Hors-série spécial 50 ans du BETA

# DOCUMENTS DE TRAVAIL

# Dossier “Economie Expérimentale”

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**Hors-série « 50 ans du BETA »**

**« Dossier Economie expérimentale »**

**Notice introductive**

D'après Eber et Willinger (2012, 8), l'économie expérimentale peut se définir comme « l'utilisation de l'expérimentation comme méthode d'investigation en économie ». L'expérimentation en économie consiste ainsi à recréer, en laboratoire, sur le terrain ou même en ligne, une situation économique simplifiée, contrôlée par l'expérimentateur et reproductible afin d'étudier les comportements et décisions des individus. Elle peut remplir plusieurs fonctions. Elle constitue tout d'abord un outil de validation empirique des modèles (théoriques) de décisions économiques. De ce fait, elle est alors susceptible d'aider à la décision publique en évaluant, par exemple, l'impact de différents instruments de politiques publiques sur les comportements individuels. Enfin, elle a pour but de produire des connaissances nouvelles lorsque la théorie est incomplète ou inexistante. Il est alors question d'expériences exploratoires.

La reconstitution d'une situation économique en laboratoire ou sur le terrain est incontournable, car l'observation des données dans leur environnement naturel est très compliquée. Il n'est en effet pas possible d'isoler, ni de quantifier avec précision les différentes variables d'environnement susceptibles d'influencer les comportements des individus. De plus, il faudrait que les situations ou phénomènes qui intéressent l'expérimentateur se présentent aux moments et dans les lieux choisis par celui-ci, ce qui est difficilement envisageable. Cette reconstitution permet donc au concepteur de l'expérience de contrôler l'environnement auquel font face les individus, et notamment l'information dont ils disposent et la façon avec laquelle ils peuvent interagir entre eux. Ceci permet alors d'isoler et de quantifier précisément les phénomènes que l'expérimentateur cherche à mesurer : « le contrôle est l'essence de la méthodologie expérimentale » (Smith 1976, 275 ; cité aussi par Serra 2012a, 25). En économie expérimentale, les participants sont rémunérés et les gains qu'ils perçoivent durant une expérience dépendent de leurs décisions, voire des décisions des autres participants en cas de jeux en interactions. Ceci distingue en particulier cette discipline des autres qui ont recours à l'expérimentation, comme par exemple en psychologie ou en médecine, où tous les participants sont rémunérés de manière égale. Un autre élément de différenciation est l'absence de mensonge ou de surprise à l'égard des sujets expérimentaux, que l'on retrouve parfois dans des expériences en psychologie (comme pour l'expérience de Milgram par exemple). Dans une expérience économique, tous les éléments du jeu sont expliqués et explicités. Il n'y a pas de manipulation à l'égard des sujets.

S'il est habituellement mentionné que la première expérience en économie remonte au paradoxe de Saint-Pétersbourg tel que mis au jour par Bernoulli (Roth 1995, Serra 2012b, Cot et Ferey 2016, Igersheim et Lefebvre 2022), c'est après la seconde guerre mondiale que l'on peut situer la naissance de l'économie expérimentale en tant que sous-discipline véritable de la science économique dans le sillage de la théorie des jeux. Suivant en cela Serra (2012b), cette histoire peut être découpée en quatre grands moments : (1) l'émergence proprement dite qui court jusqu'au début des années soixante ; (2) le démarrage et la consolidation des années soixante aux années 80 notamment grâce aux figures tutélaires de Vernon Smith et Charles Plott ; (3) le décollage des années quatre-vingt avec la création croissante de laboratoires d'économie expérimentale aux Etats-Unis, l'acceptation des études employant cette méthode dans des revues prisées et la stabilisation d'une communauté scientifique lui étant acquise ; (4) enfin, la phase de maturité des années quatre-vingt-dix à nos jours qui a notamment vu la reconnaissance de cette sous-discipline via le prix Nobel accordé pour moitié à Vernon Smith en 2002 « pour avoir fait de l'expérience en laboratoire un instrument d'analyse économique empirique, en particulier dans l'étude de différentes structures de marché ».

En France, le BETA est l'un des tout premiers laboratoires de recherche à bénéficier d'une plateforme dédiée à l'économie expérimentale avec la création du Laboratoire d'Économie Expérimentale de Strasbourg (LEES) dès janvier 1997. Véritable moteur de la recherche en économie expérimentale au BETA, le LEES est aujourd'hui nationalement reconnu et apte à effectuer tout type d'expérimentations, que ce soit en laboratoire, sur le terrain ou en ligne. En outre, le LEES dispose depuis 2012 d'une plateforme web innovante destinée à l'enseignement et à la recherche (EconPlay). Il est accessible à tous les membres du BETA et peut accueillir également des chercheurs externes. Actuellement en cours de labellisation auprès de l'Université de Strasbourg (Réseau CORTECS), le LEES a également été récompensé en 2022 par une distinction scientifique d'envergure via l'attribution de la médaille de Cristal du CNRS à Kene Boun My, ingénieur CNRS et Lab Manager du LEES depuis ses débuts.

La plateforme économie expérimentale du BETA, qui se verra enrichie tant géographiquement que méthodologiquement dans un avenir proche, a ainsi fortement contribué à la visibilité et à la reconnaissance de notre laboratoire. De nombreux membres y ont fréquemment recours, quel que soit le site où ils sont localisés (Strasbourg, Nancy, …). Plus remarquable encore, nos chercheurs y font appel quel que soit leur domaine de recherche. La plateforme économie expérimentale du BETA est ainsi peu à peu devenue un outil incontournable et un atout majeur de notre laboratoire. Les quatre papiers réunis dans ce dossier « spécial 50 ans » consacré à l'économie expérimentale ont pour objectif de montrer la richesse et la diversité des travaux conduits au BETA - des premières expérimentations menées au sein du LEES et étudiant qui un jeu de coordination, qui un jeu d'investissement jusqu'à des études plus récentes en économie du droit ou en économie forestière -, non sans mentionner leur excellence scientifique.

Le papier de Kene Boun My, Marc Willinger et Anthony Ziegelmeyer, paru initialement en 1999 sous forme de WP BETA puis publié en 2006 dans la *Revue d'Économie Industrielle*, s'intéresse aux effets des modes d'interaction dans un jeu de coordination répété. L'expérience, réalisée au printemps 1997, est la première effectuée au sein du LEES. Elle consiste à faire jouer 50 fois les sujets au jeu de coordination dit de la chasse au cerf (*Stag Hunt*) en faisant varier la taille du bassin d'attraction de l'équilibre risque dominant en considérant différentes matrices de gains, ainsi que le mode d'appariement. Ce jeu possède deux équilibres de Nash en stratégies pures : un dominant du point de vue des paiements, l'autre dominant du point de vue du risque. Le problème est donc de se coordonner sur l'équilibre Pareto optimal. Les auteurs cherchent à voir l'influence de la règle d'appariement des joueurs sur ces choix d'équilibres.

La première méthode d'appariement est standard et consiste à faire jouer chaque jouer dans un groupe de 8 avec l'un des 7 autres sujets de manière aléatoire et anonyme. Les auteurs introduisent une règle d'interaction locale selon laquelle chaque jouer ne peut jouer qu'avec ses deux plus proches voisins dans un groupe de 8 sujets répartis en cercle. Les résultats expérimentaux montrent que cette méthode d'appariement *local* amène les sujets à se coordonner plus souvent sur l'équilibre risque-dominant que dans le cas d'un appariement *global*. La convergence vers un équilibre n'est pas affectée par la règle d'appariement mais dépend de la taille du bassin d'attraction de l'équilibre risque dominant.

L'article de François Cochard, Phu Nguyen Van et Marc Willinger a été publié en 2003 dans le *Journal of Economic Behavior & Organization*. Les auteurs s'intéressent aux conséquences de l'introduction d'une répétition dans un jeu d'investissement sur les comportements des deux joueurs. L'expérience consistait à contraster les résultats du jeu joué une seule fois avec ceux observés lorsque le jeu est répété à 7 reprises. Les résultats montrent que dans ce dernier cas les joueurs investissent et renvoient plus que dans un cas sans répétition. Cependant cet effet n'est présent que sur les 5 premières périodes : les deux dernières montrent un brutal déclin des montants investis et renvoyés allant même en-deçà des montants du jeu non répété. Les auteurs estiment empiriquement un modèle de réciprocité pour expliquer les comportements observés. Les résultats sont contrastés et le comportement de retours du second joueur semblent indiquer une certaine érosion de la réciprocité au cours du temps ou un comportement d'égoïsme déguisé pour gagner la confiance du joueur en charge de l'investissement.

L'article de Yannick Gabuthy, Nicolas Jacquemet et Nadège Marchand a été publié en 2008 dans l'*European Economic Review*. Alliant modèle théorique et expérience, les auteurs cherchent à voir comment la résolution automatique de litiges en ligne impacte le taux d'accord lors de ce type de conflit. La méthode de résolution automatique de litige consiste pour les deux parties à soumettre de manière privée le montant souhaité ou offert et le litige sera résolu si les offres convergent ou si les offres divergent tout en restant au sein d'un certain niveau de compatibilité. L'apport principal de ce papier est de voir comment la marge de compatibilité affecte le taux d'accord. Théoriquement, et de manière contre-intuitive, les auteurs montrent qu'une plus grande marge de comptabilité nuit aux accords. Les deux parties vont en effet chercher à tirer profit de celle-ci et à adopter des comportements extrêmes. L'expérience vise à tester cette prédiction en observant les taux d'accord lors que la zone de compatibilité est nulle ou positive et lorsque les désaccords entre les deux parties sont élevés ou faibles. Les résultats montrent que l'introduction de cette marge de compatibilité ne joue pas sur le comportement du plaintif mais que le défendeur aura lui un comportement plus agressif lorsque les désaccords sont modérés. En termes de résolution de conflit le passage à une résolution automatique se traduit par des accords plus récurrents uniquement en présence des désaccords élevés. Cette expérience met en évidence l'importance du niveau de désaccord initial et de la marge de comptabilité autorisée dans la gestion automatique des litiges.

L'article de Marielle Brunette, Jérôme Foncel et Eric Nazindigouba Kéré a été publié dans *Environmental Modeling & Assessment* en 2017. Ce papier s'intéresse à l'attitude face au risque des propriétaires forestiers et son lien avec leur décision de coupe. Les auteurs combinent les méthodes de préférences révélées et déclarées. L'attitude face au risque est estimée à l'aide d'un choix hypothétique de loterie et est ensuite reliée aux comportements de coupes et à diverses caractéristiques des exploitants et de leurs exploitations. Les résultats indiquent que les forestiers français présentent une aversion au risque et que celle-ci peut s'expliquer par leur exposition au risque, la localisation géographique et leur revenu. De plus cette aversion au risque joue de manière significative sur la décision de coupe en complément de divers facteurs démographiques. Cette étude met donc en avant le rôle prépondérant des attitudes face au risque dans le comportement des exploitants forestiers.

Kene Boun My, Herrade Igersheim, Sébastien Massoni, août 2022

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# Global versus local interaction in coordination games: an experimental investigation♣

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**Abstract.** We study experimentally the outcome of a 50 periods repetition of a two-player coordination game, which admits two-pure strategy Nash equilibria that are Pareto-ranked: a payoff-dominant equilibrium and a risk-dominant equilibrium. The experiment consists of a 2x3 factorial design, with two different matching rules –global an local interaction–, and three sizes for the basin of attraction of the risk-dominant equilibrium. Under global interaction, each player can be matched in each period with any player in the population. Under local interaction, each player can be matched only with one of his two neighbours. Our results confirm earlier experimental results obtained under global interaction (for a survey see Ochs (1995)). On the contrary, the results contrast sharply with Keser, Ehrhart & Berninghaus (1998), who found that subjects interacting 'locally' with their neighbours around a circle, coordinate mostly on the risk-dominant equilibrium. Moreover, we found no evidence for a faster convergence to an equilibrium under local interaction than under global interaction.

**Key words:** Coordination games – Experimental economics – Evolutionary game theory – Local interactions

**JEL-classification:** C92; C72; C73

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## 1. Introduction

This paper reports an experiment designed to study the influence of a local interaction structure on equilibrium selection in a coordination game. A 'global interaction' is a situation in which the behaviour of an agent is directly affected by choices of all other agents in the population. Conversely, interactions are 'local' if agents take into account only the information coming from a strict subset of the population, that is, if only choices of a small group of people are relevant whenever an individual performs his or her decisions. The assumption of 'local interactions' implies the introduction of a spatial dimension in the economy (Kirman (1994)). Agents are physically distributed in some spatial environment and interactions are modelled by means of the distances between agents. The distance between two agents might reflect a geographic characteristic or different socio-economic characteristics of agents themselves. In recent years, models with 'local interactions' have been applied to many economic contexts, such as, for instance, regional economics (Krugman (1994)), technological adoption (Allen (1982a)) or the diffusion of information and the contagion of opinions (Allen B. (1982b)).

The reference treatment is a *Global Interaction* treatment in which subjects interact globally. We compare the results of 12 groups of the *Global Interaction* treatment with the results of 12 groups of the *Local Interaction* treatment. Under global interaction, a player can be matched with any other player in the population, while under local interaction a player can be matched only with players belonging to a subset of players within the whole population. Although under local interaction each player interacts only with the players of his neighbourhood, he interacts indirectly with all the players of the population, because neighbourhoods are overlapping. Each player is therefore also affected by decisions taken by players who do not belong to his own neighbourhood and his own decisions also affect players outside his neighbourhood. We consider a 2x2 symmetric coordination game with two symmetric, strict Nash equilibria and a mixed Nash equilibrium. The two pure-strategy Nash equilibria are Pareto-ranked: one is a *payoff-dominant* equilibrium and the other one is a *risk-dominant* equilibrium[1] in the sense of Harsanyi & Selten (1988). A game with this structure is commonly referred to as a S*tag Hunt game*. Which equilibrium will be selected is a matter of considerable debate since all strict Nash equilibria survive any of the established refinement tests. Therefore, and while the mixed-strategy equilibrium is commonly dismissed, the literature does not provide a clear conclusion as to which of the two pure-strategy equilibria will be selected.

In this paper we contrast previous experimental findings under global interaction with new experimental data on local interaction. In contrast to Keser et al. (1998), our experiment relies on the same size of population of 8 subjects in both the *Global Interaction* treatment and in the *Local Interaction* treatment. In the local interaction structure subjects are spatially distributed on a circle and each one interacts with his adjacent neighbours. We compare the two interaction conditions for three different payoff structures with increasing attractiveness for the risk-dominant equilibrium. Our experimental results weakly support the prediction that under local interaction risk-dominance is the dominant outcome. Indeed, not all the subject groups interacting in the *Local Interaction* treatment did coordinate on the less risky equilibrium, even if more coordination on the payoff-dominant equilibrium is observed in the *Global Interaction* treatment. Moreover, this difference between the two interaction structures is not statistically significant. In this respect, this conclusion contrast sharply with the previous experimental result obtained by Keser et al. (1998) for different population sizes between the local and the global interaction conditions. Nevertheless, we observe that when the risk-dominant equilibrium becomes more attractive, the population "converges"[2] more frequently towards that outcome. Our results also show that "convergence" is not faster under local interaction than under global interaction.

The balance of the paper is as follows. In the next section we survey some theoretical and experimental litterature concerning equilibrium selection. Section 3 introduces the structure of the

[1] The risk-dominant equilibrium is the equilibrium with the largest Nash product, that is, the equilibrium for which the product of the deviation losses is largest.
[2] What is meant by convergence is defined in section 6.3.

game and section 4 describes the matching rules used in the experiment. In section 5 we present the practical procedures. Our results are commented in section 6. Final comments conclude.

## 2. Some theoretical and experimental literature on the coordination problem

### 2.1 Theory

We distinguish between the "classical" theories as opposed to the evolutionary theories. Among classical theories, based on models of substantively rational agents, a few do discriminate between the two strict Nash equilibria of such a game (e.g. Harsanyi & Selten (1988), Carlsson & Van Damme (1993), Harsanyi (1995)). Harsanyi & Selten (1988) rely on collective rationality to predict payoff dominance. Carlsson & Van Damme (1993) predict the risk-dominant equilibrium, on the ground that it is robust to a specific type of uncertainty about payoffs. More recently, Harsanyi (1995) revised his position and proposed a new theory of equilibrium selection that relies only on risk dominance as a criterion for choosing among different equilibria. He claimed that the new theory has a much "higher degree of theoretical unity and of direct intuitive understandability", compared to Harsanyi & Selten (1988). Theories which rely on eductive reasoning neglect complicated learning processes that induce equilibrium and therefore they neglect also the history of the process. While classical theories consider only global interaction structures, evolutionary game theory studies both global and local interaction structures. We take therefore as a reference the predictions of evolutionary game theory.

Evolutionary models put forward learning and adaptive behaviour as important features for understanding the strategic choices in a game where players gain experience. Theories based on deterministic dynamics, such as myopic best response dynamic, predict history-dependent equilibrium selection and predict either the payoff-dominant or the risk-dominant equilibrium, depending on the basin of attraction which contains the initial state. Kandori, Mailath & Rob (1993) (henceforth KMR) and Young (1993) reconsidered the learning dynamics, and showed that the addition of a small mutation probability, changes significantly the result of the deterministic dynamics. Stochastic models predict that the limit distribution will concentrate all the probability mass on the risk-dominant equilibrium. Robson & Vega-Redondo (1996) showed that the matching rule of the players may affect the equilibrium outcome. Under random rematching in each period, the payoff-dominant equilibrium will be selected. In these models, the relative sizes of the basins of attraction strongly affect the outcome. This result, however, is weakened if one takes into account other factors, such as the "strength of learning". Binmore & Samuelson (1997) showed that by taking into account this factor, either of the two equilibria will be reached. Finally, Bergin & Lipman (1996) showed that any refinement effect obtained by adding small mutations, as in KMR (1993), is solely due to restrictions on how mutation rates vary across states. They show that virtually any outcome can be obtained, in the limit as the probability of a mutation approaches zero, if in the process the relative probabilities of the strategies to which a mutation switches a player can approach zero or infinity. Besides, some authors studied the impact of local interactions.

Berninghaus & Schwalbe (1996) consider a deterministic interaction model in which each player interacts only with a subset of the population. In their model, risk-dominance, as a selection criterion, is stronger than Pareto superiority. Ellison (1993), who extended KMR's (1993) model to local interactions, also showed that the risk-dominant equilibrium is always selected in the long-run. Blume (1993) studied the play of 2 x 2 games in an infinite two-dimensional lattice, in which agents deviate from their best reply strategy with a probability that depends on the prospective loss in payoff from such a deviation. Blume (1993) considers a log linear response model with parameter $\beta > 0$ and establishes that when the log linear strategy revision approaches the best-reply rule ($\beta \to \infty$), the limit distribution puts probability one on the risk-dominant convention as in the uniform error model. Models of local interactions have also established that "convergence" to the equilibrium is faster under local interactions. Starting from an initial state where most of the players adopt the payoff-dominant action, and for a given rate of mutation, the expected waiting time before all the players adopt the risk-dominant action, is much lower under local interaction than under global interaction.[3] Therefore, under global interaction "..play should exhibit great inertia with a historically determined equilibrium repeated over and over again.", and under local interaction, "…evolutionary forces will be a powerful determinant of play…"[4] (Ellison (1993)). This implies that in an experiment with a finite number of periods of play, under the assumption of best-reply stochastic dynamics, we should observe much more risk-dominant outcomes than payoff-dominant outcomes under local interaction. On the contrary, depending on the payoff structure of the stage game, as much payoff-dominant outcomes as risk-dominant outcomes can be observed under global interaction.

## 2.2 Previous experiments

Because there is no single theoretical prediction, coordination games have been extensively studied by experimentalists under global interaction (for a survey see Ochs (1995)). The available evidence can be summarised as follows : although the coordination problem is solved by the repeated interaction between subjects, i.e. disequilibrium outcomes are rare, strategic uncertainty leads to coordination failure, i.e. convergence is towards the inefficient equilibrium outcome. Experiments have also shown that factors which are irrelevant according to classical theories affect the outcome. For example, Van Huyck, Battalio & Beil (1990) (henceforth VHBB) observed in a finitely repeated 'weakest link' game[5], that the larger the number of players, the greater the chance that players will end up coordinating on the least profitable equilibrium[6]. More recently, experimental studies sought to identify conditions under which evolutionary game theory adequately characterises observed play in the repeated Stag Hunt game. Battalio, Samuelson & Van Huyck (1997) provide a comprehensive summary about human behaviour in Stag Hunt games

[3] By assuming pairwise asymmetric information structures, Durieu & Solal (1999) rule out cycles in Ellison's deterministic dynamics and reduce the expected first passage time from one Nash equilibrium to another in stochastic dynamics.

[4] More details concerning the expected waiting time under both interaction structures will be given afterwards.

[5] A 'weakest link' game is a pure coordination game in which individual payoffs are partly determined by the minimum effort chosen in the population.

under global interaction structures: 1) non-equilibrium outcomes are rare, 2) in the first period of play the payoff-dominant strategy is generally the modal choice, 3) the final outcome of the game is generally accurately predicted by the location of the initial outcome in a particular basin of attraction. The experiment of Keser, Ehrhart & Berninghaus (1998) showed that if the interaction structure is local the equilibrium selection is drastically modified. If all players are located around a circle, with each player having 2 neighbours (the adjacent players), the strategy choices converge towards the risk-dominant equilibrium. Moreover, in their fixed group treatment without local interaction, they observed that the payoff-dominant equilibrium was more often selected than the risk-dominant equilibrium.

## 3. The coordination game

The stage game is a 2x2 symmetric game illustrated in figure 1, where each player has to choose strategy X or strategy Y. If both players choose X, then both get a payoff of a; if both players choose Y, then both get d. If one player chooses X while the other chooses Y, then the former player gets c while the latter player gets b. We consider the case where a > b and d > c so that the stage game has two pure-strategy Nash equilibria: (X,X) and (Y,Y). We also require that d – c > a – b, which implies that (Y,Y) is the risk-dominant equilibrium. Finally, we assume that the two equilibria are Pareto-ranked, and that a > d, which implies that (X,X) is the payoff-dominant equilibrium.[7]

| | X | Y |
|---|---|---|
| X | **a, a** | **c, b** |
| Y | **b, c** | **d, d** |

Figure 1: The stage coordination game.

[6] Crawford (1991) gives an evolutionary interpretation of these experimental results and Carlsson & Ganslandt (1998) by perturbing symmetric coordination games provide a theoretical foundation for VHBB's results.

[7] The stage game has also an equilibrium in mixed strategies in which each player chooses strategy X with probability k* = (d - c) / (a + d – b - c).

Defined like this, this stage game is commonly referred to as the Stag Hunt game and poses the potential conflict between efficiency and security. Although, strategy X might yield the highest payoff (a) if the opponent chooses also X, it is risky since it yields the lowest payoff (c) if the opponent chooses the safe strategy Y. More precisely, one strict Nash equilibrium risk dominates the other if, after a normalisation of payoffs which preserves best-reply correspondences and dominance relations between strategies, it strictly Pareto dominates the second (see Weibull (1995)). For example, the payoff matrix of figure 1 can be normalised in the following manner:

| | X | Y |
|---|---|---|
| X | **a - b, a - b** | **0, 0** |
| Y | **0, 0** | **d – c, d - c** |

After such a normalisation of payoffs, the strict Nash equilibrium (X,X) appears no longer attractive since d – c > a – b.

In the experiment we used three different payoff matrices in both treatments. Thus, we have a 2x3 factorial design, with 2 different matching rules and 3 different payoff matrices. Figure 2 shows the parameter values considered in the experiment.

| | X | Y |
|---|---|---|
| X | 50, 50 | 0, 25 |
| Y | 25, 0 | 30, 30 |

i

| | X | Y |
|---|---|---|
| X | 50, 50 | 0, 30 |
| Y | 30, 0 | 40, 40 |

ii

| | X | Y |
|---|---|---|
| X | 45, 45 | 0, 35 |
| Y | 35, 0 | 40, 40 |

iii

Figure 2: Parameter values used in the experiment.

Let k be the probability with which each player chooses strategy and define k* as the value of k for which a player is indifferent between choosing strategy Y and choosing strategy X, i.e. k* is the value of k for which there is a mixed-strategy equilibrium. k* depends on the payoff matrix: k* = 0.54 for payoff matrix i, k* = 0.67 for payoff matrix ii, and k* = 0.80 for payoff matrix iii. In fact, Y is a k*-dominant strategy which implies that if k* = 1 then strategy Y weakly dominates strategy X. Moreover, in the normalised payoff matrix, the gain resulting from strategy profile (Y,Y) is k* / (1-k*) times the gain resulting from strategy profile (X,X). In other words, the greater k*, the more attractive is the risk-dominant equilibrium.

From the evolutionary perspective, the risk-dominant equilibrium has the larger basin of attraction under the best-reply as well as the replicator dynamics.[8] Under global interaction k* is commonly referred to as the "separatrix" because it divides the state space into two basins of attraction: the basin of attraction of the payoff-dominant equilibrium and the basin of attraction of the risk-dominant equilibrium. Each basin of attraction has an absorbing state in which all players adopt the same strategy[9]. Henceforth we note Y° the steady state in which all players adopt strategy Y and X° the steady state in which all the players adopt strategy X. Moving from payoff matrix i to payoff matrix ii and iii implies that, under global interaction, we allow more and more initial conditions to converge to the state Y° under deterministic dynamics. On the contrary, when each player interacts only with two neighbours the value of k* becomes irrelevant since the basin of attraction of X° contains only one state, X° itself. Thus, under the local interaction condition, the magnitude of k* has no impact on the relative sizes of the basins of attraction and we therefore expect the likelihood of observing Y° to be high. Nevertheless, as noted by Fudenberg & Levine (1998), "..this implicitly supposes a more-or-less uniform prior over possible initial positions".

## 4. Matching rules

We introduce now two different matching rules that we used in our experiment.

4.1 The *Global Interaction* treatment

The stage coordination game is repeated 50 times by the same group of 8 players. Under global interaction, each player in the population can be matched with any of the 7 other players in the population. However, his actual payoff depends only on the action taken by his actual opponent. At the end of each round, each player is informed about the distribution of decisions in his group for the current round. No information about the individual decisions of the other players is given. A player's payoff is determined by the sum of his payoffs over all 50 rounds. The players have complete information about the game. They know each player's payoff function (the same for each player) and that the game ends after 50 repetitions.

In this treatment, under deterministic dynamics, the basins of attraction of the two strict Nash equilibria have the same size when the stage game relies on payoff matrix i. For the two others matrices, payoff matrix ii and payoff matrix iii, the risk-dominant equilibrium has the largest basin of attraction. Thus, KMR (1993) and Young (1993) predict that, for payoff matrix ii and payoff matrix iii, the limit distribution concentrates all of its probability on the risk-dominant equilibrium.

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[8] Due to integer problems such a result is true only for large populations of players under global interaction and for small neighbourhoods under local interaction.
[9] Be aware that the mixed-strategy equilibrium can not be an absorbing state in a symmetric game.

