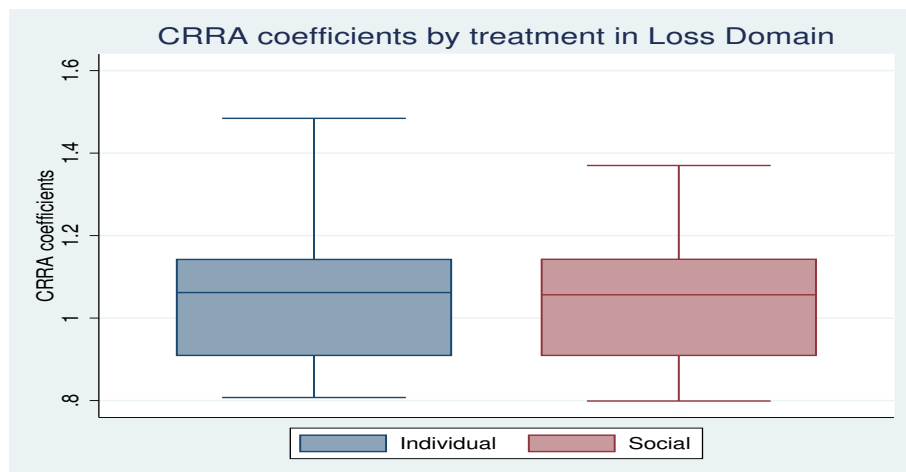


FIGURE 10: CRRA coefficients for subjects per treatment in Loss Domain

Table 67 shows Fisher's test table. The result suggests that there is a statistically significant difference in proportion of risk averse and risk seeing subjects in both treatments (P-value = 0.020). This result is confirmed by a fisher exact test for estimated CRRA coefficients with $\epsilon = 0.05$ (P-value = 0.021). Thus, in the loss domain, social context has a significant effect on risk preferences.

TABLE 67: Fisher's exact test with $\epsilon = 0$

Individual \ Social	Risk averse	Risk seeking	Total
	Risk averse	10	10
Risk seeking	3	18	21
Total	13	28	41

TABLE 68: Fisher's exact test with $\epsilon = 0.05$

Individual \ Social	Risk averse ($r < 0.95$)	Risk neutral ($0.95 < r < 1.05$)	Risk seeking ($r > 1.05$)	Total
	Risk averse ($r < 0.95$)	0	0	0
Risk neutral ($0.95 < r < 1.05$)	0	23	3	26
Risk seeking ($r > 1.05$)	0	5	10	15
Total	0	28	13	41

.5 Initial Experiment: Structural Estimation: Reference Dependent Utility by Quiggin (1982)

Quiggin (1982) presented the Rank Dependent Utility (RDU) to resolve the issue of the independence axiom, the key behavioral assumption of the expected utility (EU). The RDU allows for subjective probability weighting in a rank dependent manner and allows non linear utility functions.

Decision weights under RDU for an urn of n balls.

$$RDU_i = \sum_{k=1,k} [w_k \times u_k] \quad (1)$$

$$w_i = \omega(p_i + \dots + p_n) - \omega(p_{i+1} + \dots + p_n) \quad (2)$$

for $i=1, \dots, n-1$ and

$$w_i = \omega(p_i) \quad (3)$$

for $i= n$ where the subscript indicates outcomes ranked from worst to best and $\omega(p)$ is a probability weighting function. The probability weighting function $\omega(\cdot)$ is applied to the aggregated probabilities and the decision weights w_i then derived by the differences in these transformed aggregate probabilities.

$$RDU_i = w_{1/3} \times u_1 + (w_{2/3} - w_{1/3}) \times u_2 + (1 - w_{2/3}) \times u_3 \quad (4)$$

.5.1 All domains included

At the aggregate level, pooling all responses from the 84 subjects, in the individual treatment, the maximum likelihood estimation for $r= 0.488$, $w_{1/3}= 0.029$ and $w_{2/3}=0.99$. In the social treatment, the maximum likelihood estimation for $r= 0.863$, $w_{1/3}= 0.025$ and $w_{2/3}=1$.

The parameters of the RDU model for each subject can only be estimated for 27 of out 84 subjects in the individual treatment and 24 out of 84 subjects in the social treatment. Table 70 and 69 report the descriptive statistics of RDU model parameters in the individual and the social treatment. In the individual treatment, the risk aversion parameter has lower mean, median, maximum and IQR than those in the social treatment. $w_{1/3}$ has higher median and IQR and lower mean and maximum than those in the social treatment. $w_{2/3}$ has lower mean, median, maximum and IQR than those in the social treatment. On average, probability weighting has an effect in the individual treatment. $w_{1/3}$ and $w_{2/3}$ are less than 1/3 and 2/3 respectively. However, in the social treatment, $w_{1/3}$ is less than 1/3 and $w_{2/3}$ is higher than 2/3, but $w_{1/3}$ and $w_{2/3}$ are close to 1/3 and 2/3 respectively.

Regarding the variances of risk aversion parameters in the individual and social treatment, the hypothesis of the equality of variances is rejected at 10% significance

level (P-value=0.066). Figure 11 displays a box plot of risk aversion parameters in the individual and social treatment.

TABLE 69: Descriptive Statistics of RDU model parameters in the individual treatment

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1 - Q_3]
Risk aversion parameter	0.329	0.211	0	1.988	[0-0.398]
$W_{1/3}$	0.229	0.135	0	0.675	[0.037-0.5]
$W_{2/3}$	0.551	0.5	0	1	[0.175-0.993]

TABLE 70: Descriptive Statistics of RDU model parameters in the social treatment

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1 - Q_3]
Risk aversion parameter	0.523	0.326	0	2.757	[0-0.645]
$W_{1/3}$	0.284	0.122	0.001	1	[0.045-0.5]
$W_{2/3}$	0.649	0.691	0	1	[0.442-0.999]

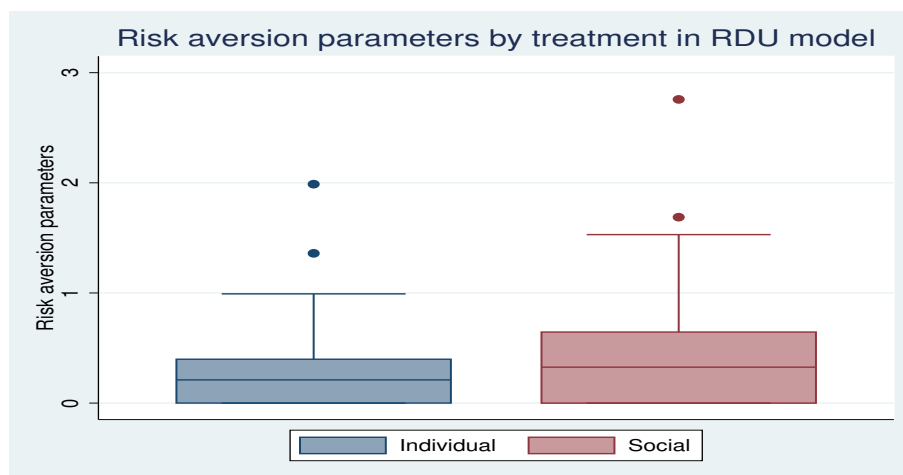


FIGURE 11: Risk aversion parameters per treatment in RDU model

Table 71 shows the classification of subjects according to their probability weighting. In the individual treatment, around 44% of the subjects underestimate the probabilities of 1/3 and 2/3 ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 26% of the subjects underestimate the probability 1/3 and overestimate the probability 2/3 ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). 15% of the subjects overestimate the probabilities 1/3 and 2/3 ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$).

15% of the subjects overestimate the probability 1/3 and underestimate the probability 2/3 ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). In the social treatment, around 37% of the subjects underestimate the probability 1/3 and overestimate the probability 2/3 ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). 25% of the subjects underestimate the probabilities of 1/3 and 2/3 ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 21% of the subjects overestimate the probability 1/3 and underestimate the probability 2/3 ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). 17% of the subjects overestimate the probabilities 1/3 and 2/3 ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$).

TABLE 71: Classification of subjects according to their probability weighting

Treatment	Individual	Social
$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	4	4
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	4	5
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	7	9
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	12	6
Total	27	24

Table 72 shows the classification of subjects according their probability weighting in both treatments. Fisher's exact test result suggests that there is no significant difference in probability weighting by treatment (P-value=0.54)

TABLE 72: Classification of subjects according to their probability weighting in both treatments^a

Individual \ Social	$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	Total
	$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	0	0	0	1
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	1	1	0	1	3
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	1	0	1	0	2
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	0	1	3	1	5
Total	2	2	4	3	11

^a The table includes 11 subjects for whom the estimation of $W_{1/3}$ and $W_{2/3}$ in both treatments were possible

Table 73 shows the classifications of subjects according to their risk aversion parameters in RDU model. When estimating risk aversion parameters for each subject based on his responses in the 21 tasks of the individual treatment, around 92.6% of the subjects are risk averse and 7.4% are risk seeking. In the social treatment, around 79.2% of

the subjects are risk averse and 20.8% are risk seeking. Thus, risk aversion decreases in the social treatment.

TABLE 73: Classification of subjects according to their risk aversion parameters in RDU model

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	25	0	2	27
Social	19	0	5	24

Figure 12 displays a scatter plot of risk aversion parameters in the individual and social treatment. Different correlation coefficients show that there is a strong positive correlation between risk aversion parameters in both treatments (Pearson correlation coefficient= 0.78, Spearman correlation coefficient= 0.77 and Kendall's tau= 0.60).

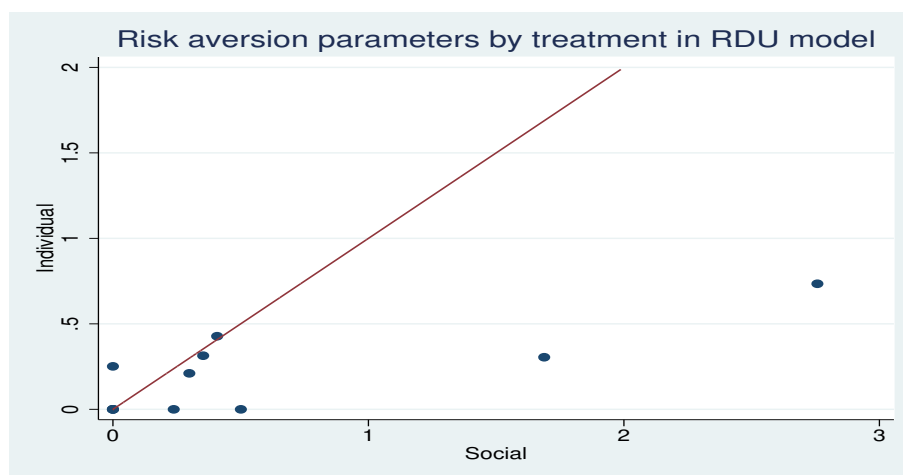


FIGURE 12: Risk aversion parameters per treatment in RDU model

Kolmogorov-Smirnov test result shows that risk aversion parameters in the individual and social treatment do not have the same distribution (P-value=0). Figure 13 presents the cumulative density functions of risk aversion parameters in both treatments.

Table 74 displays the classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments. There are no risk seeking subjects in the individual treatment. 9 subjects out of 11 are risk averse in both treatments. 2 subjects are risk averse in the individual treatment and risk seeking in the social treatment.

