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Inter-Generational Games with Dynamic Externalities and Climate Change Experiments

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Abstract

Dynamic externalities are at the core of many long-term environmental problems, from species preservation to climate change mitigation. We use laboratory experiments to compare welfare outcomes and underlying behavior in games with dynamic externalities under two distinct settings: traditionally-studied games with infinitely-lived decision makers, and more realistic inter-generational games. We show that if decision makers change across generations, resolving dynamic externalities becomes more challenging for two distinct reasons. First, decision makers' actions may be short-sighted due to their limited incentives to care about the future generations' welfare. Second, even when the incentives are perfectly aligned across generations, strategic uncertainty about the follower actions may lead to an increased inconsistency of own actions and beliefs about the others, making own actions more myopic. Inter-generational learning through history and advice from previous generations may improve dynamic efficiency, but may also lead to persistent myopia.

JEL codes: C92, D62, D90, Q54.
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 through 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 policy makers over institutional arrangements that enhance cooperation in such contexts (Aldy and Stavins 2009, Barrett 2003). 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, IPCC 2007 Chapter 10, Dutta and Radner 2009). 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.[1]

This study contributes to the growing literature on international treaties for climate change mitigation by providing insights from experimental laboratory. We use controlled laboratory experiments to investigate the likely behavior of parties and overall welfare implications in the presence of dynamic externalities. Experimental methods have proven extremely useful in evaluating alternative policy instruments, particularly those that are prohibitively costly to test in the field (Eckel and Lutz, 2003). A growing experimental literature indicates that appropriately designed and tested economic mechanisms 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 and Carl, 1999; Cason, 2003) or national (Holt et al. 2007) aspects of the problem, while our research focuses on the global (international) and dynamic long-term aspects.

Our experiment compares games with dynamic externalitites played by multiple generations of decision makers and games played by long- (indefinitely-) lived decision makers. We investigate the differences in strategic interactions brought in by the differences in the inter-

[1]Extensive literature in political economy indicates that politician's actions are largely motivated by the their incentives to be reelected, and that the success of such reelections is predominantly determined by current economic performances; e.g. Fiorina 1981. This may lower efforts to reduce risks of natural disasters and potentially catastrophic impacts of climate change as their low frequency or futureness "tends to lessen incentives for politicians to invest in prevention, as the expected political benefits of investing, or the drawbacks of failing to invest, might not occur during a political mandate" (Charvériat 2000, p.68).

temporal structure, and the implications for overall dynamic efficiency. We observe that whereas socially optimal outcomes are often achieved and sustained by long-lived players in the simple environment we study, achieving dynamic efficiency becomes a lot more challenging in the presence of multiple generations of decision makers, and the observed action paths become more myopic. We further use a unique experimental design to identify and disentangle two distinct sources of difficulties brought in by the inter-generational aspect: limited incentives for caring for the future, and increased inconsistency of actions and beliefs about the others' actions. While the former difficulty comes from the dynamic-externality nature of the problem, the latter is due to increased strategic uncertainty about the followers' actions, a feature brought in by the inter-generational aspect. Finally, we investigate the role of access to history and inter-temporal advice on decision makers' actions and outcomes.

The unique contribution of this paper can be summarized as follows. First, we compare, in a unified framework, dynamic-externality games across the long-lived and the inter-generational settings, which allows us to distinguish the features of the outcomes that are brought in by the dynamic-externality aspect from those that are due to the inter-generational aspect. In contrast, the majority of theoretical studies investigate dynamic strategic interactions by infinitely-lived players or countries (e.g. Dockner et al. 1996, Dutta and Radner 2004, 2009, Hårstad 2012; see Long 2011 for a review). Only a few recent theoretical studies focus on the strategic interactions among generations of different players and characterize the Markov perfect equilibrium outcomes (e.g. Karp and Tsur 2011), where each generation is treated as a single player and thus strategic interactions within each generation are absent. Among experimental studies, some address the problem in a long-lived setting (Herr et al. 1997; Pevnitskaya and Ryvkin 2013) while others consider the problem as an inter-generational game (Chermak and Krause 2002; Fischer et al. 2004).[2] To the best of our knowledge, no study has compared the two settings within a unified framework. In addition, unlike most previous studies, we consider the dynamic externality problem in a more realistic infinite-horizon setting by applying a random continuation method (Roth and Murnighan 1978; Dal Bo 2005). This method has been increasingly used in economic experiments to induce proper motivation in infinite-horizon repeated game settings, but has been rarely applied to dynamic externality games (see Vespa 2013 and Pevnitskaya and Ryvkin 2013 for two exceptions).