4.2 The *Local Interaction* treatment

Like under global interaction, the stage coordination game is repeated 50 times by the same group of 8 players. Under local interaction, each player in the population can be matched only with one of his neighbours. In our experiment we considered only neighbourhoods containing two players. The different neighbourhoods are arranged on a circle design, so that the neighbourhood of a given player contains his two adjacent players. Figure 3 describes the interaction structure (a similar figure has been used in the instructions of the *Local Interaction* treatment in order to make the subjects aware of the local interaction condition). In this circle design, player 1 plays either with player 2 or with player 8. Player 2 interacts either with 1 or with player 3, and so on. Player 1's payoff depends on his own choice and on the choice of his actual opponent either player 8 or player 2. At the end of each round, each player is informed about the distribution of his neighbours' choices for the current round. But he is neither informed about the individual decisions of his neighbours, nor about his neighbours' neighbours' decisions. Each player's final payoff depends on the cumulative payoff over all 50 rounds. Players have complete information about the game. They know each player's payoff function (the same for everyone), they know that their neighbours also interact with other neighbours, they know that they are allocated around a circle of 8 players, and that the game ends after 50 repetitions.

In the *Local Interaction* treatment, whatever the payoff matrix considered, the risk-dominant equilibrium has the same largest basin of attraction under best-reply deterministic dynamics. Consequently, Ellison (1993) and Berninghaus & Schwalbe (1996) predict the risk-dominant equilibrium as an outcome in all cases.

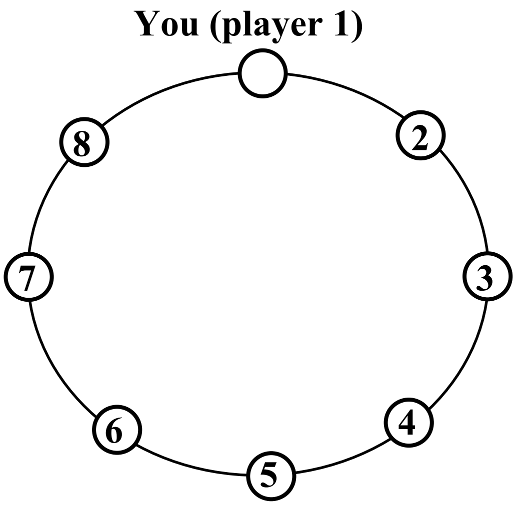


Figure 3: Local interactions on the circle.

Note that our experimental design is not specifically based on one of the models reviewed in the introduction, for two reasons. First, there is no reference model available for this literature. The existing models make different assumptions about behavioral rules, matching rules or mutation probabilities. Furthermore, except for Ellison (1993), the models based on global interaction cannot be easily compared to those which study local interaction. Finally, all models are based on a large population and a very large number of periods, two features which cannot be reproduced in the lab. Second, our aim is essentially to study how the interaction structure affects coordination in a simple game. In this respect, those models are not very useful since their primary focus is the long run outcome of the interaction process.

Nevertheless, our experimental design is able to provide some useful insights about the aggregate behavior of a population of human players interacting in a controlled environment. As in the case of market experiments, the primary interest of the experimental methodology is to discover which factors affect the outcome of the process and which factors play a negligible role. In this respect we are essentially interested in the influence of the interaction structure and the payoff matrix on the aggregate outcome of the interaction process.

As previously noted, the easiest way to compare our results between both interaction structures and between the different payoff matrices will be to rely on best-reply dynamics with a uniform error model as considered by KMR (1993) and Ellison (1993). In such settings, we have clear results concerning the impact of k*, the impact of the interaction structure and the speed of convergence of the interaction process. In this respect, we will mainly rely on this framework in order to evaluate our experimental results.

**5. Practical Procedures**

The experiment was run on a computer network[10] in Spring 1997, using 192 inexperienced students, at the Laboratory of Experimental Economics of Strasbourg (LEES[11]). The subjects were recruited by phone from a pool of 600 students. Subjects were students from various disciplines. Twelve sessions were organised, with 2 groups of 8 subjects per session. The experiment consisted of a 2x3 factorial design {global interaction, local interaction}x{k* = 0.54, k* = 0.67, k* = 0.80} with 4 observations per cell. Subjects were randomly assigned to a group of 8 players, to play a 50-fold repetition of the stage coordination game, the stage game being either based on payoff matrix i, payoff matrix ii or payoff matrix iii. Each subject was seated at a computer terminal, which was physically isolated from other terminals. Communication, other than through the decisions made, was not allowed. The subjects were instructed about the rules of the game and the use of the computer program through written instructions (available upon request), which were also read aloud by a research assistant. A short questionnaire was submitted to the subjects to check their understanding of the instructions, followed by two training periods, during which subjects were told that they would simply play "against" a computer program.[12] After each period

[10] Based on an application developed by K. Boun My (1997) designed for Visual Basic.
[11] BETA, Université Louis Pasteur, Strasbourg, France.
[12] In pilot sessions we observed that the initial period of play in the experiment, was strongly influenced by the outcomes during the training sessions when training sessions involved subjects playing against each other. If they coordinated on X during the training sessions, they tended to do the same in period 1 of the experiment, and similarly when the coordinated on Y. Therefore, we tried to neutralize the training sessions by letting them play "against" the computer, and announcing in advance the computer's "choice".

subjects were informed about the individual number of points gained for that period. They were also informed about the number of points earned by the other player, with whom they interacted, the decision that he had taken in that period, the number of players of their neighbourhood who played X and the number of players of their neighbourhood who played Y. The accumulated number of points since the beginning of the experiment was on permanent display. Rewards were counted in points and converted at the end of the experiment into cash (1 point = 0.04 Francs). Subjects were also paid a show-up fee of 30 Francs that was added to their cash earnings for the experiment at the end of the session.

**6. Results**

We present the results with respect to the three stylised facts observed under global interaction and summarised by Battalio et al. (1997): non-equilibrium outcomes are rare, the modal first period outcome is the payoff-dominant strategy, and convergence is accurately predicted by the first period state. Besides, we analyse our experimental results by comparing them to, either deterministic or stochastic, best-reply dynamics. Indeed, clear predictions exist in such a theoretical framework concerning at once the outcome of the interaction process and the speed of "convergence". Thus, we compare the myopic best reply rates between both matching rules. Note that subsection 6.1 summarizes results concerning the coordination problem at the individual level, whereas subsection 6.2 and 6.3 deal with the outcome of the process constituted by the whole group of subjects. Although we have few independent observations (4 groups for each payoff matrix both in the *Global Interaction* treatment and in the *Local Interaction* treatment) we shall indicate the significance level of the comparison between the two treatments for each payoff matrix or between two payoff matrices in the same treatment.[13] Appendix A presents the time path of the number of subjects who choose X for each group.

6.1 Equilibrium outcomes

Tables 1 summarises the data for the 50 periods. For both interaction structures, the first column identifies the groups, the second column indicates the overall proportion of Nash equilibria observed in the 50 periods, and the last column indicates among the Nash equilibria the overall proportion of Pareto outcomes (X°). Each group label has three items. The letter refers to the interaction structure (Global or Local), the first number refers to the payoff matrix (0.54, 0.67 or 0.80) and the last number refers to the group number.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Nash | Pareto | Group | Nash | Pareto |
| G54.1 | 94% | 99% | L54.1 | 77% | 93% |
| G54.2 | 90% | 98% | L54.2 | 78% | 91% |
| G54.3 | 84% | 99% | L54.3 | 80% | 96% |
| G54.4 | 84% | 99% | L54.4 | 76% | 97% |

(a): k* = 0.54.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Nash | Pareto | Group | Nash | Pareto |
| G67.1 | 100% | 100% | L67.1 | 93% | 1% |
| G67.2 | 95% | 100% | L67.2 | 77% | 99% |
| G67.3 | 86% | 9% | L67.3 | 97% | 100% |
| G67.4 | 87% | 100% | L67.4 | 74% | 3% |

(b): k* = 0.67.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Nash | Pareto | Group | Nash | Pareto |
| G80.1 | 65% | 20% | L80.1 | 92% | 4% |
| G80.2 | 80% | 98% | L80.2 | 83% | 6% |
| G80.3 | 86% | 16% | L80.3 | 60% | 75% |
| G80.4 | 88% | 100% | L80.4 | 80% | 9% |

(c): k* = 0.80.

Table 1: Overall proportion of Nash equilibria and payoff-dominant (Pareto) equilibria.

[13] All comparison are tested with the Wilcoxon-Mann-Whitney test and we set the significance level at 5 %.

Under global interaction the average proportion of Nash equilibria over the three payoff matrices is equal to 86.58 % and under local interaction it is equal to 80.58 %; this difference is not statistically significant. Concerning the proportion of Pareto outcomes among Nash equilibria, the average proportion over the three payoff matrices is equal to 78.17 % under global interaction and it is equal to 56.17 % under local interaction; once again, this difference is not statistically significant. For k* = 0.54, there is a high frequency of payoff-dominant equilibria, both under local and under global interaction. The situation is more contrasted for k* = 0.67 and k* = 0.80. In some groups, the payoff-dominant equilibrium is the more frequent, while in others it is the risk-dominant one which is outstanding. More precisely, for k* = 0.54, both the proportion of Nash equilibria and the proportion of payoff-dominant equilibria among the Nash equilibria are significantly larger under global interaction than under local interaction ($p = 0.014$). If k* = 0.67 or k* = 0.80, neither the proportion of Nash equilibria nor the proportion of payoff-dominant equilibria among the Nash equilibria is significantly affected by the type of interactions. Indeed, for k* = 0.67, there are clearly three groups which are close to the payoff-dominant equilibrium under global interaction, while the other one is closer to the risk-dominant solution. For k* = 0.80, there are two groups which are close to the payoff-dominant equilibrium under global interaction, while the two others are closer to the risk-dominant solution. Under local interaction, for k* = 0.67, in two groups there is a high frequency of risk-dominant equilibria, while the remaining groups get closer to the payoff-dominant equilibrium and for k* = 0.80 there are three groups which are close to the risk-dominant equilibrium and the last one is close to the payoff-dominant solution.

Under both types of interaction structures, there is no significant difference in the proportion of Nash equilibria between k* = 0.54, k* = 0.67 and k* = 0.80. However, under local interaction for k* = 0.54 there is a significant larger proportion of payoff-dominant equilibria than with k* = 0.80

(p = 0.014). There is no such a significant difference between k* = 0.67 and the two other values of k*.

Finally, note that as in previous experiments under global interaction, we observe a high rate of equilibrium plays in our *Global Interaction* treatment.

6.2 Initial and Final States

Table 2 compares the initial state, observed in period 1, with the final state, observed in period 50. Previous experiments found that under global interaction are that the modal first period outcome is the payoff-dominant strategy, and that convergence is accurately predicted by the first period state which is in accordance with best-reply deterministic dynamics. Accordingly, we report in table 2 the number of players choosing X in the first period and in the last period for global interaction. Concerning local interaction, since we rely on best-reply dynamics, we have to be more precise. For the local interaction structure, table 2 reports not only the total number of players who chose X in the first and in the last period, but describes also each subject's decision for these periods as a string of X's and Y's. Subjects are arranged in accordance with Figure 3, i.e. the subject who corresponds to player 1 is on the left and the subject who corresponds to player 8 is on the right. This implies that subject 1 has interacted in each period either with the subject who is on his right, i.e. subject 2, or with the subject who is on the right, i.e. subject 8.

| Global interaction | | | Local interaction | | |
|---|---|---|---|---|---|
| **Group** | **Period 1** | **Period 50** | **Group** | **Period 1** | **Period 50** |
| G54.1 | 6/8 | 8/8 | L54.1 | 7/8 XYXXXXXX | 7/8 XXXXYXXX |
| G54.2 | 6/8 | 7/8 | L54.2 | 8/8 XXXXXXXX | 8/8 XXXXXXXX |
| G54.3 | 7/8 | 8/8 | L54.3 | 7/8 XXXXXXYX | 8/8 XXXXXXXX |
| G54.4 | 7/8 | 8/8 | L54.4 | 7/8 XXXXXYXX | 7/8 XYXXXXXX |
| G67.1 | 7/8 | 8/8 | L67.1 | 3/8 YYXYYXYX | 0/8 YYYYYYYY |
| G67.2 | 6/8 | 8/8 | L67.2 | 7/8 XXXXXXXY | 8/8 XXXXXXXX |
| G67.3 | 5/8 | 0/8 | L67.3 | 8/8 XXXXXXXX | 8/8 XXXXXXXX |
| G67.4 | 8/8 | 8/8 | L67.4 | 4/8 XXYYXYXY | 0/8 YYYYYYYY |
| G80.1 | 5/8 | 0/8 | L80.1 | 2/8 YYYYYYXX | 0/8 YYYYYYYY |
| G80.2 | 7/8 | 7/8 | L80.2 | 5/8 XYYXYXXX | 0/8 YYYYYYYY |
| G80.3 | 6/8 | 1/8 | L80.3 | 7/8 XXXYXXXX | 4/8 XYYXYXYX |
| G80.4 | 7/8 | 8/8 | L80.4 | 7/8 XXXXYXXX | 0/8 YYYYYYYY |

Table 2: Initial and final states.

As an example, in group G54.1, in period 1, 6 subjects out of 8 played X and two played Y. Our results support the stylised fact that under global interaction the modal first period outcome is the payoff-dominant strategy. Moreover, no significant differences in the number of players choosing X in the first period are observed when comparing different values of k* in our *Global Interaction* treatment.

Changing the interaction rule has little impact on initial conditions. A comparison of both types of interaction structures reveals that no significant difference is observed concerning the number of players choosing X in the first period; this fact is true for each payoff matrix. Besides, no significant differences in the number of players choosing X in the first period are observed when comparing different values of k* in our *Local Interaction* treatment. Let us turn now to the third stylised fact : the final outcome of the game is accurately predicted by the location of the initial outcome in a particular basin of attraction

For the *Global Interaction* treatment we observe that in all cases the final state lies in the same basin of attraction as the initial state. Let us note nX the state where n players have adopted strategy X, n = 0, 1, …, 8, and let $D_{Y^\circ}$ be the set of states which belong to the basin of attraction of

Y°, and $D_{X°}$ the set of states which belong to the basin of attraction of X°. For k* = 0.54 we have $D_{Y°}$ = {0X, 1X, 2X, 3X}, $D_{X°}$ = {5X, 6X, 7X, 8X}[14], for k* = 0.67 we have $D_{Y°}$ = {0X, 1X, 2X, 3X, 4X, 5X}, $D_{X°}$ = {6X, 7X, 8X} for k* = 0.67 and for k* = 0.80 we have $D_{Y°}$ = {0X, 1X, 2X, 4X, 5X, 6X}, $D_{X°}$ = {7X, 8X}. Separatrix crossing in rarely observed (one occurs in group G80.1, two occur in group G80.2 and one occurs in group G80.4). Battalio et al. (1997) noted already that such events are rare in experimental data concerning Stag Hunt games under global interaction. Thus, stochastic dynamics, as considered for example by KMR (1993), agree poorly with our observations. Even if convergence in such dynamics often relies on long periods of time, note that for payoff matrix iii the expected waiting time is less than 50 periods as long as the rate of mutation is greater or equal to 0.03.

In our *Local Interaction* treatment things are less in accordance with deterministic best-reply dynamics. Indeed, all states which consist of 7 players choosing X in the first period imply a cycle under these dynamics, in which each player switches from the pareto-dominant to the risk-dominant action and vice-versa. We never observe the emergence of such a cycle. On the contrary, in some cases such an initial state implies convergence to state X°, whereas in an other case it implies convergence to state Y° depending on the payoff matrix. Nevertheless, the larger the value of k* the less players are choosing X in the last period. This result can be explained by the fact that a larger value of k* implies a larger number of initial states in favour of Y° and simultaneously less observed convergence to X° when 7 subjects already played X in the first period. Besides, deterministic best-reply dynamics disagrees with behaviours in groups L54.3 and L67.2. Indeed, in both groups the number of subjects who choseY declines between the first and the last period of interactions. Such a decline is not predicted under local interaction with two neighbours. Finally, concerning the number of players choosing X in the last period, no significant difference is observed between both types of interaction structures, for either payoff matrix. Again our experimental results under local interaction are in contradiction with stochastic dynamics, as

[14] The state {4X} is part of a two-states cycle in which each player switch from the pareto-dominant to the risk-

considered for example by Ellison (1993). In fact, the expected waiting time is independent of the magnitude of k* when each player has only two neighbours and is generally less than 50 periods even if we allow for very small mutation rates. Thus, the process should rapidly converge to state Y° whatever the payoff matrix and whatever the initial state.

### 6.3 Convergence

To study the convergence within the population with respect to the steady states X° and Y°, we take the point of view of the stochastic dynamics which determines the most likely equilibrium. We therefore take into account a tolerance bound of 1/8: if, for some period, at least 7 players adopt the same strategy for all the remaining periods, we assume that convergence has been reached.[15] We define this period as the convergence period. We also consider a weaker indicator, corresponding to the number of periods for which at least 7 subjects chose the same strategy, since in many cases at least 7 subjects chose the same strategy before the convergence period. Table 3 summarizes the results with respect to convergence. For both matching rules, the first column identifies the groups, the second column shows the convergence period with its associated outcome (X° or Y°), and the last column indicates the number of periods spent by the process inside the convergence bound (CB), i.e. at least 7 players adopt the same strategy in each of these periods. Although there is no convergence observed for the L80.3 group, for the purpose of statistical analysis, we set the convergence period at 51 and the number of periods spent by the population within the CB at 0. Appendix B presents the same analysis with a larger tolerance bound of 2/8.

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dominant action and vice-versa.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Convergence Period | # of periods inside CB | Group | Convergence Period | # of periods inside CB |
| G54.1 | 5 (X°) | 46 | L54.1 | 49 (X°) | 28 |
| G54.2 | 11 (X°) | 43 | L54.2 | 38 (X°) | 27 |
| G54.3 | 41 (X°) | 43 | L54.3 | 29 (X°) | 38 |
| G54.4 | 15 (X°) | 41 | L54.4 | 50 (X°) | 35 |

(a): k* = 0.54.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Convergence Period | # of periods inside CB | Group | Convergence Period | # of periods inside CB |
| G67.1 | 1 (X°) | 50 | L67.1 | 22 (Y°) | 44 |
| G67.2 | 8 (X°) | 47 | L67.2 | 31 (X°) | 41 |
| G67.3 | 9 (Y°) | 42 | L67.3 | 1 (X°) | 50 |
| G67.4 | 28 (X°) | 43 | L67.4 | 42 (Y°) | 31 |

(b): k* = 0.67.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Convergence Period | # of periods inside CB | Group | Convergence Period | # of periods inside CB |
| G80.1 | 43 (Y°) | 16 | L80.1 | 12 (Y°) | 40 |
| G80.2 | 43 (X°) | 43 | L80.2 | 38 (Y°) | 33 |
| G80.3 | 15 (Y°) | 36 | L80.3 | - | - |
| G80.4 | 22 (X°) | 48 | L80.4 | 31 (Y°) | 33 |

(c): k* = 0.80.

Table 3: Convergence analysis (tolerance bound of 1/8).

[15] Although the procedure is somehow arbitrary, it is reasonable to admit that convergence is reached if deviations from a given steady state are small (see e.g. D. Friedman (1996)).

For each payoff matrix we observe that on average convergence takes more periods under local interaction than under global interaction. However, for none of the payoff matrices is this difference statistically significant. We observe also that the average number of periods spent by the population within the CB is larger under global interaction than under local interaction for each payoff matrix. For $k^* = 0.54$, the population spends significantly more periods at equilibrium under global interaction than under local interaction ($p = 0.014$). For $k^* = 0.67$ and $k^* = 0.80$ there is no statistically significant difference with respect to the time spent at equilibrium.

Again, we can remark that stochastic best-reply dynamics contrast sharply with our experimental results. Even when these dynamics are in accordance with the observed final state, the number of periods spent around this well predicted state (Y°) is not higher under local interaction than under global interaction. In the next section we try to give some insights concerning this disturbing fact.

### 6.4 Myopic best reply

Myopic best response is one of the central hypotheses for the evolutionary learning dynamics analysis (see for example KMR (1993) or Ellison (1993)). It assumes that players react to the distribution of play in the previous period, capturing the intuitive notion that players react myopically to their environment. We studied whether the decisions of the players satisfy the myopic best response by measuring the best reply rate (BRR). In order to do that, we counted for each player the number of decisions which were equivalent to a myopic best reply and made the average over the 50 periods and all the players in the group. Table 4 shows that in all games subjects have a significant tendency to take decisions in accordance with the myopic best reply prediction with respect to the proportion of the population (*Global Interaction* treatment) or of their neighbourhood (*Local Interaction* treatment).

| *Global Interaction* | | | | | | *Local Interaction* | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Group | BRR | Group | BRR | Group | BRR | Group | BRR | Group | BRR | Group | BRR |
| **G54.1** | 92% | **G67.1** | 100%. | **G80.1** | 71% | **L54.1** | 72% | **L67.1** | 96% | **L80.1** | 93% |
| **G54.2** | 84% | **G67.2** | 92% | **G80.2** | 83% | **L54.2** | 71% | **L67.2** | 71% | **L80.2** | 89% |
| **G54.3** | 80% | **G67.3** | 90% | **G80.3** | 84% | **L54.3** | 76% | **L67.3** | 95% | **L80.3** | 56% |
| **G54.4** | 79% | **G67.4** | 81% | **G80.4** | 91% | **L54.4** | 76% | **L67.4** | 83% | **L80.4** | 88% |

Table 4: Best reply rates (BRR).

One observes slightly lower rates of best reply under local interaction than under global interaction. Indeed, for each payoff matrix, the average rate of BR over all 4 groups is larger under global interaction than under local interaction which implies that the average rate of BR over all 12 groups is larger under global interaction (85.58 %) than under local interaction (80.50 %). Nevertheless, the only significant difference is observed for $k^* = 0.54$ where the average rate of BR is significantly larger under global interaction (83.75 %) than under local interaction (73.75 %) ($p = 0.014$). From the evolutionary theoretical point of view, all the results discussed in this sub-section are in accordance with the results observed in 6.2 and 6.3. Indeed, we simultaneously observe lower rates of myopic best reply and a lower number of periods spent by the population within the CB under local interaction than under global interaction. Both differences are only statistically significant for $k^* = 0.54$. In the meantime, whereas best-reply dynamics are in accordance with the observed initial and final state in the *Global Interaction* treatment, they contrast sharply with our results in the *Local Interaction* treatment.

## 7. Concluding remarks

The purpose of our experiment was to compare the outcome of a simple coordination game, when interactions are repeated among players of the whole population (*Global Interaction* treatment) with a context where interactions are restricted to small overlapping neighbourhoods of players

(*Local Interaction* treatment). We compared the outcomes of the two interaction structures for different sizes of the basin of attraction of the risk-dominant equilibrium; k* = 0.54, k* = 0.67 and k* = 0.80. We summarise our results as follows.

Firstly, some of the stylised facts observed in earlier studies on global interaction, are reproduced in our global interaction treatment and two are preserved for local interaction. More precisely, i) non-equilibrium outcomes are rarely observed both under local and under global interaction, ii) the first period modal choice is the payoff-dominant strategy both under local and under global interaction, iii) under global interaction, the first period play determines strongly the steady-state which will be reached, as it generally lies in the same basin of attraction as the initial state.

Secondly, in the local interaction treatment we observe a clear difference between k* = 0.54 and k* = 0.80. Convergence is towards the payoff-dominant steady state for k* = 0.54 and towards the risk-dominant steady state only for k* = 0.80 under local interaction. The larger the basin of attraction of the risk-dominant equilibrium the more we observe convergence to the risk-dominant equilibrium.

Thirdly, there is no evidence in our analysis that convergence is faster under local interaction than under global interaction. On the contrary, for k* = 0.54 the population spent significantly more periods near the equilibrium under global interaction than under local interaction. The most notable difference between both types of interaction structures is with respect to the number of subjects playing X in the final state. There is slightly more convergence to the risk-dominant solution under local interaction for k* = 0.67 and for k* = 0.80.

In accordance with Keser et al. (1998), we find that on average subjects play the myopic best response under global interaction. But in contrast to their result (1998), myopic best reply fits much less our data under local interaction. A possible reason for that is due to the fact that myopic best reply takes only into account past periods of play. It is possible that under local interaction, behaviors wer more forward oriented, in the sense that subjects could have tried to "persuade" their neighbours to play the pareto-dominating strategy by playing themselves that strategy. They could have felt that it is easier to persuade two neighbours rather than 7 persons at a time, even though their neighbours are not isolated from the rest of the population

Note that in our experimental work we have opposed risk-dominance and Pareto-dominance. Nevertheless, (Y, Y) is not only the risk-dominant equilibrium in the three payoff matrices we have considered, but it is also the secure equilibrium. Indeed, action Y always has its minimum payoff greater than action X's minimum payoff. Further work could be devoted to analyse subjects' behavior in a controlled environment where two strict Nash equilibria coexist, one which is Pareto-dominant and risk-dominant and the second one which is the secure equilibrium.

