Games with Dynamic Externalities and Climate Change Experiments

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Abstract

We report on laboratory experiments with series of games with dynamic externalities, where the current actions of each player affect not only the player's payoff today, but also the group payoffs levels of the game that will be played tomorrow. The motivating example is the climate change problem, where welfare opportunities (payoff levels) in the present depend on the stock of greenhouse gases (GHG) accumulated in the past, with higher current emissions leading to lower future payoffs. We investigate whether socially optimal actions may be sustained in such dynamic externality games with changing payoffs if no explicit enforcement mechanisms are present. Two main experimental treatments are studied. In the Long-Lived treatment, the dynamic game is played by the same group of subjects who interact for many periods (generations). This represents an idealistic setting where countries' decision-makers and citizens are motivated by long-term welfare of their countries. In the Inter-Generational treatment, the dynamic game is played by several groups (generations) of subjects, with later generations having access to history and advice from previous generations. This represents a more realistic setting in which the countries' decision-makers and citizens may be motivated more by the immediate welfare and may care only partially about the future generations' payoffs. Experimental results indicate that in the Long-Lived treatment, many groups of subjects were able to avoid the myopic Nash outcome and to sustain or come back close to the socially optimal emissions and GHG stock levels. In the Inter-Generational treatments, subject decisions were often myopic. These findings suggest that international dynamic enforcement mechanisms (treaties) are necessary to control GHG emissions.

Key words: economic experiments; dynamic externalities; inter-generational games; climate change

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1 Introduction

Many economic problems involve dynamic externalities, where agents' decisions in the current period influence the welfare of the agents in the future periods. Global environmental issues such as climate change, management of international water resources, and loss of biodiversity provide examples. The actions by the current decision makers influence the welfare of the future generations due to changes in state variables such as the atmospheric concentration of greenhouse gases, water availability, or species richness.

Efficient resource allocations with global dynamic externalities require cooperation by sovereign countries over a long time horizon, possibly involving multiple generations of decision makers. There is an increased interest among researchers as well as policymakers over institutional arrangements that enhance cooperation in such contexts. A large scientific literature warns of the dangers of failing to successfully address these issues and continuing business-as-usual. As for climate change, the Intergovernmental Panel on Climate Change concluded that continued emissions of greenhouse gases (GHG) would likely lead to significant warming over the coming centuries with the potential for large consequences on the global economy (IPCC 2007).

While natural and environmental scientists may inform the policy-makers about the physical consequence of GHG emission reductions, implementation of mitigation efforts by specific countries remains a global economic problem. Global dynamic externalities are especially challenging because they have the features of the global public goods, where each country's mitigation efforts benefit all countries but impose private costs, giving rise to the free-rider problem among countries; and long term aspects, where the effect of current actions can be felt into the distant future (Nordhaus 1994, Schlenker and Roberts 2006, Schlenker et al. 2006, IPCC 2007 Chapter 10, Dutta and Radner, forthcoming). The countries' governments may be short-sighted and motivated by their countries' immediate welfare, rather than the long-term effect of emissions on future generations.

Though many studies analyze international treaties for climate change mitigation, research that takes into account the above features is only starting to emerge. In practice, countries have adopted a number of international environmental agreements that differ in their performances and specifications of mechanisms to support cooperation. Some agreements adopt a voluntary, non-legally binding framework (e.g. the Asia-Pacific Partnership on Clean Development and Climate that promotes cooperation over technology development to reduce greenhouse gas emissions) while others specify binding targets (e.g. the Montreal Protocol on Substances That Deplete the Ozone Layer, the Kyoto Protocol to the United Nations Framework Convention on Climate Change). It is still an open question whether strict enforcement mechanisms are necessary to support long-term cooperation among countries, or whether a voluntary cooperation may sustain dynamically socially optimal outcomes.

This paper uses the experimental economics methodology to investigate whether socially optimal actions may be sustained in dynamic externality games with changing payoffs if no explicit enforcement mechanisms (treaties) are present. We first model infinitely lived decision makers (representing an idealistic setting where the countries' governments are motivated by long-term welfare for their countries), and then extend the analysis to an intergenerational decision making framework (representing a more realistic setting in which the countries' governments may be motivated more by their countries' immediate welfare). The study considers the role of intergenerational caring, access to history and information about future consequences of current actions, and social learning in establishing and sustaining cooperation.

Experimental research has proven extremely useful in evaluating alternative policy instruments, particularly those that are prohibitively costly to test in the field (Eckel and Lutz, 2003). The use of university students as subjects allows to evaluate, on a small scale, performances of different treaties, before such treaties may be tested with policy-makers, either in the laboratory or in the field (e.g., Bohm, 1999). A growing experimental literature indicates that appropriately designed and tested economic mechanism may help to alleviate environmental problems and provide useful advice to policy-makers (Bohm, 2003; Cason and Gangadharan, 2006). However, most experimental studies on climate change mitigation focus on relatively short-term (Bohm, 1999; Cason, 2003) or national (Holt et al, 2007) aspects of the problem, while the current research focuses on the global (international) and dynamic long-term aspects.

The paper builds on several existing streams of experimental literature, as we discuss next.

In its dynamic feature, the climate change problem is similar to dynamic common pool resource (CPR) games. Herr et al. (1997) study static and dynamic externalities in the commons using finite-period CPR games. They report that subject behavior was generally away from the social optimum and more consistent with non-cooperative solution benchmarks. Chermak and Krause (2002) study the dynamic CPR problem in an overlapping generations setting. The dynamic externality was present in that today's resource use determined the future resource constraint. The authors report that subject behavior was heterogeneous; yet, in 16% of cases, groups depleted the resource prior to the terminal period. Fischer et al. (2004) investigate altruistic restraint in CPR exploitation when subjects are explicitly informed that their resource use affects the resource level that will be available to the subjects in the next generation. The subjects were given no monetary incentives to care about future generations. They find no effect of intergenerational concerns on subject behavior, but the subjects expected others to care about the future generations and to cut down their resource use, the behavior that the authors call "optimistic free-riding:" "I free-ride, but I expect others not to".

Several experimental studies explore intergenerational games in contexts other than CPR. Using a finite-horizon pension game experiment, van der Heijden et al. (1998) found a substantial degree of voluntary transfers across generations of players. On the other hand, Offerman et al. (2001) report that subjects in their overlapping generations game seldom supported cooperative actions even when they were recommended to play grim-trigger strategies.

The intergenerational aspect of the climate change problem suggests that findings on intergenerational learning and advice (Schotter and Sopher, 2003; Ballinger et al. 2003; Chaudhuri et al, 2009) are relevant. For a setting with chains of groups of subjects playing recurring voluntary contributions public good games, Chaudhuri et al. (2006) report that common knowledge of advice had a positive and significant effect on contributions. For the climate change mitigation problem, social learning may play a significant role, since histories of past actions, opinions and recommendations of scientists and politicians could be made available to the public and to the future generations. We give the subjects in our experiment access to history and advice from previous generations to enhance the possibility of sustaining dynamically optimal outcomes.

In this paper we describe an experiment that was designed and conducted to investigate how games with dynamic externalities, such as climate change, may evolve without explicit treaties among players. The rest of the paper is organized as follows. Section 2 overviews the underlying theoretical model of games with dynamic externalities and defines theoretical benchmarks that would be further used to evaluate experimental results. Section 3 discusses experimental design, and Section 4 presents the results. Section 5 discusses conclusions and open questions.

2 Theoretical model

The underlying model of the dynamic externality game among countries is very similar to the one developed by Dutta and Radner for infinitely live palyers (2004, 2005, 2006, forthcoming). We now review the model and benchmark solutions with infinite horizon governments, as discussed by Dutta and Radner. We then discuss how the setting may be extended to multiple, finitely lived generations of governments in each country using an alternative generational game framework.

2.1 Games with infinitely-lived players

Model environment: The set of players consists of $N \geq 2$ countries. In each period $t = 1, 2, \ldots$, country i chooses an emission $x_{it} \in [0, \bar{x}_i > 0]$, where $\bar{x}_i$ is the maximum feasible emission level. The pollution stock S evolves across periods according to the following equation:

$$S_{t+1} = \lambda S_t + X_t, \quad t = 0, 1, \ldots, \tag{1}$$

where $\lambda \in [0, 1]$ represents the retention rate of the pollution stock; hence $1 - \lambda$ represents the natural rate of decay of pollution ($0 \leq \lambda < 1$), and $X_t \equiv \sum_i x_{it}$. The initial stock S_0 is given.