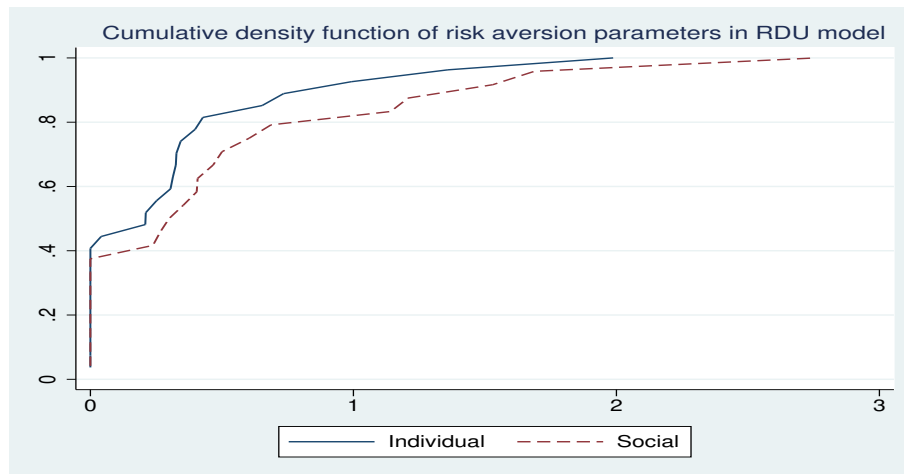


FIGURE 13: Cumulative density functions of risk aversion parameters in RDU model

TABLE 74: Classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments^a

	Social		Total
	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Individual			
Risk averse ($r < 1$)	9	2	11
Risk seeking ($r > 1$)	0	0	0
Total	9	2	11

^a The table includes 11 subjects for whom the estimation of risk aversion parameters in both treatments was possible.

.5.2 Loss Domain

At the aggregate level, pooling all responses from the 84 subjects, in the individual treatment, the maximum likelihood estimation for $r = 1.833$, $w_{1/3} = 0.005$ and $w_{2/3} = 0.995$. In the social treatment, the maximum likelihood estimation for $r = 3.162$, $w_{1/3} = 0.00023$ and $w_{2/3} = 0.999$.

The parameters of the RDU model for each subject can only be estimated for 12 out of 84 subjects in the individual treatment and 14 out of 84 subjects in the social treatment. Table 75 and 76 report the descriptive statistics of RDU model parameters in

the individual and the social treatment in Loss Domain. In the individual treatment, the risk aversion parameter has lower mean, median, maximum and IQR than those in the social treatment. $w_{1/3}$ has higher median and lower mean and Q_3 than those in the social treatment. $w_{2/3}$ has lower mean, median and IQR than those in the social treatment. On average, probability weighting has an effect in the individual treatment. $w_{1/3}$ and $w_{2/3}$ are less than $1/3$ and $2/3$ respectively. In the social treatment, on average, $w_{1/3}$ is less than $1/3$ and $w_{2/3}$ is higher than $2/3$. In both treatments, $w_{1/3}$ is less than that estimated based on choices in all domains (subsection rduall). In the individual treatment, $w_{2/3}$ is less than that estimated choices in all domains. However, in the social treatment, $w_{2/3}$ is higher than that estimated choices in all domains. Regarding the variances of risk aversion parameters in the individual and social treatment, the hypothesis of the equality of variances is not rejected (P-value > 0.1). Figure 14 displays a box plot of risk aversion parameters in the individual and social treatment.

TABLE 75: Descriptive Statistics of RDU model parameters in the individual treatment in Loss Domain

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1 - Q_3]
Risk aversion parameter	1.857	0.473	0	9.199	[0.025-2.903]
$W_{1/3}$	0.155	0.064	0	0.5	[0.005-0.294]
$W_{2/3}$	0.539	0.500	0	1	[0-0.991]

TABLE 76: Descriptive Statistics of RDU model parameters in the social treatment in Loss Domain

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1 - Q_3]
Risk aversion parameter	2.553	0.992	0	9.304	[0-4.071]
$W_{1/3}$	0.184	0.033	0	0.5	[0-0.486]
$W_{2/3}$	0.749	0.991	0	1	[0.5-0.999]

Table 77 shows the classification of subjects according to their probability weighting. In the individual treatment, one third of the subjects underestimate the probabilities of $1/3$ and $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 42% of the subjects underestimate the probability $1/3$ and overestimate the probability $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). None of the subjects overestimate the probabilities $1/3$ and $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$).

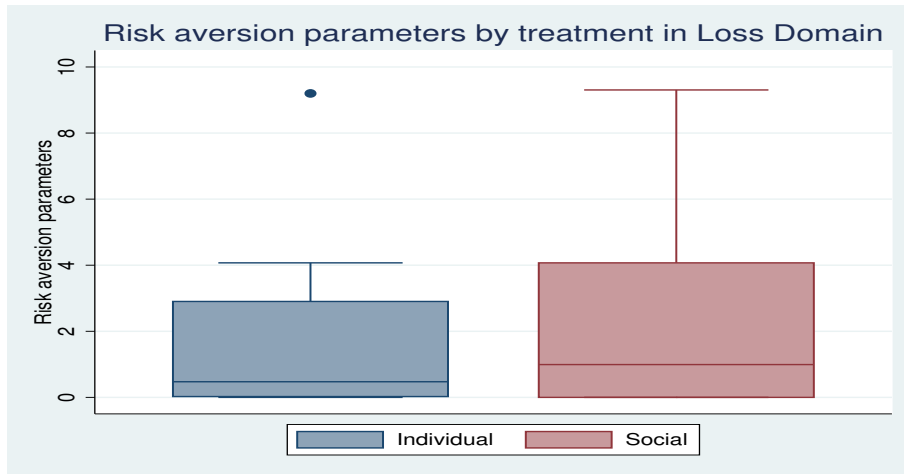


FIGURE 14: Risk aversion parameters per treatment in RDU model in Loss Domain

25% of the subjects overestimate the probability $1/3$ and underestimate the probability $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). In the social treatment, around 57% of the subjects underestimate the probability $1/3$ and overestimate the probability $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). 7% of the subjects underestimate the probabilities of $1/3$ and $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 36% of the subjects overestimate the probability $1/3$ and underestimate the probability $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). None of the subjects overestimate the probabilities $1/3$ and $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$). In the social treatment, the share of subjects overestimating $W_{1/3}$ and underestimating $W_{2/3}$ is higher than in the individual treatment.

TABLE 77: Classification of subjects according to their probability weighting

Treatment	Individual	Social
$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	0	0
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	3	5
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	5	8
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	4	1
Total	12	14

Table 78 shows the classification of subjects according to their probability weighting in both treatments in the Loss Domain. Fisher's exact test suggests that there is no significant difference in probability weighting by treatment (P-value=0.67).

TABLE 78: Classification of subjects according to their probability weighting in both treatments in the Loss Domain^a

Individual \ Social	$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	Total
	$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	0	0	0	0
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	0	0	0	0	0
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	0	0	1	0	1
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	0	1	1	0	2
Total	0	1	2	0	3

^a The table includes 3 subjects for whom the estimation of $W_{1/3}$ and $W_{2/3}$ in both treatments were possible

Table 79 shows the classification of subjects according to their risk aversion parameters in RDU model in Loss Domain. When estimating risk aversion parameters for each subject based on his responses in the 7 loss tasks of the individual treatment, around 58% of the subjects are risk averse and 42% are risk seeking. In the social treatment, around 50% of the subjects are risk averse and 50% are risk seeking. Thus, risk aversion decreases in the social treatment.

TABLE 79: Classification of subjects according to their risk aversion parameters in RDU model

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	7	0	5	12
Social	7	0	7	14

Table 80 displays the classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments. There are no risk seeking subjects in the individual treatment. One subject is risk averse in both treatments. One subject is risk averse in the individual treatment and risk seeking in the social treatment. And one subject is risk seeking in both treatments. Fisher's exact test result suggests that there is no significant difference in the proportions of risk averse and risk seeking subjects in both treatments (P-value = 0.67)

TABLE 80: Classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments^a

	Social		
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	Total
Risk averse ($r < 1$)	1	1	2
Risk seeking ($r > 1$)	0	1	1
Total	1	2	3

^a The table includes 3 subjects for whom the estimation of risk aversion parameters in both treatments was possible.

.6 Robustness Experiment: Structural Estimation: Expected Utility Theory by Von Neumann and Morgenstern (1947) in the Gain Domain

In this section, I limit the analysis to the 7 tasks of the Gain Domain. Pooling all responses from each of the 93 subjects in the gain domain, the maximum likelihood estimates of the risk aversion parameter $r = 0.723$ with a standard error of 0.005 in the individual treatment. In the social treatment, the maximum likelihood estimates of the risk aversion parameter $r = 0.721$ with a standard error of 0.003 in the social treatment. Table 81 reports the classification of subjects according to their risk preferences in the gain domain represented by their CRRA coefficients. When estimating CRRA coefficient for each subject based on his responses in the 7 tasks of the Gain Domain in the individual treatment, I find that 44% of the subjects (41 out of 93 subjects) are considered as risk averse (their CRRA parameter $r < 1$). 56% of the subjects (52 out of 93 subjects) are risk seeking (their CRRA parameter $r > 1$) and no subjects are risk neutral ($r = 1$). Nevertheless, in the social treatment, I find that 41% of the subjects (38 out of 93 subjects) are considered as risk averse (their CRRA parameter $r < 1$). 59% of the subjects (55 out of 93 subjects) are risk seeking (their CRRA parameter $r > 1$) and no subjects are risk neutral ($r = 1$). The share of risk seeking subjects is higher than that in

the experiment where risks are correlated. Correlation of risks increases risk aversion which is not in line with Schmidt et al. (2015) and Friedl et al. (2014).

TABLE 81: Classification of subjects according to their CRRA coefficients in the Gain Domain

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	41	0	52	93
Social	38	0	55	93

Figure 15 presents a scatter plot of CRRA coefficients for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak positive correlation between CRRA coefficients for each subject in the individual and social treatment (Pearson correlation= 0.32, Spearman correlation coefficient= 0.47 and Kendall's tau coefficient =0.33).

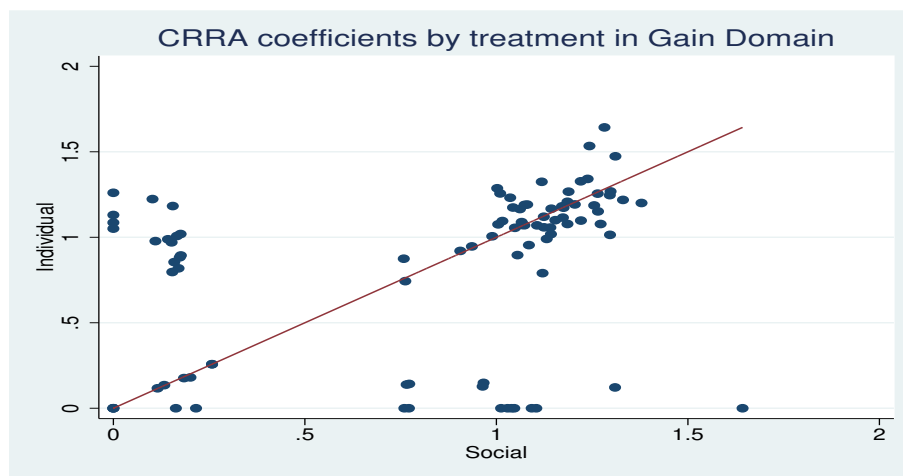


FIGURE 15: CRRA coefficients for subjects per treatment in Gain Domain

Kolmogrov-Smirnov test result rejects the hypothesis the equality of distribution functions of CRRA coefficients in the individual and social treatment (P-value=0). Cumulative density functions of CRRA coefficients in the individual and social treatment are presented in figure 16.