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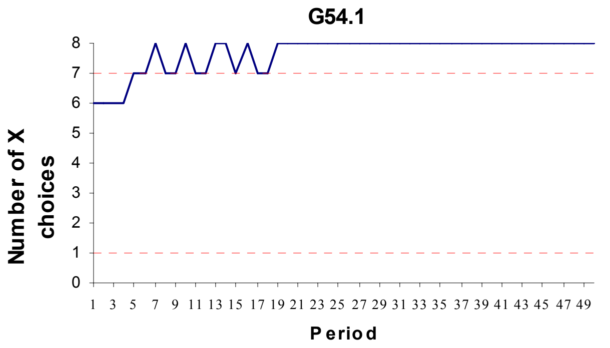
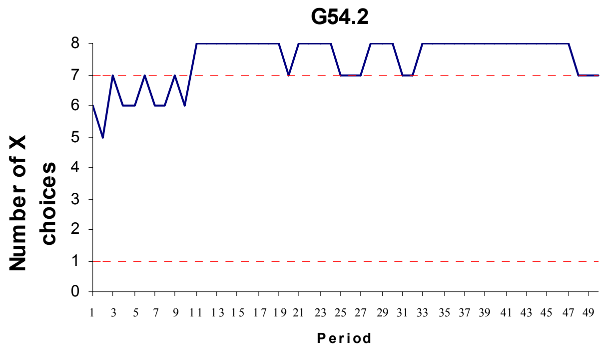
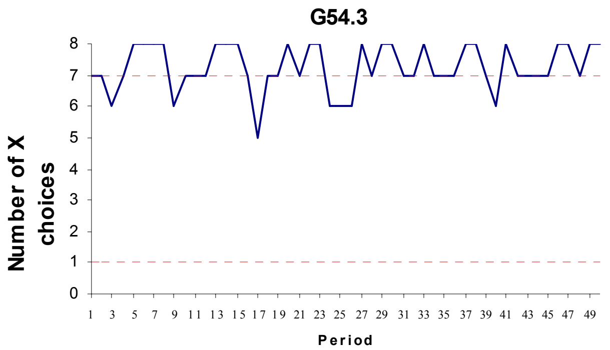
# APPENDIX A

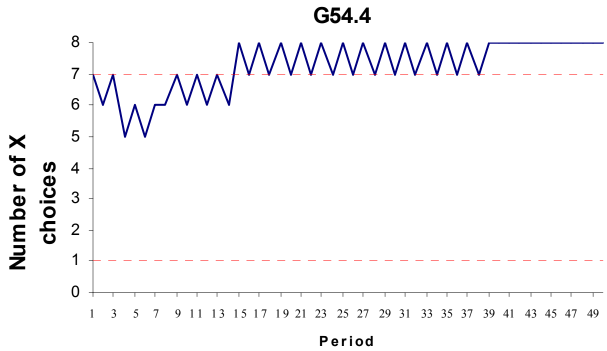
## k* = 0.54

### Global Interaction

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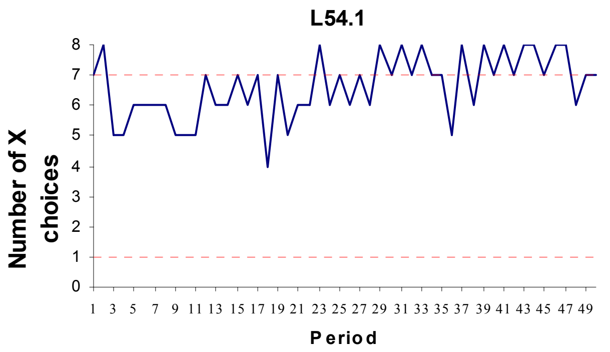
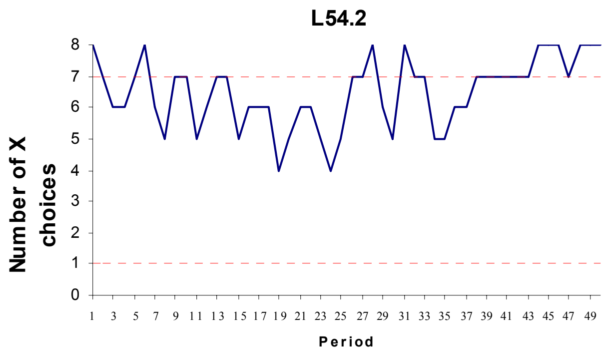
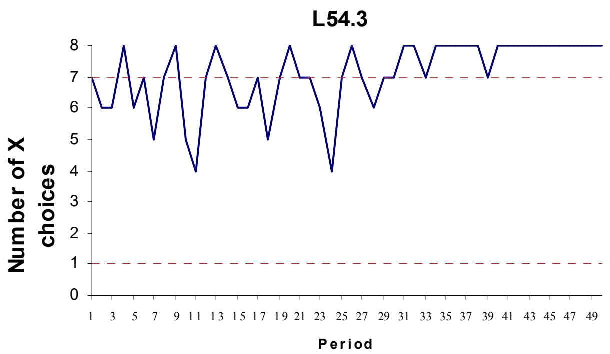
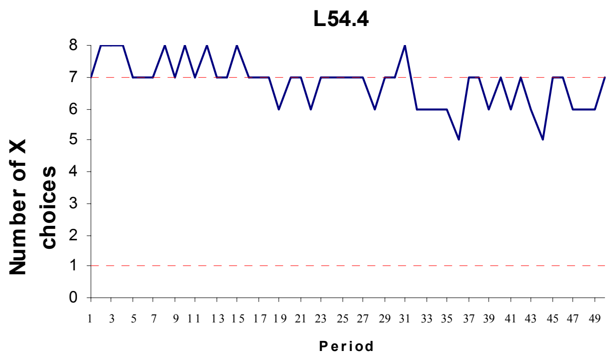


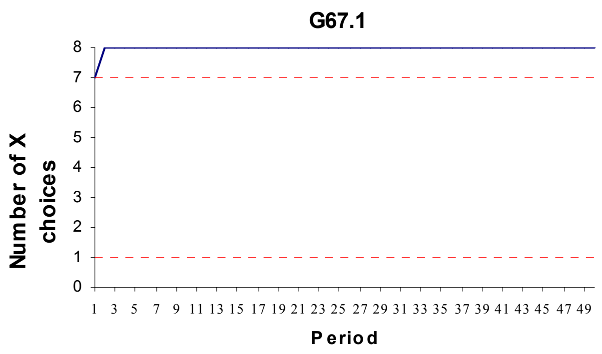



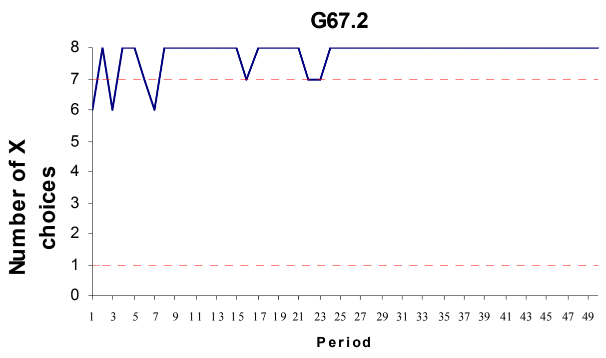



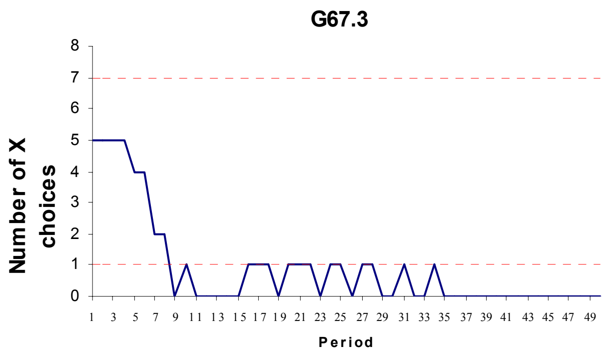



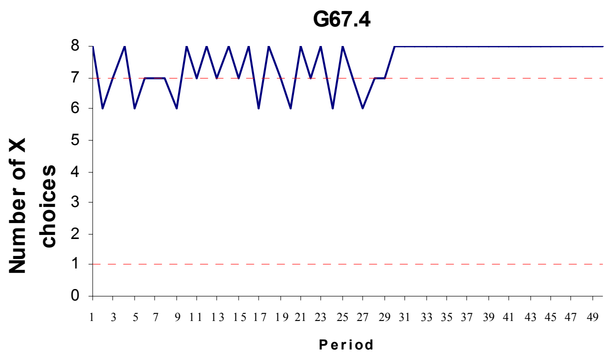
# k* = 0.67

## Global Interaction

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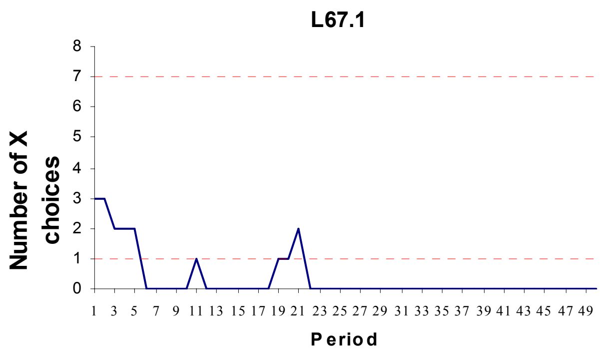


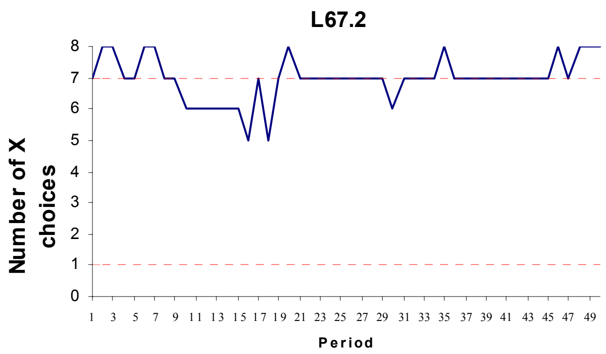


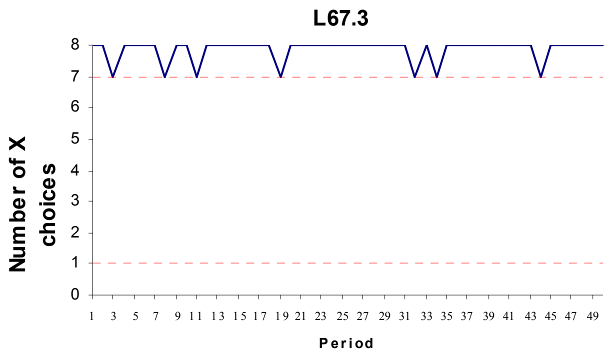


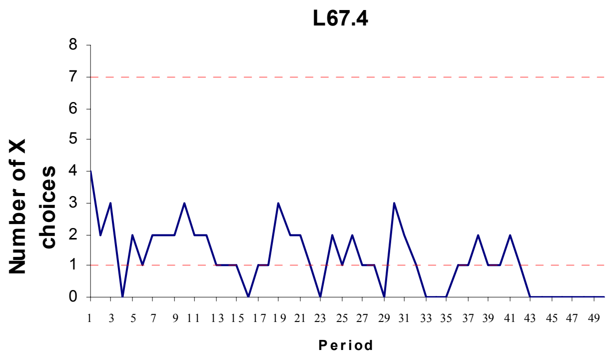

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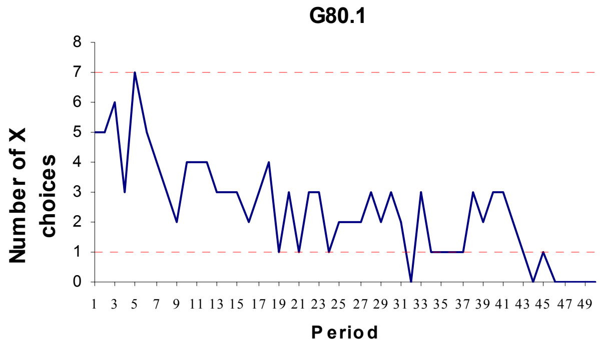
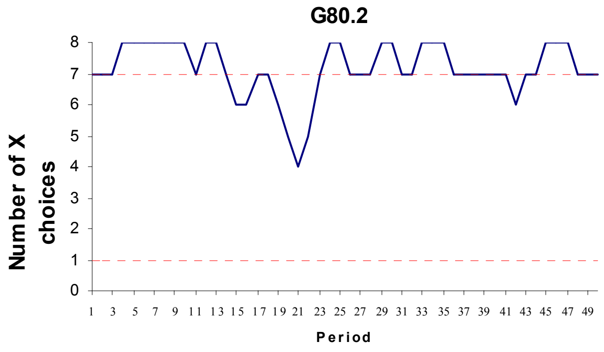
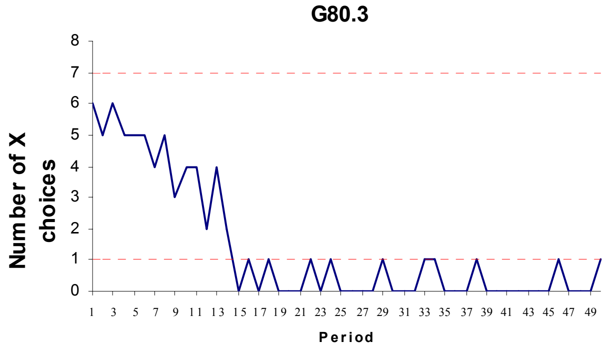
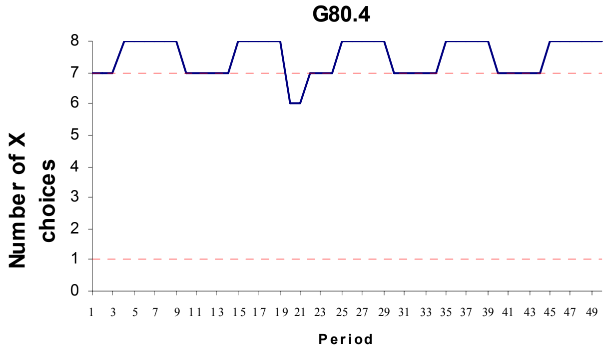
## Global Interaction

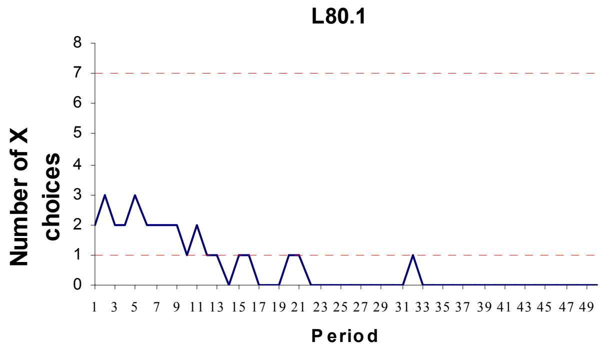


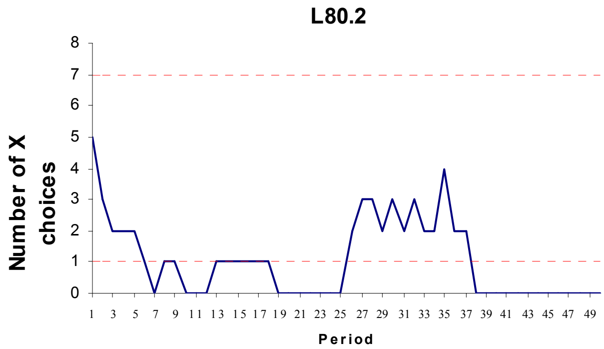



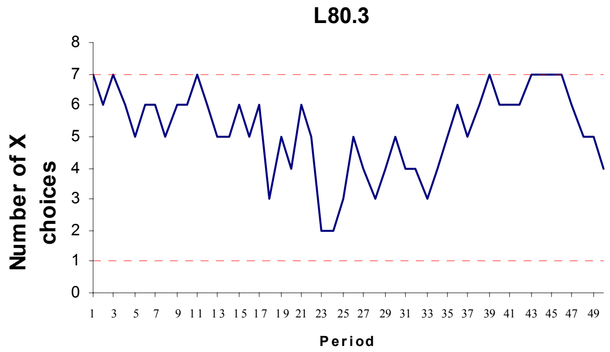



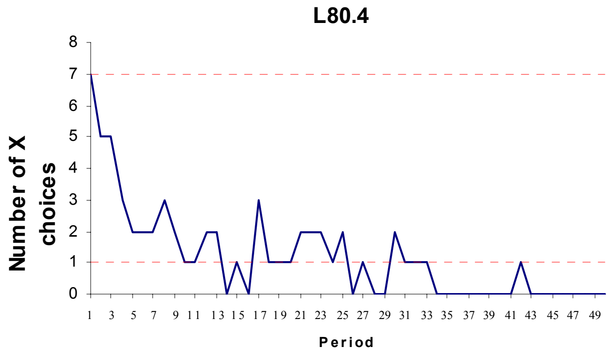




## Local Interaction



# APPENDIX B

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Convergence Period | # of periods inside CB | Group | Convergence Period | # of periods inside CB |
| G54.1 | 1 | 50 | L54.1 | 37 | 42 |
| G54.2 | 3 | 49 | L54.2 | 36 | 39 |
| G54.3 | 18 | 49 | L54.3 | 25 | 45 |
| G54.4 | 7 | 48 | L54.4 | 45 | 48 |

(a): k* = 0.54.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Convergence Period | # of periods inside CB | Group | Convergence Period | # of periods inside CB |
| G67.1 | 1 | 50 | L67.1 | 3 | 48 |
| G67.2 | 1 | 50 | L67.2 | 19 | 48 |
| G67.3 | 7 | 44 | L67.3 | 1 | 50 |
| G67.4 | 1 | 50 | L67.4 | 31 | 45 |

(b): k* = 0.67.

| *Global Interaction* | | | *Local Interaction* | | |
|---|---|---|---|---|---|
| Group | Convergence Period | # of periods inside CB | Group | Convergence Period | # of periods inside CB |
| G80.1 | 42 | 25 | L80.1 | 6 | 48 |
| G80.2 | 23 | 47 | L80.2 | 36 | 43 |
| G80.3 | 14 | 40 | L80.3 | - | - |
| G80.4 | 1 | 50 | L80.4 | 18 | 44 |

(c): k* = 0.80.

Table 5: Convergence analysis (tolerance bound of 2/8).

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# Trusting behavior in a repeated investment game

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**Abstract**

We compare a seven period repeated investment game to the one-shot investment game. On an average, in the repeated game, player A (the "trustor") sends more and player B (the "trustee") returns a larger percentage than in the one-shot game. Both the amount sent and the percentage returned increase up to period 5 and drop sharply thereafter. The "reciprocity hypothesis" for B players' behavior is compatible with the first five periods, but in the two end periods, most B players behaved strategically by not returning. The "reciprocity hypothesis" for A players' behavior is compatible for all periods of the game.


*JEL classification:* C72; C91; D63

*Keywords:* Investment game; Trust; Reciprocity; Repetition

## 1. Introduction

Trust, like norms and other codes of behavior, plays an important role in social and economic interactions. Recent empirical studies by La Porta et al. (1997) and Knack and Keefer (1997) showed that trust affects various economic and social performance indicators. However, these studies rely on a measure of trust derived from survey data, a fact that has been strongly criticized. For instance, Gleaser et al. (2000) show that people who respond

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*positively* to the trust question[1] of the General Society Survey do not necessarily send more money in an experimental game of trust. In experimental games of trust, subjects have to make commitments for real amounts of money. Since trusting behavior in real life also involves commitments, behavior observed in experimental games is more likely to represent trusting behavior than answers to hypothetical questions.

Our experimental investigation relies on the investment game, introduced by Berg et al. (1995), which provides a nice environment for observing trusting behavior in the lab. Berg et al. found strong evidence of trusting behavior in their experiment, a fact confirmed by other experimental studies (e.g. Güth et al., 1997; Ortmann et al., 2000; Gneezy et al., 2000).

In the investment game two players (A and B) are each endowed with 10 experimental currency units. Player A can send any integer amount $S$, with $0 \leq S \leq 10$, to an anonymous player B. The amount sent is tripled by the experimenter, and player B can decide to return any amount $R$ to player A, with $0 \leq R \leq 3S$. For rational and selfish players, the investment game has a unique subgame perfect equilibrium, characterized by $S = R = 0$ for which each player ends up with his endowment. On the other hand, positive investment by player A increases the players joint payoff, which is equal to $20 + 2S$ and maximal for $S = 10$.

In this paper we are interested in the evolution of trust when subjects interact repeatedly. Our experimental design is based on a finitely repeated investment game with matched player pairs. By repeating the game, trust and reciprocity can evolve over time. More precisely, repetition may create a context in which trust can emerge as the outcome of a sustained social relationship in a controlled environment. This context adds a mechanism that eventually favors trusting behavior beyond the propensity to trust unknown people. We compare the results of the repeated investment game to the results of the one-shot investment game: the one-shot investment game captures pre-existing trust, and the repeated investment game allows for reinforcement or breakdown of trusting behavior. We observe that the amount sent increases over time, that the proportion returned increases, and that there is a sharp end effect characterized by low return followed by low sending.

In the repeated investment game, the level of trust in period $t$ will be influenced by history and past experiences of trusting behavior, as well as by subjects' expectations. The amount sent by player A can evolve as a reaction to the amounts returned by player B in earlier periods. This contrasts with the one-shot investment game, where player B does not need to care for player A's reaction. Taking into account player A's future reaction might for example lead player B in period 1 to return a larger amount than sent by player A, intending to induce player A to increase the amount sent in the next period. Player A will do so if he believes that player B will return at least the same proportion as in period 1, but why should player B act in such a way in period 1?

Two possible explanations can be provided: reputation building and reciprocity. The reputation hypothesis assumes that player A is uncertain about player B's type. For example, one can think of player B being a "reciprocal type" or a "selfish type". If player B is selfish he will try to hide his type so that player A does not stop sending. Player B will return at least the amount sent by player A with a high probability in the early rounds of the repeated game. By acting in this way, player B takes advantage of player A's state of uncertainty,

[1] This question asks which of two alternatives is preferable in the sentence: "Generally speaking would you say that most people can be trusted or that you cannot be too careful in dealing with people"?

but as the game proceeds towards the end round, the probability that player B keeps the amount received by player A approaches unity. Following earlier experiments (Camerer and Weigelt, 1988; Neral and Ochs, 1992; Brandts and Figueras, 2003), Cochard et al. (2002) investigated the sequential equilibrium concept (Kreps and Wilson, 1982), on the basis of a restricted investment game for the data reported in their paper. They found that the sequential equilibrium does not provide an adequate framework for organizing the data, except for the end effect.[2] Furthermore, there are many possibilities that define types in the investment game.

Therefore we investigate an alternative explanation based on the reciprocity hypothesis (Fehr and Gächter, 1998). The reciprocity assumption for player B's behavior states that the proportion returned by player B is positively related to the amount sent by player A. Any increase in the amount sent is rewarded by player B by returning a larger share of the generated surplus, and any decrease in the amount sent is punished by player B by returning a lower share of the generated surplus. Note that rewards and punishments are expressed in relative terms since player B could not use absolute rewards and punishment in the game. The reciprocity assumption for player A's behavior states that the amount sent by player A in the current period is positively related to the proportion returned by player B in the previous period.

Section 2 presents the experimental design, and Section 3 our main findings. Section 4 discusses the predictability of the reciprocity hypothesis, and Section 5 concludes.

## 2. Experimental design

Sixteen pairs of subjects who participated in the repeated experimental investment game were split into two sessions of eight pairs, and 20 pairs of subjects who participated in the one-shot experimental investment game were split into two sessions of 10 pairs. For each session, subjects were randomly selected in a subject pool of volunteers (about 600 subjects) and informed individually that they were invited to participate in an experiment. We managed to get very heterogeneous samples with subjects of both sexes, of ages ranging from 17 to 30, from different universities (scientific or not).

Upon arriving at the experimental lab, each subject was randomly assigned either to room A or B, which defined his role for the rest of the experiment (players A or B). For the one-shot game, we used a double-blind procedure similar to Berg et al. For the repeated game the double-blind procedure required some slight adaptation as explained below. For both games, the double-blind procedure guarantees that subject's decisions are completely anonymous with respect to the other subjects, the experimenter and the monitor and, therefore, that they are not influenced by other persons. For the repeated game, each subject in room A was randomly paired with a subject in room B. Subject pairs were informed that they would play the investment game for seven periods. For practical reasons, we could not use real money for the repeated game. Instead, each subject pair communicated through envelopes

[2] Anderhub et al. (2002) found that if subjects can learn through the repetition of the repeated trust game, the reputation hypothesis does fairly well organize the data. However, their trust game differs in many respects from the investment game chosen for our experiment.

Table 1
Summary data for the one-shot and the repeated investment game (averages)

| | Repeated | One-shot |
|---|---|---|
| Amount sent | 7.47 | 5.00 |
| Percentage returned[a] | 56.14 | 38.21 |
| Payoff of player A | 15.20 | 10.65 |
| Payoff of player B | 19.74 | 19.35 |
| Joint payoff | 34.95 | 30.00 |

[a] Calculated only for positive sendings.

with code numbers. At the end of the experiment, the subjects received their cash-payoff in local currency in the same envelopes. For comparative purposes the same procedure was applied for the one-shot game. In each period of the repeated game and at the beginning of the one-shot game, each subject was given an endowment of 10 experimental currency units (ECU). The conversion rate was equal to 1.20 FF per ECU for the repeated investment game and 8.40 FF per ECU for the one-shot game. These conversion rates was chosen in order to keep incentives comparable across treatments, assuming subgame perfection[3] (i.e., player A sends zero and player B returns zero if he receives a positive amount).[4]

## 3. Results

In this section we provide a summary of our main results. The complete data set for the repeated game is reported in Appendix A.

**Result 1.** On average, in the repeated game player A sends more and player B returns a larger percentage than in the one-shot investment game.

In the repeated investment game the overall average level of investment is equal to 7.5, and the overall average percentage returned (for positive amounts sent) is equal to 56 percent. These amounts are significantly larger than zero (binomial test, 1 percent level).[5] This of course also implies that the average gain is significantly larger than 10 for both types of players, 15.2 for A players and 19.7 for B players. Only one player A earned slightly less than 10 units (9.82). Investment was therefore advantageous for both types of players, with an overall average joint payoff equal to 34.95, significantly larger than predicted and close to its maximum possible value. As shown in Table 1, these figures are larger than the corresponding figures for the one-shot game, and all differences between the two games

[3] For the repeated investment game, the "sequential equilibrium" concept introduced by Kreps and Wilson would be more meaningful. However, depending on how one defines types for this game, there are several possibilities for defining a sequential equilibrium.

[4] The instructions of the experiment are available from the authors upon request.

[5] All nonparametric tests are performed using strictly independent data. For the repeated game, we have 16 independent observations, each one corresponding to an average over the seven periods for each pair of subjects.

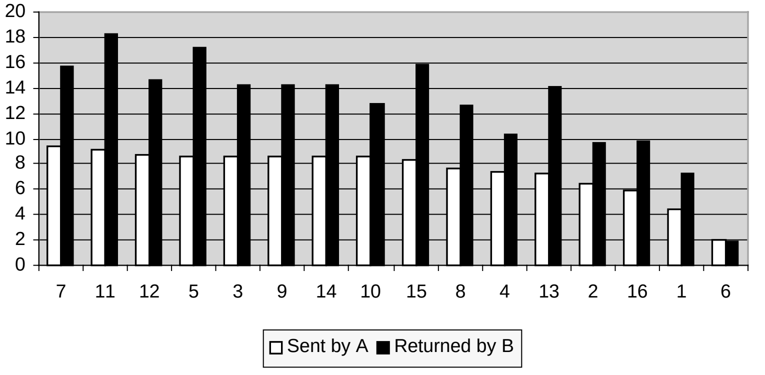


Fig. 1. Average amount sent and returned per player pair in the repeated investment game (sorted by amount sent and amount returned).

are significant at the 5 percent level (one-sided, Mann–Whitney). This is summarized in Table 1.

Let us define the *payoff ratio* as player A's payoff in percentage terms of player B's payoff.

**Result 2.** The payoff ratio is larger in the first six periods of the repeated investment game than in the one-shot game. In the last period it is equal to the average payoff ratio of the one-shot game.

The average payoff ratio is equal to 86 percent for the repeated investment game and 63 percent for the one-shot game. The difference is significant at the 5 percent level (Mann–Whitney, one-sided). In the repeated investment game, the average payoff ratio first increases, starting at 90 percent in period 1 and reaching 98 percent in period 5, and declines sharply in period 6 ending at 59 percent in period 7, below the corresponding value for the one-shot game. The payoff ratio is significantly larger in the repeated game for periods 1–6 than in the one-shot game (Mann–Whitney, one-sided, 1 percent level), but not for period 7.

Fig. 1 shows for each player pair on the horizontal axis, the amount sent and the amount returned averaged over the seven periods of the repeated game. As can be seen, player B returned at least the amount sent by player A (except for player pair 6). Therefore, for the whole repeated game, trust was not misplaced, since in all player pairs and in a majority of periods, player B returned more than the amount sent. Fig. 2 shows for each player pair the amount sent and the amount returned in the one-shot game. Even though most of the B players returned more than the amount sent by player A, one-third of them returned less than the amount sent.

**Result 3.** In the last period of the repeated game the average amount sent is not different from the one-shot game, but the percentage returned is lower. Furthermore, most A players either sent their whole endowment or nothing.