The period-wise return of player i, π_i, in period t consists of two components: the (net) benefit from its own emission and the damages due to the existing pollution stock in period t:

$$\pi_i(x_{it}, S_t) = B_i(x_{it}) - D_i(S_t), \tag{2}$$

where B_i is strictly concave, differentiable, and has a unique finite maximum $\hat{x}_i$ that lies between 0 and $\bar{x}_i$. For simplicity, we adopt a simple and common to all players quadratic benefit function $B(x) = ax - \frac{1}{2}cx^2$, which implies a unique finite maximum $\hat{x} = a/c$. The damage function satisfies $D_i' > 0, D_i'' \geq 0$. Following Dutta and Radner, we assume a linear (and common among players) damage function $D(S_t) = dS_t$. The parameter $d > 0$ represents the marginal damages due to the stock of pollution.

Given a discount factor $\delta \in (0, 1)$, country i's payoff is given by the present value of the period-wise returns $\sum_{t=0}^{\infty} \delta^t \pi_i(x_{it}, S_t)$. Countries have complete information and there is no uncertainty in the model. In each period, each country observes the history of pollution stock transition and all countries' previous emissions.

Benchmark solutions Consider the following four benchmark emissions allocations.

First Best solution (FB): Assume that all countries' return functions are measured in terms of a common metric. Then the First Best, or the cooperative emission allocation maximizes the sum of N countries' payoffs and hence solves the following problem:

$$\max \sum_{t=0}^{\infty} \sum_{i=1}^{N} \delta^t \pi_i(x_{it}, S_t) \quad \text{subject to the constraints (1).} \tag{3}$$

The solution to this problem generates a sequence of emissions $\{x_t^*\}_{t=0}^{\infty}$ where $x_t^* = \{x_{it}^*\}_{i=1}^{N}$. With the linear damage function, the solution is constant over periods, is independent of stock level and satisfies: $B'(x_{it}^*) = \frac{\delta N d}{1 - \delta\lambda}$, for all i, t.

Sustainable solution (Sus): This is a special case of the first best solution when $\delta = 1$, i.e. the social discount factor is set equal to one. Sus corresponds to the optimal GHG emission control supported by the Stern Review (2006) and several other economic studies, which adopt very low social discount rates in their analysis.

Myopic Nash solution (MN): With $\delta = 0$, the Nash equilibrium emission of player i, $\hat{x}_i$, solves $B_i'(\hat{x}_i) = 0$. Because there is no static externality, this emission level is optimal for generation t as a whole as well. We call $\{\hat{x}_i\}$ the Myopic Nash (MN) solution.[1] The quadratic benefit function $B(x) = ax - \frac{1}{2}cx^2$ implies a unique MN solution $\hat{x} = a/c$.

Markov Perfect equilibrium (MP): The above dynamic game has many subgame perfect equilibria. We take the outcome of a Markov perfect equilibrium (MPE), where each country conditions its emission in each period on the current pollution stock, as a natural benchmark of the noncooperative outcome. In particular, an MPE of a simple form exists under some further assumptions on the period-wise return functions. For the above model specification, the unique Markov perfect equilibrium where each country's emission is independent of the pollution stock level is given by $\tilde{x}$ such that $b'(\tilde{x}) = \frac{\delta d}{1-\lambda\delta}$.

2.2 Games with multiple generations of players

To extend the above framework to a game with multiple generations of players (countries), we assume that each period in the model described above represents a distinct generation of players. Hence, there are infinite number of generations of players, starting with generation 0. Each generation consists of N players, and plays for one period. Let (i, t) represent the ith player in generation t. With this alternative setup, we call π_i in equation (2) the concurrent payoff of player (i, t). Assume the (total) payoff of player (i, t), Π_{it}, is a δ-weighted sum of the concurrent payoff and player $(i, t + 1)$'s payoff:

$$\Pi_{it} = \pi_{it} + \delta \Pi_{it+1}. \tag{4}$$

This specification allows for inter-generational caring, where $0 \leq \delta \leq 1$ is interpreted as the weight that player i in generation t puts on the on the next generation's total payoff relative to own concurrent payoff. As in section 2.1, we can then define four benchmark solutions. The First Best solution (FB) given the intergenrational welfare weights δ solves the problem (3), and hence is the same as the first best allocation in the original model. For the special cases where $\delta = 1$ and $\delta = 0$, we have the Sustainable solution (Sus) and the Myopic Nash solution (MN) as defined in the previous subsection. A simple Markov Perfect equilibrium (MP) is also defined analogously.

[1] Dutta and Randner refer to $\hat{x}_i$ as the "business-as-usual" emission level of country i.

3 Experimental design

Overall design The experiment is designed to study subject behavior in dynamic externality games modeled as in section 2. Groups consisting of $N = 3$ subjects each participated in chains of linked decision series (generations). In each decision series, each subject in a group chose between 1 and 11 tokens (representing a level of emissions by his country), given information about the current payoffs from own token choices, and the effect of group token choices on future series' (generations') payoffs.[2] The payoffs were given in a tabular form, as illustrated in Figure 1.

FIGURE 1 AROUND HERE

From the figure, a subject's current payoff is not affected by current choices of others in the group (no static externality) and is maximized at $x_i = 7$ (Myopic Nash solution); however, the total number of tokens invested by the group in the current series affects the payoff level in the next series. The payoff level represents the current welfare opportunities; it decreases as the underlying GHG emissions stock increases. The payoff scenario in the figure illustrates how the payoffs would evolve across series if the total number of tokens ordered by the group stays at 21 in each series (corresponding to MN outcome).

The parameter values are chosen so that all four theoretical benchmarks (Sustainable: $x_i = 3$; First Best: $x_i = 4$; Markov Perfect: $x_i = 6$; and Myopic Nash: $x_i = 7$) for individual token investments (emission levels) are distinct from each other and integer-valued. The cooperative FB outcome path gives the subjects substantially higher expected stream of payoffs than the MN or the MP outcome.

To study whether sustaining cooperation without explicit treaties is at all possible under some conditions, we chose parameter values favorable for cooperation (rather than realistic): Payoff functions were identical across subjects; the starting stock S_0 was set at the First Best steady state level; and the GHG stock retention rate was low, $\lambda = 0.3$, which allowed for fast recovery from high stock levels.

The experiment continued for several series (generations). To model an infinitely repeated game and eliminate end-game effects, a random termination rule was used. A randomization device (a bingo cage) was applied after each series (generation) to determine whether the

[2] In fact, each series consisted of three decision rounds, where subjects made token choices. One of the rounds was then chosen randomly as a paid round, and was also used to determine next series' payoff level. We decided to have more than one round in a series to give the subjects an opportunity to learn better the behavior of other subjects in their group, and also to allow subjects in inter-generational treatments (to be discussed below) make more than one decision. Subject decisions were rather consistent across rounds within series. In what follows, we will therefore focus on the data analysis for the chosen (paid) rounds of each series; see Section 4 below.

experiment continues to the next series. The continuation probability induces the corresponding discount factor in the experimental setting; the random termination is important to closely follow the theoretical model (Dal Bo, 2005). To obtain reasonably (but not excessively) long chains of series (generations), the continuation probability of 3/4 was used between series. This induced the corresponding discount factor $\delta = 0.75$.

Treatments To study how games with dynamic externalities evolve with infinitely-lived players as compared to generations of short-lived players, the experimental design includes the following treatments:

(1) Baseline Long-Lived (LL): The same group of subjects makes decisions for all generations; each subject's payoff is her cumulative payoff across all generations. This treatment corresponds to the model as discussed in section 2.1, and represents an idealistic setting where decision makers are motivated by long-term welfare for their countries. The treatment investigates whether social optimum may be sustained in dynamic externality games played by infinitely lived players.

(2) Intergenerational Selfish (IS) : A separate group of subjects makes decisions for each generation; each subjects' total payoff is equal to her concurrent payoff, i.e., it is based on her performance in her own generation only. Theoretically, this payoff structure induces no weight to be put on the next generations' welfare, thus suggesting Myopic Nash behavior if subjects are motivated solely by own monetary payoffs. This treatment represents a possibly more realistic setting in which the countries' decision makers are motivated mostly by their countries' immediate welfare. The treatment studies whether subjects may exhibit inter-generational caring when they are made aware of the dynamic effect of their decisions on the follower's payoffs.