A box plot of CRRA coefficients in the individual and social treatment is presented in figure 17. Table 82 presents the descriptive statistics of CRRA coefficients in the

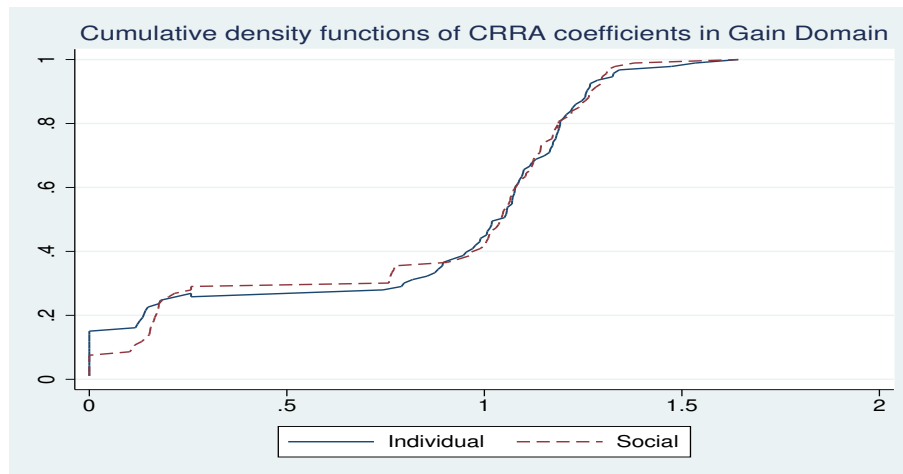


FIGURE 16: Cumulative density functions of CRRA coefficients in Gain

gain domain. CRRA coefficients in the individual treatment have higher mean, median, standard deviation and maximum and interquartile range (Q_1 - Q_3) than those in the social treatment. However, the minimum and maximum are the same in both treatments. Regarding the variances of CRRA coefficients in the individual and social treatment, the hypothesis of the equality of variances is not rejected (P-value = 0.77).

TABLE 82: Descriptive Statistics of CRRA coefficients in the Gain Domain

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1 - Q_3]
Individual	0.830	1.051	0.486	0	1.643	[0.258-1.181]
Social	0.822	1.043	0.472	0	1.643	[0.201-1.171]

Table 83 shows the classification of subjects according to their CRRA coefficients in both treatments in the Gain Domain. Fisher's exact test result suggests rejecting the hypothesis of the equality of proportions of risk averse, risk seeking subjects in the both treatments (P-value=0). Nevertheless, when running a Fisher's exact test for CRRA coefficients estimated with $\epsilon = 0.05$ in table 84, the hypothesis of the equality of proportions in both treatments is also rejected (P-value = 0.002) which means that the introduction of social comparison has a significant effect on risk preferences.

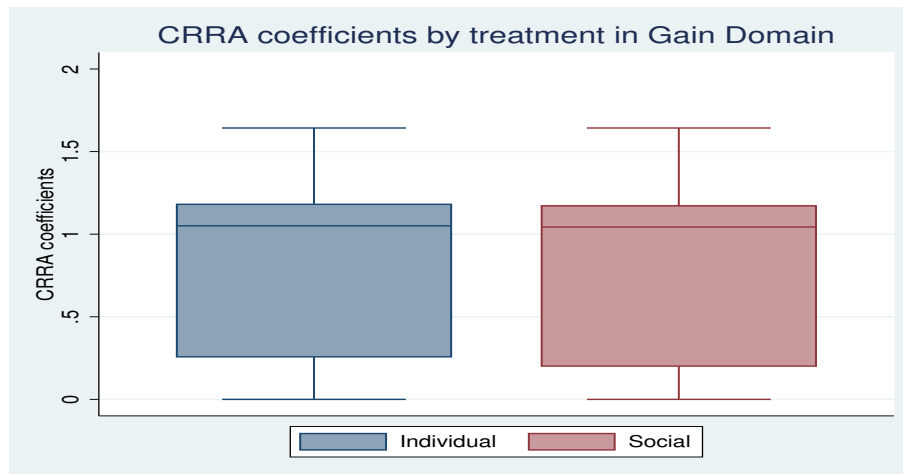


FIGURE 17: CRRA coefficients per treatment in the Gain Domain

TABLE 83: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0$ in both treatments in the Gain Domain

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	29	12	41
Risk seeking ($r > 1$)	9	43	52
Total	38	55	93

TABLE 84: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0.05$ in both treatments in the Gain Domain

	Social			Total
Individual	Risk averse ($r < 0.95$)	Risk neutral ($0.95 < r < 1.05$)	Risk seeking ($r > 1.05$)	
Risk averse ($r < 0.95$)	10	10	3	23
Risk neutral ($0.95 < r < 1.05$)	11	11	10	32
Risk seeking ($r > 1.05$)	5	8	23	36
Total	26	29	36	91

^a CRRA coefficients with $\epsilon=0.05$ couldn't be estimated for two subjects out of 93

7 Robustness Experiment: Structural Estimation: Expected Utility Theory by Von Neumann and Morgenstern (1947) in the Loss Domain

In this section, I limit the analysis to the 7 tasks of the Loss Domain. Pooling all responses from each of the 93 subjects in the gain domain, the maximum likelihood

estimates of the risk aversion parameter $r= 0.945$ with a standard error of 0.03 in the individual treatment. In the social treatment, the maximum likelihood estimates of the risk aversion parameter $r= 0.975$ with a standard error of 0.03 in the social treatment. Table 85 reports the classification of subjects according to their risk preferences in the loss domain represented by their CRRA coefficients. When estimating CRRA coefficient for each subject based on his responses in the 7 tasks of the Loss Domain in the individual treatment, I find that 60% of the subjects (53 out of 89 subjects) are considered as averse (their CRRA parameter $r < 1$). 40% of the subjects (36 out of 89 subjects) are risk seeking (their CRRA parameter $r > 1$) and no subjects are risk neutral ($r = 1$). Nevertheless, in the social treatment, I find that 68% of the subjects (57 out of 84 subjects) are considered as risk averse (their CRRA parameter $r < 1$). 32% of the subjects (27 out of 84 subjects) are risk seeking (their CRRA parameter $r > 1$) and no subjects are risk neutral ($r = 1$). The share of risk averse subjects is higher than that in the experiment where risks are correlated.

TABLE 85: Classification of subjects according to their CRRA coefficients in the Gain Domain

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	53	0	36	89
Social	57	0	27	84

Figure 18 presents a scatter plot of CRRA coefficients for each subject in the individual and social treatment. Different correlation coefficients show that there is a weak negative correlation between CRRA coefficients for each subject in the individual and social treatment (Pearson correlation = -0.48, Spearman correlation coefficient = 0.5 and Kendall's tau coefficient = 0.33).

Kolmogrov-Smirnov test result rejects the hypothesis the equality of distribution functions of CRRA coefficients in the individual and social treatment (P-value = 0). Cumulative density functions of CRRA coefficients in the individual and social treatment are presented in figure 19.

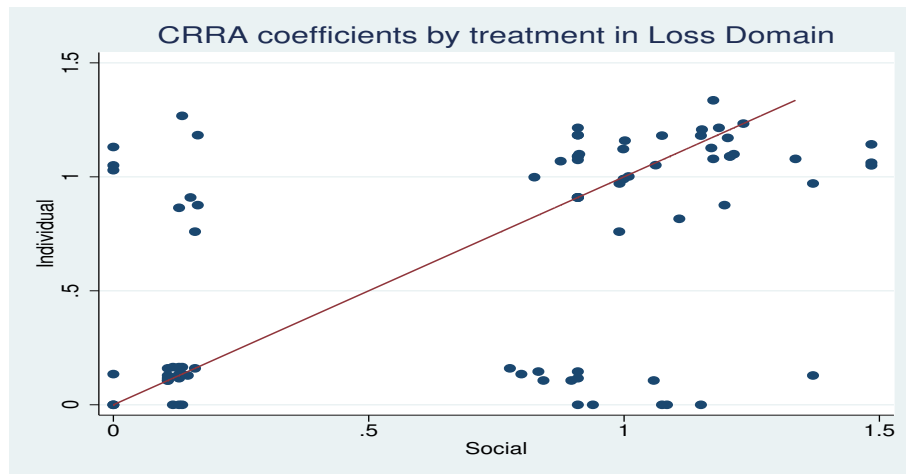


FIGURE 18: CRRA coefficients for subjects per treatment in Loss Domain

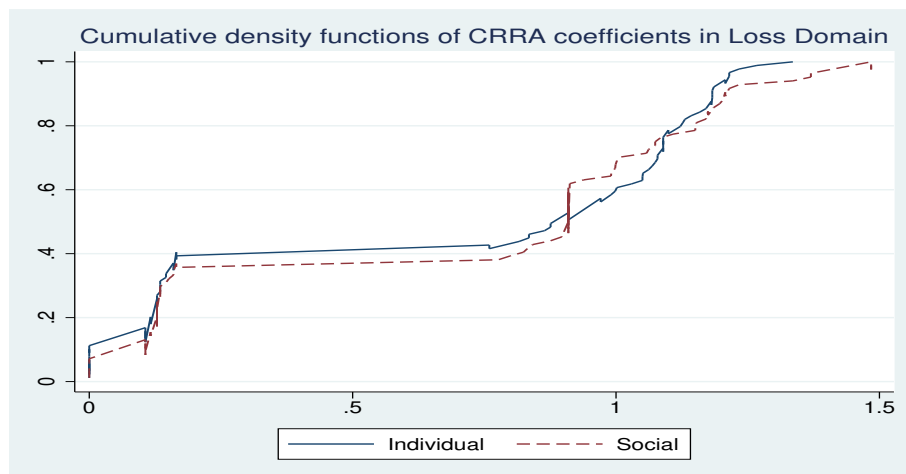


FIGURE 19: Cumulative density functions of CRRA coefficients in Loss Domain

A box plot of CRRA coefficients in the individual and social treatment is presented in figure 20. Table 86 presents the descriptive statistics of CRRA coefficients in the loss domain. CRRA coefficients in the social treatment have higher mean, standard deviation and maximum than those in the individual treatment. However, they have lower interquartile range (Q_1-Q_3) than that in the individual treatment. The median and minimum are the same in both treatments. Regarding the variances of CRRA coefficients in the individual and social treatment, the hypothesis of the equality of variances is not rejected (P-value = 0.97).

TABLE 86: Descriptive Statistics of CRRA coefficients in the Loss Domain

Treatment	Mean	Median	Standard deviation	Minimum	Maximum	IQR [Q_1 - Q_3]
Individual	0.667	0.909	0.486	0	1.335	[0.129-1.336]
Social	0.705	0.909	0.484	0	1.484	[0.132-1.079]

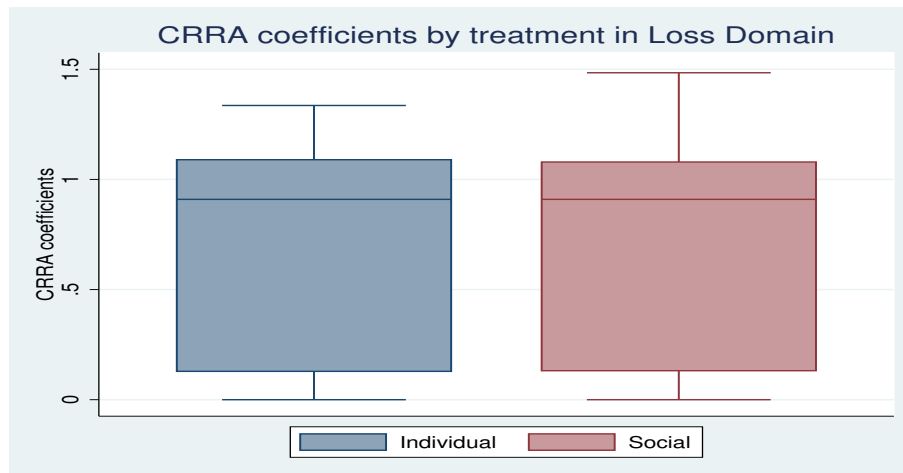


FIGURE 20: CRRA coefficients per treatment in the Loss Domain

Table 87 shows the classification of subjects according to their CRRA coefficients in both treatment in the Loss Domain. Fisher's exact test result suggests not rejecting the hypothesis of the equality of proportions of risk averse, risk seeking subjects in the both treatments (P-value=0). Nevertheless, when running Fisher's exact test for CRRA coefficients estimated with $\epsilon = 0.05$ in table 88, the hypothesis of the equality of proportions in both treatments is also rejected (P-value = 0.001).