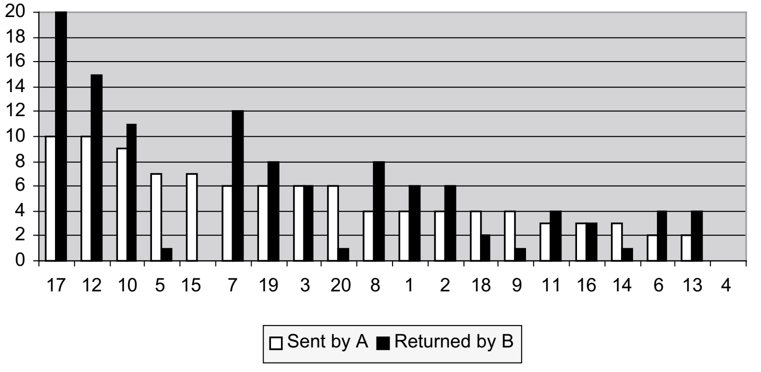


Fig. 2. Amount sent and returned per player pair in the one-shot investment game (sorted by amount sent and amount returned).

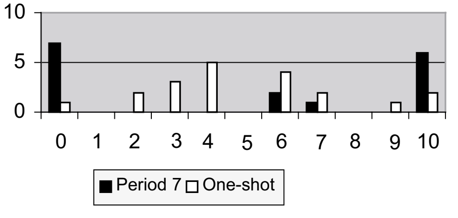


Fig. 3. Comparison of the frequency distributions of amount sent for the one-shot game and the last period of the repeated game.

In period 7, the average level of investment is very close to the level observed in the one-shot game, but the percentage returned is much lower (18 percent compared to 38 percent). This difference is not significant, but the payoff of player A is significantly larger in the one-shot game than in the last period of the repeated game (Mann–Whitney, one-sided, 5 percent). About half of the A players no longer sent in period 7. Among those, four experienced a null return by player B in period 6. The payoffs of both players are not significantly different from 10 (six of the A players and seven of the B players earned exactly 10 in period 7). Most B players kept the whole amount received. In three of the player pairs (pairs 1, 11 and 16) in which player A still sent a positive amount, player B returned a larger positive amount.

Fig. 3 compares the frequency distributions of amounts sent in period 7 with the amounts sent in the one-shot game. In the one-shot game the distribution has a single mode at 4. In contrast, in period 7 we observe two modes on extreme sendings: 44 percent of the A players send 0 while 38 percent send 10. In contrast to the one-shot game where the amounts sent are spread all over the strategy set, they are concentrated on extreme values in the last period of the repeated game. While the difference appears clearly in Fig. 3, a two-sided Kolmogorov–Smirnov test does not reject the null hypothesis at the 5 percent level.[6] As a consequence 44 percent of the B players earned 10 in period 7 and 19 percent earned 40.

[6] The null hypothesis is rejected only at the 10% level.

Table 2
Percentage of extreme sendings and equitable returns

| Period | Amount sent | | Percentage returned[a] | |
|---|---|---|---|---|
| | 0 | 10 | 0 | ≥2/3 |
| 1 | 0 | 44 | 0 | 62 |
| 2 | 0 | 37 | 0 | 75 |
| 3 | 0 | 50 | 0 | 75 |
| 4 | 6 | 50 | 0 | 80 |
| 5 | 6 | 62 | 0 | 93 |
| 6 | 0 | 69 | 31 | 56 |
| 7 | 44 | 38 | 56 | 11 |

[a] Calculated only for positive sendings.

**Result 4.** The average amount sent increases until period 6 and the average payoff ratio until period 5. Both indicators decline sharply thereafter.

Table 2 provides details about extreme choices period by period. The number of A players who send their whole endowment increases until period 6 and collapses in period 7 (see Appendix A). The amount sent in all player pairs increases until period 6. We also observe that the number of B players who return at least 2/3 of the amount received increases until period 5, where all B players except 1 return at least 2/3. Therefore, the average payoff ratio reaches its maximum in period 5. Several B players stop returning in period 6, leading a decrease in the payoff ratio and inducing the corresponding A players to stop sending in the last period. Half of the B players who still return in period 6 do not return in period 7 whenever player A keeps on sending (only four of the B players returned a positive amount in the last period). There are only three pairs in which the “defection” by player B is anticipated. The behavior of A players also changes, but only in the last period and in a less systematic way. Still many A players send positive amounts in period 7.

Table 3 draws a distinction between the last period of the repeated game and the earlier periods. For the six initial periods, with the exception of player B’s payoff, all the indicators are at a higher level compared to the overall repeated game. The percentage returned by player B and player A’s payoff are significantly larger than in the last period of the repeated game (Wilcoxon sign rank test, one-sided, 5 percent), but the amounts sent by A players and the payoffs of B players are not significantly different for periods 1–6 and 7, implying that the total payoff of the player pairs do not differ either.

Table 3
Comparison of averages of the first six periods and period 7

| | Periods 1–6 | Period 7 |
|---|---|---|
| Amount sent | 7.90 | 4.94 |
| Percentage returned | 59.74 | 18.47[a] |
| Payoff of player A | 16.42 | 7.94 |
| Payoff of player B | 19.38 | 21.94 |
| Total payoff | 35.79 | 29.87 |

[a] For period 7, there are only nine observations for which the amount sent is positive.

## 4. The reciprocity hypothesis

Reciprocal behavior assumes that each player relies on "rewards" and "punishments" to react to the observed action of the other player. We assume that in periods $t = 1, \dots, 7$, player B reacts to an increase (decrease) of the amount sent ($S_t$) by increasing (decreasing) the percentage returned ($R_t/3S_t$). For periods $t = 2, \dots, 7$, player A reacts to an increase (decrease) in $R_{t-1}/3S_{t-1}$ by increasing (decreasing) $S_t$. Taken together we call these two behavioral assumptions the *reciprocity hypothesis*.

According to the reciprocity hypothesis, the percentage returned by player B increases with the amount sent by player A: $R/3S = f(S)$, $f'(S) > 0$, $S \neq 0$. Assuming a linear specification, we have $R/3S = \bar{\beta}_1 + \bar{\beta}_2 S$. To avoid dividing by zero we get $R = 3\bar{\beta}_1 S + 3\bar{\beta}_2 S^2$ or $R = \beta_1 S + \beta_2 S^2$, where $\beta_1 = 3\bar{\beta}_1$ and $\beta_2 = 3\bar{\beta}_2$. The reciprocity hypothesis implies that $\beta_2$ is positive and significantly different from zero.

Since $R_{it}$, the observed amount returned, is bounded by 0 and $3S_{it}$, we use a double censored specification:

$$R_{it} = \begin{cases} 0 & \text{if } R^*_{it} \leq 0 \\ R^*_{it} & \text{if } 0 < R^*_{it} < 3S_{it} \\ 3S_{it} & \text{if } R^*_{it} \geq 3S_{it} \end{cases}$$

We assume that

$$R^*_{it} = \alpha + \beta_1 S_{it} + \beta_2 S^2_{it} + \gamma_2 P_2 + \cdots + \gamma_7 P_7 + u_{it}$$

where $R^*_{it}$ is the true (unobservable) amount returned by player B, and $S_{it}$ the amount sent by player A in pair $i$ for period $t$. $P_t$ are dummy variables for the period of play (period 1 being taken as the reference period) and $u_{it}$ the error term. When $S_{it} = 0$, we do not know whether the observation is left or right censored. In this case, we may interpret $R^*_{it} < 0$, as if player B would like to "punish" player A for not sending. We shall refer to that case as the "*punishment hypothesis*". If $R^*_{it} > 0$, player B's attitude can be interpreted as altruistic since he would like to increase player A's payoff without any compensation. We shall refer to that case as the "*altruistic hypothesis*".

Assume that $u_{it} = \mu_i + \varepsilon_{it}$, where $\mu_i$ is an effect specific to pair $i$, and $\varepsilon_{it}$ is an idiosyncratic error term ($\varepsilon_{it} \left| X_{it} \sim N(0, \sigma^2_\varepsilon)\right.$), where $X_{it}$ is the vector of regressors). We may assume $\mu_i$ as fixed effects (FE) or random effects (RE), $\mu_i \left| X_{it} \sim N(0, \sigma^2_\mu)\right.$. The RE model is estimated by the maximum likelihood (ML) method. The FE model can be estimated by ML as in the RE case or by an iterative ML method proposed by Heckman and MaCurdy (1980).[7] For our data sample, the two approaches give similar results.

A critical hypothesis for the consistency of the RE estimator is that $\mu_i$ are uncorrelated with the regressors ($E(\mu_i | X_{it}) = 0$). To check this hypothesis, we perform a Hausman test

[7] See also Maddala (1987). The iterative method consists in estimating separately and iteratively the coefficients of regressors and FE by ML.

Table 4
Estimation results for the regression of $R_{it}$ on $S_{it}$ for the repeated game

| Variable | Altruistic hypothesis | | Punishment hypothesis | |
|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. |
| $S_{it}$ | −1.148 | 0.832 | 3.516[a] | 0.958 |
| $S_{it}^2$ | 0.194[a] | 0.066 | −0.119 | 0.072 |
| $P_2$ | 1.556 | 1.860 | 0.567 | 1.718 |
| $P_3$ | 1.830 | 1.872 | 0.355 | 1.734 |
| $P_4$ | 1.973 | 1.899 | 0.569 | 1.740 |
| $P_5$ | 2.280 | 1.917 | 0.809 | 1.755 |
| $P_6$ | −4.505[a] | 1.904 | −5.570[a] | 1.760 |
| $P_7$ | −8.525[a] | 2.101 | −13.224[a] | 2.177 |
| Intercept | 9.401[a] | 2.575 | −4.755 | 2.944 |
| Log-likelihood | −303.699 | | −291.654 | |
| Wald's statistic[b] | 109.22[a] | | 159.08[a] | |

Number of observations: 112.
[a] Indicates significance at the 5 percent level.
[b] Wald's test is used to compare the constrained model (the model with only the intercept) and the current model. Its statistic follows a $\chi^2_{(8)}$.

that compares the RE model with the FE model.[8] In computing the statistic, we use the estimates obtained by iterative ML for the FE model. The test statistic is 8.60 and 21.23 for the altruistic and the punishment hypotheses, respectively. Comparing these values with $\chi^2_{(8)} = 15.51$ at the 5 percent level, we conclude that the RE model is preferable in the case of the altruistic hypothesis while the FE model is preferable in the case of the punishment hypothesis.

Now we turn to compare these models with the pooled model (without pair effects) by using a likelihood ratio (LR) test. First, considering the altruistic hypothesis, the null is $H_0$: $\sigma_\mu = 0$ (the pooled model) and the alternative is $H_1$: $\sigma_\mu > 0$ (the RE model). The LR statistic is approximately $0 < \chi^2_{(1)} = 3.84$ at the 5 percent level, then we cannot reject the pooled model against the RE model. Second, in the case of the punishment hypothesis, the null is $H_0$: $\mu_i = 0, \forall i$ (the pooled model) and the alternative is $H_1$: $\mu_i \neq 0$ for at least one $i$ (the FE model). The LR statistic is $17.87 < \chi^2_{(15)} = 24.99$ at the 5 percent level, implying that the pooled model is preferred to the FE model. As a result, we observe that the pooled model (without pair effect) is preferable in both the altruistic and the punishment hypotheses. Estimation results of the pooled model for the repeated game are presented in Table 4. Results of the one-shot game are reported in Table 5.

As indicated in Tables 4 and 5, our regressions are significant for both hypotheses (the Wald statistic is significant at the 5 percent level). For the repeated game, there is a positive influence of the amount sent on the amount returned under both hypotheses. We also observe a strong and significant end effect under both hypotheses (the effects of $P_6$ and $P_7$

[8] One computational difficulty is that the Hausman statistic may be negative. In this case, we use a correction as by Lee (1996, pp. 20–21) in order to obtain a positive value.

Table 5
Estimation results for the one-shot game

| Variable | Altruistic hypothesis | | Punishment hypothesis | |
|---|---|---|---|---|
| | Coefficient | S.E. | Coefficient | S.E. |
| $S_{it}$ | −3.051 | 1.690 | −0.348 | 1.319 |
| $S_{it}^2$ | 0.369[a] | 0.139 | 0.161 | 0.114 |
| Intercept | 9.552[a] | 4.497 | 2.058 | 3.376 |
| Log-likelihood | −49.849 | | −52.284 | |
| Wald's statistic[b] | 23.14[a] | | 20.10[a] | |

Number of observations: 20.

[a] Indicates significance at the 5 percent level.

[b] Wald's test is used to compare the constrained model (the model with only the intercept) and the current model. Its statistic follows a $\chi^2_{(2)}$.

Table 6
Estimation results for the regression of $S_{it}$ on $R_{i,t-1}/3S_{i,t-1}$ for the repeated game

| Variable | Coefficient | S.E. |
|---|---|---|
| $R_{i,t-1}/3S_{i,t-1}$ | 18.237[a] | 3.556 |
| $P_3$ | 0.363 | 1.647 |
| $P_4$ | 0.257 | 1.647 |
| $P_5$ | 1.879 | 1.802 |
| $P_6$ | 2.940 | 1.880 |
| $P_7$ | −1.392 | 1.697 |
| Intercept | −1.837 | 2.412 |
| Log-likelihood | −140.008 | |
| Wald's statistic[b] | 40.56[a] | |

Number of observations: 94.

[a] Indicates significance at the 5 percent level.

[b] Wald's test is used to compare the constrained model (the model with only the intercept) and the current model. Its statistic follows a $\chi^2_{(6)}$.

are negative). In both the repeated and the one-shot games, the behavior of player B is compatible with the prediction of the reciprocity assumption ($\beta_2 > 0$) only under the altruistic hypothesis. According to the log-likelihood values, the punishment hypothesis provides better statistical results in the repeated game whereas the altruistic hypothesis does in the one-shot game.

We carry out a similar analysis for the behavior of player A using a double censored model for the relationship between $S_{it}$ and $R_{it-1}/3S_{it-1}$.[9] Test results (Hausman test and LR test) show that the RE model provides a better approximation of the data than the FE and pooled models. Estimation results of the RE model are reported in Table 6. The regression

[9] As the dependent variable, $S_{it}$, is censored between 0 and 10, the distinction between the altruistic and punishment hypothesis is now irrelevant. Two observations for which $S_{it-1} = 0$ had to be removed for the estimation to avoid division by zero.

is also significant (the Wald statistic is significant at the 5 percent level). $R_{it-1}/3S_{it-1}$ has a significant and positive effect on $S_{it}$. Trusting by A players was therefore reinforced when they received larger shares from B players, in accordance with the reciprocity assumption. None of the period dummies $P_3$–$P_7$ has a significant impact on the amount sent. The absence of a significant end effect for A players is therefore a further indication that amounts sent are essentially attributable to trusting behavior. The fact that A players did not change their behavior in the last period indicates that their expectations were mainly based on their history of amounts returned in previous period, leading almost all of them to trust even in the last period.

## 5. Conclusion

We designed an experiment to study the behavior of subjects in a repeated investment game. By repeating the investment game with the same pair of players, our primary purpose was to try to separate "pre-existing motives" that could lead player A to send money to player B from motives derived by the repeated interaction between the players. A second objective was to compare subjects' decisions in the repeated investment game with the subjects' decisions in the one-shot investment game. Repetition can induce more cooperation among players and, therefore, more trust and more reciprocity. In particular, we compared the outcome of the last period of the repeated game with the outcome of the one-shot game.

Our data show that on average the amount sent and the percentage returned increase with repetition. We estimated a double censored model which partly supports the reciprocity hypothesis. However, the end effect seems to indicate that B players returned fair amounts in early periods for strategic purposes: reinforcing player A's trust in the fairness and reciprocity of player B. By playing fair, player B could build a reputation of fairness for player A. Either B players acted in a purely selfish way or changed their behavior over time, starting with a reciprocal behavior and ending playing selfish by discovering that player A became more and more confident. A plausible reason why B players changed their behavior over time is "erosion of reciprocity". B players start behaving reciprocally, but as periods elapse they might feel that they have been reciprocal enough in earlier periods to allow themselves to act more selfishly, which is like a kind of "warm-glow reciprocity".

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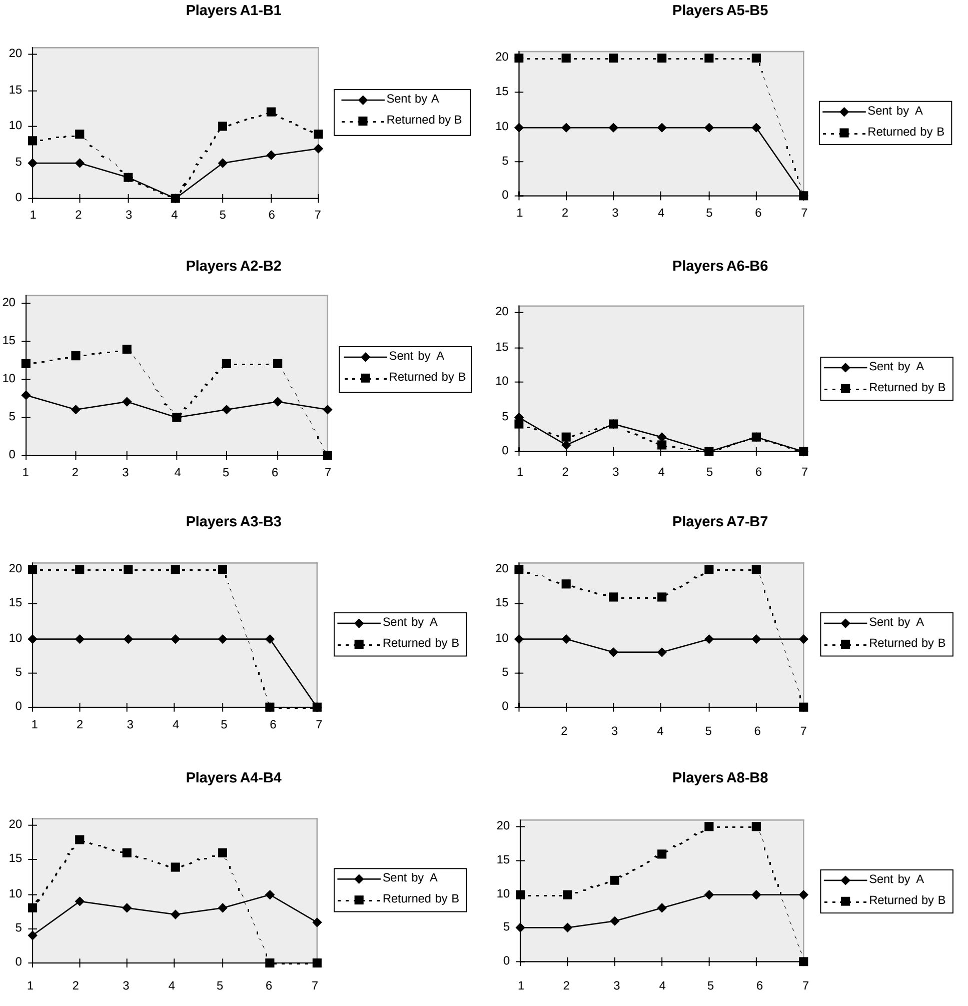
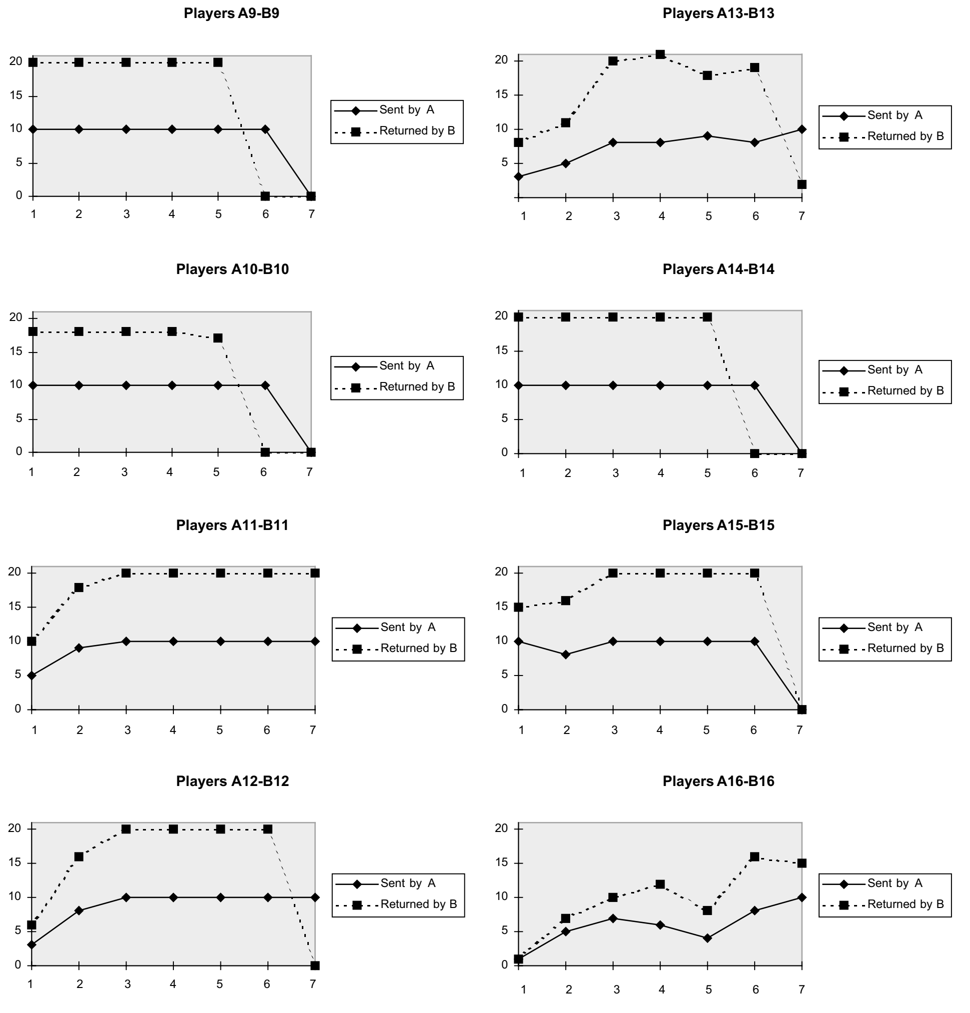
## Appendix A

Amounts sent and amounts returned per period and per player pair in the repeated investment game



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# Does Resorting to Online Dispute Resolution Promote Agreements? Experimental Evidence

Yannick Gabuthy, Nicolas Jacquemet, Nadège Marchand

# Does Resorting to Online Dispute Resolution Promote Agreements? Experimental Evidence*

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**Abstract**

This paper presents an experiment performed to test the properties of an innovative bargaining mechanism (called *automated negotiation*) used to resolve disputes arising from Internet-based transactions. The main result shows that the settlement rule tends to *chill* bargaining as it creates incentives for individuals to misrepresent their true valuations, which implies that automated negotiation is not able to promote agreements. However, this perverse effect depends strongly on the conflict situation. When the threat that a disagreement occurs is more credible, the strategic effect is reduced since defendants are more interested in maximizing the efficiency of a settlement than their own expected profit. The implications of these results are then used to discuss the potential role of *public regulation* and *reputation* mechanisms in Cyberspace.

**Keywords:** Online Dispute Resolution, Electronic Commerce, Bargaining, Arbitration, Experimental Economics.

**JEL classification:** C78, C91, D74, K41.

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# 1 Introduction

By reducing transaction costs, the open structure of the Internet offers businesses and consumers a new and powerful tool for electronic trade (Shapiro and Varian 1998). For example, Internet technology lowers buyer search costs by providing them a wider array of products and services from different sellers than they would have in geographically defined markets. The Internet reduces seller search costs as well, by allowing them to communicate product information cost effectively to potential buyers, and by offering sellers new ways to reach buyers through targeted advertising and one-to-one marketing (Bakos 2001, Garicano and Kaplan 2001). From this point of view, electronic commerce is widely expected to increase social welfare by intensifying competition and helping the consumers to enjoy lower prices and more choices.

However, what makes the Internet such an interesting medium for exchange creates also a number of legal obstacles which could hinder the full economic potential of electronic commerce from being reaped. The characteristics of the Internet make traditional dispute resolution through judicial procedures unsatisfactory for many controversies that arise in electronic commerce (Froomkin 1997). For instance, suppose that a buyer purchases a product from an auction site and something goes wrong with the sale (e.g., the seller may ship a damaged item or the item may have been incorrectly described in the auction). Such a problematic Internet-based transaction raises several issues about how disputes can be resolved in the virtual environment of electronic markets. First, such a transboundary transaction creates legal uncertainty about which jurisdiction is competent and about the applicable law. Second, given that the parties are physically distant, it seems difficult to haul them into court. Third, the low transaction value may simply discourages the parties to resort to a costly legal process. Consumers who participate in this type of commerce expose themselves to a heightened level of risk due to the anonymity and location of the individual making a sale or purchase.[1] During the medieval period, such international trade was governed by rules of private international law, the *lex mercatoria*.[2] Following

[1] This uncertainty can explain why buyers lack trust and confidence in online transactions. For example, 62% of the european consumers declare that the lack of legal protection is the main reason for not purchasing goods online (OCDE 2002). Furthermore, despite the rapid growth in business-to-consumer e-commerce sales, they still account for a very small share of overall transactions. For example, in United States, where most Internet transactions take place, business-to-consumer penetration was just 0.48% of retail sales (Coppel 2000).

[2] The *lex mercatoria* (or *law merchant*) is a body of principles and regulations applied to commercial transactions and derived from the established customs of merchants and traders rather than the jurisprudence of a particular nation or state. The law merchant owed its origin to the fact that the civil law was not sufficiently responsive to the growing demands of commerce, as well as the fact that trade in medieval times was practically in the hands of cosmopolitan merchants who wanted a prompt and effective jurisdiction

this idea, many authors have argued that a distinct set of substantive rules should be created in order to regulate the electronic commerce insofar as the application of legal rules which focus on the concept of territory is questionable in the case of ubiquitous computer networks such as the Internet (Johnson and Post 1996).

The need to regulate the electronic commerce has precipitated the creation of several *online dispute resolution* companies that offer computer-aided bargaining forums in order to settle conflict situations. These mechanisms consist of proprietary software which utilize the Internet as a means to more efficiently engage parties in *automated negotiation* of monetary sums. Automated negotiation appears to be an attractive solution to an important part of the jurisdictional challenges presented by the electronic commerce and promotes the idea of *lex electronica* by providing a self-applying settlement tool in which the legal location and anonymity of the parties do not matter: the resolution is crafted based on the preferences of the parties and does not require the physical presence of them (Mefford 1997, Rule 2002). In this context, many organizations have called for a variety of Internet companies to integrate online dispute resolution into their practices. Participants to the Hague Conference on Private International Law (11-12 December 2000) explored how online dispute resolution can improve trust for electronic commerce by helping to resolve business-to-consumer disputes. In the same way, the OECD Guidelines for Consumer Protection in the Context of Electronic Commerce, completed in December 1999, encourages the use of online dispute resolution.

Let us elaborate the automated negotiation procedure. The resolution process begins when a plaintiff registers with an online dispute resolution service provider, such as "AllSettle" or "SettleItNow".[3] The provider then uses the information provided by the plaintiff to contact the defendant party and invite him/her to participate in online dispute resolution. If the other party accepts the invitation, they will then file a response to the plaintiff's complaint.[4] From this point, the software accepts sealed offers from the

(Greif *et al.* 1994, Benson 1996).

[3]The provider is simply the website delivering the online dispute resolution process. See http://www.allsettle.com/ and http://www.settleitnow.com/ respectively. For example, "SettleItNow" is the premier and independent online settlement service developed and supported in Australia.