Our second contribution is to disentangle difficulties that may arise in inter-generational settings into two types: (i) difficulties arising due to decision makers' limited caring about the future, and (ii) difficulties due to other elements of the inter-generational setting that may exist within chains of decision makers when their monetary payoffs induce inter-generational caring. As an example of the latter, a decision maker may doubt the benefits of adopting

[2] Herr et al. (1997) study static and dynamic externalities in the commons using finite-period common pool resources (CPR) games with long-lived players, and find that the tragedy of commons is exacerbated in the dynamic externality setting due to the subject myopic behavior. Pevnitskaya and Ryvkin (2013) report a strong effect of environmental context. Chermak and Krause (2002) study the dynamic CPR problem in a finite-horizon overlapping generations setting, and report that in a number of cases groups depleted the resource prior to the terminal period. Fischer et al. (2004) investigate altruistic restraint in an inter-generational CPR setting. They report that the subjects in their study expected others to care about the future generations, but showed little evidence of inter-generational concerns in own actions. Other studies suggest that subjects may exhibit future-regarding behavior even in an inter-generational setting. For example, Van der Heijden et al. (1998) find a substantial degree of voluntary transfers across generations of players in a finite-horizon pension game experiment.

a long-sighted policy because of uncertainty about whether his policy recommendations will be followed in the future by the followers. No previous study considers difficulties beyond the lack of direct motivation. For example, Fischer et al. (2004) consider whether caring exists due to purely altruistic motives, and finds limited evidence of it. We find that the lack of direct motivation and the lack of consistency between actions and beliefs both play a role in making inter-generational players more myopic than long-lived players. This suggests the need for inducing long-term motivation for the real-world decision makers, and for ensuring that environmental policies are dynamically consistent, even if they are to be implemented over time by different decision makers.

The third important contribution of this paper is consideration of the range of instruments that are being discussed as possible means to help resolve the climate change mitigation problem—in particular, raising the awareness through access to information, history, and recommendations by the scientists and policy makers. We give the subjects in our experiment access to information about the consequences of their actions, history and advice from previous generations to enhance the possibility of sustaining dynamically optimal outcomes in our dynamic externality setting. In this respect, our paper builds upon and adds to the existing literature on social learning and inter-generational advice in recurring games (Schotter and Sopher, 2003; Ballinger et al. 2003; Chaudhuri et al. 2006). These studies suggest that social learning is an important determinant of the dynamic paths. We document the effect of information and social learning in dynamic externality games, a class of games that is arguably more complex than recurring (or repeated) games.

We find that emphasizing the dynamic externality aspects of the problem to the decision makers makes their actions somewhat future-regarding even in the absence of direct financial incentives to care about the future. This suggests the need to persistently inform and remind decision makers and the public at large about the future environmental consequences of their current actions. Regarding social learning, we find that learning through access to history and advice can be very effective in the long-lived setting, as advice is used as a communication device between decision makers. In inter-generational settings, advice from previous generations may improve dynamic efficiency, but it may also lead to persistent myopia. This finding points to the danger of current myopic policies persisting into the future through social learning channels.

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

Given that the prior evidence of cooperation in dynamic externality settings is limited, we choose a relatively simple setting with no underlying uncertainty about the dynamic externality, and no asymmetry in decision makers' costs and benefits from cooperation.