TABLE 87: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0$ in both treatments in the Loss Domain

	Social		Total
Individual	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	43	8	51
Risk seeking ($r > 1$)	14	19	33
Total	57	27	84

TABLE 88: Classification of subjects according to their CRRA coefficients estimated with $\epsilon=0.5$ in both treatments in the Loss Domain

	Social			
Individual	Risk averse ($r < 0.95$)	Risk neutral ($0.95 < r < 1.05$)	Risk seeking ($r > 1.05$)	Total
Risk averse ($r < 0.95$)	31	0	5	36
Risk neutral ($0.95 < r < 1.05$)	15	3	11	29
Risk seeking ($r > 1.05$)	7	2	10	19
Total	53	5	26	84

.8 Robustness Experiment: Structural Estimation: Reference Dependent Utility by Quiggin (1982)

.8.1 All domains

At the aggregate level, pooling all responses from the 93 subjects, in the individual treatment, the maximum likelihood estimation for $r= 0.445$, $w_{1/3}= 0.048$ and $w_{2/3}=0.986$. In the social treatment, the maximum likelihood estimation for $r= 0.456$, $w_{1/3}= 0.037$ and $w_{2/3}=0.972$.

The parameters of the RDU model for each subject can only be estimated for 26 of out 93 subjects in the individual treatment and 30 out of 93 subjects in the social treatment. Table 90 and 89 report the descriptive statistics of RDU model parameters in the individual and the social treatment. In the individual treatment, the risk aversion parameters have lower mean, maximum and IQR and a lower median than those in the social treatment. $w_{1/3}$ has higher median and lower mean and IQR than those in the social treatment. $w_{2/3}$ has higher mean, lower median and narrower IQR than those in the social treatment. On average, probability weighting has an effect in the individual and social treatment. $w_{1/3}$ is higher than $1/3$ and $w_{2/3}$ is less than $2/3$. Regarding the

variances of risk aversion parameters in the individual and social treatment, the hypothesis of the equality of variances is not rejected (P-value=0.574). Figure 21 displays a box plot of risk aversion parameters in the individual and social treatment.

TABLE 89: Descriptive Statistics of RDU model parameters in the individual treatment

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1 - Q_3]
Risk aversion parameter	0.280	0	0	1.566	[0-0.523]
$W_{1/3}$	0.358	0.357	0	1	[0.132-0.5]
$W_{2/3}$	0.651	0.537	0	1	[0.5-0.999]

TABLE 90: Descriptive Statistics of RDU model parameters in the social treatment

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1 - Q_3]
Risk aversion parameter	0.232	0.005	0	1.191	[0-0.425]
$W_{1/3}$	0.366	0.257	0	1	[0.073-0.592]
$W_{2/3}$	0.631	0.681	0	1	[0.434-0.998]

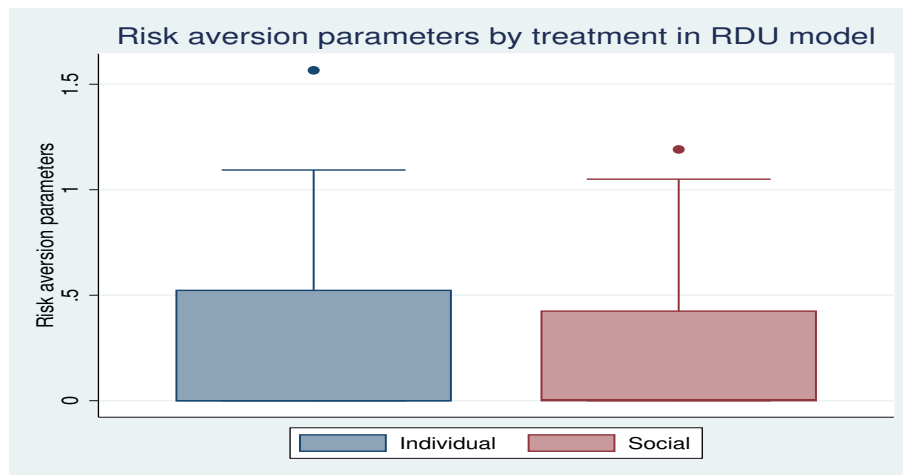


FIGURE 21: Risk aversion parameters per treatment in RDU model

Table 91 shows the classification of subjects according to their probability weighting. In the individual treatment, around 31% of the subjects underestimate the probabilities of 1/3 and 2/3 ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 15% of the subjects underestimate the probability 1/3 and overestimate the probability 2/3 ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). 27%

of the subjects overestimate the probabilities $1/3$ and $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$). 27% of the subjects overestimate the probability $1/3$ and underestimate the probability $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). In the social treatment, around 30% of the subjects underestimate the probability $1/3$ and overestimate the probability $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). 20% of the subjects underestimate the probabilities of $1/3$ and $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 27% of the subjects overestimate the probability $1/3$ and underestimate the probability $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). 23% of the subjects overestimate the probabilities $1/3$ and $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$).

TABLE 91: Classification of subjects according to their probability weighting

Treatment	Individual	Social
$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	7	7
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	7	8
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	4	9
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	8	6
Total	26	30

Table 92 shows the classification of subjects according to their probability weighting in both treatments. Fisher's exact test result suggests that there is a significant difference in probability weighting by treatment (P-value=0).

TABLE 92: Classification of subjects according to their probability weighting in both treatments^a

Individual \ Social					Total
	$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	
$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	7	0	0	0	7
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	0	7	0	0	7
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	0	0	4	0	4
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	0	0	0	8	8
Total	7	7	4	8	26

^a The table includes 26 subjects for whom the estimation of $W_{1/3}$ and $W_{2/3}$ in both treatments were possible.

Table 93 shows the classifications of subjects according to their risk aversion parameters in RDU model. When estimating risk aversion parameters for each subject based

on his responses in the 21 tasks of the individual treatment, around 92.3% of the subjects are risk averse and 7.7% are risk seeking. In the social treatment, around 93.3% of the subjects are risk averse and 6.7% are risk seeking. Thus, risk aversion increases in the social treatment contrary to the experiment where risks are correlated.

TABLE 93: Classification of subjects according to their risk aversion parameters in RDU model

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	24	0	2	26
Social	28	0	2	30

Figure 22 displays a scatter plot of risk aversion parameters in the individual and social treatment. Different correlation coefficients show that there is a strong positive correlation between risk aversion parameters in both treatments (Pearson correlation coefficient= 0.24, Spearman correlation coefficient= 0.29 and Kendall's tau= 0.26).

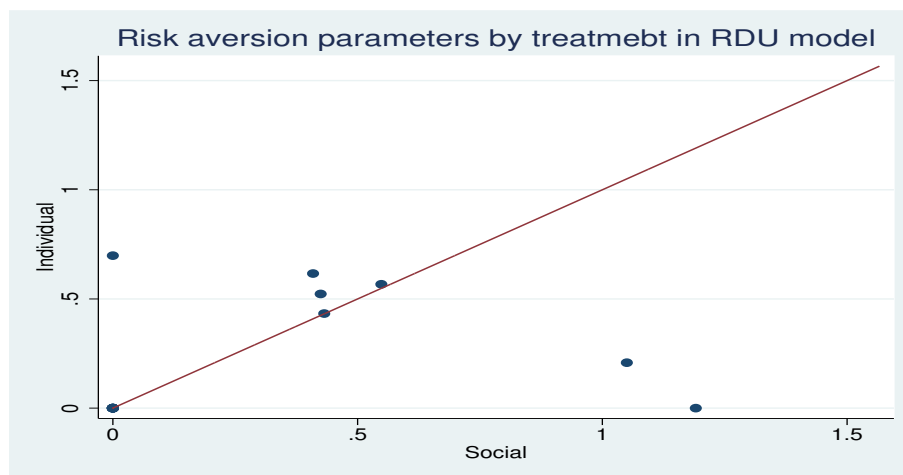


FIGURE 22: Risk aversion parameters per treatment in RDU model

Kolmogorov-Smirnov test result shows that risk aversion parameters in the individual and social treatment do not have the same distribution (P-value=0). Figure 23 presents the cumulative density functions of risk aversion parameters in both treatments.

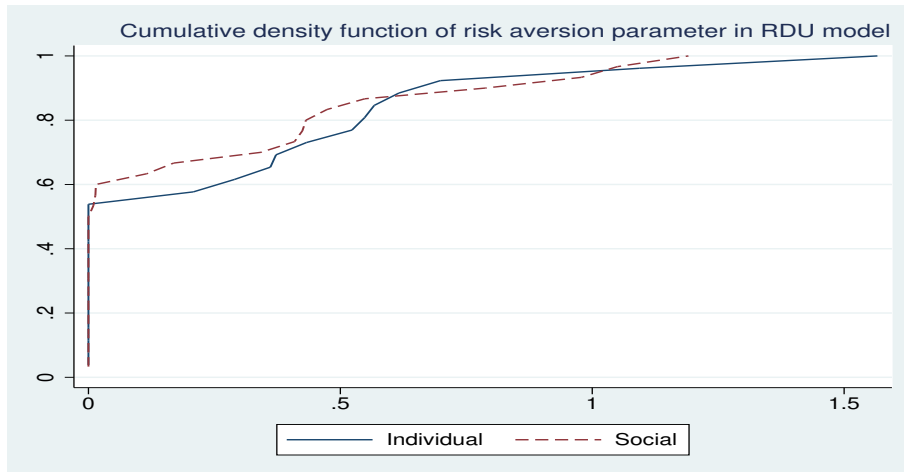


FIGURE 23: Cumulative density functions of risk aversion parameters in RDU model

Table 94 displays the classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments. There are no risk seeking subjects in the individual treatment. The majority of the subjects are risk averse in both treatments.

TABLE 94: Classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments^a

Individual \ Social	Social		Total
	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	13	2	15
Risk seeking ($r > 1$)	0	0	0
Total	13	2	15

^a The table includes 15 subjects for whom the estimation of risk aversion parameters in both treatments was possible.

.8.2 Loss Domain

At the aggregate level, pooling all responses from the 93 subjects, in the 7 loss tasks of the individual treatment, the maximum likelihood estimation for $r = 2.14$, $w_{1/3} =$

0.003 and $w_{2/3}=0.999$. In the social treatment, the maximum likelihood estimation for $r= 1.845$, $w_{1/3}= 0.005$ and $w_{2/3}=0.995$.

The parameters of the RDU model for each subject can only be estimated for 18 of out 93 subjects in the individual treatment and 15 out of 93 subjects in the social treatment. Table 95 and 96 report the descriptive statistics of RDU model parameters in the individual and the social treatment in Loss Domain. In the individual treatment, the risk aversion parameter has lower mean and IQR but higher median than those in the social treatment. The minimum and maximum of the risk aversion parameter are equal in both treatments. $w_{1/3}$ has higher mean, median and IQR than those in the social treatment. $w_{2/3}$ has lower mean and IQR than those in the social treatment. The median of $w_{2/3}$ is equal in both treatments. On average, probability weighting has an effect in the individual treatment. $w_{1/3}$ and $w_{2/3}$ are less than $1/3$ and $2/3$ respectively. In the social treatment, on average, $w_{1/3}$ is less than $1/3$ and $w_{2/3}$ is higher than $2/3$.