[4]The defendant party has a strong incentive to accept the provider's invitation. Indeed, many of the online market sites (e.g., eBay, Amazon) have developed reputation management systems that allow the trading parties to submit a rating of the counterpart's performance in a specific transaction (Keser 2003, Cabral and Hortaçsu 2004, Houser and Wooders 2006). Recent empirical studies of online auction platforms find that such feedback systems have many positive effects in the sense reputable sellers are more likely to sell their items (Laureti *et al.* 2002, Resnick and Zeckhauser 2002), and can expect price premiums (Kalyanam and McIntyre 2001, Lucking-Reiley *et al.* 2006, Resnick *et al.* 2006). However, laboratory evidence shows that reputation systems fail to match the performance of one-on-one long-term relationships and a kind of public good problem may emerge (Bolton *et al.* 2004a, 2004b, 2005; Bolton and

parties and determine whether a settlement occurs according to the following bargaining rule (Gabuthy 2004). Acting independently and without prior communication, plaintiff and defendant submit price offers $b_P$ and $b_D$ respectively. If the offers converge or criss-cross (*i.e.* $b_D \geq b_P$), then the case is settled and the defendant has to pay the price asked by the plaintiff: $b = b_P$. If the offers diverge but are within a specified range (*i.e.* $b_D(1+\delta) \geq b_P > b_D$), then the settlement price is determined by splitting the difference between the parties' offers: $b = (b_P + b_D)/2$.[5] Compared to traditional bargaining, it seems that the automated negotiation procedure would be able to help the disputants to reach an agreement by providing them an additional possibility to settle their dispute (*i.e.* when $b_D - b_P < 0$), through an enlargement of the *settlement zone* proportional to the *compatibility factor*, $\delta \in [0,1)$ (*i.e.* provided that $b_D(1+\delta) - b_P \geq 0$).

Our main concern is to investigate this issue by evaluating whether automated negotiation is effectively able to generate efficiency and help the parties to resolve their conflict. In order to do so, we formulate a simple model of bargaining under *incomplete information* that captures many of the important elements of the automated negotiation process, and then test it by conducting an experiment where we compare the individuals' behavior to the derived theoretical predictions. Laboratory experiments serve as a powerful tool for investigating many kinds of economic phenomena because they provide the means to fully control the economic environment and simulate the basic assumptions of the model under consideration (Smith 1982). Furthermore, the use of experiments to generate original data on automated negotiation is necessary for an even practical reason: the confidentiality which characterizes the online dispute resolution procedures creates important limitations to get field data. The experimental methodology offers the only way to obtain initial data on automated negotiation and therefore to shed some empirical light on how disputants respond to the incentives of this innovative settlement mechanism.

In literature, one mechanism that has been proposed to structure two-person bargaining under conditions of two-sided incomplete information is the well-known sealed bid $k$-double auction. The sealed bid $k$-double auction is a one-parameter family of bargaining rules for determining the terms of trade when a single seller and a single buyer voluntarily negotiate the transfer of an indivisible item. Under this mechanism, buyer and seller simultaneously choose bids $p_b$ and $p_s$, respectively. Trade occurs if and only if $p_b \geq p_s$; in this case, the buyer pays the seller $p = kp_b + (1-k)p_s$, where $k \in [0,1]$. In other words, when the compatibility factor is set equal to 0, the automated negotiation

Ockenfels, 2006). See Dellarocas (2005, Table 1, p.3) for a survey of online platforms providing feedback systems.

[5] The value ascribed to $\delta$ is common knowledge and depends upon the online dispute resolution provider (5%, 20%, ...).

procedure investigated in our paper reduces to the sealed bid $k$-double auction mechanism where $k = 0$ (*i.e.* where the seller – or the plaintiff – sets the price unilaterally if an agreement is reached with the buyer – or the defendant). In order to clearly understand the analogy between our bargaining situation and the sealed bid $k$-double auction, it is helpful to think of the seller ($S$) as a plaintiff ($P$) and the buyer ($B$) as a defendant ($D$) who bargain over the price at which the plaintiff which sell his claim to the lawsuit. Starting with the seminal paper of Chatterjee and Samuelson (1983), considerable theoretical attention has been given to the sealed-bid mechanism (Leininger *et al.* 1989, Satterthwaite and Williams 1989, 1993, Brams and Kilgour 1996, Ausubel *et al.* 2002) and, recently, a number of authors have experimentally investigated its empirical properties (Daniel *et al.* 1998, Rapoport *et al.* 1998, Seale *et al.* 2001, Parco *et al.* 2004, Parco 2006 and many others).[6]

We depart from these previous studies precisely by focusing the analysis on the role that the compatibility factor may have on the individuals' bargaining behavior. Indeed, our main insightful result shows that, contrary to what may appear to be intuitive on an *a priori* basis, an increase in the parameter $\delta$ does not enhance the extent to which agreement is struck. As $\delta$ increases, the disputants are discouraged to converge on their own which induce that the automated negotiation procedure does not significantly increase the range of possible settlements: each party has a strong individual incentive to exploit strategically the compatibility factor and to adopt aggressive positions, which leads to a collective inefficient result. The results of the experiment state that the compatibility factor plagues human interaction and show that the ability of the procedure to generate efficiency increases only when the threat that a disagreement occurs becomes more credible. When the threat that a disagreement occurs is more credible, the strategic effect due to $\delta$ is reduced since defendants are more interested in maximizing the efficiency of a settlement than their own expected profit.

The remainder of the paper is organized as follows. Section 2 presents the game theoretical analysis of automated negotiation which is based on Gabuthy (2004). Section 3 then describes the experiment designed to examine the strategic behavior of subjects and presents the theoretical predictions. The results of the experiment are analyzed in Section 4, and conclusions are drawn with respect to the observed behavior and the factors contributing to it. The implications of these results are used finally in Section 5 to discuss the potential role of public regulation and reputation mechanisms in Cyberspace.

[6]However, most experimental papers focus the analysis on situations with $k = 1/2$. Parco (2006) is, to the best of our knowledge, the only study reporting experimental results with $k = 0$. For a survey of earlier papers, see Schotter (1990) and the collection of articles in the book *Bargaining with Incomplete Information* edited by Linhart *et al.* (1992).

## 2 Theoretical Background

We consider two players, a defendant and a plaintiff who bargain over the price at which the plaintiff will sell his claim to the lawsuit. Let $v_P$ denote the plaintiff's reservation price (*i.e.* the smallest monetary sum he will accept in exchange for the damage). Similarly, let $v_D$ denote the defendant's reservation price (*i.e.* the greatest sum he is willing to pay for the damage). The valuations of the damage of the defendant and plaintiff are their private information: each party knows his own reservation price, but is uncertain about his adversary's, assessing a subjective probability distribution over the range of possible values that his opponent might hold. Specifically, each bargainer $i$ regards the opponent's reservation value $v_j$ as a random variable drawn from an independent uniform distribution on $\left[\underline{v}_j, \overline{v}_j\right]$, and these distribution functions are common knowledge. Therefore, the type spaces are respectively $V_D = \{\underline{v}_D \leq v_D \leq \overline{v}_D\}$ and $V_P = \{\underline{v}_P \leq v_P \leq \overline{v}_P\}$. We focus on the case of incomplete information essentially because the requirement of the complete information approach that each bargainer is assumed to know the other's preferences and payoffs is often regarded as an idealization, incapable of concrete realization.[7] The automated negotiation procedure provides the following bargaining structure.

Acting independently and without prior communication, defendant and plaintiff submit simultaneous offers $b_D$ and $b_P$ respectively, defining the action spaces $B_D = \{b_D \geq 0\}$ and $B_P = \{b_P \geq 0\}$. The computer software then analyzes these proposals in order to see if a settlement has been reached. If the offers converge or crisscross (*i.e.* $b_D \geq b_P$), then the case is settled and the damage is sold at price $b = b_P$. If they are not, but differ by less than or equal to $\delta$ (*i.e.* $b_D(1+\delta) \geq b_P > b_D$), then the case is also settled and the damage is sold at price $b = (b_P + b_D)/2$, where $\delta \in [0, 1)$ is the compatibility factor associated with the automated negotiation procedure. In this latter case, the rule determines the settlement price by splitting the difference between the players' offers. If the offers differ by more than $\delta$, then the agreement is not reached. In this case, there is no settlement and no money trades hands since each player's payoff from disagreement is zero.[8] In this context, a main focus of attention concerns the role and impact that $\delta$ may have on the bargaining behavior and the likelihood of a settlement. In order to conduct our analysis in a simplified manner and isolate this potential role of the compatibility factor,

[7] For example, the plaintiff may have more accurate information on the value of the damage, and the defendant may know whether or not he was negligent.

[8] While this feature seems to be in the best interest of the defendant, notice that it is a classical normalization in the literature on bargaining games under incomplete information, which is furthermore consistent with the actual automated negotiation mechanism: the defendant is not constrained to give any money to the plaintiff if no agreement is struck in the bargaining process (particularly since the plaintiff cannot take legal proceedings in such disputes).

Table 1: Players' payoffs

| | $\phi_D$ | $\phi_P$ |
|---|---|---|
| if $b_D \geq b_P$ | $v_D - b_P$ | $b_P - v_P$ |
| if $b_D(1+\delta) \geq b_P > b_D$ | $v_D - (b_P + b_D)/2$ | $(b_P + b_D)/2 - v_P$ |
| if $b_D(1+\delta) < b_P$ | 0 | 0 |

**Note.** For each condition reported in *row*, the first column describes the payoff earned by the defendant (denoted $\phi_D$), the second column describes the payoff earned by the plaintiff (denoted $\phi_P$).

we deliberately omit from our model various other elements of the settlement mechanism that would have some role and impact on the issue under study. Especially, some restrictive assumptions are made in order to develop understanding and intuition about the role of the forces under study in a sharper manner.

First, we substitute a single-stage bargaining procedure for the multi-stage representation usually considered in the automated negotiation procedure, in which the disputants are involved in a finite sequence of the one-shot game described above. Although this might be seen as a limitation of the model, such a one-shot framework is arguably rich enough to generate a wide set of results concerning the equilibrium role of the compatibility factor.[9] Through abstracting from the dynamics of the negotiation process, the single-stage bargaining procedure emphasizes the basic strategy trade-off faced by each player: by making a more aggressive offer, a player earns a greater profit in the event of an agreement but, at the same time, increases the risk of a disagreement, depending on the value of $\delta$. Second, we assume, without any loss of generality, that there is no direct cost for the parties from using the automated negotiation service - this is a simplifying modeling assumption. Currently the automated negotiation providers use a wide range of fee structures - that is, a submission fee (incurred only by the party requesting the resolution) and a settlement fee (incurred by both parties if and only if a successful settlement is reached).

Framing the single-stage bargain as a non-cooperative game, we will characterize the resulting *(Bayesian) Nash equilibrium.* In the event of an agreement, each player earns a profit measured by the difference between the agreed price and his reservation value ($b - v_P$ for the plaintiff and $v_D - b$ for the defendant). In the event of no agreement, each earns a zero profit. The resulting payoffs to both the defendant and the plaintiff are summarized in Table 1.

[9] Parco *et al.* (2004) experimentally investigate the empirical properties of multistage sealed bid $k$-double auctions (by extending the double auction to two-round of bargaining) and state a similar conclusion.

We assume that each bargainer makes offers to maximize his expected profit and we restrict attention to strictly monotonic and differentiable strategies for the two players. In this static Bayesian game, a *pure strategy* for player $i$ is a function $b_i(v_i)$, where for each type $v_i$ in $V_i$, $b_i(v_i)$ specifies the action from the feasible set $B_i$ that type $i$ would choose if drawn by Nature ($i = D, P$). The player $i$'s *best reply* is then defined by the following maximization problem:

$$\max_{b_i} \Pi_i = E\phi_i \qquad (i = D, P) \tag{1}$$

where the expectation is taken with respect to the probability distributions of $v_i$.

Then player $i$ employs a best response strategy if for each $v_i$ his offer is a best response against his opponent's strategy. In the automated negotiation procedure, disputants face a complex choice when choosing their offers. Both parties know that while their optimal independent behavior is to play strategically, they could be better off by bidding truthfully (*i.e.* $b_D = v_D$ and $b_P = v_P$). However, they also know that each bid they place involves a trade-off between increasing the odds of a successful trade (accomplished by placing a bid closer to their reservation value) and increasing their share of the joint gain should a settlement occur (enhanced by placing a more aggressive bid). The central idea of the analysis is to investigate how the compatibility factor affects the way individuals resolve this trade-off. It would appear at first blush that an increase in the value of $\delta$ improves the efficiency of the bargaining situation by increasing the settlement zone. In the case where $\delta = 0$, an agreement occurs only when there is some "bargaining space" between the two offers (*i.e.* when $b_D - b_P \geq 0$), while a positive $\delta$ provides the parties a possibility to reach an agreement even when this "bargaining space" does not exist (*i.e.* when $b_D - b_P < 0$, provided that $b_D(1+\delta) - b_P \geq 0$). The flaw in this line of reasoning is that it implicitly assumes that the bargaining strategies are unaffected by the changes in compatibility factor. This is not the case, however, since it is easy to show that changes in the compatibility factor have a drastic effect on the equilibrium behavior of the parties: *ceteris paribus*, when $\delta$ increases, the defendant becomes more aggressive by moving away from his reservation value (*i.e.* by offering a lower price). Furthermore, automated negotiation induces an asymmetric interaction between players since the compatibility factor is only assigned to the defendant's proposal. Under this bargaining rule, the plaintiff's strategy is very slightly affected by $\delta$.[10]

**Lemma 1** *Under the automated negotiation bargaining rule, the equilibrium offer strate-*

[10] The automated negotiation puts a downward pressure on the plaintiff's demand only if we consider extreme values of $\delta$ which do not exist in the actual procedures.

*gies are:*

$$b_D^*(v_D,\delta) = \alpha(\delta)\, v_D \;\; ; \; b_P^*(v_P,\delta) = \beta(\delta)\, v_P + \gamma(\delta)\, \overline{v}_D$$

*where* $\alpha(\delta) = \dfrac{2(1+\delta)}{(\delta^2+4\delta+2)}$, $\beta(\delta) = \dfrac{2(1+\delta)}{(2+\delta)^2}$ *and* $\gamma(\delta) = \dfrac{4(1+\delta)^3}{(2+\delta)^2(\delta^2+4\delta+2)}$.

**Proof** See the Appendix. ∎

As mentioned in the Introduction, the case where $\delta = 0$ in the automated negotiation procedure is equivalent to the case where $k = 0$ in the sealed bid $k$-double auction mechanism. However, we consider a linear characterization of the equilibrium, which is different from the *piece-wise* linear representation assumed in Chatterjee and Samuelson (1983).[11] As an illustration, consider the special case in which $\delta = 0$ and $v_P$ ($v_D$) is uniformly distributed over the closed interval $[0,60]$ ($[40,100]$). A straightforward manipulation of Lemma 1 gives $b_D^*(v_D) = v_D$ and $b_P^*(v_P) = 1/2 v_P + 50$ (for all $v_i$, $i = D,P$), while Chatterjee and Samuelson (1983) specify the following strategies for the two players:[12]

$$b_P^{CS} = \frac{1}{2} v_P + 50 \quad \text{for all} \quad 0 \leq v_P \leq 60$$

$$b_D^{CS} = \left| \begin{array}{ll} v_D & \text{if } 40 \leq v_D < 80 \\ \\ 80 & \text{if } 80 \leq v_D \leq 100 \end{array} \right.$$

The linear characterization has been introduced to simplify the analysis and is consistent with our experimental data which do not reveal any discontinuity in the individuals' bargaining behavior.

Following Lemma 1, the compatibility factor has two opposite implications on the settlement zone, defined by:

$$b_D(1+\delta) \geq b_P \tag{2}$$

First, by providing the parties an additional possibility to reach an agreement, the compatibility factor increases the settlement zone for given bargaining strategies: it is straightforward to show that the compatibility factor has a positive impact on the left-hand side of (2).

However, at the same time, the compatibility factor leads the defendant to become more aggressive and move away from his true valuation (while the plaintiff's demand is

[11] The multiplicity of equilibria is a well known feature of such games. We differ from Chatterjee and Samuelson (1983) in the way we get a unique equilibrium.

[12] These intervals correspond to the *low conflict situation* in our experimental design (see Figure 1, p.11). The piece-wise linear equilibrium solution of Chatterjee and Samuelson (1983) can be derived from equations given by Parco (2006, p. 414).

constant):

$$\frac{\partial b_D^*(v_D,\delta)}{\partial \delta} = \frac{-2\left(\delta^2+2\delta+2\right)}{\left(\delta^2+4\delta+2\right)^2} v_D \leq 0, \text{ since } \delta > 0 \text{ and } v_D \geq 0$$

The defendant's offer strategy is sensitive to changes in the compatibility factor in a natural way. In the case where $\delta = 0$, the defendant's equilibrium proposal coincides with his reservation value (*i.e.* $b_D = v_D$ for all $v_D$). The intuition behind this result is the following. When an agreement is reached, the case is settled at price $b = b_P$, therefore the rule is equivalent to granting the plaintiff the right to make a first and final offer that the defendant can accept or reject. In this instance, the transaction price is determined solely by the plaintiff's demand, while the defendant's offer serves only to determine whether there is an agreement or not. The defendant's dominant strategy is then to make a truthful offer in order to maximize the probability of settlement. On the contrary, when the compatibility factor increases the marginal increment in profit associated with a slightly more aggressive offer becomes weighted more heavily than the possible loss, if as a result of the change, an agreement is precluded. Concerning the plaintiff's offer strategy, we could think intuitively that the defendant's aggressiveness would force the plaintiff to adopt a more concessionary bargaining behavior in order to increase the probability to reach an agreement. This is not the case however because the more compromising party, while enhancing her chances of reaching an agreement, does so at the expense of lowering her expected payoff.

Given these two opposite implications, the global effect of the compatibility factor on the probability that a settlement occurs is not significant, except for extreme values of $\delta$ which do not exist in the real automated negotiation procedures. The gain in efficiency due to the increase in the "potential" settlement zone is approximately offset by the efficiency loss due to the parties' strategic behavior, causing the "actual" settlement zone to be slightly affected by changes in $\delta$.

**Proposition 1** *Under the automated negotiation bargaining rule, the compatibility factor does not improve the efficiency of the settlement zone.*

The intuition behind this result is the following: the parties are more reluctant to concede during negotiations because the threat that a disagreement occurs is less credible for high values of $\delta$. This result is consistent with the predictions of the arbitration models and the well-known *chilling effect* (Farber 1981): automated negotiation tends to "chill" bargaining as it creates incentives for individuals to misrepresent their true valuations and discourage them to converge on their own (*i.e.* with $b_D \geq b_P$). In fact, the computer software seems to become a neutral third party who drives the parties' strategies outside the range of potential negotiated settlements. This result suggests that the automated negotiation design is not a good way for increasing the likelihood of a settlement: each party has a strong individual incentive to exploit strategically the compatibility factor and adopt aggressive positions, which leads to a collective inefficient result. However, while this result is theoretically appealing, we have no idea about whether it characterizes bargaining realities. The next section aims at filling the gap.

# 3 Experimental protocol

## 3.1 Experimental design

We experimentally implement the negotiation game described in Section 2. At the beginning of each period, each subject $i$ is assigned a private reservation value $v_i$ $(i = D, P)$. Then, the defendant and the plaintiff choose simultaneously a bidding price (*i.e.* $b_D$ for the defendant and $b_P$ for the plaintiff). The experiment is based on a factorial 2x2 design combining two levels of conflict (high/low) with two levels of the compatibility factor ($\delta = 0$ / $\delta = 30\%$).

The basic question in our study is whether the compatibility factor affects the bargaining behavior of the parties and under which circumstances does it increase the probability of reaching an agreement. Therefore, in some of the treatments, participants play under the conditions of "pure" negotiation in which there is no compatibility factor (*i.e.* $\delta = 0$) and the parties may reach an agreement only if their offers are strictly convergent (*i.e.* $b_D \geq b_P$). In other treatments, subjects interact under the conditions of automated negotiation where the compatibility factor equals 30% and the parties have the possibility to settle their dispute even when $b_D < b_P$ (provided that $1.3b_D \geq b_P$, since $\delta = 0.3$).[13] However, we can think intuitively that the ability of the automated negotiation mechanism to generate efficiency (if any) depends on the extent of the conflict between the parties. Therefore, the following treatments are introduced in order to analyze whether the impact of the compatibility factor depends on the conflict situation. In a first case, the private values $v_D$ and $v_P$ are independently drawn from a uniform distribution with supports $\{40, 41, ..., 100\}$ and $\{0, 1, ..., 60\}$ respectively, while in a second case the respective uniform distribution sets are $\{20, 21, ..., 100\}$ and $\{0, 1, ..., 80\}$. The last case obviously characterizes a high conflict situation, as illustrated in Figure 1.

Notice that, whatever the conflict situation, the plaintiff's valuation may be equal

[13] $\delta = 30\%$ appears to be a reasonable value in order to give the subjects a sufficient opportunity to take into account this parameter.

Figure 1: Conflict situations used in the experiment


(a) Low conflict situation (b) High conflict situation

**Note.** In each Figure, $v_P$ denotes the private value of the plaintiff, $v_D$ the private value of the defendant. The bold line illustrates the conflict zone settled by the treatment, set either to Low conflict (Figure a) or High Conflict (Figure b).

to 0 (since $\underline{v}_P = 0$), while the defendant's valuation is strictly positive (since $\underline{v}_D > 0$). This assumption may seem to be surprising since we could intuitively consider that the plaintiff should *inherently* award a positive value to his claim. However, the assumption made on the lower bound of the plaintiff's private value has two motivations. First, the players' reservation values may be considered as their disagreement payoffs in the bargaining process. In our analysis, we implicitly assume that *i/* there is no cost for the parties from using the automated negotiation procedure, and *ii/* the parties may incur some difficulties to resort to alternative dispute resolution systems if they fail to reach an agreement during the automated bargaining (due to jurisdictional challenges presented by such disputes). In other words, the intuition behind the zero value ascribed to $\underline{v}_P$ is that the plaintiff may have no *outside option* and gets nothing if no settlement is struck in the bargaining process. Second, assuming that $\underline{v}_P = 0$ allows us to extend the settlement zone (*e.g.* $v_D - v_P$ when $\delta = 0$) in order to increase the likelihood of a settlement (for given bargaining strategies). This way, we avoid that the main result of the paper concerning the (in)efficiency of automated negotiation be due to the incentives given to the plaintiff in the experimental protocol.

The information provided to the participants maps the information structure of the game analyzed in Section 2. At the end of each period, each pair of subjects was therefore privately informed on whether or not they have reached an agreement, about the price to be paid by the defendant, their own bid, their own payoff in the current period and their total profit up to this time. As well, payments were determined according to the automated negotiation rules and the submitted offers. The theoretical predictions for the experimental game are consequently derived from the background developed above, as summarized in Table 2.

Recall that our basic issue is a positive question: given that the automated negotiation

Table 2: Overview of theoretical predictions

| | $\delta = 0$ | $\delta = 30\%$ |
|---|---|---|
| *Equilibrium Bidding Strategies* | | |
| Plaintiff | $b_P^*(v_P) = 0.5v_P + 50$ | $b_P^*(v_P, 30\%) = 0.49v_P + 50.49$ |
| Defendant | $b_D^*(v_D) = v_D$ | $b_D^*(v_D, 30\%) = 0.79v_D$ |
| *Efficient Bidding Strategies* | | |
| Plaintiff | $b_P^e = v_P$ | $b_P^e(v_P, 30\%) = v_P$ |
| Defendant | $b_D^e = v_D$ | $b_D^e(v_D, 30\%) = v_D$ |
| *Equilibrium Settlement Zone* | $SZ^* = v_D - 0.5v_P - 50$ | $SZ^*(30\%) = 1.03v_D - 0.49v_P - 50.49$ |
| *Efficient Settlement Zone* | $SZ^e = v_D - v_P$ | $SZ^e(30\%) = 1.3v_D - v_P$ |

**Note.** The conflict situation is neutral on the formal theoretical predictions. The settlement zone ($SZ$) is given by $SZ = b_D^*(v_D, \delta)(1+\delta) - b_P^*(v_P, \delta)$, where $b_D^*(.)$ and $b_P^*(.)$ are the players' equilibrium strategies.

procedure is designed in a particular manner, does the individual's behavior corresponds to what the designer intended, and what causes the deviations? Therefore, summarizing the theoretical predictions, the experimental data are analyzed according to the three following hypotheses.

***Hypothesis 1*** *In equilibrium, when $\delta = 0$:*

- *The defendant adopts a truth revealing behavior. The equilibrium offer coincides with his reservation value: $b_D^*(v_D) = b_D^e(v_D) = v_D$.*
- *The plaintiff's behavior is untruthful, his proposal being higher than his reservation value: $b_P^*(v_P) > b_P^e(v_P) = v_P$.*

According to Hypothesis 1, the settlement rule associated with $\delta = 0$ induces a truthful bidding behavior on the part of the defendant, while the plaintiff's asking price is biased upward with respect to his valuation. As a result, even when the defendant values the damage more highly than the plaintiff, a successful settlement may be impossible: $SZ^* < SZ^e$.

***Hypothesis 2 (Chilling effect)*** *In equilibrium, when $\delta$ is increased (set equal to 30%):*

- *The defendant becomes more aggressive, adopting an under-bidding behavior:*

$$b_D^*(v_D, 30\%) < b_D^e(v_D, 30\%) = v_D$$

- *The plaintiff's behavior remains the same, over-bidding according to:*

$$b_P^*(v_P, 30\%) > b_P^e(v_P, 30\%) = v_P$$

As stated in Hypothesis 2, only the defendant's behavior is affected by the rise in the compatibility factor, moving bidding behavior to more aggressive – untruthful – offers. Increasing the compatibility factor hence fails to improve efficiency: it is still the case that not all mutually beneficial agreements can be attained *via* the automated negotiation procedure: $SZ^{*}(30\%) < SZ^{e}(30\%)$. The parties are then discouraged to converge on their own, resulting in a chilling effect.

***Hypothesis 3*** *When the extent of the conflict increases, the settlement zone decreases ; an agreement is hence less likely.*

When the conflict situation is high, the distribution sets induce a reduced settlement zone and do not affect the equilibrium bargaining strategies (for given reservation values). However, we could think intuitively that this result does not characterize bargaining realities: we conjecture that a higher conflict situation should encourage more concessionary behavior by the parties in order to increase the probability to reach an agreement. In other words, the disputants should take more reasonable bargaining positions by moving closer to their true values because the threat that a disagreement occurs is more credible in a high conflict situation. In this context, we believe that this concessionary behavior could compensate for the perverse effect induced by the compatibility factor. Such a result would imply that the conflict situation alters fundamentally the way the individuals use the compatibility factor: in a high conflict situation, the parties could be incited to use the compatibility factor more efficiently (as a means to increase their chances to reach an agreement) and less strategically (as a means to increase their payoffs).