(3) Intergenerational Long-sighted (IL): A separate group of subjects makes decisions for each generation; each subjects' payoff is equal to her concurrent payoff (i.e., her payoff in her own generation), plus the sum of all her followers' concurrent payoffs.[3] The cumulative payment in IL keeps the setup consistent with the theory in Section 2.2. This suggests that the behavior in this treatment should theoretically be no different than in the baseline LL treatment. This treatment studies whether subjects restrain their emissions in the inter-generational setting when they are made aware of the dynamic effect of their

[3]Unlike experimental studies on intergenerational advice in recurring games without random termination, such as Chaudhuri et al. (2006), our experimental design does not allow to put only partial weight on future generations payoff, as it would induce double discounting across generations: through continuation probability and through partial weight put on future payoffs. An alternative of paying for one of the generations randomly can also be shown to create the present generation bias, as we show in a companion paper; see Saijo et al. (2009). Making a subjects' payoff depend on own concurrent payoff and on the immediate follower's concurrent payoff only creates incentives for myopic advice.

decisions on the follower's payoffs and are fully motivated by monetary incentives to care about the future.

In all treatments, the experimental design included elements that may help cooperation in the context of climate change mitigation. First, subjects' expectations about the others' choices were solicited, to study whether subjects' willingness to cut down own emissions (tokens) is correlated with their expectations of similar actions by others.

Further, to study social learning, at the end of each series each subject was asked to send "advice" to the next series (generations) in the form of suggested token levels, and any verbal comment. This advice, along with the history of token orders, was then displayed to all subjects in his group in all the the following series (generations). For the climate change mitigation problem, knowledge of history and social learning may play a significant role, since histories of past actions, opinions and recommendations of scientists and politicians could be made available to the public and to the future generations.

Procedures The experiments were computerized using z-tree software (Fischbacher, 2007). Several (up to three) independent groups of subjects, with three subjects in each group, participated in each experimental session. In the baseline LL sessions, the same groups of subjects made token decisions in all decision series carried out within the same session , until the experiment stopped. In the inter-generational IS and IL sessions, each group of subjects participated in one decision series only, after which the randomization device determined if the experiment would continue to the next series which would take place in the next session with new participants. Decision series of the same group in LL treatment (or a chain of groups in IS and IL treatments) were inter-linked through the dynamic externality feature of payoffs, as explained above, and through history and advice from previous series that was passed on to the next series in a chain.

In all treatments and sessions, the subjects went through extensive training before participating in paid series. The training included: (a) Detailed instruction period (see Experimental Instructions, given in Appendix A), which included examples of dynamic payoff scenarios as illustrated in Figure 1 (see Examples of Payoff Scenarios, Appendix B); followed by (b) Practice, consisting of five to seven linked series, for which the subjects were paid a flat fee of $10. Extensive practice was necessary to allow the subjects an opportunity to learn through experience the effect of dynamic externalities on future payoffs.[4] In addition, during each decision round the subjects had access to a payoff calculator which allowed them to evaluate payoff opportunities for several series (generations) ahead given own token choices

[4]We felt that extensive training was especially important to ensure that the subjects fully understood the dynamic externality aspect of the game in the inter-generational treatments, where each subject participated in only one paid decision series.

and choices of the others in the group.

Each experimental session lasted up to three hours in the LL treatment, and up to two hours in the IS and IL treatment, including 60-75 minutes of instructions and training. The exchange rates were set at \$ 100 experimental = \$ 1 US in the LL and IL treatments, and \$ 100 experimental = \$ 4 US in the IS treatment (note that the expected length of a chain, given the continuation probability of 3/4, is 4 series; hence the exchange rates were adjusted across the treatments accordingly). The expected payment per subject was set at around \$35 per subject, including \$10 flat training fee.

4 Results

Four to five independent chains of groups of subjects were conducted under each of the baseline LL, intergenerational IS and intergenerational IL treatments at the University of Hawaii at Manoa. Subjects were recruited from undergraduate students in the college of social sciences. Each chain lasted between 3 and 9 series (generations). Table 1 lists the duration of each chain, along with average group tokens and average recommended group tokens by treatment. Figures 2-3 illustrate the evolution of group tokens and the corresponding stock levels for each chain, grouped by treatment.

TABLE 1 and FIGURES 2-3 AROUND HERE

Figures 2 and 3 suggest very different dynamics of group tokens (and, correspondingly, of the stock) across treatments. Figure 2 indicates that, in the LL treatment, all groups of subjects were able to avoid the Myopic Nash outcome and to sustain or come back close to the First Best group tokens and stock levels. In comparison, group tokens in the IS and IL treatments were considerably higher. The mean group token order in the LL was 13.34 and not significantly different from the FB level of 12. This compares to the mean group token order of 18.00 in IS, which is still below the Myopic Nash level of 21. The mean group token order in the IL treatment was significantly more variable across chains, with a mean of 15.28, which is almost exactly half-way between the FB level of 12 and MP level of 18. Casual comparison of the stock dynamics across treatments again suggests that the groups in the LL treatment were moving towards the FB stock levels, whereas the stock was increasing rapidly in the IS treatment, and exhibited large variance within the IL treatment.

While comparison of chain averages, as given in Table 1, is suggestive of differences across treatments, it may be misleading since it does not capture the dynamics of group tokens and stock within chains. An analysis of evolution of variables of interest in time is necessary to capture the adjustment dynamics across series, and to evaluate and compare long-term convergence levels for group tokens and stocks across treatments. The following model, adopted from Noussair et al (1997), is used to analyze the effect of time on the outcome variable (group tokens or stock) within each treatment:

$$y_{it} = \sum_{i=1}^{N} B_{0i} D_i (1/t) + (B_{LL} D_{LL} + B_{IS} D_{IS} + B_{IL} D_{IL})(t-1)/t + u_{it}, \tag{5}$$

where $i = 1, .., N$, is the chain index, $N = 13$ is the number of independent chains in all three treatments, and t is the series index. D_i is the dummy variable for chain i, while D_{LL}, D_{IS} and D_{IL} are the dummy variables for the corresponding treatments LL, IS and IL. Coefficients B_{0i} estimate chain-specific starting levels for the variable of interest,[5] whereas B_{LL}, B_{IS} and B_{IL} are the treatment-specific asymptotes for the dependent variable. Thus, we allow a different origin of convergence process for each chain, but estimate common, within treatments, asymptotes. The error term u_{it} is assumed to be distributed normally with mean zero. We performed panel regressions using feasible generalized least squares estimation, allowing for first-order autocorrelation within panels and heteroscedastisity across panels.

The results of regression estimations of group tokens and stock convergence levels are given in Tables 2 and 3. Along with listing the estimated asymptotes for each treatment, the tables also display p-values for the test of their equivalence to the four theoretical benchmarks: Sus, FB, MP and MN.

The regression results are very clear. While the group tokens in the LL treatment converge to 11.52, which is not significantly different from the FB level of 12 (p-value is 0.3941), the group tokens in the IS treatment converge to 18.14, which is not significantly different from the MP level of 18 (p-value is 0.7953), but is nevertheless below the MN level of 21. The group tokens in the IL treatment converge to 15.94, which is above the FB level of 12 but below the MP of 18. The stocks converge to the FB level in the LL treatment (p-value is 0.327), just under the MN level in the IS treatment, and the MP level in the IL treatment (p-value is 0.837). We conclude the following.

Conclusion 1 *In the Long-Lived treatment, groups of subjects were able to avoid myopic decisions, with group tokens and stock levels converging to the First Best levels. In contrast, in the Intergenerational Selfish treatment, group tokens and stock levels were converging to levels just under the Myopic Nash benchmarks. Chains in the Intergenerational Long-sighted treatment exhibited dynamics in between the FB and the MP predictions.*

[5] Chain-specific starting coefficients B_{0i} were estimated for group tokens and recommended group tokens. For the stock variable, we estimated a common starting level B_0, as the starting stock was set at the First Best level for all chains.

We next consider the evolution of group advice across treatments. Table 1 suggests that while the average group number of recommended tokens in each treatment was slightly below the actual group tokens, the ranking of recommended tokens across treatments was the same as the ranking of actual group tokens. The average number of recommended tokens for a group was 12.58 in the LL treatment, as compared to 16.62 in the IS treatment, as compared to 13.63 in the IL treatment. Evolution of recommended group tokens by treatment, illustrated in Figure 4, suggests that recommended tokens in each treatment and chain followed a trend similar to that of actual tokens.