We first model dynamic externality games with infinitely-lived decision makers, representing an idealistic setting where the countries' governments are long-lived and therefore motivated by long-term welfare for their countries. The underlying model is very similar to the one developed by Dutta and Radner for infinitely-lived players (2004, 2009). We then discuss how the model may be extended to multiple generations of governments in each country. This represents a more realistic setting in which the countries' governments are relatively short-lived, but the effects of their present actions are felt far into the future.

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 $x_{it} \in [0, \bar{x}_i]$, where $\bar{x}_i > 0$ is the maximum feasible emission level. Countries' emissions influence the stock of pollution S, which evolves across periods according to the following equation:

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

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

Country i's period-wise return, 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 quadratic benefit function $B(x) = ax - \frac{1}{2}cx^2$. The damage function satisfies $D_i' > 0, D_i'' \geq 0$. Following Dutta and Radner, we assume a linear and common 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:

$$\max \sum_{t=0}^{\infty} \sum_{i=1}^{N} \delta^t \pi_i(x_{it}, S_t) \quad \text{subject to the constraints (1), (2).} \tag{3}$$

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 the social discount factor is set equal to one, $\delta = 1$. 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 country 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.[3] 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

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

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 is an 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 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 inter-generational 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.

3 Experimental design

The experiment is designed to study decision makers' behavior and overall performance in dynamic externality games, and to consider how the games evolve with infinitely-lived players as compared to generations of short-lived players.

Overall design Dynamic externality games are modeled as discussed 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 the subject), given information about the current payoffs from own token choices, and the effect of group token choices on future series' (generations') payoffs.[4] The payoffs were given in a tabular form, as illustrated in Figure 1.

FIGURE 1 AROUND HERE

Each 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

[4] 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 the next series' stock. 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.

the underlying GHG stock increases.[5] 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 a 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_1 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.

[5]The period-wise payoffs of player i in series t, given their emission level x_{it}, were calculated as $\pi_i(x_{it}, S_t) = B_i(x_{it}) - D_i(S_t) + K$, with the benefit function $B(x) = ax - \frac{1}{2}cx^2$, the damage function $D(S_t) = dS_t$, and the evolution of stock $S_{t+1} = \lambda S_t + X_t$. We used the following parameter values: $a = 208$, $c = 13$, $d = 26.876$, $K = 424.4$, $\lambda = 0.3$. The token choices τ_{it} were translated into emission levels x_{it} using the the linear transformation $x_{it} = 2\tau_{it} + 2$. Series 1 stock was set at the first-best level $S_1 = 42.86$. The payoff levels as given in Figure 1 were negatively related to the stock. The Experimental Instructions (available in Appendix A) explain the payoff level as follows: "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... The payoff level in the next series will depend on your group's total token order in this series."

Each chain continued for several series (generations). To model an infinitely repeated game and eliminate end-game effects, we used a random continuation rule. A randomization device (a bingo cage) was applied after each series (generation) to determine whether the chain continues to the next series. The continuation probability induces the corresponding discount factor in the experimental setting; the random continuation 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 between series was set at 3/4, yielding the expected chain length of four series. This induced the corresponding discount factor $\delta = 0.75$.

Treatments There are three experimental treatments which differ in whether the dynamic game is played by the same or by different groups of participants across generations, and in how the participants are motivated in the inter-generational setting.

(1) 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 baseline 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.[6] 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 be theoretically the same as in the baseline LL treatment. This treatment allows us to investigate whether the subjects restrain their emissions in the inter-generational setting as much as in the long-lived setting when they are fully motivated (by monetary incentives) to care about the future.

Beliefs and advice For dynamic problems such as climate change mitigation, beliefs about others' behavior, knowledge of history and social learning may play a significant role. Histories of past actions, opinions and recommendations of scientists and policy makers could

[6] Unlike experimental studies on inter-generational advice in recurring games without random termination, such as Chaudhuri et al. (2006), our experimental design does not permit partial weights on future generations' payoffs, 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 also creates the present generation bias, as demonstrated in Sherstyuk et al. (2013). Making a subjects' payoff depend on own concurrent payoff and only the immediate follower's concurrent payoff creates incentives for myopic advice.

be made available to the public and to the future generations.