### 3.2 Experimental Procedures

In all experimental conditions described above, subjects participated as a defendant or as a plaintiff in a sealed-bid double auction (one defendant and one plaintiff forming a group). Role assignment remained the same throughout the entire session. Each pair of participants had to agree on the exchange price of the claim.[14] The experiments were run in the GATE experimental laboratory with 160 participants over a total of 8 sessions, with each session comprising 40 periods, hence providing 6400 observations. The participants were randomly recruited from a subject pool of students of several universities and the graduate school of management (Lyon). All of them were inexperienced in auction experiments and no subject participated in more than one of the sessions. In each of the 40 periods, the

[14] In the experiment, we used a more neutral terminology: a buyer (the defendant) and a seller (the plaintiff) bargain over the transfer of an indivisible good (the claim). A successful trade is determined by the automated negotiation mechanism.

defendant-plaintiff pairs were re-matched such that the same defendant-plaintiff pair did not interact in two consecutive periods. Therefore, in our setup, all the theoretical results hold for all periods: since interaction is anonymous and one-shot, the 40 periods are repetitions of static games and not a dynamic game giving rise to further equilibria. In other words, the random-matching design allow us to minimize (if not completely eliminate) reputation effects.

Upon arrival, participants were randomly assigned to a specific computer terminal. In the beginning of each session, instructions were distributed and read aloud (an English translation of the original instructions in french as well as raw data are available from the authors upon request). Clarifying questions were asked and answered privately. Then, we asked the participants to fill in a control questionnaire in order to check for understanding. Only after all questions had been correctly answered, the experiment started. The experiment was computerized using the REGATE software (Zeiliger 2000). On average, each session lasted one hour, excluding payment of subjects. All amounts were given in ECU (*Experimental Currency Unit*), with conversion into Euros at a rate of 2 Euros for 100 ECUs upon completion of the session. The total payment was the sum of the single payoffs of the 40 periods plus a 2 Euros show-up fee. Each subject earned on average slightly more than 14 Euros.

# 4 Experimental Results

Following the above discussion, our three hypothesis are tested here by assessing the impact of the compatibility factor and the conflict situation on bidding behavior of each party and the resulting conflict resolution implemented by the negotiation procedure.

## 4.1 Bidding Behavior

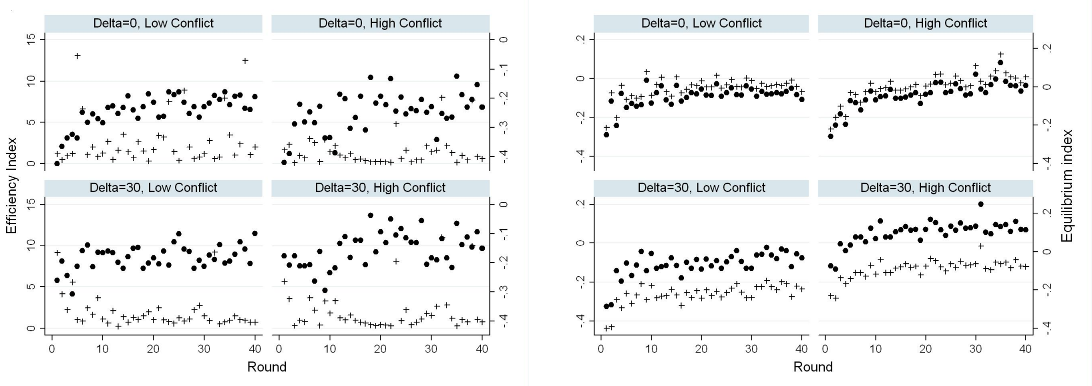
We provide a preliminary picture of individual behavior of plaintiffs and defendants using the following indexes:

- Relative deviation from the linear equilibrium strategy – This index ($I_i^*$) measures the relative difference between observed proposal ($b_i$) and the equilibrium bidding strategy ($b_i^*$):

$$I_i^* = \frac{b_i - b_i^*}{b_i^*} \quad (i = D, P) \tag{3}$$

- Relative deviation from efficiency – This index ($I_i^e$) measures the relative difference

Figure 2: Overview of bidding behavior




(a) Plaintiffs (b) Defendants

**Legend.** + Efficiency index (Y axis plotted on the left); • Equilibrium index (Y axis plotted on the right).

**Note.** Average observed deviation from equilibrium and efficiency for plaintiffs (Figure a) and defendants (Figure b) under $\delta = 0$ (*upper part*) or $\delta = 30\%$ (*bottom part*) and under Low (*left-hand side* Figures for each party) or High (*right-hand side* Figures for each party) conlict situation. The indexes are calculated using (3) and (4).

between observed proposal ($b_i$) and the efficient bidding strategy ($b_i^e$):

$$I_i^e = \frac{b_i - b_i^e}{b_i^e} \quad (i = D, P) \tag{4}$$

By way of definition, each index provides a comparison between observed behavior and either equilibrium or efficient strategies. A positive value of $I_i^*$ indicates that the plaintiff (defendant) follows a more (less) aggressive pricing strategy than the Nash equilibrium. Similarly, a positive value of $I_i^e$ reflects an over-bidding behavior, the plaintiff (defendant) asking for a compensation higher (offering more) than his reservation value – a negative value of each index indicates the other way round.

Figure 2 plots the average indexes across rounds for each party, depending on the conflict situation and the value of the compatibility factor. In line with the results summarized in Table 2, the two indexes mechanically coincides for defendant when $\delta = 0$, since equilibrium and efficient strategies are the same. An overall salient feature is a slight learning pattern in the first ten periods, suggesting that experience with the mechanism matters in bidding behavior. This will be addressed in the econometric analysis of the data.[15]

[15] The efficiency index sometimes appears to be driven by outliers, dropping to very high values. This is due to an over-reaction of indexes to deviations associated with very low private values. Just as an illustration, all 531 individual observations for which the efficiency index is above 2 have private values lower than 21. This upper bound on private values falls to 15 when only those observations for which the efficiency index is above 3 (what amounts to 382 observations out of our 6400) are considered.

We now turn to a discussion of parties' behavior in line with experimental treatments. Consider first our benchmark situation, namely bidding behavior when the compatibility factor is set equal to 0. The defendants' proposals appear to be relatively efficient. Indeed, the overall average indexes amount to $I_D^* = I_D^e = -5\%$ or $-6\%$, depending on the conflict situation. On the opposite, plaintiffs' behavior seems largely inefficient since the price required is strongly higher than their reservation values (the overall average efficiency index is $I_P^e = 73\%$ when the conflict is low, 32% when the conflict is high). Regarding comparisons with equilibrium behavior, Parco (2006) states that conferring a price-setting power to the information advantaged player induces a less aggressive behavior. This seems to hold as well in our game, characterized by symmetric information conditions. While defendants choose bids close to equilibrium, plaintiffs adopt strategies less aggressive than those predicted by the Nash equilibrium (the average efficiency index is $I_P^* = -24\%$ and $-23\%$ under low and high conflict situations). As a result, the defendants' deviation from equilibrium is significantly lower than the plaintiffs' one (Mann-Withney U test and Kolmogorov-Smirnov test, both with p-value: $p = 0.0001$).

**Result 1** *When $\delta = 0$, the defendants' behavior is more truthful revealing than the plaintiffs' behavior.*

This asymmetric behavior between defendants and plaintiffs supports the first hypothesis. This makes intuitive sense by referring to the parallel between our double auction game and the first- and second-price sealed-bid auctions in which several purchasers compete to obtain a good.

1. The problem confronting a defendant in automated negotiation (with $\delta = 0$) is strategically similar to the problem faced by a buyer in a second-price auction. In second-price auctions, the highest bidder gets the object and pays the second highest bid. From a theoretical point of view, this procedure is efficient since bidders have a dominant strategy of bidding up to their private valuation, irrespective of attitudes toward risk (Vickrey 1961). Indeed, the bid made by the player has no impact on the transaction price he pays and affects only his probability of winning (which is maximized by offering the highest price corresponding to his reservation value).[16]

[16] However, this behavior is not consistent with laboratory experiments in which subjects are found to exhibit a consistent pattern of overbidding (Kagel *et al.* 1987, Kagel and Levin 1993, Harstad 2000). Economists have very little understanding of why it happens. Recently, Cooper and Fang (2006) provide an explanation by considering that individuals overbid because they derive positive utility from winning, over and beyond any monetary payoffs. See also Morgan *et al.* (2003) and Andreoni *et al.* (2006) for alternative explanations of this phenomenon.

Similarly, in automated negotiation (with $\delta = 0$), the settlement price is determined solely by the plaintiff's demand (*i.e.* $b = b_P$). The settlement rule is therefore equivalent to granting the plaintiff the right to make a first and final offer that the defendant can accept or reject. The defendant's offer serves only to determine whether there is an agreement or not. The defendant maximizes the probability to reach an agreement – conditional on earning positive profits – by bidding an amount corresponding to his valuation.

2. The problem confronting a plaintiff in automated negotiation (with $\delta = 0$) is strategically similar to the problem faced by a buyer in a first-price auction. In first-price auctions, the highest bidder gets the object and pays the amount he bids. The decision-making in first-price auctions is more complex than that in second-price auctions since each players' bid involves a trade-off between increasing the probability of winning (by placing a bid closer to their reservation value) and increasing their profit (by placing a more aggressive bid). The experimental literature shows that buyers underbid compared to efficiency (because of this trade-off) and overbid compared to the equilibrium (in order to improve their chances of winning). This standard result is developed in Kagel and Roth (1995).[17]

   Similarly, in automated negotiation (with $\delta = 0$), the plaintiff's proposal determines both his profit and the probability of conflict resolution. Therefore, he adopts an inefficient behavior which consists of asking for an amount higher than his reservation value. However, he tends to be less aggressive than predicted by the Nash equilibrium in order to improve the likelihood of a settlement (as buyers maximize their probability of winning in first-price auctions).

Now turn to bidding behavior under our mechanism of interest (*i.e.* when a positive compatibility factor is implemented). Under $\delta = 30\%$, remember that when the proposals do not converge but differ by less than $\delta$, the bargaining rule determines the settlement price by splitting the difference between the parties' offers. Therefore, contrary to the case where $\delta = 0$, the defendant faces a trade-off between enhancing the probability to reach an agreement and increasing his expected payoff. In that sense, the defendants reply to the change in the compatibility factor in a natural way. As shown in Figure 2, this settlement rule indeed induces defendants to move away from their valuations and behave closer to the equilibrium prediction (the average indexes across rounds are $I_D^e = -27\%$ or $I_D^e = -14\%$, and $I_D^* = -8\%$ or $I_D^* = 8\%$, depending on the conflict situation). The

[17] See also Cox *et al.* (1988), and Harrison (1989).

strategic problem faced by the plaintiff is not fundamentally modified by the split-the-difference rule. Whatever the level of $\delta$ is, the plaintiff faces a similar trade-off since the settlement price corresponds to his own demand (as soon as the offers converge or overlap). As a result, the compatibility factor does not significantly affect the plaintiff's behavior. When $\delta = 30\%$, the plaintiffs are therefore still encouraged to adopt inefficient behavior which is closer to the equilibrium prediction (average indexes amount to $I_P^e = 69\%$ or $I_P^e = 48\%$ and $I_P^* = -18\%$ or $I_P^* = -14\%$, depending on the conflict situation).

The statistical significance of the patterns described above are assessed using the following regression. The price offered by a party $n$ at time $t$, $y_{nt}$, is specified as a linear combination of the covariates, denoted $X_{nt}$. This includes our main variables of interest, namely the level of the compatibility factor, the conflict situation and their interaction. We also account for learning by including a dummy variable set equal to one during the first ten periods only. Last, the reservation value is included jointly with its squared and cubic values in order to test the linearity of the strategies.[18] In this linear specification, $y_{nt} = X_{nt}\beta + \varepsilon_{nt}$, we account for the panel dimension of our observations by considering a composed error model: $\varepsilon_{nt} = u_n + w_{nt}$. The individual specific error term $u_n$ is assumed normal in the estimation and captures the distribution of heterogeneity in the population. The model is separately estimated by maximum likelihood for plaintiffs and defendants. The results are presented in Table 3. First note that the two coefficients on the last dummy variable strongly suggest that learning occurs during the first ten periods. The structural motives underlying bidding behavior are therefore better estimated by regressions that include such dummies.

As expected, the proposals of both parties are increasing in their reservation values. The coefficients on powers of the reservation values moreover support the linearity of the bidding strategies followed by both plaintiffs and defendants. Regarding the impact of the settlement rule on bidding behavior, the estimated coefficients on the compatibility factor variable support the asymmetric impact stated in Hypothesis 2.

**Result 2** *The compatibility factor does not significantly affect the plaintiffs' behavior, while defendants become more aggressive by offering lower compensations.*

As a result, automated negotiation tends to "chill" bargaining as it creates incentives for individuals to misrepresent their true valuations and discourage them to converge on their own. Beyond this overall effect, the coefficient on the interaction variable suggests

[18] A similar analysis is developed by Radner and Schotter (1989) who show that the behavior of the subjects is consistent with the linear equilibrium. Notice, however, that their analysis is quite distinct from ours since they consider symmetric prior distributions and the midpoint trade rule (*i.e.* $k = 1/2$). Their experiment 4 set $k = 1$ but was only briefly mentioned without results or analysis.

Table 3: Determinants of proposals by plaintiffs and defendants

| | Plaintiff | | Defendant | |
|---|---|---|---|---|
| | Coef. | St. Dev. | Coef. | St. Dev. |
| Constant | 35.60*** | (1.550) | 1.18 | (3.459) |
| Compatibility factor | 3.30 | (2.023) | -14.99*** | (2.336) |
| Conflict situation | -3.57* | (2.027) | -0.34 | (2.338) |
| Interaction | 2.97 | (2.861) | 9.30*** | (3.303) |
| Reservation value ($v_i$) | 0.38*** | (0.069) | 1.18*** | (0.168) |
| $v_i^2$ | 0.00 | (0.002) | -0.00 | (0.003) |
| $v_i^3$ | 0.00 | (0.000) | 0.00 | (0.000) |
| Learning | -2.98*** | (0.376) | -5.20*** | (0.359) |
| Log-likelihood | -12227 | – | -12321 | – |

**Legend.** Significance levels: * 10%, ** 5%, *** 1%.

**Note.** Random effects OLS regression. The dependent variable is the bid. The *Compatibility factor* is treated as a Dummy variable, set equal to 1 if $\delta = 0.3$ ; The *High conflict situation* is included as dummy variable ; The *Interaction* variable is set equal to one when $\delta = 0.3$ under an high conflict situation, 0 otherwise; The *Learning* variable is equal to one during the first ten periods. The regression is run on 80 individuals ($N = 80$) observed during 40 periods ($T = 40$). Each regression is therefore run on 3200 observations.

that the impact of the compatibility factor is significantly affected by the conflict situation. This last variable fundamentally alters the way the defendant uses the compatibility factor:

**Result 3** *The compatibility factor associated with higher conflict situations encourages defendants to adopt a more concessionary behavior.*

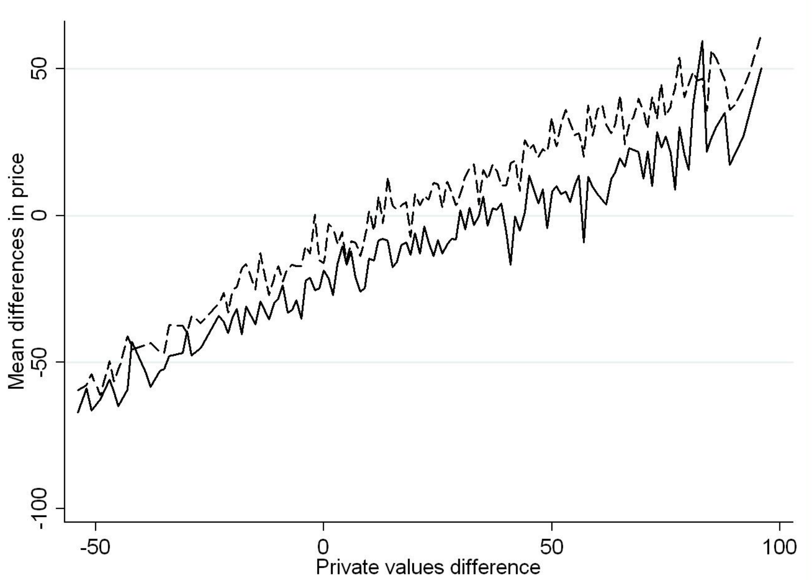
The threat of a disagreement becomes more credible in a high conflict situation, which encourages defendants to use the compatibility factor less strategically. In this context, a higher conflict reduces the chilling effect : the defendant uses the automated negotiation mechanism more efficiently in order to increase the probability to reach an agreement – conditional on positive earnings. The asymmetry between defendants and plaintiffs still remains effective, and the plaintiffs' proposals are not affected by the compatibility factor in higher conflict situations.

Overall, our main variables of interest strongly impact the way the surplus raised by an agreement is split between parties. More interestingly with regard to efficiency, we now turn to the ability of the settlement rule to promote an agreement between parties.

## 4.2 Conflict Resolution

An overview of the observed conflict resolution is provided in Figure 3. For each difference in the private values of defendants and plaintiffs (hence measured by $v_D - v_P$), we draw

Figure 3: Average differences in the bid posted by plaintiffs and defendants




**Legend.** Dash line: $\delta = 0$ ; Solid line $\delta = 30\%$.

**Note.** The figure plots the average difference between defendant's and plaintiff's bids (measured as $b_D - b_P$) for a given difference between private values (measured as $v_D - v_P$).

the average difference between bids (*i.e.* $b_D - b_P$) when the compatibility factor is set equal to 0 (dash line) or 30% (solid line). A "perfect" conflict resolution would imply that price differences are positive as soon as the difference between private values is so. The observed trend does support an increase in bid differences in line with the difference between private values.

Regarding the impact of the compatibility factor, the figure illustrates the strategic exploitation by parties of the settlement rule stressed above. As compared to what happens when $\delta = 30\%$, the defendants' offers are more often higher than the plaintiffs' demands when the compatibility factor is set equal to 0 (*i.e.* the dash line is almost always above the solid one). The parties therefore seems more reluctant to concede during negotiations following an increase in the compatibility factor. Under the automated negotiation procedure the occurrence of a "straight" settlement then appears to be less likely, due to parties being discouraged to converge on their own.

Even though individual behavior is an important determinant of conflict resolution, automated negotiation is precisely aimed at improving the ability of parties to reach an agreement. Indeed, actual settlements differ from straight ones due to the compatibility factor enlarging the settlement zone under automated negotiation. To illustrate this point,

Table 4: Settlement rates

| | Low conflict | High conflict | Overall |
|---|---|---|---|
| $\delta = 0$ | 76.50% (612) | 54.25% (434) | 65.38% (1046) |
| $\delta = 30\%$ | 69.25% (554) | 57.75% (462) | 63.50% (1016) |
| Overall | 72.88% (1166) | 56.00% (896) | 64.44% (2062) |

**Note.** Each cell provides the proportion of observations that reached an agreement in the treatment defined by row/column combination. The corresponding number of observations is provided in parenthesis.

we summarize the actual settlement rates per level of the compatibility factor and conflict situation in Table 4. Despite this mechanism, the automated negotiation procedure appears to fail in promoting efficiency. The compatibility factor induces a slight overall increase in the conflict rate, the rate of agreements decreasing from 65.38% when $\delta = 0$ to 63.50% when $\delta = 30\%$.

Desegregating those settlement rates as regards to the conflict situation, a huge heterogeneity however appears. In low conflict situations, the chilling effect associated with the compatibility factor seems to over-compensate for the positive effect of this factor on the probability to reach an agreement: the settlement rate decreases from 76.5% (when $\delta = 0$) to 69.25% (when $\delta = 30\%$). In higher conflict situations, the chilling effect is reduced since the threat that a disagreement occurs is more credible. This implies that automated negotiation in this case slightly promotes agreements, as suggested by the increase in the settlement rate from 54.25% (when $\delta = 0$) to 57.75% (when $\delta = 30\%$).

The robustness of those observations is checked using a Probit regression. The ability to reach an agreement is specified as a latent variable, denoted $y^*_{nt}$, and linked to the observed settlement, $y_{nt}$, through:

$$y_{nt} = \begin{cases} 1 & \text{if } y^*_{nt} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

The latent variable is assumed linear in the observables: $y^*_{nt} = X_{nt}\beta + \varepsilon_{nt}$ , where $X_{nt}$ includes the same variables as before, namely: the levels of the compatibility factor and the conflict situation as well as their interaction (dummies), the private values of both the plaintiff and the defendant. The panel dimension is accounted for by estimating a random effects model, in which the error term is decomposed into and individual specific term, a time-specific term and an i.i.d. variable: $\varepsilon_{nt} = u_n + v_t + w_{nt}$.

As is well known (*e.g.* Greene 2003, p. 667), the marginal effects of explanatory variables differ from the estimated coefficients in Probit models. Calculated marginal

Table 5: Determinants of conflict resolution

| | Estimation results | | Marginal effects | |
|---|---|---|---|---|
| | Coef. | (St. Dev.) | Coef. | (St. Dev.) |
| Constant | -1.67*** | (0.118) | -0.56*** | (0.048) |
| Compatibility factor | -0.14 | (0.099) | -0.05 | (0.033) |
| High conflict situation | 0.07 | (0.087) | 0.02 | (0.029) |
| Interaction | 0.31*** | (0.113) | 0.10*** | (0.037) |
| $v_P$ | -3.57*** | (0.120) | -1.19*** | (0.056) |
| $v_D$ | 5.32*** | (0.135) | 1.78*** | (0.072) |
| $\rho$ | 0.06*** | (0.018) | | |
| Log-likelihood | -1207 | | | |
| Chi-squared | 22.73 | | | |
| % of predicted observations | 83.66% | | | |

**Legend.** Significance levels: * 10%, ** 5%, *** 1%.

**Note.** Probit regression. The dependent variable is a dummy, set equal to one when the defendant/plaintiff pair has reached an agreement. The *Compatibility factor* is treated as a Dummy variable, set equal to 1 if $\delta = 0.3$ ; The *High conflict situation* is included as dummy variable ; The *Interaction* variable is set equal to one when $\delta = 0.3$ under an high conflict situation, 0 otherwise; The reservation values of the plaintiff ($v_P$) and defendant ($v_D$) are included in thousands. 3200 observations are used.

effects are thus provided jointly with estimation results in Table 5. First, remember that the higher the value placed on the damage by the plaintiff (defendant), the higher the amount he demands (offers). One should therefore expect an agreement to be less and less likely as the private value of defendants is decreased and/or the private value of plaintiffs is increased. This rather intuitive pattern is supported by our data, since the coefficients on private values are both significant with the expected sign. Both marginal effects are moreover close in absolute value, suggesting a symmetric impact of private values on the likelihood of reaching an agreement.

Regarding the way the settlement rule influences conflict resolution, the estimation results corroborate the above observations. We summarize them as our last result.

**Result 4** *The compatibility factor does not significantly affect the likelihood of a settlement. In higher conflict situation, the compatibility factor increases the likelihood of a settlement.*

The first part of Result 4 is consistent with Hypothesis 2: despite its purpose, the compatibility factor does not improve the efficiency of the settlement zone. As stressed before, the reason is the strategic reply of parties to the settlement rule overcomes the apparent improvement in the conflict resolution for given offers. Due to a lower chilling effect, an high conflict situation however improves the ability of the compatibility factor to promote conflict resolution.

## 5 Conclusion

In this paper, we analyze the theoretical properties of the automated negotiation procedure and derive equilibrium strategies for the plaintiff and the defendant. The empirical properties of this innovative bargaining mechanism are also tested by performing a set of experiments. In particular, we consider the factors that appear to determine whether a subject places bids that are close to, or exaggerated from, his reservation value. Following the experimental results, we can state that the value of the compatibility factor and the extent of the conflict are such factors: the compatibility factor creates a chilling effect insofar as the settlement rule deliberately splits the difference between the disputants' proposals and give them incentives to adopt aggressive bargaining positions, while this effect is reduced when the extent of the conflict is higher.

The intuition behind these results is consistent with a basic finding of studies on arbitration which show that arbitration procedures, by lowering the overall cost of disagreement, increases the incidence of disagreement: bargaining with arbitration lessens the likelihood that bargainers will reach a settlement on their own (Currie and McConnell 1991, Ashenfelter *et al.* 1992, Dickinson 2004). In other words, despite the significant evidence that arbitrators do not simply split the difference (Bloom 1986, Farber and Bazerman 1986), there does appear to be empirical evidence of a chilling effect to arbitration.[19] Another source of evidence is the *narcotic effect* of arbitration: going to arbitration engenders "dependence" on the procedure (Currie 1989, Bolton and Katok 1998, 2004). More precisely, a dispute decreases the probability a dispute will happen in subsequent rounds, however this learning effect with arbitration tends to be lower than it is without.

Furthermore, our experimental results raise the crucial question of how to enforce agreements reached *via* automated negotiation and give some elements of thinking about the potential role of public regulation and reputation mechanisms in Cyberspace. Indeed, such automated negotiation systems are offered by private companies on the electronic justice market and are, by definition, contractual. Therefore, the problem is to know how a private electronic constraint can ensure that the disputants will enter in this type of procedure *ex ante* and will accept not to renegotiate the settlement *ex post* (given that nothing other than public justice can force an agent to settle a conflict and/or execute a

[19] Theoretically, Farber (1981) shows that what appears to be splitting the difference may actually be disputants strategically bracketing their final offers around the expected arbitration award.

settlement decision).

In this context, we could argue that the reputation mechanisms existing on the Internet would be a powerful way to enforce such contracts. As mentioned in the Introduction, many of the online market sites (*e.g.* eBay, Amazon) offer reputation management systems that allow the trading parties to submit a rating of the counterpart's performance. Therefore, we could conjecture that if one of the disputants does not respect the settlement stated by the automated algorithm, then a *naming and shaming* strategy would occur and allow to enforce it. Furthermore, the question concerning the acceptance (or not) of the settlement by the parties arises obviously only if the latter managed to reach an agreement during the automated negotiation process. In other words, what happens if no agreement is reached at the end of the negotiation? This question is not trivial given the poor economic performance of the mechanism and we could think intuitively that the parties will recourse to an alternative dispute resolution system, such as arbitration or mediation (which are also available online).

In summary, this paper may be considered as a first step in the empirical investigation of online dispute resolution. Indeed, following the above arguments, it is obvious that further experiments will have to be done before a clear picture of how the type of mechanisms studied here perform well. Such experiments would take into account, for example, the impact of reputation and the role of alternative dispute resolution mechanisms. In this context, we feel confident that the types of question raised by our experiment will be central to the final unraveling of the puzzles presented by the computer-aided bargaining systems available in the online environment.