FIGURE 4 and TABLE 4 AROUND HERE

Regression analysis of recommended group tokens presented in Table 4 confirms that actual group tokens and recommended tokens were converging to the same theoretical benchmarks. In particular, the recommended tokens asymptote in the LL treatment was 11.48, which is not different from the FB level of 12 (p-value is 0.1161). The recommended tokens asymptote in the IS treatment was 17.21, which is much higher than in the LL treatment, but is nevertheless below the MN level. Finally, the recommended tokens asymptote in the IL treatment was 14.19, which is above the FB level but below the MP (or MN) level.

Conclusion 2 *Recommended tokens followed the same trend as the actual tokens, with LL recommended tokens converging to First Best level, IS recommended tokens converging to slightly under the Myopic Nash level, and IL recommended tokens converging to above the First Best but below the Markov perfect level.*

It is also interesting to consider verbal advice. Figures 5- 7 list examples of verbal advice for the LL, IS and IL treatments.

FIGURES 5- 7 AROUND HERE

Note that, in the LL treatment, verbal advice was passed from one series to the next by the same group of subjects; while in the intergenerational treatments, advice was passed from predecessor groups to the follower groups in a chain. Figure 5 suggests that in the LL treatment, verbal advice was used as an effective communication device among the group members. The subjects were able to exchange ideas and further coordinate on cooperative token choices. The evolution of advice in the IL treatment indicates that some chains of subjects used advice to coordinate on a cooperative action path in this treatment as well (Figure 7). In contrast, as it is evident from Figure 6, in the Intergenerational Selfish treatment, attempts by individual subjects to convince the followers to cut down their tokens were often unsuccessful.

Conclusion 3 *Analysis of verbal advice suggests that the advice was used as a communication device and helped to coordinate on cooperative decisions in the Long-Lived treatment, and sometimes in the Intergenerational Long-sighted treatment. In the Intergenerational Selfish treatment, subjects often advised the followers to act in a myopic manner.*

5 Discussion

Our results indicate that, for the baseline Long-Lived treatment, all groups of subjects were able to avoid myopic Nash outcome and to sustain or come back close to the First Best group tokens and stock levels. Verbal advice was used as an effective communication device among the group members. In contrast, in the intergenerational treatments, cooperation among subjects within and between generations was less successful. In the Intergenerational Selfish treatment, group dynamics were converging to non-cooperative levels, and individual advices were often myopic. Attempts made by some subjects to cut down tokens were not very successful, and advice evolved from suggesting the First Best token level in early series to Myopic Nash action in later series. It is worth noting, however, that both group tokens and recommended group tokens in the IS treatment were about one token per person below the Myopic Nash prediction. This suggests that subjects in the IS treatment did show some, although quite minimal, concerns for future generations (not just in advices, but also in actual choices).

The evidence from the Intergenerational Long-sighted treatment is less clear-cut. Apparently, some chains in this treatment were converging to cooperative token and stock levels, while others stayed at non-cooperative levels; the average performance was between the cooperative First Best and non-cooperative Markov Perfect benchmarks. We note that the monetary incentive structure was identical between the LL and IL treatments. Thus, the differences between these two treatments may be attributed to strategic uncertainty regarding followers' behavior that was absent in the LL treatment (where all generations were represented by the same subjects) but was present in the IL treatment (where each generation was represented by different subjects). This difference may be also partially due to less effective communication among generations in the intergenerational IL treatment as compared to the Long-Lived treatment.

These preliminary findings suggest that international dynamic enforcement mechanisms (treaties) may be necessary to control GHG emissions if the countries' governments are not explicitly motivated by the future generations' welfare. Further, coordination and communication across generations appears important even if each generation in motivated by the welfare of the future generations, as it is apparent from the Intergenerational Long-sighted treatment. Even though the outcomes in the IL treatment are closer to cooperative benchmarks as compared to the IS treatment, they are further away from the First Best than those in the LL treatment.

Further analysis will focus on individual behavior.

Appendix A: Experimental Instructions (IL)

Appendix B: Payoff Scenarios

EXAMPLE 1 SCENARIOS HERE

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TABLE 1: Experimental Summary

Treatment	Chain	No of series	Group Tokens* Mean (StDv)	Group Token Advice* Mean (StDv)
LL	1	7	14.86	14.29
			(4.10)	(2.50)
LL	2	5	15.00	13.40
			(4.24)	(2.30)
LL	3	5	11.60	11.20
			(3.05)	(1.10)
LL	4	9	11.89	11.44
			(2.15)	(1.51)
LL all	**mean**		**13.34**	**12.58**
	(stddv)		**(1.84)**	**(1.50)**
IS	1	5	14.40	13.00
			(2.88)	(4.76)
IS	2	4	20.00	19.67
			(1.41)	(1.53)
IS	3	5	18.20	15.80
			(1.48)	(1.92)
IS	4	5	19.40	18.00
			(0.55)	(1.87)
IS all	**mean**		**18.00**	**16.62**
	(stddv)		**(0.97)**	**(1.50)**
IL	1	6	17.67	16.00
			(2.42)	(4.00)
IL	2	6	17.50	15.17
			(2.35)	(1.60)
IL	3	7	13.00	11.29
			(1.83)	(2.06)
IL	4	7	17.57	16.71
			(1.27)	(1.60)
IL	5	3	10.67	9.00
			(3.79)	(4.58)
IL all	**mean**		**15.28**	**13.63**
	(stddv)		**(3.25)**	**(3.33)**

*Benchmark predictions for Group Tokens are: Sus=9, FB=12, MP=18, and MN=21

TABLE 2. Group tokens: convergence by treatment

Group tokens: Cross-sectional time-series GLS regression

Group tokens	Coef.	Std. Err.	z	[95% Conf.	Interval]	p-value: Tokens=9 (Sus)	p-value: Tokens=12 (FB)	p-value: Tokens=18 (MP)	p-value: Tokens=21 (MN)
LL, chain 1 origin	20.71	1.76	11.80	17.27	24.16				
LL, chain 2 origin	19.83	2.12	9.34	15.67	23.99				
LL, chain 3 origin	10.54	2.00	5.28	6.62	14.45				
LL, chain 4 origin	12.99	1.28	10.17	10.49	15.50				
IS, chain 1 origin	10.79	1.39	7.74	8.06	13.52				
IS, chain 2 origin	21.68	0.83	26.20	20.06	23.30				
IS, chain 3 origin	18.28	0.91	20.11	16.50	20.06				
IS, chain 4 origin	19.02	1.29	14.72	16.49	21.55				
IL, chain 1 origin	22.13	0.72	30.80	20.72	23.54				
IL, chain 2 origin	17.91	2.20	8.13	13.59	22.23				
IL, chain 3 origin	11.82	2.19	5.40	7.53	16.10				
IL, chain 4 origin	17.05	1.76	9.71	13.61	20.49				
IL, chain 5 origin	6.19	0.38	16.31	5.44	6.93				
LL asymptote	11.52	0.56	20.43	10.41	12.62	0	0.3941	0	0
IS asymptote	18.14	0.53	34.09	17.10	19.18	0	0	0.7953	0
IL asymptote	15.94	0.43	37.18	15.10	16.78	0	0	0	0

Coefficients: generalized least squares
Panels: heteroskedastic
Correlation: panel-specific AR(1)

Estimated covariances = 13		Number of obs =	74
Estimated autocorrelations = 13		Number of groups =	13
Estimated coefficients = 16		Obs per group: min =	3
		avg =	5.69
		max =	9
		Wald chi2(16) =	11499.64
Log likelihood = -135.649		Prob > chi2 =	0

TABLE 3. Stock: convergence by treatment

Cross-sectional time-series FGLS regression

Stock	Coef.	Std. Err.	z	[95% Conf.	Interval]	p-value: Stock=34.3 (Sus)	p-value: Stock=42.9 (FB)	p-value: Stock=60 (MP)	p-value: Stock=68.9 (MN)
Origin	43.13	1.13	38.25	40.92	45.34				
LL asymptote	45.85	3.01	15.23	39.95	51.75	0.0001	0.327	0	0
IS asymptote	65.84	1.09	60.35	63.70	67.98	0	0	0	0.005
IL asymptote	60.53	2.59	23.36	55.45	65.61	0	0	0.837	0.0012

Coefficients: generalized least squares
Panels: heteroskedastic
Correlation: panel-specific AR(1)