Regarding the variances of risk aversion parameters in the individual and social treatment, the hypothesis of the equality of variances is not rejected (P-value = 0.203). Figure 24 displays a box plot of risk aversion parameters in the individual and social treatment.

TABLE 95: Descriptive Statistics of RDU model parameters in the individual treatment in Loss Domain

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1-Q_3]
Risk aversion parameter	0.950	0.0316	0	9.304	[0-0.063]
$W_{1/3}$	0.297	0.322	0	0.5	[0.158-0.5]
$W_{2/3}$	0.417	0.5	0	1	[0-0.5]

TABLE 96: Descriptive Statistics of RDU model parameters in the social treatment in Loss Domain

Parameters	Mean	Median	Minimum	Maximum	IQR [Q_1-Q_3]
Risk aversion parameter	1.828	0.001	0	9.304	[0-2.934]
$W_{1/3}$	0.244	0.158	0	0.5	[0-0.499]
$W_{2/3}$	0.682	0.5	0	1	[0.5-0.999]

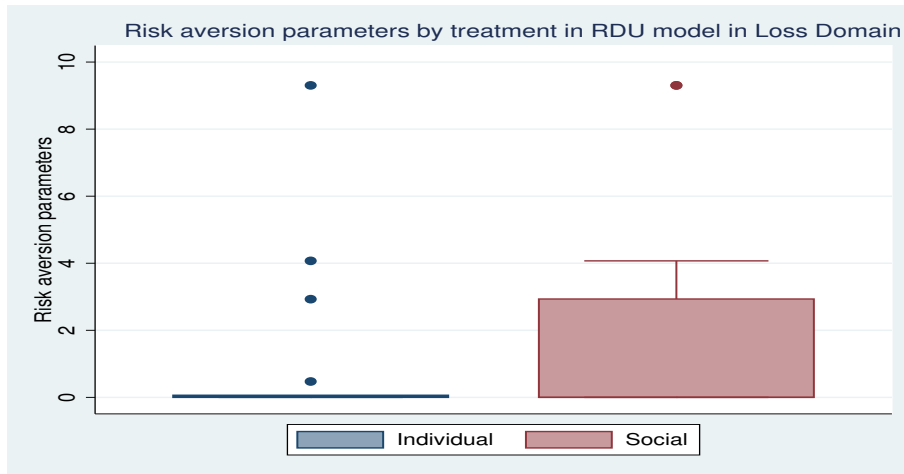


FIGURE 24: Risk aversion parameters per treatment in RDU model in Loss Domain

Table 97 shows the classification of subjects according to their probability weighting. In the individual treatment, 33% of the subjects underestimate the probabilities of $1/3$ and $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 17% of the subjects underestimate the probability $1/3$ and overestimate the probability $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). None of the subjects overestimate the probabilities $1/3$ and $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$). 50% of the subjects overestimate the probability $1/3$ and underestimate the probability $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). In the social treatment, around 40% of the subjects underestimate the probability $1/3$ and overestimate the probability $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} > 2/3$). 13% of the subjects underestimate the probabilities of $1/3$ and $2/3$ ($W_{1/3} < 1/3$ and $W_{2/3} < 2/3$). 40% of the subjects overestimate the probability $1/3$ and underestimate the probability $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} < 2/3$). 7% of the subjects overestimate the probabilities $1/3$ and $2/3$ ($W_{1/3} > 1/3$ and $W_{2/3} > 2/3$).

TABLE 97: Classification of subjects according to their probability weighting

Treatment	Individual	Social
$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	0	1
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	9	6
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	3	6
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	6	2
Total	18	15

Table 98 displays the classification of subjects according to their probability weighting in both treatments in the Loss Domain. Fisher's exact test, comparing probability weighting by treatment, suggests that there is no significant difference in probability weighting by treatment (P-value= 1).

TABLE 98: Classification of subjects according to their probability weighting in both treatments in the Loss Domain^a

Individual \ Social	$W_{1/3} > 1/3$	$W_{1/3} > 1/3$	$W_{1/3} < 1/3$	$W_{1/3} < 1/3$	Total
	and $W_{2/3} > 2/3$	and $W_{2/3} < 2/3$	and $W_{2/3} > 2/3$	and $W_{2/3} < 2/3$	
$W_{1/3} > 1/3$ and $W_{2/3} > 2/3$	0	0	0	0	0
$W_{1/3} > 1/3$ and $W_{2/3} < 2/3$	0	1	0	0	1
$W_{1/3} < 1/3$ and $W_{2/3} > 2/3$	0	0	0	1	1
$W_{1/3} < 1/3$ and $W_{2/3} < 2/3$	0	0	1	0	1
Total	0	1	1	1	3

^a The table includes 3 subjects for whom the estimation of $W_{1/3}$ and $W_{2/3}$ in both treatments were possible.

Table 99 shows the classification of subjects according to their risk aversion parameters in RDU model in Loss Domain. When estimating risk aversion parameters for each subject based on his responses in the 7 loss tasks of the individual treatment, around 83% of the subjects are risk averse and 17% are risk seeking. In the social treatment, around 67% of the subjects are risk averse and 13% are risk seeking. Thus, risk aversion decreases in the social treatment.

TABLE 99: Classification of subjects according to their risk aversion parameters in RDU model

Treatment	Risk averse ($r < 1$)	Risk neutral ($r = 1$)	Risk seeking ($r > 1$)	Total
Individual	15	0	3	18
Social	10	0	5	15

Table 100 displays the classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments in the Loss Domain. There are no risk seeking subjects in both treatments.

TABLE 100: Classification of subjects according to their risk aversion parameters estimated with $\epsilon = 0$ in both treatments^a

Individual \ Social	Social		Total
	Risk averse ($r < 1$)	Risk seeking ($r > 1$)	
Risk averse ($r < 1$)	1	1	2
Risk seeking ($r > 1$)	1	0	0
Total	2	1	3

^a The table includes 3 subjects for whom the estimation of risk aversion parameters in both treatments was possible.

TABLE 101: 21 Choice Situations used in the experiment

Choice Situation	Left Urn			Right Urn		
	Value of Ball 1	Value of Ball 2	Value of Ball 3	Value of Ball 1	Value of Ball 2	Value of Ball 3
1	1	15	15	8	8	15
2	1	15	15	1	8	22
3	8	8	15	5	11	15
4	8	8	15	1	8	22
5	5	5	21	5	13	13
6	5	5	21	9	9	13
7	5	13	13	10	10	11
8	-15	-15	-1	-15	-8	-8
9	-15	-15	-1	-22	-8	-1
10	-15	-8	-8	-15	-11	-5
11	-15	-8	-8	-22	-8	-1
12	-21	-5	-5	-13	-13	-5
13	-21	-5	-5	-13	-9	-9
14	-13	-13	-5	-11	-10	-10
15	-5	5	7	-6	6	7
16	-6	6	9	-7	7	9
17	-7	-3	7	-8	-3	8
18	-8	3	8	-9	3	9
19	-9	0	9	-10	0	10
20	-2	2	10	-3	3	10
21	-3	0	3	-4	0	4

.9 Instructions

Welcome to this experiment. This experiment aims to study decision making under risk. You will make a number of choices that are described in the following instructions. You will receive 5 euros for your presence. In addition to these five euros, you will get 11 euros as initial endowment. You will be paid according to your gains or losses during the experiment following the procedures described in the instructions. Throughout the experiment, your earnings will be expressed in ECU (Experimental Currency Units). They will be converted into euros at the end of the experiment, with the following conversion rate: 1 Euro = 2 ECU

You indicate your choices to your computer. The choice situations that will be presented to you are not made to test you. There is no right or wrong answers. We just want to know what choices you make in these situations. The only right answer is what you actually chose. Make your decisions carefully. Pay particular attention to the possible outcomes before making a decision. Remember that your final earnings in this experiment depend on your decisions (and randomness of course). You can check these instructions at any time during the experiment. If you still have questions, raise your hand and the organizer will then come to you and answer your question in private. During the whole experiment, you are not allowed to communicate with other participants and you are requested to switch off your phones and electronic devices otherwise you will be excluded from the session. The experiment consists of two parts. Each part consists of 21 situations. There will be a potential gain determined for each part. For the final payment, we will use your gain in one of two parts of the experience. It is therefore essential that you take your decisions very carefully in each situation. At the end of the experiment, your earnings will be paid out privately and confidentially in check.

I. Part one

In the first part of the experiment, you will face 21 choice situations. In each situation, you have to choose between two urns (left and right urn). Each urn contains 3 balls.

The value of the ball in ECU can be positive or negative. Each ball has a color (White, Grey or Black). You will have to classify those colors in order of preference. Here's an example of what will appear on your screen in that time of the experiment.

Rank the following colors in order of your preference (1 = the color you like the most and 3 = the color you like the least).

White

Grey

Black

Validate

If you do not have any preference between the three colors, you should click on "No Preference".

No Preference

If you have a preference for three colors: White, Grey and Black, you must rank the colors in order of preference (1 = the color you like the most and 3 = the color you like the least). You can validate this choice by clicking on "Confirm". You can also cancel your choice if you change your mind by clicking "Cancel". On the other hand, if you do not have any preference between the three colors, you should click on "No Preference". You can validate this choice by clicking on "Confirm". You can also cancel your choice if you change your mind by clicking "Cancel".

Rank the following colors in order of your preference (1 = the color you like the most and 3 = the color you like the least).

White

Grey

Black

Validate

If you do not have any preference between the three colors, you should click on "No Preference".

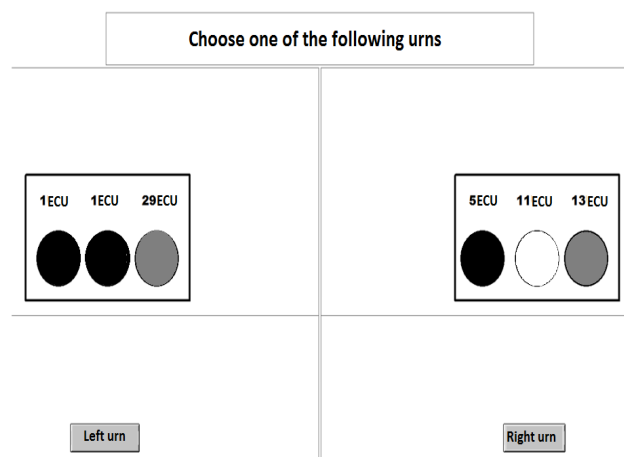
No Preference

Dialog
You chose "No Preference".
Please confirm your choice.
Confirm
Cancel

If you choose to rank the colors in order of preference, the ball having the maximum value (in ECU) will be represented by the color you like the most (ranked 1). The ball having the minimum value (in ECU) will be represented by the color you like the least (ranked 3). The ball with the middle value (in ECU) will be represented by the color you have ranked 2. By cons, if you do not have a preference between the three colors, the computer will choose a random ranking for the three colors.

Then, you will face 21 choice situations. For each of them, you have to choose between two urns (left and right urn). The following figure shows an example of a situation where you will have to make a choice:

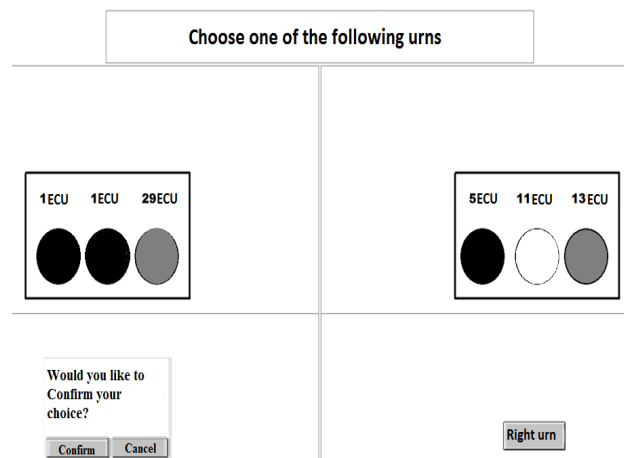
To indicate your choices, you click "Urn Left" or "Right Urn". The screen will allow you to validate this choice by clicking on "Confirm". You can also change your choice by clicking "Cancel".