Our experimental design allows us to study the effect of beliefs, advice, and access to history on subject behavior across treatments. First, subjects' expectations about the others' choices are solicited, and the subjects are induced with monetary payoffs (as in, e.g., Van Hyuck et al. 1990) to submit accurate predictions. Further, at the end of each series each subject is 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, is then passed on to all subjects in the group in all of the following series (generations). See Appendix A, Experimental Instructions.

Procedures The experiments were computerized using z-tree software (Fischbacher, 2007). Several (up to three) independent groups of three subjects each participated in each experimental session. Each group in a session corresponded to an independent chain. In the baseline LL sessions, the same groups of subjects made token decisions in all decision series carried out within the same session. 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.

In all treatments and sessions, the subjects went through training before participating in paid series. The training consisted of: (a) 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. This practice was necessary to allow the subjects an opportunity to learn through experience the effect of dynamic externalities on future payoffs.[7] In addition, during each decision period the subjects had access to a payoff calculator which allowed them to evaluate payoff opportunities for several series (generations) ahead given token choices 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 treatments. The exchange rates were set at \$100 experimental = US \$0.5 in the LL and IL treatments, and \$100 experimental = US \$2 in the IS treatment, to equalize expected payoffs across treatments.[8] The average payment per subject was US \$28.90, including \$10 training fee.

4 Results

4.1 Overall comparison of treatments

The total of 162 subjects participated in the experiment. Four to six independent chains of groups of subjects were conducted under each of the baseline LL, inter-generational IS and inter-generational IL treatments. Each chain lasted between 3 and 9 series (generations). Table 1 lists the duration of each chain, along with average group tokens, stock and average

[7]We felt that such 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.

[8]The exchange rates differed across treatments because the participants were paid for all series in a chain in LL and IL treatments, but only for one series in IS treatment.

recommended group tokens by treatment. Figure 2 illustrates the evolution of group tokens (top panel), corresponding stock levels (middle panel) and recommended group tokens (bottom panel) for each chain, grouped by treatment.

TABLE 1 and FIGURE 2 AROUND HERE

We focus on the group tokens and the corresponding stock levels first, and discuss recommended tokens later. Figure 2 suggests the group tokens evolved differently across treatments. 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 levels. In contrast, group tokens in the IS and IL treatments were considerably higher. The mean group token value in LL was 13.56 and not significantly different from the FB level of 12. This compares to the mean group token level of 18.00 in IS, which is right at the MP prediction. The mean group token value in IL was significantly more variable across chains, with a mean of 15.28, 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.

Comparison of chain averages (Table 1) is suggestive of differences across treatments. However, 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 over 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. We apply the following model (adopted from Noussair et al. 1997) to analyze the effect of time on the outcome variable y_{it} (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, $N = 15$ 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, whereas B_{LL}, B_{IS} and B_{IL} are the treatment-specific asymptotes for the dependent variable. Thus we allow for a different origin of convergence process for each chain,[9] but estimate common, within-treatment, 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 Table 2. Along with listing the estimated asymptotes for each treatment, the table also displays p-values for the test of their equivalence to the four theoretical benchmarks: Sus, FB, MP and MN.

TABLE 2 AROUND HERE

The regression results are very clear. While the group tokens in the LL treatment converge to 11.98, which is not significantly different from the FB level of 12 ($p = 0.9613$), the group tokens in the IS treatment converge to 18.48, which is not significantly different from the MP level of 18 ($p = 0.4454$), but is nevertheless below the MN level of 21. The group tokens

[9]For the stock level, we estimate a common origin for all chains, as the initial stock was set at the FB level in all treatments.

in the IL treatment converge to 15.27, which is above the FB level of 12 but below the MP of 18. The stock converges to the level above FB but below the MP in the LL treatment. In contrast, it converges the MN level in the IS treatment ($p = 0.8062$), and to the MP level in the IL treatment ($p = 0.6662$). We conclude the following.