## Appendix: Proof of Lemma 1

Considering linear strategies, we assume that the defendant's strategy is $b_D(v_D) = a_D + c_D v_D$ and the plaintiff's one is $b_P(v_P) = a_P + c_P v_P$. Then $b_D$ is uniformly distributed on $[a_D + c_D \underline{v}_D, a_D + c_D \overline{v}_D]$ and $b_P$ is uniformly distributed on $[a_P + c_P \underline{v}_P, a_P + c_P \overline{v}_P]$. Following Table 1, the maximization problem (1) for the defendant and plaintiff respectively becomes

$$\max_{b_D} \left( v_D - \frac{b_D + a_P + c_P \underline{v}_P}{2} \right) \frac{b_D - a_P - c_P \underline{v}_P}{c_P \left( \overline{v}_P - \underline{v}_P \right)} + \left( v_D - \frac{b_D \left( 4 + \delta \right)}{4} \right) \frac{\delta b_D}{c_P \left( \overline{v}_P - \underline{v}_P \right)}$$

$$\max_{b_P} \left( b_P - v_P \right) \frac{a_D + c_D \overline{v}_D - b_P}{c_D \left( \overline{v}_D - \underline{v}_D \right)} + \left( \frac{b_P \left( 4 + 3\delta \right)}{4 \left( 1 + \delta \right)} - v_P \right) \frac{\delta b_P}{c_D \left( \overline{v}_D - \underline{v}_D \right) \left( 1 + \delta \right)}$$

The first-order conditions for which yield

$$b_D = \frac{2(1+\delta)}{\delta^2+4\delta+2} v_D, \text{ and } b_P = \frac{2(1+\delta)}{(2+\delta)^2} v_P + \frac{2(1+\delta)^2}{(2+\delta)^2} (a_D + c_D \overline{v}_D) \tag{5}$$

Given the linear strategies $b_D(v_D) = a_D + c_D v_D$ and $b_P(v_P) = a_P + c_P v_P$, by manipulating (5), the linear equilibrium strategies are

$$b_D^*(v_D, \delta) = \frac{2(1+\delta)}{\delta^2+4\delta+2} v_D, \text{ and } b_P^*(v_P, \delta) = \frac{2(1+\delta)}{(2+\delta)^2} v_P + \frac{4(1+\delta)^3}{(2+\delta)^2(\delta^2+4\delta+2)} \overline{v}_D$$

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# Attitude towards Risk and Production Decision : An Empirical analysis on French private forest owners

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**Abstract**

This paper deals with the forest owner's attitude towards risk and the harvesting decision in several ways. First, we propose to characterize and quantify the forest owner's attitude towards risk. Second, we analyze the determinants of the forest owner's risk attitude. Finally, we determine the impact of the forest owner's risk attitude on the harvesting decision. The French forest owner's risk attitude is tackled by implementing a questionnaire, including a context-free measure borrowed from experimental economics. The determinants of the forest owner's risk attitude and harvesting decision are estimated through a recursive bivariate ordered probit model. We show that French forest owners are characterized by a relative risk aversion coefficient close to 1 with a DARA assumption. In addition, we find that the forest owner's risk aversion is influenced positively and significantly by the level of risk exposure, the geographical location of the forest and the fact to be a forester, and negatively by the income. Finally, we obtain that the forest owner's risk aversion has a positive and significant impact on the harvesting decision.

***Keywords:*** Forest owner's risk attitude; Risk aversion; Harvesting decision; Simultaneous Equation Models; Experimental elicitation.

***JEL classification:*** D81, C35, Q23

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# 1 Introduction

Forest management is exposed to several risks. These risks may be categorized as production risk or market risk. Market risk is due to potential variations of the discount rate and timber prices. Indeed, forest management is a long-term investment such that the discount rate and the price may fluctuate during the rotation.[1] Production risk is essentially due to natural events. In Europe, windstorms Lothar and Martin in 1999 damaged 140 million cubic meters in France and 30 million in Germany. Wildfires on summer 2003 burnt 500,000 hectares in Portugal, 150,000 in Spain and 95,000 in France. More generally, in Europe, natural hazards damage each year an average of 35 million $m^3$ of wood (1950-2000). Storms are responsible for 53% of these damages, fires for 16% and biotic factors for 16% respectively (Schelhaas et al., 2003). Climate change will have a serious impact on these disturbances. The occurrence of harmful disasters such as drought, flooding, wind and fire is assumed to increase (Fuhrer et al., 2006). Populations of pests such as bark beetles and the frequency of the outbreak of tree diseases will be enhanced (Williams and Liebhold, 1995). Natural disasters represent then a major treat for forest owners.

These natural events may represent important losses both for forest owners and for the economy. Indeed, forest owners may suffer loss in present and future value, additional costs of forest restoration, loss of other income and loss of regular income (Birot and Gollier, 2001). Other losses may include loss of carbon sequestration (Thürig et al., 2005) and amenities. In such a context, the forest owners take risky decisions as regard to management, harvesting, adaptation, coverage, etc. Consequently, the knowledge of the forest owner's risk preferences seems to be essential to implement forest risk management measure, to set up relevant adaptation strategy to cope with climate change, and also for public policy issue. Indeed, the forest owners' decisions vary in function of their attitude towards risk. For example, we can imagine that those who are risk averse should be more inclined to insure their forest against natural events, or to reduce the degree of exposure of their stand by reducing rotation length. In the same vein, those who express a risk loving behavior should be more favorable to riskier management strategies in exchange of higher financial return. Then, several questions arise: what are the forest owner's risk preferences? What are the determinants of these risk preferences? And finally, what is the impact of these risk preferences on harvesting? In this paper we try to answer these questions.

Investigating the forest owner's risk preferences leads to few papers. Some of them focused on preferences towards risk of Swedish forest owners (Andersson, 2012; Andersson and Gong, 2010; Lönnstedt and Svensson, 2000). They used questionnaires to ellicit these preferences. Andersson and Gong (2010) find that a majority of private forest owners are risk-neutral or risk-prone while Lönnstedt and Svensson (2000) proved that preferences depend on the amount at stakes. Some papers provide a measurement of these preferences towards risk. In Andersson (2012), an index of private forest owners' attitudes towards risk is derived from a hypothetical survey question involving financial risk, which is the owner's willingness-to-pay for reduction of the risk measured in terms of the variance of the outcome. In Musshof and Maart-Noelck (2014), the risk attitude of decision makers from forestry organizations is inferred from a Holt and Laury's lottery (Holt and Laury (2002)). Musshof and Maart-Noelck (2014) show that participants are mostly risk averse (average number of safe choices of 5.87 among ten choices); they also show that risk aversion has a negative impact on the timing in sales decisions. Sauter et al. (2016) also derive the measurement of risk preferences on a Holt and Laury's task. The sample is composed with 107 participants (foresters from private forest companies, public forest agencies and forest service providers). The estimate of risk aversion is then used in a more generalized analysis of the compliance between risky harvesting decisions and economic theories about the decision of when to harvest a stand. The authors obtained an average number of 11.69 safe choices among twenty choices, suggesting a low degree of risk aversion. Regarding the determinants of forest owner's risk preferences, to our

[1]Due to the lack of data on market risk, we rather focus in this paper on production risk.

knowledge, only one paper deals with this question. Andersson (2012) analyzes the private forest owners' attitudes to financial risk-taking in forestry decisions. He shows that a longer period of ownership increases the probability that the owner is risk-averse, while an increased time spent in the forest conducting silvicultural work increases the likelihood that an owner is risk-seeking.

This literature highlights some important features. First, few papers try to quantify the forest owner's risk preferences and none of them provide an econometric estimation of the risk aversion coefficient of private forest owners. Second, even if the impact of risk preferences on the timing in sales and harvesting is analyzed, the impact of risk aversion on the probability to harvest is not evaluated. Finally, the determinants of the forest owner's risk attitude are only partially investigated, forgetting some important characteristics such as the forest owner's income.

Many theoretical papers also study the impact of owner's risk aversion on various type of decisions implying risk like rotation length (Alvarez and Koskela, 2006; Clarke and Reed, 1989; Gong and Löfgren, 2003; Uusivuori, 2002), forest investments (Kangas (1994)) and decision to replant or not after a clear cutting (Lien et al. (2007b)). In a general way, they derive a relationship between risk aversion and the decision they focused on. In addition, the impact of risk aversion on harvesting has also been studied by (Brunette et al., 2015a; Koskela, 1989). These papers find that, as risk aversion increases, the probability to harvest reduces. However, to our knowledge, no empirical test of this theoretical result exists.

Finally, several papers investigate the determinants of private forest owners' harvesting decisions. For instance, Conway et al. (2003) focus on the role of non-timber activities, bequest motives and debt. They find that debt is a strong motivator for harvesting, that non-timber amenities are substitute to harvesting and that bequest motives decrease the probability of harvesting. Størdal et al. (2008) study the impact of personal socio-economic characteristics, mainly the level of forest income and non-forest income of owners on harvesting. More precisely they find that forest management plans, property size, forested area, income from agriculture, income from engagement in other outfield-related productions and debt burden increase the propensity to harvest while wage income decreases the propensity to harvest. Garcia et al. (2014) focus on social interactions and show that the behavior of private forest owners varies with the behavior of the group to which they belong. This effect is the result of mimicking mechanisms or social conditioning. Forest owners from the same region, therefore, tend to have the same production behavior. However, to our knowledge none of these studies consider the forest owner's risk attitude as a potential explanatory variable for harvesting decision.

In the present paper, we propose i) to characterize the forest owner's attitude towards risk; ii) to analyze the determinants of the forest owner's risk attitude; and iii) to determine the impact of the forest owner's risk attitude (and other exogenous variables as well) on the probability of harvesting. For this purpose, we assess the French forest owner's risk attitude by means of a questionnaire, using a context-free measure borrowed from experimental economics (Eckel and Grossman, 2008). The determinants of the forest owner's risk attitude and harvesting decision are estimated through a recursive bivariate ordered probit model. We show that French forest owners are characterized by a relative risk aversion coefficient equals to 1.0025 when we use a power utility function (implying DARA and CRRA). It is the first time that such a risk aversion parameter is estimated for private forest owners. In addition, we find that the forest owner's risk aversion is influenced positively and significantly by the level of risk exposure, geographical location of the forest, and the fact to be a forester, while the income has a negative effect. Finally, we obtain that the forest owner's risk aversion has a positive and significant impact on the harvesting decision. More generally, we propose a methodology combining stated preference data on risk attitude with revealed preference data on harvesting decision, that may be applied to other research questions and other production decisions.

The rest of the paper is structured as follows. Section 2 gives some contextual information about the forest owners and harvesting decision in France. Section 3 presents the methodology we use.

Section 4 describes the data. Section 5 presents the estimation strategy. Section 6 presents the results, and Section 7 and 8 discuss these results and conclude.

## 2 Forest owners and harvesting decision in France

In France the forest occupies a third of the territory, which represents about 16.7 million hectares. The timber stock is estimated at 2.6 billion $m^3$ according to IGN (2012). About 75% of the total forest area is private, which amounts to 12.5 million hectares. There are about 3.5 million of private forest owners in France, and 1.1 million of them own at least one hectare of forest. A survey, conducted in France on the structure of the private forest ownership in 2012 (Agreste (2014)), reveals disparities in terms of forest area distribution between regions. Then, it is in Aquitaine region that the private forest area is the larger (with around 20% of the French private forest area) and in Nord-pas-de-Calais and Alsace that it is the lower, with Bourgogne at the 5th position, Provence-Alpes-Côte-d'Azur (PACA) at the 6th, Auvergne at 9th, Pays-de-la-Loire at 12th and Lorraine at 13th. Agreste (2014) also indicates that the private forest area is very fragmented in France. The average area of the property of one hectare or more is estimated at 8.5 hectares. Properties between 1 and 4 hectares represent 62% of the total number of properties of one hectare or more, but they only cover 15% of the total forest area. In addition, properties of more than 25 hectares represent only 5% of the properties but cover more than 50 % of the total area of private forests. This survey also indicates that 1/4 of the French private forest area, of one hectare or more, has a certification of sustainable management. The aims of forest owners in acquiring the forest are mainly the constitution of a natural asset (35%) and timber production (34%). The preservation of biodiversity and the establishment of a hunting territory concern 11% of owners. This result is in accordance with several studies indicating that the French private forest owners are non-industrial private forest owners, in the sense that they value not only the income from the production of timber but also non-timber amenities of their forest (Garcia et al. (2014); Petucco et al. (2015)). According to Agreste (2014) about half of the private owners harvests wood from their property for an average estimated volume of 28 million $m^3$ per year of which 23.2 million $m^3$ are sold and 5.2 million are for self-consumption. This average harvesting is computed as an average annual volume over the past five years. A five-year period is then used to analyze harvesting decisions of forest owners in the present study but also in the literature (Conway et al. (2003); Garcia et al. (2014)).

## 3 Methodology

Methods for valuating risk preferences belong to two main categories, revealed preferences and stated preferences methods. Revealed preferences methods rely on observed individual behavior; they have been largely used to quantify risk preferences (see for example Bontems and Thomas (2000) for a study on farmers' risk attitude).

Unfortunately, our survey data based on observed harvesting decision do not allow us to construct a direct measure of risk aversion. Due to the lack of additional information on observed risky behavior we cannot empirically identify the link between risk aversion and harvesting decision in a structural model. In addition, elicitation of risk attitude through revealed preferences data have sometimes been criticized in the literature, in particular because it confuses behavior toward risk with other factors such as resource constraints faced by decision makers (Eswaran and Kotwal (1990)). It may also appear that individuals are more risk-averse than they truly are (Binswanger (1982)). These facts support our chosen methodology that relies on the elicitation of risk aversion by the mean of a stated preferences approach coming from experimental economics. Then, we combine these experimental data with our survey data to estimate the effect of risk aversion on harvesting in a reduced-form model.

The experimental data are generated from lottery choices as in Musshof and Maart-Noelck (2014) and Sauter et al. (2016). Five procedures range in this category: Multiple Price List, Random Lottery Pairs, Becker-DeGroot-Marschak auction, Trade-Off design and Ordered Lottery Selection (Cox and Harrison, 2008). Previous studies (Musshof and Maart-Noelck, 2014; Sauter et al., 2016) favored the Multiple Price List approach proposed by Holt and Laury (2002). However, we retained the Ordered Lottery Selection (OLS) method originally developed in Binswanger (1978), popularized by Eckel and Grossman (2008) and extended by Reynaud and Couture (2012). Three major reasons explained this choice. First, and probably the most important one for us, the measurement of risk attitude bears only on one lottery choice while the other procedures imply up to twenty lottery choices (as in Sauter et al. (2016)). Furthermore, this lottery task is only a brief part of a longer survey, so that we think that a shorter elicitation procedure makes the forest owner's answers more likely. Second, the procedure of Eckel and Grossman (2008) has already been used to elicit the risk attitude of a population of other managers of natural resources (Reynaud and Couture, 2012), namely farmers facing similar natural risks. The third reason why OLS is fine is that we use expected utility theory. In OLS probabilities are always 1/2 and do not allow the use of alternatives to expected utility theory involving probability distortion.

In the literature, such a context-free method may also be criticized especially because attitude towards risk may be context dependent. For example, Hershey and Schoemaker (1990) observe a strong context effect in which insurance choices presented in an insurance context are judged with greater risk aversion than mathematically identical choices presented as standard gambles. Another critic may be about the potential uncertainty aversion generated by the first gamble of the procedure of Eckel and Grossman (2008). However, Reynaud and Couture (2012) rule out such an hypothesis. Nevertheless, a context-free measure allows characterizing individual's risk attitude in general and is not linked to a particular framework.

Our approach combining data about forest owner's elicitation of risk preferences (in a stated preferences approach) and revealed preferences data on forest property and harvesting decision has been already used in the past. For instance, Azevedo et al. (2003) study the demand for recreation in Iowa wetlands. In the field of consumers' decisions, Guiso and Paiella (2006) use household survey data to construct a direct measure of absolute risk aversion based on the maximum price a consumer is willing to pay to buy a risky asset in an experiment. Then, they relate this measure to a set of observed individual choices that in theory should vary with attitude towards risk. This methodology can be fruitfully reproduced to empirically analyze the role of individual's risk attitude on any type of production or individual decision.

# 4 Data

This paper combines stated and revealed preferences data. The stated preferences data are used to estimate forest owner preferences towards risk while the revealed preferences data provide potential determinants to explain owner's risk preferences and probability of harvesting.

## 4.1 The stated preferences data

As indicated previously, we implemented an OLS procedure. In this procedure, the subject must choose one gamble that s/he accepts to participate in among five possible ones. This choice allows to infer risk aversion and risk neutrality but not risk-prone behavior. Then, Reynaud and Couture (2012) extend the procedure of Eckel and Grossman (2008) to risk-prone attitudes. The subject must now choose the gamble she/he accepts out of nine options. We assume that individuals have a power utility function, which in turn implies Decreasing Absolute Risk Aversion (DARA), a standard assumption in the literature (Gollier, 2001). Table 1 presents the procedure of Reynaud and Couture (2012).

Table 1: Procedure of Reynaud and Couture (2012)

| Choice 50/50 gamble | Payoff 1 | Payoff 2 | Coef. of RRA ranges | Coef. of RRA code |
|---|---|---|---|---|
| Gamble 1 | 40 | 40 | $r > 1.37$ | RA5 |
| Gamble 2 | 32 | 51 | $0.68 < r < 1.37$ | RA4 |
| Gamble 3 | 24 | 64 | $0.44 < r < 0.68$ | RA3 |
| Gamble 4 | 16 | 78 | $0.4 < r < 0.44$ | RA2 |
| Gamble 5 | 12 | 86 | $0.15 < r < 0.4$ | RA1 |
| Gamble 6 | 8 | 91.5 | $-0.13 < r < 0.15$ | RN |
| Gamble 7 | 6 | 92.9 | $-0.47 < r < -0.13$ | RP1 |
| Gamble 8 | 4 | 93.4 | $-0.93 < r < -0.47$ | RP2 |
| Gamble 9 | 1 | 93.5 | $r < -0.93$ | RP3 |

This table presents the nine gambles available to our sample of private forest owners. Each gamble provides payoff 1 and 2 with an equal probability of 50%. Then, the choice of gamble 1 ensures a gain of 40 euros, corresponding to a coefficient of Relative Risk Aversion (RRA) of $r > 1.37$, *i.e.*, extreme risk-aversion (RA5). Risk Neutrality (RN) appears with the choice of gamble 6, while the choice of gambles 7, 8 or 9 characterizes Risk-Prone (RP) behaviors from RP1, low risk-prone attitude, to RP3, high risk-prone attitude. The procedure here is not incentivized, *i.e.*, gains are purely hypothetical. Several reasons explain this choice. First, traditionally in experimental economics, financial outcome comes from a random selection of one or several decisions taken during the experiment. However, in Eckel and Grossman (2008) task, as we used, the individual has only one choice to realize, so that potential financial outcome will depend on this only choice, and we find this option not relevant. Second, a lump-sum payment may also be an option. However, based on our experiences with forest owners, we anticipated that they might not like a lump-sum payment option. Brunette et al. (2009) and Brunette et al. (2013) conducted another experiment with forest owners. They explicitly stated that receiving money from us for taking part in the experiment would suggest that they were not interested in the experiment *per se* but only in the financial incentive. Third, some papers conclude to the absence of difference in terms of decisions between lottery choices using hypothetical or real payoffs (Battalio et al. (1990); Wik et al. (2004)). Finally, the fact that the procedure that we used needs only one lottery choice, and the fact that the literature indicates that as soon as the decision that individual has to take is simple lottery task; incentives have no impact on the decision (Beattie and Loomes (1997)), encourage us to not consider incentive mechanism.

## 4.2 The revealed preferences data

The data come from a survey implemented in 2010 to analyze the capacity of wood mobilization in France, in the context of the European project Newforex. The database is detailed in Darses et al. (2012) and in Abildtrup et al. (2012). The questionnaire was sent to French private forest owners in five regions with different challenges and forest dynamics: Bourgogne, Pays-de-la-Loire, Auvergne, Lorraine, and Provence-Alpes-Côte-d'Azur. Indeed, they have different rates of forest cover (more than 45% in Lorraine compared to less than 15% in Pays-de-la-Loire) and different proportions of private forest (more than 50% public forests in Lorraine compared to less than 20% in Pays-de-la-Loire, Auvergne, and Bourgogne). In France, the size of properties may be very different (more than 2 million properties are less than 1 ha and nearly 10,000 properties are over 100 ha), so we stratified the sample by size class in each region. We then randomly selected owners from each stratum. The sample was drawn from the database of the association of French private forest owners. The questionnaire was sent by mail to 15,000 private forest owners and 590 questionnaires were completed, corresponding to a response rate of approximately 3.5%. Among these 590 questionnaires, 324 were usable for our study. The questionnaire was composed of three different parts: 1) forest property; 2) wood production; and 3) forest owners.

We analyze the representativeness of our sample by comparing some descriptive statistics with those obtained by the survey recently conducted on French private forest owners (Agreste, 2014). First, the average forest area is 65.93 hectares in our sample while in Agreste (2014) the average area among the French private forest owners of one hectare or more is 8.5 ha. Large forest owners are clearly over-represented. This can be explained by the fact that large forest owners interested in forest management are more willing to participate on a voluntary basis. Second, the average age in the sample is 63.86 years, which is comparable with Agreste (2014), which indicates that French private forest owners are on average 64 years old. Third, our sample is composed with 16% of women and 84% of men. In Agreste (2014), these percentages are 30% and 70% respectively. Consequently, the proportion of women is underestimated in our sample. To reduce the over-representation of large forest properties we assign a different weight to each observation, which is the ratio of the total number of properties in the region of the forest owner over the number of properties in the database in the same region.[2] Considering only the forest properties of more than one hectare, the average area of forest properties after weighting is 8.23 ha, which is close to 8.5 ha in Agreste (2014). The average age of forest owners is 65.23 years. The percentage of women is 20%, which remains a bit lower than the one observed in Agreste (2014). Table 2 displays descriptive statistics for both the initial unweighted sample and a weighted one. We detail the descriptive statistics results for the "Without weighting" column.

**Forest property.** The average forest area in the database is 65 hectares. Note that 15% of the owners delegate the management of the forest property to a professional. We can observe that 38% of the properties is crossed by a paved road. Table 2 also reveals that 18% of the forest properties are located in the region Lorraine, 17% in Auvergne, 14% in Provence-Alpes-Côte-d'Azur ($PACA$), 28% in Pays-de-la-Loire ($PDL$) and 21% in Bourgogne. Finally, the variable $EXPO\_RISK$ represents the number of potential risks (nuclear, industrial, technological, earthquake, transport of dangerous goods, landslide, etc.) faced by inhabitants of the department. It is a proxy of the forest owner's level of exposure to risk. This variable was generated from the GASPAR[3] database (assisted management of administrative procedures relating to natural and technological risks) of the French Ministry of Ecology and Sustainable Development. This means that, on average, in the private forest owner's environment, 522.46 potential hazards are listed. Finally, we can also observe that 33% of the forests of our sample are certified. Indeed, they have the PEFC (Program for the Endorsement of Forest Certification schemes) or FSC (Forest Stewardship Council) environmental label.

[2] The total number of properties in a given region is available in Darses et al. (2012) and in Abildtrup et al. (2012).

[3] Gestion ASsistée des Procédures Administratives relatives aux Risques naturels et technologiques: http://macommune.prim.net/gaspar/

Table 2: Definition of variables and descriptive statistics

| | | Without weighting | | With weighting | |
|---|---|---|---|---|---|
| **Variable** | **Definition** | **Mean** | **Std. Err.** | **Mean** | **Std. Err.** |
| ***Forest property*** | | . | . | . | . |
| AREA | Forest area of the property (in ha) | 65.93 | 140.93 | 8.23 | 19.37 |
| DELEGATION | Binary variable = 1 if the owner delegates the management of her/his property to a professional (expert) | 0.15 | 0.36 | 0.02 | 0.16 |
| PAVED_ROAD | Binary variable = 1 if the property is crossed by a paved road | 0.38 | 0.48 | 0.22 | 0.41 |
| AUVERGNE | Binary variable = 1 if the forest is in the administrative region Auvergne | 0.17 | 0.38 | 0.22 | 0.41 |
| BOURGOGNE | Binary variable = 1 if the forest is in the administrative region Bourgogne | 0.21 | 0.41 | 0.13 | 0.33 |
| LORRAINE | Binary variable = 1 if the forest is in the administrative region Lorraine | 0.18 | 0.38 | 0.34 | 0.47 |
| PACA | Binary variable = 1 if the forest is in the administrative region Provence-Alpes-Côte-d'Azur | 0.14 | 0.35 | 0.18 | 0.38 |
| PDL | Binary variable = 1 if the forest is in the administrative region Pays de la Loire | 0.28 | 0.45 | 0.11 | 0.32 |
| EXPO_RISK | level of exposure to risk (natural and technological) | 522.46 | 153.11 | 524.92 | 193.22 |
| CERT | Binary variable = 1 if the timber is certified (PEFC or FSC) | 0.33 | 0.47 | 0.04 | 0.21 |
| ***Wood production*** | | . | . | . | . |
| HARVEST | Binary variable = 1 if timber was harvested over the past five years | 0.61 | 0.48 | 0.27 | 0.44 |
| PRICE | Average regional price (in €) of ONF | 55.28 | 6.54 | 54.59 | 6.09 |
| LEISURE | Binary variable = 1 if the owner or members of her/his family have leisure activities in the forest | 0.22 | 0.42 | 0.11 | 0.31 |
| ***Forest owners*** | | . | . | . | . |
| FORESTER | Binary variable = 1 if the owner is a forester | 0.02 | 0.14 | 0.02 | 0.16 |
| GENDER | Binary variable = 1 if owner is a woman | 0.16 | 0.37 | 0.20 | 0.40 |
| AGE | Age (years) | 63.86 | 12.11 | 65.23 | 10.83 |
| EDUC | Binary variable = 1 if the owner has a level of education equivalent or superior to Master's degree | 0.14 | 0.35 | 0.27 | 0.44 |
| FOREST-INCOME | Percentage of forest income | 4.15 | 12.11 | 0.94 | 2.56 |
| INCOME_CSP | The average income by socio-professional categories (in thousands of €) | 28.87 | 9.17 | 27.47 | 7.39 |
| INCOME_RANGE | The income range excluding forest income (in thousands of €) | 48.38 | 29.94 | 45.49 | 30.08 |

All the data come from the survey conducted as part of the Newforex Project except the variable PRICE, provided by ONF, that is measured at regional level.

**Wood production.** The key variable $HARVEST$ takes the value 1 if the owner has harvested timber over the past five years and 0 otherwise. We think that a five-year period is long enough to capture any cause of harvesting timber. A shorter period could prevent us to observe harvesting that could have been postponed in the near future because owners expect a price increase in the short run. Conway et al. (2003) and Garcia et al. (2014) use the same period length. We observe that 61% of the 324 French private forest owners harvested timber over the past five years. In addition, the average regional timber price is 55.28€. This corresponds to the average selling price of wood (roadside) by region of the "Office National des Forêts" (National Forest Office). Moreover, 22% of the forest owners in our sample report that they have leisure activities in their forests (variable $LEISURE$), indicating that amenities are clearly associated with forest management by these owners.

**Forest owners.** The socio-demographic variables reveal that our database is composed of a majority of non-foresters, who are men, with an average age of 64 years, and 14% have a higher level of education than or equal to a Master's degree. We can also observe that forest income represents on average 4.15% in the forest owners' total wealth ($FOREST\_INCOME$). In our survey, we asked respondents their income range.[4] Taking the center of each class, the average revenue of the owners is €48,382 ($INCOME\_RANGE$). The variable $INCOME\_SPC$ is the average annual household income before taxes broken down by socio-professional categories (SPC) in France. It indicates that the average income by socio-professional category is €28,871. This variable comes from the French National Institute of Statistics (INSEE), and has ever been used in Garcia et al. (2014).