Once you confirm your choice, you can proceed to the next one. Another situation, different from the previous, is then presented. At the end of both parts of the experiment, one of these 21 situations will be randomly selected by the program for each participant. The randomly selected situation that determines your earnings for this part is similar to that of other participants. Your earnings for this part of the experiment will be determined by a draw of a ball from the urn you have chosen for this situation. You will know your earnings for that part at the very end of the experiment.

If you choose to rank the colors in order of preference, the ball having the maximum value (in ECU) will be represented by the color you like the most (ranked 1). The ball having the minimum value (in ECU) will be represented by the color you like the least (ranked 3). The ball with the middle value (in ECU) will be represented by the color you have ranked 2. By cons, if you do not have a preference between the three colors, the computer will choose a random ranking for the three colors.

Then, you will face 21 choice situations. For each of them, you have to choose between two urns (left and right urn). The following figure shows an example of a situation where you will have to make a choice:



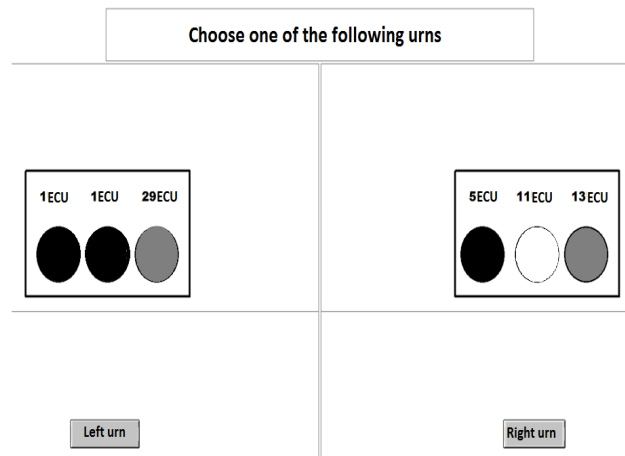
To indicate your choices, you click "Urn Left" or "Right Urn". The screen will allow you to validate this choice by clicking on "Confirm". You can also change your choice by clicking "Cancel".

Once you confirm your choice, you can proceed to the next one. Another situation, different from the previous, is then presented. At the end of both parts of the experiment, one of these 21 situations will be randomly selected by the program for each participant. **The randomly selected situation that determines your earnings for this part is similar to that of other participants. Your earnings for this part of the experiment will be determined by a draw of a ball from the urn you have chosen for this situation.** You will know your earnings for that part at the very end of the experiment.

There are three kinds of situations that you will face:

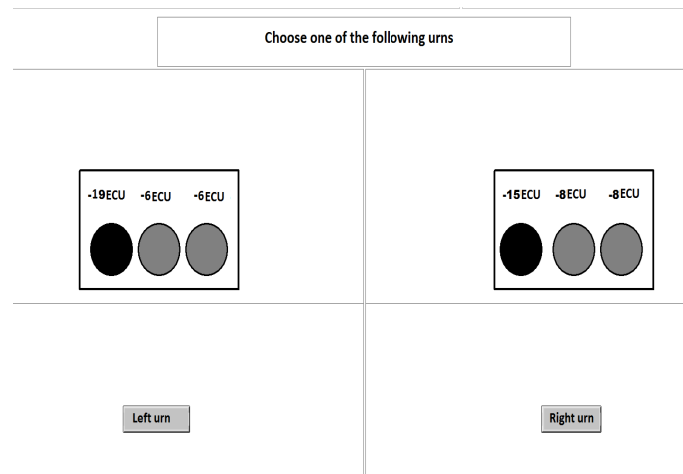
1. All balls have a positive value.
2. All balls have a negative value.
3. Some balls have a positive value and others that have a negative value.

1. The following figure shows an example of the first type of situation:



If you chose the right urn and if it is randomly selected at the end of the experiment to determine your earnings, there are three possibilities for drawing a ball from the urn:

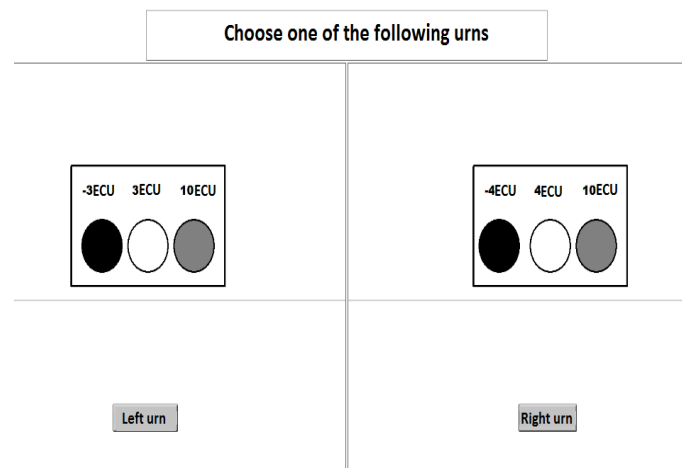
- (a) The ball having a value of 5 ECU is randomly drawn for you. So you earn 5 ECU in addition to your initial endowment.
 - (b) The ball having a value of 11 ECU is randomly drawn for you. So you earn 11 ECU in addition to your initial endowment.
 - (c) The ball having a value of 13 ECU is randomly drawn for you. So you earn 13 ECU in addition to your initial endowment.
2. The following figure shows an example of the second type of situation:



If you chose the left urn and if it is randomly selected at the end of the experiment to determine your earnings, there are three possibilities for drawing a ball from the urn:

- (a) The ball having a value of -6 ECU is randomly selected for you. You lose 6 ECU of your initial endowment.
- (b) The ball having a value of -6 ECU is randomly selected for you. You lose 6 ECU of your initial endowment.
- (c) The ball having a value of -19 ECU is randomly selected for you. You lose 19 ECU of your initial endowment.

3. The following figure shows an example of the third type of situation:



If you chose the urn left and if it is randomly selected at the end of the experiment to determine your earnings, there are three possibilities for drawing a ball from the urn:

- (a) The ball having a value of 3 ECU is randomly drawn for you, so you earn 3 ECU in addition to your initial endowment.
- (b) The ball having a value of -3 ECU is randomly drawn for you, so you lose 3 ECU your initial endowment.
- (c) The ball having a value of 10 ECU is random drawn for you, then you earn 10 ECU in addition to your initial endowment.

II. Part two:

In the second part of the experiment, you will face 21 choice situations. For each of them, you have to choose between two urns (left and right urn). Each urn contains 3 balls. After making your choice, one of the 21 choice situations is randomly selected¹. You will form a group with 2 other participants who chose the same urn as you in the randomly selected situation². The earnings of each of the three members of the group

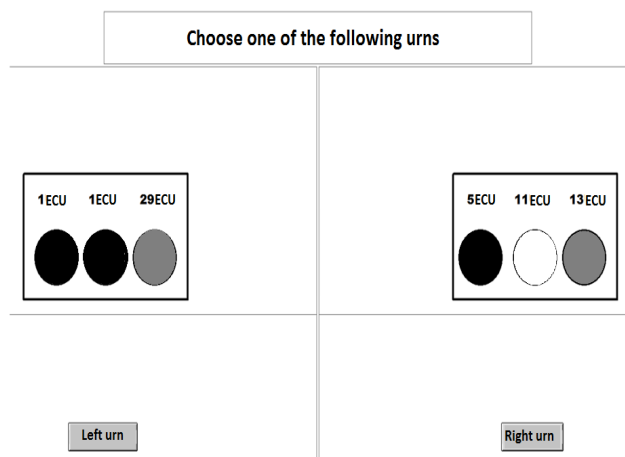
¹The randomly selected situation is the same for all participants.

²Sometimes it is impossible to make groups of three participants who chose the same urn in the randomly selected situation. In this case, a participant, randomly selected, will form a group with two other participants who have not made the same choice as him. In other words, he will draw from an urn that he did not choose.

will be determined by, without replacement, drawing ball of the urn. The order of the draw for each member is random. All the balls have the same chance of being drawn randomly from the urn. You do not know which ball will be drawn for you or for the two members of your group. There are three kinds of situations that you will face:

1. All balls have a positive value.
2. All balls have a negative value.
3. Some balls have a positive value and others that have a negative value.

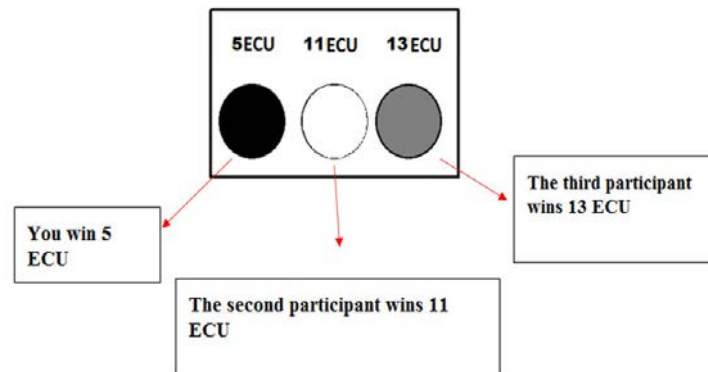
1. The following figure shows an example of the first type of situation:



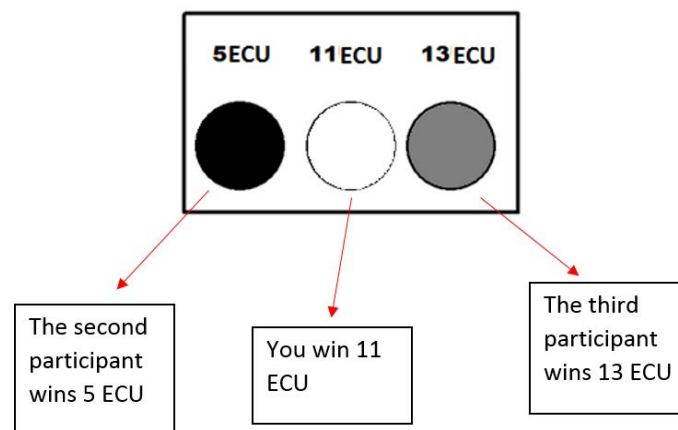
If you choose the right urn and if it is randomly selected at the end of the second part, you will therefore form a group with two other participants who made the same choice as you. In other words, they also chose the right urn in this situation. A ball is drawn from the urn to determine the earnings of each of the group members. There are three possibilities for drawing a ball from the urn:

- (a) If the ball having a value of 5 ECU is randomly drawn for you, you earn 5 ECU. The ball having a value of 11 ECU is drawn for the second member of

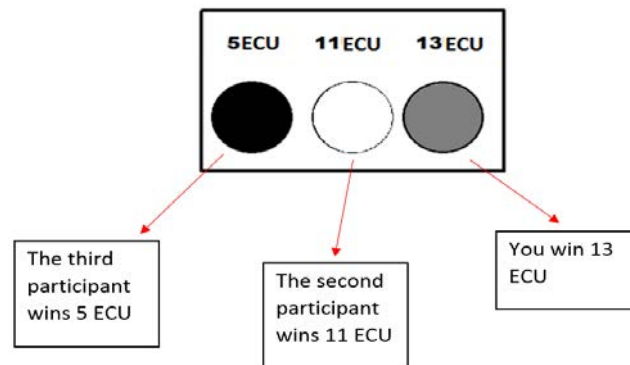
your group, so he earns 11 ECU. Finally, the ball having a value of 13 ECU is drawn for the third member of your group, so he earns 13 ECU.