Conclusion 1 *In the Long-Lived (LL) treatment, groups of subjects were able to avoid myopic decisions, with group tokens converging to the First Best levels, and stock converging to a level below the non-cooperative predictions. In contrast, in the Intergenerational Selfish (IS) treatment, group tokens and stock levels were converging to non-cooperative (Markov Perfect or Myopic Nash) benchmarks. Chains in the Intergenerational Long-sighted treatment exhibited dynamics in between the LL and the IS treatment.*

We next consider the evolution of group advice across treatments as an indicator of group dynamics. Table 1 suggests that while the average number of recommended group 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 number of recommended tokens for a group averaged 12.55 (16.62, 13.63) in the LL (IS, IL) treatment. Evolution of recommended group tokens by treatment suggests that recommended tokens in each treatment and chain followed a trend similar to that of actual tokens (Figure 2, bottom panel). The regression analysis of recommended group tokens presented in the right-most columns of Table 2 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 11.55, which is not different (at 5 percent level) from the FB level of 12 ($p = 0.072$). The recommended tokens asymptote in the IS treatment was

17.51, which is not different from the MP level of 18 ($p = 0.3575$). Finally, the recommended tokens asymptote in the IL treatment was 14.51, 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 the First Best level, IS recommended tokens converging to the Markov Perfect level, and IL recommended tokens converging to above the First Best but below the Markov perfect level.*

It is also informative to see how the verbal advice evolved. In the LL treatment, verbal advice was passed from one series to the next by the same group of subjects. In contrast, in the inter-generational treatments, advice was passed from predecessor groups to the follower groups in a chain. Table 3 lists examples of verbal advice for LL (Chain 2), IS (Chain 4) and IL (Chain 4) treatments.[10]

TABLE 3 AROUND HERE

The table illustrates 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. In fact, 72% of recommendations in LL were at the FB level of 4 tokens per person or lower, and only 3% of advices were at 7 tokens or higher. The evolution of advice in the IL treatment indicates that in this treatment as well, some chains of subjects tried to use advice to coordinate on a cooperative action path (40% of all recommendations at 4 tokens or lower); however, many advices were above the First Best levels (60% total, including 17% at 7 tokens or higher). In contrast, as evident from

[10]Complete scripts of advices given in these chains are presented in Appendix C.

Table 3, in the IS treatment, attempts by individual subjects to convince the followers to cut down their tokens were scarce and largely unsuccessful. Only 21% of recommendations in the IS treatment were at the FB level of 4 tokens per person or lower, and 39% of advices were at 7 tokens or higher. We conclude:

Conclusion 3 *Verbal advice was used as an effective communication device that 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.*

Our results so far demonstrate clear differences between all three treatments. All groups of subjects in the Long-Lived (LL) treatment were able to avoid the myopic Nash outcome and come close to the First Best group tokens levels. In contrast, in the inter-generational treatments, cooperation among subjects within and between generations was less successful. In the Intergenerational Selfish (IS) treatment, group dynamics were converging to non-cooperative Markov Perfect levels, and individual advices were often myopic. It is notable, however, that the behavior did not evolve all the way towards the Myopic Nash prediction, with group tokens converging to lower than Myopic Nash level. This indicates that making the participants aware of their effect on the followers had some impact on their behavior even in the absence of direct monetary incentives to care about the future.[11] This evidence of other-regarding preferences is consistent with the existing literature (e.g., Charness and Rabin 2002), and further suggests the importance of making the decision makers aware of

[11] For example, Participant 4 in Series 4 in IS Chain 4 advises: "Never go beyond 5 to save your future generations;" see Table 3.

the long-term effects of their actions. However, it is also clear that in the IS treatment these other-regarding preferences were largely overruled by myopic incentives.