Estimated covariances = 13   Number of obs = 74
Estimated autocorrelations = 13   Number of groups = 13
Estimated coefficients = 4   Obs per group: min = 3
avg = 5.692308
max = 9
Wald chi2(16) = 8632.2
Log likelihood = -215.061   Prob > chi2 = 0.0000

TABLE 4. Recommended group tokens: convergence by treatment

Cross-sectional time-series FGLS regression

Recommended group tokens	Coef.	Std. Err.	z	[95% Conf.	Interval]	p-value: Tokens=9 (Sus)	p-value: Tokens=12 (FB)	p-value: Tokens=18 (MP)	p-value: Tokens=21 (MN)
LL, chain 1 origin	18.99	0.97	19.60	17.09	20.88				
LL, chain 2 origin	14.87	2.83	5.26	9.33	20.41				
LL, chain 3 origin	10.73	0.56	19.09	9.63	11.83				
LL, chain 4 origin	12.09	0.95	12.77	10.23	13.94				
IS, chain 1 origin	8.77	2.67	3.28	3.53	14.00				
IS, chain 2 origin	21.57	0.04	553.61	21.49	21.64				
IS, chain 3 origin	13.77	0.99	13.86	11.82	15.71				
IS, chain 4 origin	18.13	1.13	16.09	15.92	20.34				
IL, chain 1 origin	18.15	1.60	11.36	15.02	21.28				
IL, chain 2 origin	16.94	0.99	17.05	14.99	18.88				
IL, chain 3 origin	8.32	1.72	4.83	4.94	11.69				
IL, chain 4 origin	16.33	2.17	7.52	12.08	20.59				
IL, chain 5 origin	4.49	0.56	8.08	3.40	5.58				
LL asymptote	11.48	0.33	34.81	10.84	12.13	0	0.1161	0	0
IS asymptote	17.21	0.05	319.96	17.11	17.32	0	0	0	0
IL asymptote	14.19	0.52	27.06	13.16	15.22	0	0	0	0

Coefficients: generalized least squares
Panels: heteroskedastic
Correlation: panel-specific AR(1)

Estimated covariances =	13	Number of obs =	72
Estimated autocorrelations =	13	Number of groups =	13
Estimated coefficients =	16	Obs per group: min =	3
		avg =	5.538462
		max =	9
		Wald chi2(16) =	1766836
Log likelihood =	-119.186	Prob > chi2 =	0

Figure 1: An example of subject payoff table

Payoffs with Group Tokens = 21 in each series

Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	910	-483	-197	37	219	349	427	453	427	349	219	37
Payoff in two series ahead	765	-628	-342	-108	74	204	282	308	282	204	74	-108
Payoff in three series ahead	722	-671	-385	-151	31	161	239	265	239	161	31	-151
Payoff in four series ahead	709	-684	-398	-164	18	148	226	252	226	148	18	-164