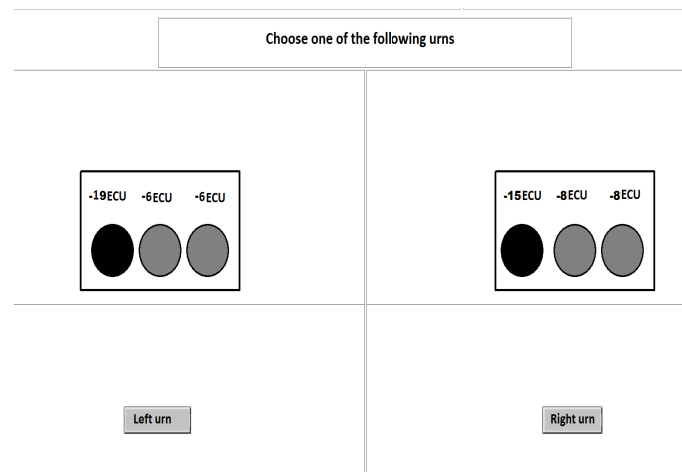
- (b) If the ball having a value of 11 ECU is randomly drawn for you, you earn 11 ECU. The ball having a value of 5 ECU is drawn for the second member of your group, so he earns 5 ECU. Finally, the ball having a value of 13 ECU is drawn for the third member of your group, so he earns 13 ECU.



- (c) If the ball having a value of 11 ECU is randomly drawn for you, you earn 11 ECU. The ball having a value of 5 ECU is drawn for the second member of your group, so he earns 5 ECU. Finally, the ball having a value of 13 ECU is drawn for the third member of your group, so he earns 13 ECU.



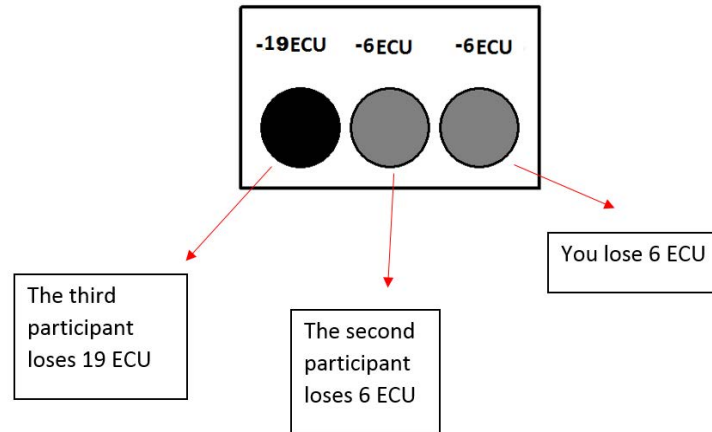
2. The following figure shows an example of the second type of situation:



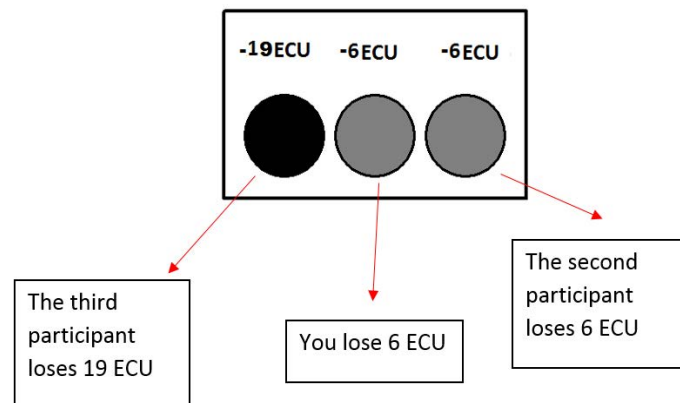
If you choose the left urn and if it is randomly selected at the end of the second part, you will therefore form a group with two other participants who made the same choice as you. In other words, they also chose the left urn in this situation. A ball is drawn from the urn to determine the earnings of each of the group members. There are three possibilities for drawing a ball from the urn:

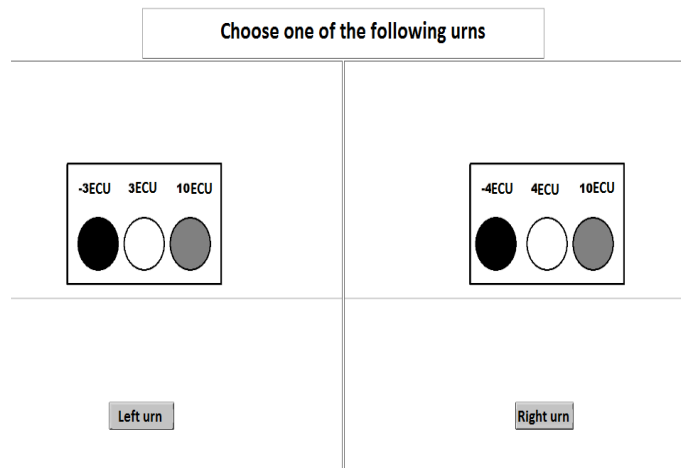
- (a) If the ball having a value of -6 ECU is randomly drawn for you, you lose 6 ECU from your initial endowment. The ball having a value of -6 ECU is drawn for the second member of your group, so he loses 6 ECU from

his initial endowment. Finally, the ball having a value of 19 ECU is drawn for the third member of your group, so he loses 19 ECU from his initial endowment.

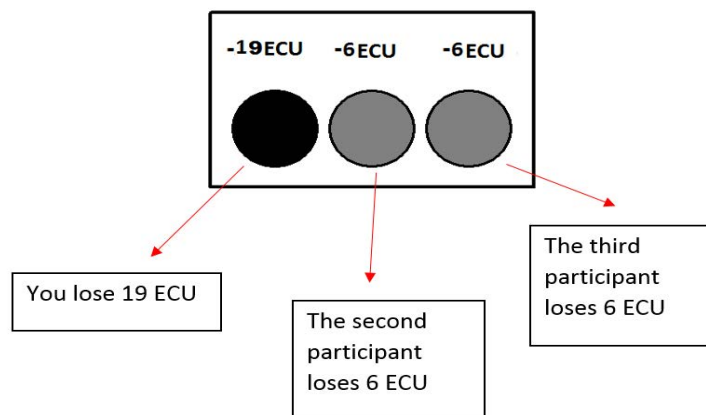


(b) If the ball having a value of -6 ECU is randomly drawn for you, you lose 6 ECU from your initial endowment. The ball having a value of -6 ECU is drawn for the second member of your group, so he loses 6 ECU from his initial endowment. Finally, the ball having a value of 19 ECU is drawn for the third member of your group, so he loses 19 ECU from his initial endowment.





- (c) If the ball having a value of -19 ECU is randomly drawn for you, you lose 19 ECU from your initial endowment. The ball having a value of -6 ECU is drawn for the second member of your group, so he loses 6 ECU from his initial endowment. Finally, the ball having a value of 6 ECU is drawn for the third member of your group, so he loses 6 ECU from his initial endowment.

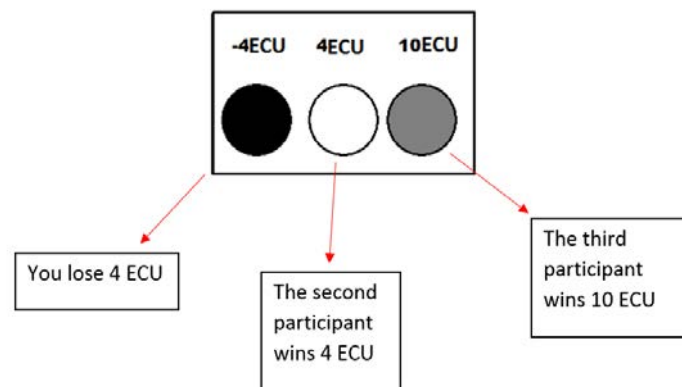


3. The following figure shows an example of the third type of situation:

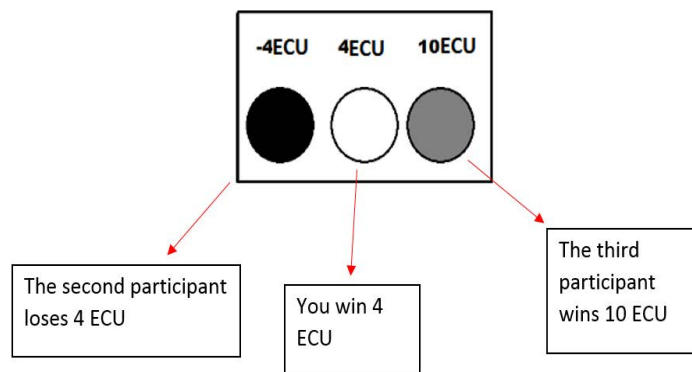
If you choose the right urn and if it is randomly selected at the end of the second part, you will therefore form a group with two other participants who made the same choice as you. In other words, they also chose the right urn in this

situation. A ball is drawn from the urn to determine the earnings of each of the group members. There are three possibilities for drawing a ball from the urn:

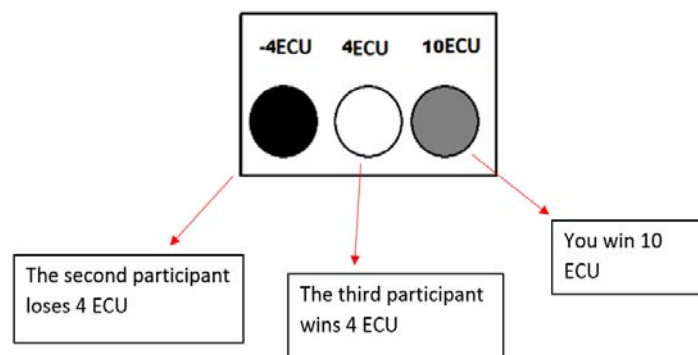
- (a) If the ball having a value of -4 ECU is randomly drawn for you, you lose 4 ECU from your initial endowment. The ball having a value of 4 ECU is drawn for the second member of your group, so he earns 4 ECU from his initial endowment. Finally, the ball having a value of 10 ECU is drawn for the third member of your group, so he earns 10 ECU from his initial endowment.



- (b) If the ball having a value of 4 ECU is randomly drawn for you, you earn 4 ECU from your initial endowment. The ball having a value of -4 ECU is drawn for the second member of your group, so he loses 4 ECU from his initial endowment. Finally, the ball having a value of 10 ECU is drawn for the third member of your group, so he earns 10 ECU from his initial endowment.



- (c) If the ball having a value of 10 ECU is randomly drawn for you, you earn 10 ECU from your initial endowment. The ball having a value of -4 ECU is drawn for the second member of your group, so he loses 4 ECU from his initial endowment. Finally, the ball having a value of 4 ECU is drawn for the third member of your group, so he earns 4 ECU from his initial endowment.



III. The Random Draw:

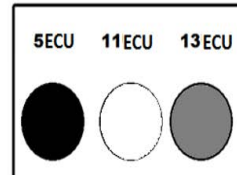
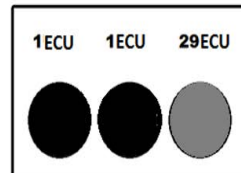
At the end of the two parts of the experience, your potential gain for the first part of the experience is determined by a draw of a ball from the urn you have chosen in the situation randomly selected by the program. The randomly selected situation will be displayed on the screen and your choice will be recalled.