The evidence from the Intergenerational Long-sighted treatment is less clear-cut. 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.

This evidence suggests that achieving the long-term First Best solution in an inter-generational setting is a lot more challenging than in the long-lived setting even if the decision makers are fully motivated to care about the future. A possible reason is an increased difficulty in coordinating actions among subjects in the inter-generational context. In the next section, we take a closer look at this issue by analyzing the relationship between individual actions and expectations of others, and individual actions and advice, across treatments.

4.2 Individual behavior: comparing actions, beliefs and advice

Comparing actions with expectations and advices on individual level helps uncover the reasons behind individual choices, and thus explain observed differences between the treatments.

FIGURE 3 AROUND HERE

Figure 3 plots the dynamics of differences between own token choice and the expectations of the other subjects' choice (panel A) and the difference between the token choice and the advised token level (panel B), by treatment. Again we see a contrast across treatments. Under LL, own token choices tend to be below the expectations of the other subjects' tokens (by 0.07 tokens, on average), and own tokens decrease relative to expectations in later series.

In series 4 and later, own tokens are below the expectations of others by an average of 0.14 tokens. Under IS, the actions are slightly above the expectations of others (by 0.18 tokens, on average), but this is not significantly different from what we observe under the LL treatment ($p = 0.435$, t-test). In contrast, under the IL treatment, the actions exceed the expectations of others by 0.40 tokens, on average; the difference between LL and IL treatments is statistically significant ($p = 0.024$). Comparing own actions with advice given to the followers, on average actions exceed advice in all treatments (Figure 3, panel B). The difference between own actions and advice decreases in later series, but stays the highest under IL. The average difference between actions and advice in series 4 and later is .24 tokens under LL, 0.2 tokens under IS, and 0.62 tokens under IL.

The same phenomena are evident if we allow for heterogeneity in behavior among individuals. Regarding own actions and beliefs about the others, we classified all experimental participants into those who mostly (in 50% or more of all cases) choose actions below expectations, mostly above expectations, or neither. Likewise, regarding own actions and advice to the future, we classified all experimental participants into those who mostly (in 50% or more of all cases) choose actions at or below advice they give, and those who mostly choose actions above advice. The results are presented in Figure 4.

FIGURE 4 AROUND HERE

Under LL, the majority (72%) of the subjects mostly choose token levels that are at or below the levels that they expect the other subjects to choose; moreover, 33% of subjects mostly choose tokens strictly below what they believe the others will do. Under IS, 75% of the subjects mostly choose tokens that are at or below their expectations of others, but fewer

(25% of subjects) choose tokens strictly below their beliefs. This contrasts with IL, where the majority (53%) of subjects mostly chose actions above their expectations of others. The difference between LL and IL treatments is significant ($p = 0.0096$, Fisher's exact test). Similarly, the majority of subjects under LL and IS (72% and 67%, respectively) choose tokens that are at or below what they advise their followers to choose. The opposite is the case under IL, where 53% of the subjects mostly choose tokens above the levels they advise to the followers. The difference between LL and IL is again significant ($p = 0.0096$).

These data suggest that under LL, many people are willing to take a lead and be the first to cut down their tokens. Under IS, overall, people's own actions, expectations of others, and advice to the followers closely match each other: the subjects expect the others to choose tokens at non-cooperative levels, and do so themselves. In contrast, under the IL treatment, the subjects exhibit "optimistic free-riding" (Fischer et al 2004), when they choose higher tokens than what they believe their contemporaries choose, and what they advise to their followers (see also Table 3, IL Chain 4, Series 7, advice by Subject 3.)[12] We conclude:

Conclusion 4 *A significant number of people under the long-lived treatment (LL) are willing to "take a lead" in cutting down tokens, even though they expect others to choose higher tokens. Under the Intergenerational Short-Sighted treatment (IS), most people choose high*