FIGURE 2: Evolution of group tokens, by treatment

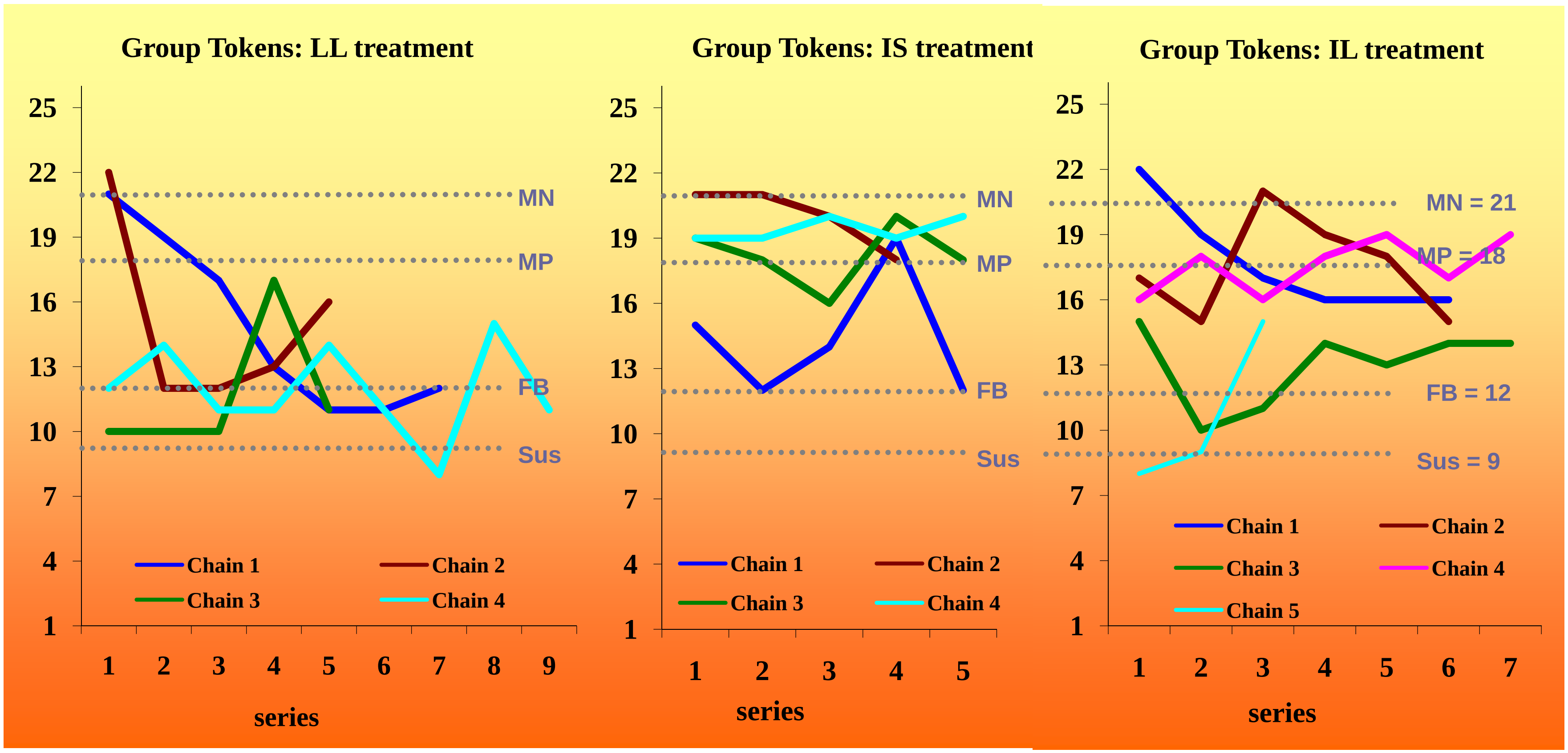


FIGURE 3: Evolution of stock, by treatment

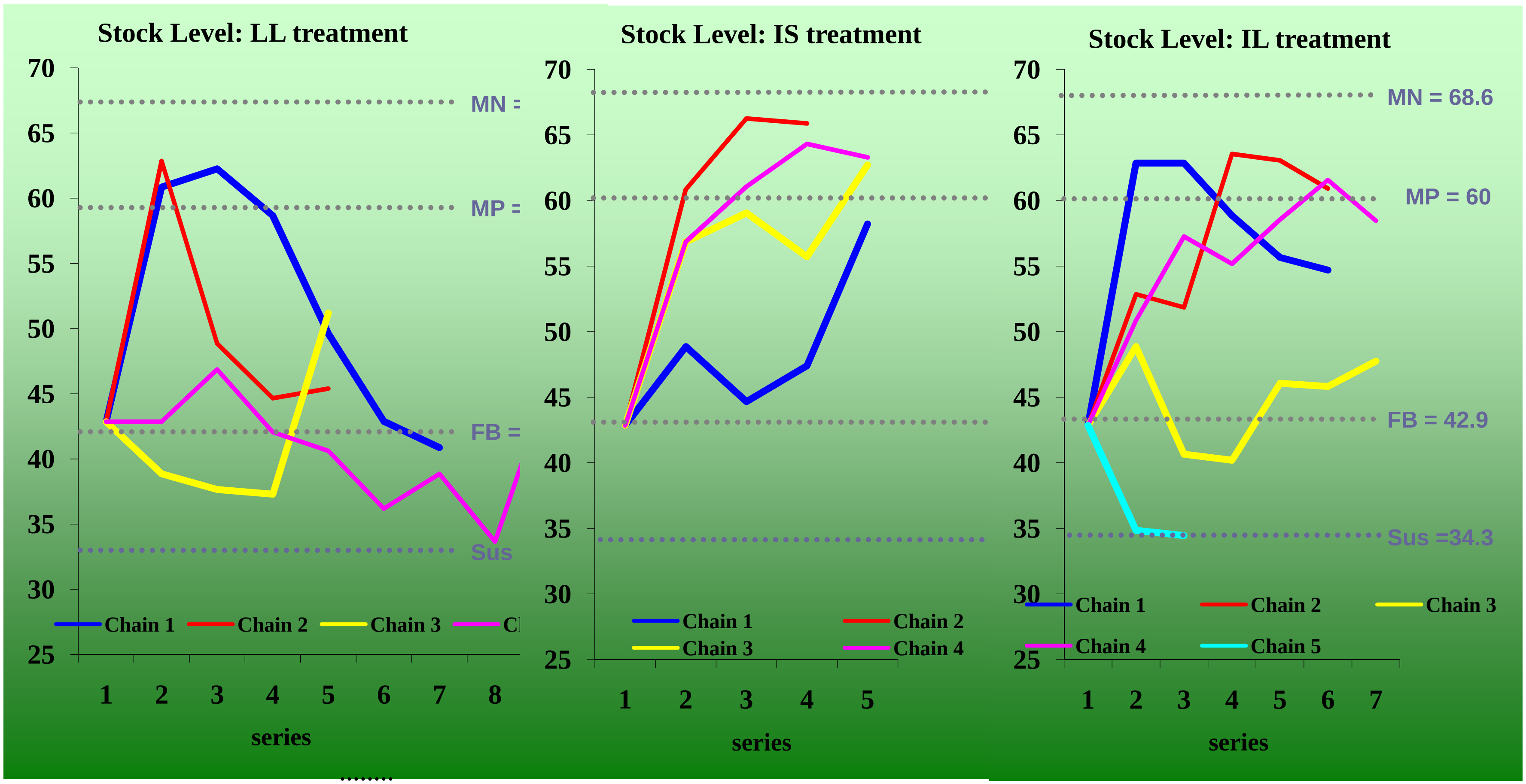


FIGURE 4: Evolution of recommended group tokens, by treatment

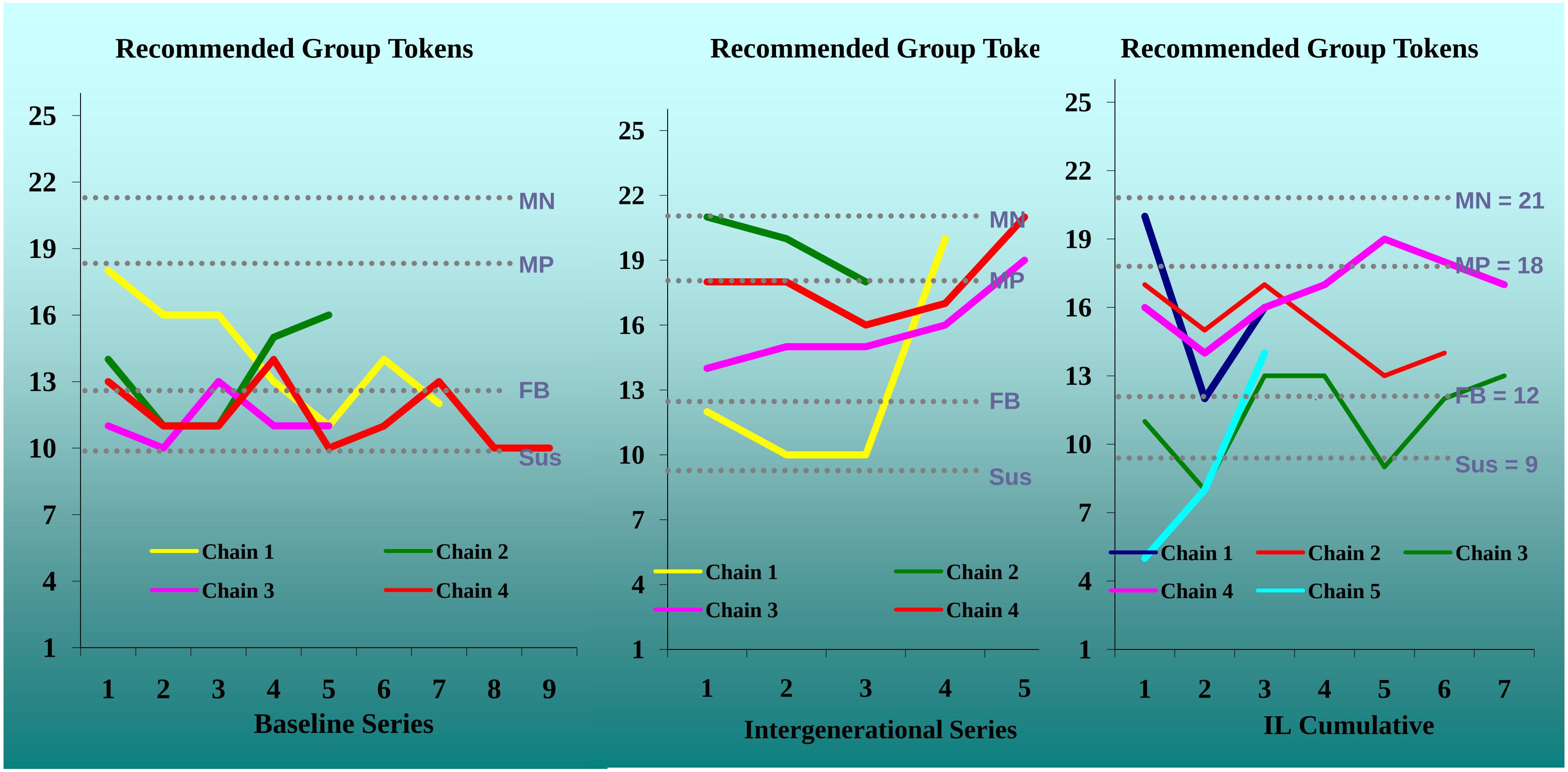


FIGURE 5: Evolution of verbal advice, LL treatment, Chain 2

Series	Subject	Advise
Series 1	1	6 as next token order
	2	we started out really high this past one. maybe we can go lower for the next trials.
	3	Start with small orders and gradually order more for each subsequent trial. The loss we take early will give us bigger payoffs in the later series.
Series 2	1	I agree with ID#3's advice on starting on smaller orders and gradually ordering more for each trial. I suffered from a loss in the beginning, but my payoffs increased as we went on. Let'
	2	better, much better. If we can keep it lower or about the same for next round then our payoff will be greater in the subsequent trials.
Series 3	1	Good, it seems to be getting better and better. Let's keep it at the same or even lower. Let's just not go greater
	2	Hmm...the tokens were around the same ballpark. Maybe keep it the same for one more series then start to push our luck and slowly increase in token counts.
	3	Let's stay with this order one more round. It gives us a good balance between payout and upping the payoff level for the next series.
Series 4	1	Payoff did increase, but I think we should increase our token rather than stay at 4. Let's try increasing it a bit
	2	I say slowly up the token count...
	3	The benefit from 4 to 5 is only a 100 point difference (50 cents) so let's stay with 4.
Series 5	1	Let's just stay at 4...doesn't look like it's increasing by much. 4 would be the best token order. 4 everyone!
	2	...I don't know what to say now. We seem to be doing whats best.

FIGURE 6: Evolution of verbal advice, IS treatment, Chain 4

Series	Subject	Advise
Series 1	4	For me I try to choose the tokens which has the highest payoff.
	5	
	6	the next set you should choose a low amount of tokens so your payoff level will increase. In the long run, as the pay off level increases, you will have a higher payoff schedule. I chose 4 because its not too low and not too high but just right.
Series 2	4	Do not choose a number beyond 6. Otherwise, our total payoff will decrease.
	5	The greatest payoff calculated against the results for the subsequent group is 6
	6	for maxmin payoff for your series, but the payoff decreases for the later series
Series 3	4	Do not choose higher than 5. Otherwise your optimal payoff will decrease.
	5	keep it fairly low until later rounds
	6	choose 7
Series 4	4	never go beyond 5 to save your future generations
	5	for everyone's best
	6	choose 6 b/c you make money plus earn more money in the following rounds.
Series 5	4	go between 6 and 8 tokens to gain max payoff and prediction bonus
	5	for your own benefit, choose the maximal payoff, ie 7; the rest is not worth considering, it's just a diversion.
	6	Get the most out of it NOW!