In the first part of the experiment, you made 21 choices. One of these choices is randomly selected

The randomly selected choice situation is: 10

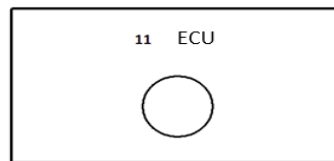
The urn you chose in this situation is: Right Urn

A ball is randomly drawn from the urn you chose



A random draw takes place in the urn

The ball that is randomly drawn from the urn



Your earnings for the first part: 11 ECU

In the second part of the experience, you have formed a group with 2 other participants who chose the same urn as you in this situation randomly selected.

Your choice will be recalled.

In the second part of the experiment, you made 21 choices.

You will form a group with two other participants who chose the same urn as you in the randomly selected choice situation

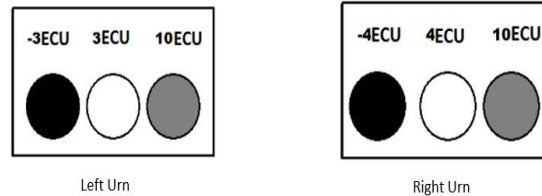
The earnings of each of the three participants is determined by a random draw, without replacement, of a ball from the urn.

The order of the draw of each participant is random.

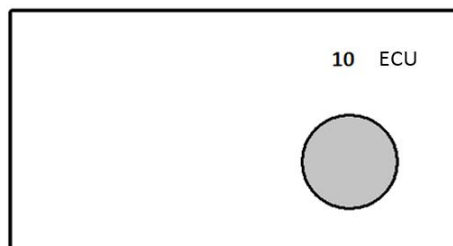
The urn you chose in this situation is: 9

The randomly selected choice situation is: Left Urn

A ball is randomly drawn from the urn you chose



To determine your potential earnings for the second part of the experiment, a ball is drawn, without replacement, from the urn for each member of the group. The order of the draw for each member is random.



Your earnings for the second part: 10 ECU

IV. Your payment for the experience:

After reading the instructions, you draw an envelope at random from two envelopes. **PLEASE DO NOT OPEN THE ENVELOPE YOURSELF OTHERWISE YOU WILL TO BE EXCLUDED OF PAYMENT.** Your envelope will be opened at the end of the experiment by the experimenter. This envelope contains a code corresponding to one of the two parts of the experience. For

payment, we will use your earnings in one of two parts of the experiment corresponding to the content of the envelope. Your final payment corresponds to the value of the ball drawn at random from the urn you have chosen in one of the situations that you have faced. **ONLY ONE SITUATION IS PAID.** It is therefore essential that you take your decisions very carefully in each situation. After the experimenter has opened your envelope, to know your payment, you must enter on your computer the code shown on the sheet in your envelope. We remind you that at the end of the experimental session, your earnings in ECU (Experimental Currency Unit) is converted into Euro at the rate of: 1 Euro = 2 ECU. To this is added a lump sum of 5 € and your initial endowment of 11€. This amount will be paid individually and privately just before leaving the room. You have time to read the instructions. If you have any questions, please raise your hand and we will answer you. Finally, the whole experience is fair play. Nothing, either in the choice of envelopes, the drawn from the urns or situations is made to be in your favor or against you.

Appendix D³

.10 Instructions

Welcome to this experiment. This experiment aims to study decision making under risk. You will make a number of choices that are described in the following instructions. You will receive 5 euros for your presence. In addition to these five euros, you will get 5 euros as initial endowment. You will be paid according to your gains or losses during the experiment following the procedures described in the instructions. Throughout the experiment, your earnings will be expressed in euros.

You indicate your choices to your computer. The choice situations that will be presented to you are not made to test you. There is no right or wrong answers. We just want to know what choices you make in these situations. The only right answer is what you actually chose. Make your decisions carefully. Pay particular attention to the possible outcomes before making a decision. Remember that your final earnings in this experiment depend on your decisions (and randomness of course).

You can check these instructions at any time during the experiment. If you still have questions, raise your hand and the organizer will then come to you and answer your question in private. During the whole experiment, you are not allowed to communicate with other participants and you are requested to switch

³Instructions for treatment group "FOUR"

off your phones and electronic devices otherwise you will be excluded from the session.

The experiment consists of 3 tables of choices with 6 rows each. Each row represents an urn. For each urn, your task is to choose one of these three colors to bet on: red, blue and green. At the end of the experiment, one of the 18 urns will be randomly selected to determine your earnings (gain or loss). It is therefore essential that you take your decisions very carefully for each urn. At the end of the experiment, your earnings will be paid out privately and confidentially in check.

The experiment: You will face 3 tables of 6 rows each. Each row represents an urn. For each urn, your task is to choose one of these three colors to bet on : red, blue and green. You will make 18 choices for 18 urns. After all participants make their choices, you will form a random group of 4 participants, the program will randomly choose the urn of the following tables that determines your earnings (gain or loss). The randomly chosen urn is the same for all the participants of the same group but may vary from one group to another.

Each of the 3 tables will be presented as follows:

Urn number	Number of red balls in the urn	Number of blue or green balls in the urn	Which color would you like to bet on?		
1	9	27	Red	Green	Blue
2	10	26	Red	Green	Blue
3	11	25	Red	Green	Blue
4	12	24	Red	Green	Blue
5	13	23	Red	Green	Blue
6	14	22	Red	Green	Blue

Each table has six rows, each row represents an urn. Each urn contains 36 balls. In each urn, there is a different but known number of red balls and the rest of the balls are either green or blue. You will not be told how many balls are blue and how many balls are green, you will only know the total number of remaining balls. In the first urn, you will be asked to make a choice when there are 9 red balls and so 27 blue or green balls. In the second row, there are 10 red balls and 26 blue or greens balls. In the sixth row, there are 14 red balls and 22 blue or green balls.

- (a) Table 1: After the participants make their choices, if one of the urns from 1 to 6 is randomly selected to determine your earnings, your potential gain is equal to :
- €5 if the randomly drawn ball from the urn has the same color as the color you bet on.
 - €0 if the randomly drawn ball from the urn does not have the same color as the color you bet on.
- (b) Table 2: After the participants make their choices, if one of the urns from 7 to 12 is randomly selected to determine your earnings, your potential gain (or loss) is equal to :
- €0 if the randomly drawn ball from the urn has the same color as the color you bet on.
 - Loss of €5 if the randomly drawn ball from the urn does not have the same color as the color you bet on.
- (c) Table 3: After the participants make their choices, if one of the urns from 12 to 18 is randomly selected to determine your earnings, your potential gain (or loss) is equal to :
- Gain of €5 if the randomly drawn ball from the urn has the same color as the color you bet on.
 - Loss of €5 if the randomly drawn ball from the urn does not have the same color as the color you bet on.

At the end of the experiment, your earnings are determined by a random draw of a ball from an urn that is randomly selected by the program. For payment, we will use your earnings for only one urn that is randomly selected by the program. **ONLY ONE CHOICE IS PAID.** It is therefore essential that you take your decisions very carefully in each situation. This amount will be paid individually and privately just before leaving the room. You have time to read the instructions. If you have any questions, please raise your hand and we will answer you. Finally, the whole experience is fair play. Nothing, either in the choice of envelopes, the drawn from the urns or situations is made to be in your favor or against you.

TABLE 102: Summary results

	Ambiguity Averse	Ambiguity Neutral	Ambiguity Seeking	Ambiguity Incoherent	Total
Treatment ZERO					
Session 1 (Gain Domain)	2	9	0	2	13
Session 1 (Loss Domain)	2	8	0	3	13
Session 1 (Mixed Domain)	2	8	0	3	13
Session 2 (Gain Domain)	2	7	0	4	13
Session 2 (Loss Domain)	1	5	0	7	13
Session 2 (Mixed Domain)	2	7	0	4	13
Treatment FOUR					
Session 1 (Gain Domain)	1	13	1	5	20
Session 1 (Loss Domain)	1	13	1	5	20
Session 1 (Mixed Domain)	1	13	0	6	20
Session 2 (Gain Domain)	0	15	1	4	20
Session 2 (Loss Domain)	2	13	1	4	20
Session 2 (Mixed Domain)	1	13	1	5	20
Session 3 (Gain Domain)	0	16	1	3	20
Session 3 (Loss Domain)	0	11	2	7	20
Session 3 (Mixed Domain)	0	11	0	9	20
Treatment SIX					
Session 1 (Gain Domain)	1	13	0	4	18
Session 1 (Loss Domain)	1	8	1	8	18
Session 1 (Mixed Domain)	2	12	0	4	18
Session 2 (Gain Domain)	1	11	0	6	18
Session 2 (Loss Domain)	1	10	1	6	18
Session 2 (Mixed Domain)	1	10	0	7	18
Session 3 (Gain Domain)	2	13	1	2	18
Session 3 (Loss Domain)	2	10	1	5	18
Session 3 (Mixed Domain)	3	11	1	3	18
Treatment ALL					
Session 1 (Gain Domain)	0	12	1	5	18
Session 1 (Loss Domain)	0	12	1	5	18
Session 1 (Mixed Domain)	1	15	0	2	18
Session 2 (Gain Domain)	0	17	1	4	22
Session 2 (Loss Domain)	0	14	2	6	22
Session 2 (Mixed Domain)	0	16	0	6	22
Session 3 (Gain Domain)	1	12	0	8	21
Session 3 (Loss Domain)	1	11	0	9	21
Session 3 (Mixed Domain)	1	12	0	8	21

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Stratégies d'acquisition d'information dans l'incertain

L'objectif de cette thèse est de présenter quatre essais en économie comportementale et expérimentale sur prise de décision dans le risque et l'ambiguïté.

Le premier essai présente une synthèse et un point de vue sur la représentativité des résultats expérimentaux en matière de préférences : préférences sociales et préférences concernant le risque et le temps dans les pays développés ainsi que dans les pays en voie de développement.

Le deuxième essai explore expérimentalement l'effet du risque et de l'ambiguïté sur le comportement de recherche d'emploi en horizon infini. Les résultats montrent qu'en risque et ambiguïté, les salaires de réservation sont inférieurs aux valeurs théoriques et diminuent au cours du processus de recherche. De même, les sujets se comportent comme des agents neutre à l'ambiguïté.

Le troisième et quatrième essai étudient l'effet du contexte social et la corrélation des paiements sur les attitudes face au risque et à l'ambiguïté respectivement dans le domaine de gain, perte et le domaine mixte. Les résultats montrent que l'introduction du contexte social a un effet significatif sur les attitudes face au risque dans les trois domaines. Néanmoins, la corrélation des risques a un effet sur les attitudes face au risque seulement dans le domaine mixte. Les attitudes face à l'ambiguïté varient selon le domaine. De même, la corrélation des paiements diminuent l'aversion à l'ambiguïté.

Mots clés : Risque; Ambiguïté; Comparaison Sociale; Recherche d'emploi; Expériences de laboratoires.

Strategies of information acquisition under uncertainty

The objective of this thesis is to present four essays in behavioral and experimental economics on decision-making under risk and ambiguity.

The first essay presents a synthesis and a point of view on the representativeness of experimental results regarding individual preferences: social preferences and risk and time preferences, in developed countries as well as in developing countries.

The second essay explores experimentally the effect of risk and ambiguity on job search behavior in an infinite horizon. The results show that in risk and ambiguity, reservation wages are lower than the theoretical values and decrease during the search process. Similarly, subjects behave as ambiguity neutral agents.

The third and fourth essay examine the effect of the social context and the correlation of payments on attitudes towards risk and ambiguity respectively in gain, loss and mixed domain. The results show that the introduction of the social context has a significant effect on attitudes towards risk in all three domains. Nevertheless, the correlation of risks has an effect on risk attitudes only in the mixed domain. As for ambiguity, ambiguity attitudes vary across domains. The correlation of payments decreases ambiguity aversion.

Keywords : Risk; Ambiguity; Social Comparison; Job search models; Laboratory experiments.