[12]Fischer et. al. (2004) report such optimistic free-riding, relative to expectations of others, in their intergenerational experiment. Fischbacher and Gächter (2010) report that a similar behavioral phenomenon is typical to repeated public goods experiments without communication: "...On average, people are 'imperfect conditional cooperators' who match others' contributions only partly..." (p. 542). Cooperation in our Long-Lived treatment is close to "perfect conditional cooperation" (a close match between own actions and expectations of others), which is most likely due to the presence of communication in the form of advice.

token levels themselves, expect the others to do so, and recommend non-cooperative token levels to the future. Under IL, many people expect the others to choose fewer tokens, and advise the followers to choose fewer tokens, than they do themselves. This inconsistency of actions, beliefs and advice is the highest under IL as compared to the other two treatments.

To gain an extra insight into these differences among treatments, we formally analyze the verbal content of advices. We had two decoders independently classify the verbal comments into the following broad categories as the reasons that explain the corresponding subjects' advice: pursuing "Own long-term interest," "Own short-term interest," and "Best for self and others," along with "No reason specified." The stated reasons and the advised token levels correlate differently across treatments. As Figure 5 indicates, "Own short-term interest" is hardly used as a reason, except in rare cases under IS. "Best for self and others" is the most prevalent reason given under IS (32% of all advices), while "Own long-term interest" is the modal reason given under both LL and IL (21% and 31% of advices, correspondingly). An interesting insight is gained by looking at the advised token levels by the subjects who state "Own long-term interest" as the reason, as displayed in Figure 6.

FIGURES 5, 6 AROUND HERE

Under LL, most such participants give advices consistent with cooperative First Best outcome, i.e. 4 tokens or less. In contrast, under IL, most such participants give advices consistent with non-cooperative Markov Perfect equilibrium, i.e. 5 to 6 tokens. Apparently, the subjects in the two long-sighted treatments advise different token levels even when the suggested reason is the same (long-term interest), and the subjects' payoff interests are also theoretically the same. What is different between the LL and IL treatments is strategic uncertainly about the follower's actions, which is absent under LL, but exists under IL because of the inter-generational setting. This uncertainly may induce the subjects under IL choose and advise higher token levels than under LL.

Conclusion 5 *"Best for self and others" and "Own long-term interest" are the two most popular reasons for the given advice in all treatments. The subjects using "Own long-term interest" reason advise the First Best cooperative actions to their followers under the Long-Lived treatment (LL), but higher non-cooperative actions under the Intergenerational Long-Sighted treatment (IL).*

The above evidence suggests that increased strategic uncertainty created by the inter-generational setting is the most likely explanation for the differences in behavior between the LL and IL treatments. As the subjects under the LL treatment interact with the same group of people in every series, they can rely more on consistent actions across generations. Thus many subjects find it worthwhile to choose cooperative token levels themselves, and convince the others to do so in the future. In contrast, new groups of subjects make choices in each series of the IL treatment, and therefore the subjects under IL are less certain about their contemporaries' and followers' behavior. As one may not trust the others to make long-sighted decisions, one oneself may take a safer, more myopic action. Conclusions 4 and 5 show that, indeed, many subjects under IL choose to act more myopically than what is dynamically optimal, and some advise the followers to do so as well.

5 Discussion

Our experimental study of a game with dynamic externalities investigated how strategic interactions among players differ in an inter-generational setting as opposed to an infinitely-lived setting. We compared three treatments: "Long-Lived" where the dynamic game is played by the same group of subjects; "Inter-generational Long-Sighted" where the game is played by generations of different subjects whose payoff functions are the same (in experimental dollars) as in the Long-Lived treatment; and "Inter-generational Selfish" where the subjects' payoffs do not depend on the payoffs of subjects in other generations. This research design allowed us to identify and disentangle two sources of inefficiency in dynamic collective actions: one due to the public-good nature of emissions reduction, and the other due to the inter-generational aspect—i.e., increased strategic uncertainty about the other players' actions brought about because the players change across generations. While the former aspect has been well known and extensively researched, the latter has been under-investigated. Our research brings the latter to attention, thereby addressing how strategic uncertainty influences the players' actions, their beliefs about the others' actions, and their advice toward the future generations of players.