FIGURE 7: Evolution of verbal advice, IL treatment, Chain 4

Series	Subject	Advice
Series 1	1	PLEASE try either try 3 or 4...dont kill the group payoff, which will affect all of you when it continues further it will affect your individual payoff too. I chose 4 for the first trial and then I stayed around that number, I wanted to stay low because I thought that the actual Payoff Group level would increase if the number of tokens ordered was low.
	2	
	3	the lower the numbers, the higher the payoff in the later series
Series 2	1	Choose Low so that we can increase the payoff level!
	2	stay low. 3 or 4 will keep it going. please!
	3	the lower the number, the higher the payoff series will be later...
Series 3	1	ok, lets all go low now. if we do this together, we will get better payoff until the end!!
	2	bid high
	3	there are three trials,so if we choose a low number between 2 and 5 for the next series, then we can increase our payoff AND our payoff levels. We ALL can GET MORE MONEY at the end of this
Series 4	1	Go with the lower orders, it'll help out later. for real.
	2	lower the better
	3	keep the numbers lower to get a higher payoff
Series 5	1	keep it at 3 or 4 please! if people get greedy, then the token prediction will be off. and people will lose money.
	2	4 The number from 2 to 5 is better. Dont go to higher number.
	3	I picked 4, so that my own payoff was somewhat average. Overall, a lower number increases the group payoff in the end.
Series 6	1	Please please please, dont be greedy now. With a 75% chance that the experiment will continue, odds are pretty good that it will keep going. The lower the pay off that the next group can get will hurt your total income in the long run.
	2	If you keep the number low, it will pay off in the end. If you are greedy, then only you benefit and no one else...but it will come back to you later.
	3	Keep it BELOW five in the first series. In the last series, BID HIGH. DON'T DO IT BEFORE THEN.
Series 7	1	Please keep the your token around 3-4.
	2	try to hit low orders first
	3	pick a middle number like 5 or 6 but assume that others will pick a low number (they will want to ensure better payoff levels)

Experimental Instructions (IL)

Introduction

You are about to participate in an experiment in the economics of decision making in which you will earn money based on the decisions you make. All earnings you make are yours to keep and will be paid to you IN CASH at the end of the experiment. During the experiment all units of account will be in experimental dollars. Upon concluding the experiment the amount of experimental dollars you receive as payoff will be converted into dollars at the conversion rate of US $1 per ______ experimental dollars, and will be paid to you in private.

Do not communicate with the other participants except according to the specific rules of the experiment. If you have a question, feel free to raise your hand. An experimenter will come over to you and answer your question in private.

In this experiment you are going to participate in a decision process along with several other participants. From now on, you will be referred to by your ID number. Your ID number will be assigned to you by the computer.

Decisions and Earnings

Decisions in this experiments will occur in a number of decision series. Decisions in each decision series are made within groups of 3 participants each. A number of these groups form a chain. At the beginning of your decision series, you will be assigned to a decision group with 2 other participant(s). You will not be told which of the other participants are in your decision group.

You and other participants in your group will make decisions in the current decision series. This decision series may have been preceded by the previous series, where decisions were made by your predecessor group in the chain. Likewise, your decision series may be followed by the next decision series, where decisions will be made by your follower group in the chain. None of the participants in the current session are in the predecessor or the follower group in your chain.

In this decision series, you will be asked to order between 1 and 11 tokens. All participants in your group will make their orders at the same time. You payoff from each series will depend on two things: (1) the current payoff level for your group, and (2) the number of tokens you order. The higher is the group payoff level for the series, the higher are your payoffs in this series. All members of your group have the same group payoff level in this series.

Given a group payoff level, the relationship between the number of tokens you order and your payoff may look something like this:

PAYOFF SCHEDULE IN THIS SERIES; GROUP PAYOFF LEVEL: 1394

Your token order	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1	287	521	703	833	911	937	911	833	703	521

For example, the table above indicates that the group payoff level in this series is 1394. At this level, if you choose to order 5 tokens, then your payoff will be 833 experimental dollars.

The group payoff level for your decision series will be given to you by the computer. This payoff level may be the result of decisions of participants in the predecessor group in your chain in the previous series. Likewise, the payoff level for the follower group in your chain in the next series will depend on your group's total token order in this series. The follower's group payoff level in the next series may increase if the number of tokens ordered by your group in this series is low; The follower's group payoff level in the next series may decrease if the number of tokens ordered by the group in this series is high; For some group token order, your follower's group payoff level in the next series may be the same as your group's payoff level in this series.

Example 1 To illustrate how payoff schedules in your chain may change from series to series, depending on your group orders, consider the attachment called "Example 1 Scenarios". Suppose, as in this attachment, that your group has a payoff level of 1394 in the current series. The table and figure A1 illustrate how the payoffs change from series to series for the groups in your chain, if the group order the sum of 3 tokens in each series. The table shows the group payoff level will increase from 1394 in this series to 1878 in the next series, resulting in increased payoffs from token orders. For example, if you order 1 token, your payoff will be 1 experimental dollar in this series, but in the next series your follower's payoff from the same order will increase to 485 experimental dollars. The table also shows that if the group order is again 3 tokens in the next series, the group payoff level will further increase in the series after next. Similarly, the table demonstrates the payoff changes in the future series up to three series ahead. The graph illustrates.

When making token orders, you will be given a calculator which will help you estimate the effect of your and the other participants' token choices on the follower groups payoff levels in the future series. In fact, you will have to use this calculator before you can order your tokens.

TRY THE CALCULATOR ON YOUR DECISION SCREEN NOW. *In the calculator box, enter "1" for your token order, and "2" for the sum of the other participants' orders. (The group tokens will be then equal to 3.) The "Calculator Outcome" box will show the changes in the payoff levels and the actual payoffs from the current series to the next and up to four series ahead, if these token orders are chosen in every series. Notice how the payoff levels and the actual payoffs increase from series to series.*

Consider now the table and figure A4. They illustrate how payoff levels change from series to series if your group and the follower groups in your chain order the total of 30 tokens in each series. Suppose, for example, that you order 11 tokens in this series. The table shows that, given the current payoff level, your payoff will be 521 experimental dollar in this series, but in the next series your follower's payoff from the same order will be -446 experimental dollars. (This is because the group payoff level will decrease from 1394 in this series to 427 in the next series.) Again, the table and the graph illustrate how the payoffs change in the future series up to three series ahead, assuming that the total group order stays at 30 tokens in each series.

TRY THE CALCULATOR WITH THE NEW NUMBERS NOW. *In the calculator box, enter "11" for your token order, and "19" for the sum of the other participants' orders. (The group tokens will be then equal to 30.) The "Calculator Outcome" box will again show the changes in the payoff levels and the actual payoffs from the current series to the next and up to four series ahead, given the new token orders. Notice how the payoff levels and the actual payoffs decrease from series to series.*

Now try the calculator with some other numbers.

After you practice with the calculator, **ENTER A TOKEN ORDER IN THE DECISION BOX.** *The decision box is located on your decision screen below the calculator box.*

Predictions Along with making your token order, you will be also asked to predict the sum of token orders by other participants in your group. You will get an extra 50 experimental dollars for an accurate prediction. Your payoff from prediction will decrease with the difference between your prediction and the actual tokens ordered by others in your group. The table below explains how you payoff from prediction depends on how accurate your prediction is.

PAYOFF FROM PREDICTIONS

Difference between predicted and actual sum of others' tokens	0	2	4	6	8	10	12	14	16	18	20
Your Payoff from Prediction	50	50	48	46	42	38	32	26	18	10	0

PLEASE ENTER A PREDICTION INTO THE DECISION BOX NOW.

Results After all participants in your group make their token orders and predictions, the computer will display the "Results" screen, which will inform you about your token order, the sum of the other participants' tokens, and your total payoff in this series. The total payoff equals the sum of your payoff from token order and your payoff from prediction. The results screen will also inform you about the change in the payoff levels from this series to the next series, and display the corresponding payoff schedules.

Trials You will be given three independent decision trials to make your token orders and predictions in this series. The payoff levels for your group will stay the same across the trials of the series. At the end of the series, the computer will randomly choose one of these three trials as a paid trial. This paid trial will determine the earnings for the series, and the payoff level for your follower group in the next series. All other trials will be unpaid. At the end of the series, the series results screen will inform you which trial is chosen as the paid trial for this series.