# 5 Estimation strategy

## 5.1 Econometric model

The harvesting decision is influenced by the forest owner's risk aversion (Alvarez and Koskela, 2006; Uusivuori, 2002) and the characteristics of the owner and her/his property (Garcia et al., 2014). First, we cannot exclude that risk aversion and the harvesting decision share common unobserved factors. Second, it is unlikely that the harvesting decision directly modifies risk aversion, since the latter is an intrinsic characteristic of the individual. Thus, we specify the following recursive bivariate ordered probit model:

$$\begin{aligned} y_{1i}^* &= X_{1i}^{'}\beta_1 + \epsilon_{1i} \\ y_{2i}^* &= X_{2i}^{'}\beta_2 + \gamma y_{1i}^* + \epsilon_{2i} \end{aligned} \tag{1}$$

where $y_{1i}^*$ stands for the relative risk aversion coefficient of individual $i$ and $y_{2i}^*$ is the latent variable underlying the harvesting decision $y_{2i}$ ($y_{2i} = 1$ if the owner has harvested timber and 0 otherwise). $X_1$ and $X_2$ correspond to the vectors of the explanatory variables of the relative risk aversion coefficient ($y_{1i}$) and the harvesting decision ($y_{2i}$), respectively. We also assume that $cov(\epsilon_{1i}, \epsilon_{2i}) = \rho$ and we define the empirical counterparts of the latent variables as:

$$y_{1i} = \begin{cases} 1 & \text{if} \quad y_{1i}^* < c_1 \\ 2 & \text{if} \quad c_1 \leq y_{1i}^* < c_2 \\ & \vdots \\ J & \text{if} \quad c_{J-1} \leq y_{1i}^* \end{cases} \tag{2}$$

[4]Under €6,000; from €6,000 to €12,000; from €12,000 to €18,000; from €18,000 to €25,000; from €25,000 to €35,000; from €35,000 to €50,000; from €50,000 to €100,000; and over €100,000.

and

$$y_{2i} = \begin{cases} 0 & \text{if} \quad y_{2i}^* < 0 \\ 1 & \text{if} \quad y_{2i}^* \geq 0 \end{cases} \tag{3}$$

with $c = [-0.93, -0.13, 0.15, 0.4, 0.44, 0.68, 1.37]$. Following Sajaia (2008), we show that the weighted log-likelihood function can be written as follows:

$$\ln\, L = \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{j=1}^{J} w_i I(y_{1i} = j, y_{2i} = k)\ \ln Pr(y_{1i} = j, y_{2i} = k) \tag{4}$$

where $w$ is the weighting vector as defined in Section 4.2. For more details on the construction of the likelihood function and weighting see Appendix A.[5] The cutoff, $c_j$, are known and will therefore not be estimated, so that the risk aversion part of the model is similar to an interval data model or generalized Tobit model (Greene and Hensher (2010), p. 133 and Cameron and Trivedi (2010), p. 548-550).[6]

## 5.2 Endogeneity issues

Two potential endogeneity issues must be addressed. First, the variable $y_{2i}$ (labeled in sections below as $RISK\_ATTITUDE$) may be endogenous in the system of equations (1). We make the assumption that the terms $\epsilon_{1i}$ and $\epsilon_{2i}$ are correlated. Indeed, common unobservable factors linked to individual tastes may both influence risk aversion and harvesting decision. This assumption allows us to take into account the potential endogeneity of risk aversion in the harvesting equation. We estimate the system of equations (1) by Full Information Maximum Likelihood with the usual exclusion restriction, *i.e.*, at least one element of $X_1$ should not be present in $X_2$, which is necessary for identification purpose (see for instance Section 18.3 in Davidson and MacKinnon (1993)). We exclude the variable $EXPO\_RISK$ from the harvesting decision equation. The variable $EXPO\_RISK$ thus plays the role of an instrument for $RISK\_ATTITUDE$ and represents the level of exposure to risk of forest owner. In order to construct this variable we do not consider risks that could potentially affect the decision to harvest (storm risk, forest fire, risk pathogen, etc.). By contrast, the risks considered in this variable (nuclear, industrial, technological, earthquake, transport of dangerous goods, etc.) have no direct impact on the harvesting decision but may negatively impact the forest owner's assets (financial, real estate, etc.). Indeed, if the risk exposure increases, then the wealth reduces and the risk aversion raises (due to the DARA assumption). As we have only one instrument for one endogenous variable, we cannot perform the test of over-identifying restrictions (test of validity of instruments). However, we believe that the variable $EXPO\_RISK$ is a good instrument for risk attitude for two reasons. First, in our estimation, presented in Table 4, the variable $EXPO\_RISK$ is significant at 1% and positive. This means that this variable is an explanatory factor of risk aversion: $Cov(RISK\_ATTITUDE, EXPO\_RISK) \neq 0$. Second, when we regress the residuals of the equation of timber harvesting our different specifications on the number of potential risks, the associated coefficient is not significantly different from zero: $Cov(EXPO\_RISK, \epsilon_{2i}) = 0$. Hence, our instrument satisfies the condition of exogeneity of instruments. We can reasonably consider that our instrument is valid. The second issue concerns individual income ($INCOME\_RANGE$). This variable is a natural candidate to explain both risk aversion and harvesting decision but it may also be correlated to unobservable factors included in error terms of the system of equations (1). Indeed, unobservable tastes certainly play a role in the determination of income, risk aversion and harvesting decision. One solution consists in adding one equation for income in the system (1) but

[5] The estimation is done using Matlab, the codes are available from the authors upon request.

[6] Regarding the measure of risk aversion, it is not possible to use the empirical counterpart of the latent variable in the harvesting equation. Indeed, it implies 8 parameters to estimate in the case of 9 classes of risk, which leads to an identification problem because of the lack of data.

this strategy is not parsimonious in regard of the additional parameters to estimate and the limited number of observations we have. Instead, we decide to replace income by its predicted counterpart obtained from an auxiliary model. Using an interval regression, we explain income classes by means of several variables, including the average income by socio-professional categories, the level of education, age, gender and percentage of forest income. The probability associated of Likelihood Ratio (LR) Chi-Square of this model is equal to 0, suggesting that we cannot reject the hypothesis that our explanatory variables have an impact on income. Using this estimation we calculate the mean predicted income for each forest owner (variable $INCOME\_PREDICT$ in the full model below). This method allows us to compute the expected income of forest owners who did not answer to this question[7]. We also use a bootstrap method to compute consistent standard errors for the full model whose results are described in Section 6. The estimation results of this auxiliary regression are shown in Table 3. According to our results, the average income per SPC, age and education are the main determinants of household income. The pseudo R-square is 0.37, which seems acceptable to use predicted income as explanatory variable in the bivariate model.

Table 3: Interval regression for Income class

| | Income class |
|---|---|
| INCOME_SPC | 1.185*** |
| | (0.325) |
| AGE | 502.8** |
| | (200.6) |
| FOREST-INCOME | -13.44 |
| | (160.1) |
| EDUC | 20105.5*** |
| | (4570.2) |
| GENDER | 5137.0 |
| | (5186.8) |
| Constant | -28329.6 |
| | (19795.5) |
| lnsigma | |
| Constant | 10.21*** |
| | (0.0572) |
| Observations | 308 |
| Log lik. | -577.8 |

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# 6 Results

Different specifications can be considered according to the number of classes of risk we define to characterize risk attitude or whether we use the weighted or the unweighted sample (see Section 4.2) at the estimation stage. Regarding the number of classes of risk, the elicitation procedure described in Table 1 implies 9 classes. We observe only three forest owners within the range $[-0.47, -0.13[$, of Risk Prone 1 (RP1) and two within the range $[-0.93, -0.47[$ of Risk Prone 2 (RP2). To cope with these very low frequencies, we aggregate these two classes into the last range ($r < -0.93$) of

[7]More precisely, 16 forest owners do not answer to the question on income, explaining the number of 308 observations in Table 3.

Risk Prone 3 (RP3). This new definition then implies 7 classes with ($r < -0.13$) defining the new last threshold for the aggregated Risk Prone (RP) group.[8] Thus, we can consider four different specifications: (1) unweighted sample and 9 classes of risk aversion; (2) unweighted sample and 7 classes; (3) weighted sample and 9 classes; (4) weighted sample and 7 classes. We display in Table 4 below the estimation results of specification (4).

Table 4: Estimation results with weighting and 7 classes of risk aversion

| | HARVESTING | | RISK | |
|---|---|---|---|---|
| Variable | Estimate | Std. Err. | Estimate | Std. Err. |
| RISK_ATTITUDE | 0.6781*** | 0.2248 | | |
| EXPO_RISK | | | 0.0047*** | 0.0005 |
| INCOME_PREDICT | 0.0506 | 0.2630 | -0.0066*** | 0.0010 |
| AREA | 0.0080 | 0.0054 | -0.0001 | 0.0006 |
| PRICE | 0.0425 | 0.0453 | 0.0055 | 0.0202 |
| GENDER | -1.1310** | 0.4991 | -0.0913 | 0.1735 |
| AGE | -0.0218* | 0.0124 | -0.0026 | 0.0058 |
| FORESTER | 0.5816 | 0.4686 | 0.5587*** | 0.2166 |
| LEISURE | 1.4892 | 1.3430 | 0.1495 | 0.1334 |
| DELEGATION | 3.6247*** | 0.7753 | -0.1930 | 0.2294 |
| EDUC | -1.3413 | 0.8833 | 0.2308 | 0.3720 |
| AUVERGNE | 1.5789*** | 0.3940 | -0.0383 | 0.1936 |
| BOURGOGNE | 0.6230 | 0.6390 | 0.4946* | 0.2873 |
| PACA | -0.0559 | 0.5779 | 0.4424* | 0.2370 |
| PDL | omitted because of collinearity | | | |
| CERT | 0.8277** | 0.3896 | -0.0301 | 0.1397 |
| PAVED_ROAD | 1.0081*** | 0.2928 | 0.0186 | 0.1195 |
| CONS | -5.1793* | 2.7880 | -1.4996 | 1.3559 |
| $\rho$ | | | -0.7907*** | 0.1305 |
| Log likelihood | -5.5927 | | | |
| Average of predicted value of risk | | | | |
| RISK_P | 1.0457 | | | |
| RISK_P_WEIGHT | 1.0025 | | | |

Standard errors in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
Standard errors take into account clustering due to regional effect.

We find that results of specifications (1) to (3) are consistent with those of specification (4), assessing the robustness of our model with respect to the representativeness of the sample and the low number of forest owners in some classes.[9] Indeed, the three main variables driving our analysis are significant and have the same sign whatever the specification. The variable *INCOME_PREDICT* has a significant and negative impact on the forest owner's risk aversion, *EXPO_RISK* has a significant and positive impact on the risk aversion, and *RISK_ATTITUDE* is positive and significant regarding its effect on harvesting. In addition, the predicted value of the risk aversion coefficient is close to 1 for all specifications. We then focus below on the results obtained from the weighted sample and the 7 classes of risk aversion.

## 6.1 Risk attitude

It appears that five variables seem to be determinant when dealing with the risk attitudes of private forest owners, four deal with characteristics of forest owners (*INCOME_PREDICT*, *FORESTER*, *BOURGOGNE*, *PACA*) and one with a characteristic of the forest property (*EXPO_RISK*). The variable *EXPO_RISK*, concerning the risks associated with the forest property, is positive and significant at the 1% level. This means that the higher the level

[8] The empirical distribution among the 7 classes of risk is the following: 43.2% for RA5, 19.1% for RA4, 10.5% for RA3, 5.9% for RA2, 4% for RA1, 8.7% for RN, 8.6% for RP.

[9] All the results are available from the authors upon request.

of risk exposure is, the higher the forest owner's risk aversion will be. The second variable, $INCOME\_PREDICT$, is negative and significant at 1%, meaning that the lower the predicted income is, the higher the risk aversion will be. This result is consistent with our initial DARA assumption and makes our reduced-form model compatible with the underlying structural model. Our estimation results also indicate that being a forester (variable $FORESTER$) has a significant (at 1%) and positive effect on the risk aversion. This is consistent with our expectations because these owners yield much more income from forest. Finally, the variable $BOURGOGNE$ and $PACA$ are positive and significant at 10%, meaning that the forest location seems to have an impact on the forest owner's risk aversion.

Using the estimated parameters of the equation of risk aversion, we can calculate the predicted value of the coefficient of relative risk aversion for each owner *i.e.*, $E\left(y_{1i}^{*}|X_{1i}, \beta_1 = \hat{\beta}_1\right) = X_{1i}\hat{\beta}_1$, and then we compute the weighted average over the sample which is equal to $\frac{1}{n}\sum_1^n w_i X_{1i}\hat{\beta}_1$. We obtain a value of 1.0025 (Std. Err. = 0.9578). To our knowledge, this is the first time that such a coefficient has been econometrically estimated for private forest owners. Until now, the value was often arbitrarily fixed and sensitivity analysis was performed (see, for example, Brunette et al. (2015a); Lobianco et al. (2015)). Such an estimation may be very useful for calibrating the model, taking into account forest owner's risk aversion. In addition, this estimation for French private forest owners is in accordance with Arrow (1970) who indicated in his seminal work that the coefficient of relative risk aversion should be approximately 1. However, our relative risk aversion coefficient of 1.0025 is higher than the estimation obtained on farmers for example[10]. Indeed, Galarza (2009) uses a Holt and Laury (2002) approach and find that the Peruvian farmers have an average coefficient of relative risk aversion of 0.45. On a sample of 30 French farmers, Bougherara et al. (2011) elicit risk preferences using the Holt and Laury (2002) approach, and find a coefficient of relative risk aversion of 0.89. This difference may be explained by the procedure itself. Indeed, Reynaud and Couture (2012) remark that the Eckel and Grossamn's procedure may generate higher values for the coefficient of RRA than the procedure of Holt and Laury (2002) (due to the difference in the number of categories of risk loving). However, using the same approach based on the Eckel and Grossman's procedure, Reynaud and Couture (2012) find a coefficient of 0.62 for the French farmers. It is also worth mentioning that one needs to be cautious when comparing coefficients when the utility function may differ. Our apparently high coefficient may be explained by the intrinsic nature of forest management. Indeed, forest management is a long-term process and the period betweeen the investment and the first financial return may be of several years/decades, so that the risk is perceived differently in agriculture and forestry. In agriculture, the occurrence of natural disasters is deeply detrimental from a financial point of view, but the farmer can start a new cycle the next year. The forest manager does not have this opportunity.

### 6.2 Harvesting decision

Concerning the harvesting decision, several variables seem to be determinant, some are about the characteristics of the forest owners ($RISK$, $GENDER$, $AGE$), while others are characteristics of the forest property ($DELEGATION$, $AUVERGNE$, $CERT$, $PAVED\_ROAD$). The variable $RISK\_ATTITUDE$ affects the harvesting decision positively and significantly. This means that the higher the risk aversion is, the higher the probability of harvesting will be. This result is of particular interest because it is the opposite of the theoretical result obtained in the literature (Brunette et al., 2015a; Koskela, 1989), *i.e.*, increases risk aversion reduces the probability to harvest. When the forest owner has a high risk aversion parameter, s/he has incentives to harvest in order to diminish future potential damage, *i.e.*, the risk-exposure effect of Couture and Reynaud (2008).

[10] Our coefficient is not directly comparable with the measures provided by Sauter et al. (2016) and Musshof and Maart-Noelck (2014) for foresters, *i.e.*, the average number of safe choices realized by the participants. Then, we compare our coefficient with the ones obtained for farmers.

The variables $GENDER$ and $AGE$ have a significant and negative impact on the probability of harvesting. This result suggests that female forest owners harvest less often than men. This result is similar to that obtained by Lidestav and Ekström (2000). According to these authors, this difference may be an expression of differences in social and cultural aspects related to gender, such as education and the division of labor in the family. In addition, this result indicates that older forest owners harvest less often then younger ones. Størdal et al. (2008) also found a similar result and suggested that younger owners may have larger debt or be facing large investments in the property, so that increased harvesting may give these owners better liquidity. Another argument is that increasing age is found to decrease the owners' technical efficiency in timber production (Lien et al., 2007a). Delegating the management of the forest (variable $DELEGATION$) to a professional has a positive and significant effect on the harvesting decision. The underlying idea of delegated forest management is to adopt best practices, allowing for better financial returns, such that the professional is encouraged to harvest more. This result is also obtained by Garcia et al. (2014) at the regional level. The variable $AUVERGNE$ is positive and significant at 1% meaning that the timber production of private forest owners is more dynamic in $AUVERGNE$ than in other regions. This result is not surprising given that Auvergne region is associated to a large forest area and a strong wood industry. The variable $CERT$ is positive and significant at 5%, meaning that a certified forest is more likely to be harvested. Indeed, certification is an indicator of sustainable and sound management of timber. The variable $PAVED\_ROAD$ is positive and significant at 1%. This result is obvious, since a paved road facilitates the access of the forest owner to the forest and then, the probability of harvesting. Surprisingly, the variable PRICE has a non-significant impact on the harvesting decision (with a positive coefficient). This result is similar to those obtained by Dennis (1990) concerning the absence of impact, and opposite to Hyberg and Holthausen (1989) who obtained a negative effect. According to these authors, this result could be the consequence of trade-offs made by the owners between forest income (income effect) and amenities (substitution effect). According to Provencher (1997), this result could also be explained by an expectation of rising prices, which pushes owners to postpone their harvests, despite relatively high prices.

# 7 Discussion

Our paper provides the determinants of harvesting decision and risk aversion, and the impact of risk aversion on this harvesting decision. In this way, our results have two main implications, in terms of timber harvesting and risk management decisions.

## 7.1 Implications for French timber harvesting

France has decided to increase harvesting by 21 million cubic meters until 2020. Although IGN (2012) proved this increase as feasible, the French private forest owners will have to provide the largest effort, as they own around 75% of the forest surface. Therefore, the decision-maker needs to know the relevant levers at their disposal in order to increase harvesting in France. Our study presents interesting results in this direction. Indeed, the analysis of the determinants of harvesting decisions reveals a positive effect of some variables, displaying several interesting levers for the decision-maker. Delegating forest management to a professional, the location of the forest in the Auvergne region, forest crossed by a paved-road and certified forest are all factors that increase the probability to harvest.

Consequently, various approaches may be prioritized by the decision-maker. First, the decision-maker may encourage timber certification through information campaign. Second, delegation of forest management should be encouraged in order to increase harvesting. A way of proceeding can be to encourage forest owner to join cooperatives or associations in order to decrease the cost of management by a professional. Third, observing the wood sector of Auvergne may be interesting to draw useful conclusions for the other regions. Finally, the paved-road is clearly a determinant of the harvesting choice and then, we can easily imagine that the government would help to build such infrastructure. In addition, in some fire prone region such road may also be useful for the firefighting brigade.

Moreover, the variables gender and age have a negative and significant effect on the harvesting decision, so that the public authority may encourage the inheritance towards young women people. Note that the variable price seems to have no effect on the forest owner's harvesting decision, meaning that the timber price do not seem to be a relevant lever for public policy.

### 7.2 Implications for forest risk management

The result of the paper show that, on average, French private forest owners are risk averse and characterized by a relative risk aversion coefficient of approximately 1. This result means that, as a risk averse decision-maker, the forest owners would like to reduce the risk linked to forest management. For that purpose, they have at their disposal two different ways. On the one hand, they can implement sylvicultural strategies aiming at reducing risk like for instance the reduction of rotation lenght, which is advocated also as an adaptation strategy to climate change (Spittlehouse and Stewart (2003)). The reduction of rotation lenght allows to reduce the height of the tree and then their sensitivity to storm event, but also reduces the time of exposure of the stand to natural events in general. On the other hand, they can also adopt risk-sharing strategies like forest insurance. Indeed, such insurance contract against storm and/or fire exist in France (and also in other European countries). However, only 5% of the French private forest area is insured, and that may be problematic for two main reasons. First, the French government has announced the disappearance of traditionnal public assistance program in case of natural event occurrence. Such public programs granted individual aid to forest owners for salvage and restoration[11]. Consequently, the only way to be indemnified for the damage caused by natural event is private insurance. Second, forest insurance is advocated as a soft adaptation strategy to face climate change, and in this case, the challenge for the governments is to encourage forest owners to adopt insurance (Brunette and Couture (2017)).

In this context, our paper brings two main insights. First, a well-known result in insurance economics is that as risk aversion increases, insurance demand increases too (Arrow (1970)). One of our result indicates that the exposition to some risks has a positive effect on risk aversion. Consequently, as climate change should have a positive impact on the occurrence and intensity of natural events, we may expect that both the exposure and the risk aversion would be higher, and as a consequence, the insurance demand would increase in the near future. Second, our results indicate that a forest located in Bourgogne or in Paca, correspond to a higher degree of risk aversion. Consequently, we could expect that the forests in these regions be more insured than those in the other regions.

## 8 Conclusion

This paper aims to analyze the forest owner's risk aversion and its impact on the probability of harvesting. For this purpose, we use a database on forest owner's characteristics, forest property and wood production. We implement an ordered probit model to jointly estimate the determinants of risk aversion and the determinants of the probability to harvest. Our results reveal that the mean relative risk aversion coefficient of the French forest owner's is 1.0025 for our specification. The risk aversion is positively and significantly impacted by the level of risk exposure, geographical location

[11]For example, after the storm Klaus in 2009, the French government provided €415 million for an eight-year programme in order to salvage and restore forest stands. The level of the financial support depended on the replanted species and was approximately €2750/hectare on average (Brunette et al. (2015b)).

of the forest, and the fact to be a forester, while the income has a negative effect. The positive and significant determinants of the probability of harvesting are the risk aversion, the delegation of the forest management, the certification of the timber and the fact that the forest is crossed by a paved road and located in Auvergne region. Finally, gender and age have a negative and significant effect on harvesting.

This study identifies a channel by which characteristics of forest owner, forest property and wood production affect the forest owner's decisions: the forest owner's attitude towards risk. The relationship between these characteristics and risk attitude, as well as the link between risk attitude and probability of harvesting are useful in several ways. First, this study indicates how the characteristics of the forest owner, forest property and wood production influence the behavior of private forest owners. The introduction of risk attitude into research on private forest owners may help to understand their decisions and guide their future management choices related to climate change adaptation for example. Previous studies showed that the private forest owner's harvesting decision is impacted by risk attitude, so that displaying the underlying relationships is essential. Second, it allows the forest owners to improve the individual knowledge and therefore to adopt more efficient management strategies. Third, this study also contributes to public policy issue. Indeed, we show that risk aversion increases the forest owner's probability to harvest. However, such a reaction to risk has numerous effects for the economy in terms of timber production, carbon storage, provision of non-market services, etc. For example, a higher risk aversion means to harvest more often, so that the time of the carbon storage is lower. In addition, the forest sector should adapt to this new harvesting planning. Consequently, such kind of studies may help to select appropriate strategies or public policy tools.

A way to improve this paper will be to take into account the dynamics of timber production. Indeed, timber comes from a long term dynamic biological process that is not considered in this research. However, to conduct such a study, we would need panel data over the long term, because some characteristics of the forest owner and the property, such as attitude towards risk for example, show very few variations in the short term. We show that the geographical location influences the coefficient of relative risk aversion. By relaxing the assumption that the risk parameter is only individual-specific, it could be interesting to analyze the existence of spatial interdependence of forest owner's attitude towards risk.

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# Appendix

## A Maximum likelihood estimation

Following Sajaia (2008), we show that the probability that $y_{1i} = j$ and $y_{2i} = 1$ or 0:

$$Pr(y_{1i} = j, y_{2i} = 0) = Pr(y_{1i}^* < c_j, y_{2i}^* < 0) - Pr(y_{1i}^* < c_{j-1}, y_{2i}^* < 0)$$

and

$$\begin{aligned} Pr(y_{1i} = j, y_{2i} = 1) &= Pr(y_{1i}^* < c_j) - Pr(y_{1i}^* < c_{j-1}) - Pr(y_{1i}^* < c_j, y_{2i}^* < 0) \\ &\quad + Pr(y_{1i}^* < c_{j-1}, y_{2i}^* < 0) \end{aligned}$$

The system of equations (1) can be estimated by the maximum likelihood method. Indeed, we assume that $(\epsilon_{1i}, \epsilon_{2i}) \sim N(0, \Omega)$ with $\Omega = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$, thus we get:

$$\begin{aligned} Pr(y_{1i} = j, y_{2i} = 0) &= Pr(\epsilon_{1i} < c_j - X_{1i}'\beta_1, \gamma\epsilon_{1i} + \epsilon_{2i} - \gamma X_{1i}'\beta_1 - X_{2i}'\beta_2) \\ &\quad Pr(\epsilon_{1i} < c_{j-1} - X_{1i}'\beta_1, \gamma\epsilon_{1i} + \epsilon_{2i} - \gamma X_{1i}'\beta_1 - X_{2i}'\beta_2) \end{aligned}$$

Given that $\begin{pmatrix} 1 & 0 \\ \gamma & 1 \end{pmatrix} \begin{pmatrix} \epsilon_{1i} \\ \epsilon_{2i} \end{pmatrix} \sim N\left(0, \begin{bmatrix} 1 & \gamma + \rho \\ \gamma + \rho & \gamma^2 + 2\gamma\rho + 1 \end{bmatrix}\right)$ we have:

$$\begin{aligned} Pr(y_{1i} = j, y_{2i} = 0) &= \Phi_2(c_j - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \\ &\quad - \Phi_2(c_{j-1} - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \end{aligned}$$

Similarly, we obtain:

$$\begin{aligned} Pr(y_{1i} = j, y_{2i} = 1) &= \Phi(c_j - X_{1i}'\beta_1) - \Phi(c_{j-1} - X_{1i}'\beta_1) - \Phi_2(c_j - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \\ &\quad + \Phi_2(c_{j-1} - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \end{aligned}$$

with $\tilde{\rho} = \gamma + \rho$, $\zeta = (\gamma^2 + 2\gamma\rho + 1)^{-1/2}$ and $\Phi$ and $\Phi_2$ the univariate and bivariate standard cumulative distribution functions, respectively. If $j = 1$, then the probabilities above shrink to:

$$\begin{aligned} Pr(y_{1i} = j, y_{2i} = 0) &= \Phi_2(c_j - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \\ Pr(y_{1i} = j, y_{2i} = 1) &= \Phi(c_j - X_{1i}'\beta_1) - \Phi_2(c_j - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \end{aligned}$$

If $j = J$, then the probabilities above shrink to:

$$\begin{aligned} Pr(y_{1i} = J, y_{2i} = 0) &= \Phi((-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta) - \Phi_2(c_{j-1} - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \\ Pr(y_{1i} = J, y_{2i} = 1) &= 1 - \Phi(c_{j-1} - X_{1i}'\beta_1) - \Phi(-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta) + \\ &\quad \Phi_2(c_{j-1} - X_{1i}'\beta_1, (-\gamma X_{1i}'\beta_1 - X_{2i}'\beta_2)\zeta, \tilde{\rho}) \end{aligned}$$

If we assume that the observations are independent, the log-likelihood function can be written as follows:

$$\ln\ L = \sum_{i=1}^{N} \sum_{k=1}^{K} \sum_{j=1}^{J} I(y_{1i} = j, y_{2i} = k)\ \ln Pr(y_{1i} = j, y_{2i} = k)$$

The maximum weighted likelihood estimator can be written as:

$$\ln\ L = \sum_{i=1}^{N} \sum_{k=1}^{K} \sum_{j=1}^{J} w_i\ I(y_{1i} = j, y_{2i} = k)\ \ln Pr(y_{1i} = j, y_{2i} = k)$$

where $w$ is the weighting vector.