Advice from the previous series and for the next series Before making token orders in your decision series, you will be given a history of token orders and advice from the participants in the predecessor groups in your chain, suggesting the number of tokens to order. At the end of your decision series, each participant in your group will be asked to send an advice message to the participants in the follower group in your chain. This will conclude a given series.

PLEASE ENTER AN ADVICE (A SUGGESTED NUMBER OF TOKENS AND A VERBAL ADVICE) NOW.

Continuation to the next decision series Upon conclusion of the decision series, we will roll an eight-sided die to determine whether the experiment ends with this series or continues to the next series with the follower group. If the die comes up with a number <u>between 1 and 6</u>, then the experiment continues to the next series. If the die shows number <u>7 or 8</u>, then the experiment stops. Thus, there are THREE CHANCES OUT OF FOUR that the experiment continues to the next series, and ONE CHANCE OUT OF FOUR that the experiments stops.

If the experiment continues, the next series that follows will be identical to the previous one except for the possible group payoff level change, depending on the token orders by your group in this series, as is explained above. The decisions in the next series will be made by the participants in the follower group in your chain.

Practice Before making decisions in the paid series, all participants will go through 5-series practice, with each practice series consisting of one trial only. You will receive a flat payment of <u>10</u> dollars for the practice.

Total payment Your total payment (earning) in this experiment will consist of two parts: (1) The flat payment for the practice, which you will receive today; plus (2) the sum of yours and your followers' series payoffs, starting from your series and including all the follower series in your chain. This payment will be calculated after the last series in your chain ends. We will invite you to receive the latter part of your payment as soon as the experiment ends.

If you have a question, please raise your hand and I will come by to answer your question.

ARE THERE ANY QUESTIONS?

Frequently asked questions

- What is the difference between a trial and a series?

  Each series consists of three decision trials. One of the decision trials is then randomly chosen by the computer to determine your payoffs in the series.

- What does my payoff in this series depend upon?

  It depends upon your GROUP PAYOFF LEVEL in this series, and YOUR TOKEN ORDER.

- What is the group payoff level?

  It is a positive number that is related to the payoffs you can get from token orders in the series. The higher is the group payoff level, the higher is the payoff you get from any token order.

- Does my payoff in a series depend upon other participants' token orders in this series?

  No. Given your group payoff level in a series, your payoff in this series is determined only by your own tokens order.

- Why do the total group tokens matter?

  Because THEY AFFECT THE PAYOFF LEVEL IN THE NEXT SERIES for the follower group in your chain. The higher is the group tokens in this series, the lower will be the group payoff level in the next series.

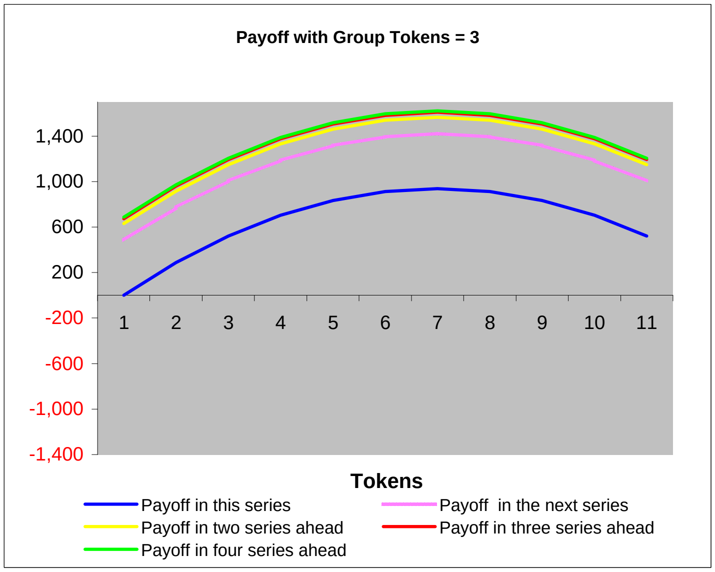
- How many series are there in this experiment?

  The number of series will be determined by a random draw. There will be 3 OUT OF 4 CHANCES that each series will continue to the next series, and 1 OUT OF 4 CHANCE that the experiment will stop after this series. We will roll a die at the end of each series to determine the outcome.

Example 1 Scenarios

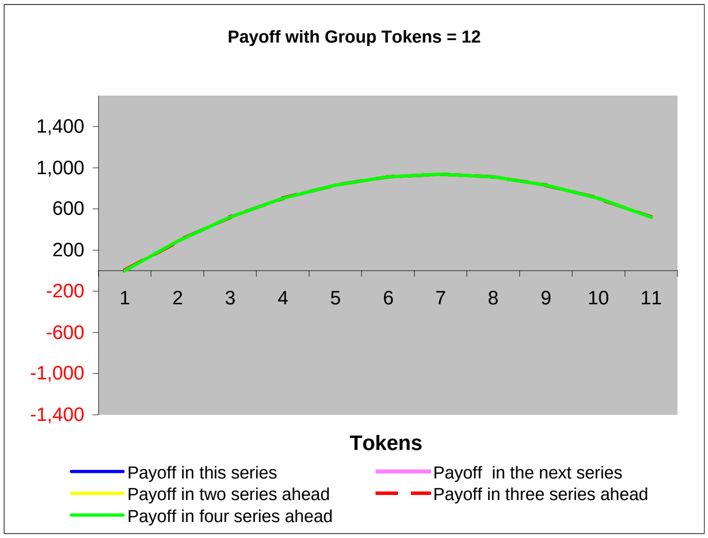
A1. Payoff with Group Tokens = 3 in each series

Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	1878	485	771	1,005	1,187	1,317	1,395	1,421	1,395	1,317	1,187	1,005
Payoff in two series ahead	2023	630	916	1,150	1,332	1,462	1,540	1,566	1,540	1,462	1,332	1,150
Payoff in three series ahead	2066	673	959	1,193	1,375	1,505	1,583	1,609	1,583	1,505	1,375	1,193
Payoff in four series ahead	2079	686	972	1,206	1,388	1,518	1,596	1,622	1,596	1,518	1,388	1,206



A2. Payoff with Group Tokens = 12 in each series

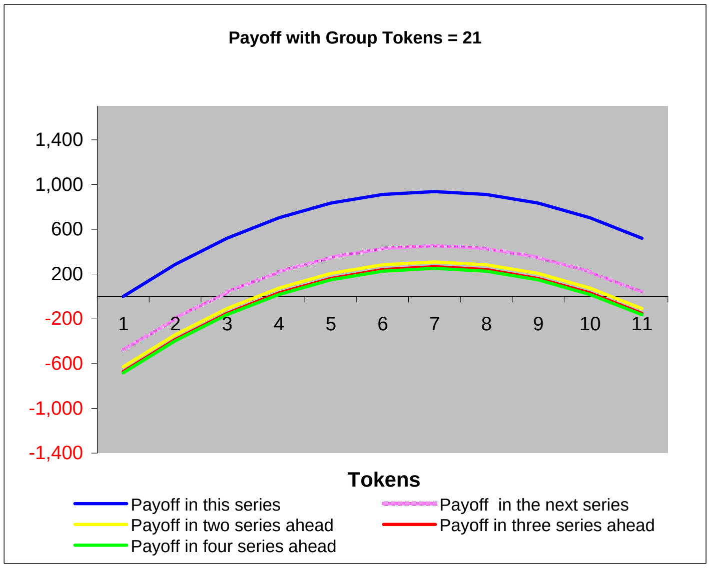
Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in two series ahead	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in three series ahead	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in four series ahead	1394	1	287	521	703	833	911	937	911	833	703	521



Example 1 Scenarios

A3. Payoff with Group Tokens = 21 in each series

Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	910	-483	-197	37	219	349	427	453	427	349	219	37
Payoff in two series ahead	765	-628	-342	-108	74	204	282	308	282	204	74	-108
Payoff in three series ahead	722	-671	-385	-151	31	161	239	265	239	161	31	-151
Payoff in four series ahead	709	-684	-398	-164	18	148	226	252	226	148	18	-164



A4. Payoff with Group Tokens = 30 in each series

Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	427	-966	-680	-446	-264	-134	-56	-30	-56	-134	-264	-446
Payoff in two series ahead	137	-1,256	-970	-736	-554	-424	-346	-320	-346	-424	-554	-736
Payoff in three series ahead	50	-1,343	-1,057	-823	-641	-511	-433	-407	-433	-511	-641	-823
Payoff in four series ahead	23	-1,370	-1,084	-850	-668	-538	-460	-434	-460	-538	-668	-850