Our experimental results indicate that in the Long-Lived treatment of our experiment, the subjects were able to achieve and sustain the cooperative First Best group outcomes; thus, in an ideal world with long-lived governments who are in recurring communication with each other, dynamically optimal environmental policies could be established and successfully pursued. In contrast, in our Intergenerational Selfish treatment, non-cooperative behavior evolved and persisted across generations; participants chose non-cooperative levels of emissions themselves, and advised the followers to do likewise. This implies, not surprisingly, that international dynamic enforcement mechanisms (treaties) would be necessary for controlling GHG emissions and avoiding non-cooperative outcomes if the countries' governments change from generation to generation and are not explicitly motivated by the futures' welfare. The evidence from the Intergenerational Long-sighted treatment contrasts with both Long-Lived and Intergenerational-Selfish treatments. Some chains in the IL treatment were converging to cooperative emission and stock levels, while others stayed at non-cooperative levels. Thus, if the government are short-lived but long-sighted, as was the case in our Intergenerational Long-sighted treatment, cooperation among countries and across generations may occur but is less likely than with long-lived governments.

A major, and often disregarded obstacle in achieving the cooperative dynamic paths in the inter-generational settings is strategic uncertainty about the follower's actions. Such uncertainly is present even if the decision makers are motivated by a common long-term welfare goal, but change from generation to generation, as was the case in our Intergenerational Long-sighted treatment. As decision makers could not rely on their followers to carry out their long-term plans of actions under IL in the same way they could rely on themselves under the Long-Lived treatment, they themselves chose safer, more myopic actions. Thus the IL treatment was characterized by higher than the LL treatment average emissions and advices, and by the highest, among all treatments, inconsistency of own actions, beliefs about others' actions, and advices given to the followers. In particular, optimistic free-riding — subjects choosing higher emission levels than they expected the others to choose, and advised their followers to choose — was present under the IL treatment to a higher degree than under the other two treatments. These results point to the importance of inducing long-term motivation for the real-world decision makers, and of ensuring that environmental policies are dynamically consistent across generations of decision makers.

Our experimental results further document the presence of some inter-generational caring among experimental participants even in the absence of direct monetary incentives to care about the future. While the behavior under the Intergenerational Selfish treatment was predominantly non-cooperative, it did not converge all the way to Myopic Nash prediction, as one would expect in the absence of inter-generational caring. This suggests that it is important to make the decision makers (and the general public who may influence the decision makers' actions) aware of the long-term consequences of their actions, and to expose them to the history of previous actions and outcomes.

Finally, our experiments once again demonstrate the role of inter-generational learning thorough history and advice. Verbal advice was used as an effective communication device that helped the participants to coordinate on cooperative outcomes in the Long-Lived treatment, and it also helped to coordinate behavior across generations in the inter-generational treatments. However, as evidenced by the Inter-generational Selfish treatment, in the absence of direct incentives to care about the future, the inter-generational advice often led the participants to coordinate on non-cooperative emission paths.

These findings indicate that caution is necessary when interpreting studies on long-run dynamic externalities where the players are assumed to be infinitely-lived. While in the Long-Lived treatment the subjects chose emission levels lower than the benchmark non-cooperative level (the Markov perfect equilibrium level), the inter-generational setup resulted in higher emission levels. Our findings also indicate that mechanisms to reduce strategic uncertainty would be necessary to enhance collective action in long-term dynamic externality issues.

Future research could address such mechanisms for inter-generational games.

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Table 1: Experimental Summary

Treatment	Chain	No of series	Group Tokens* Mean (Stdv)	Stock* Mean (Stdv)	Advised Group Tokens* Mean (Stdv)
LL	1	7	14.86	51.14	14.29
			(4.10)	(9.31)	(2.50)
LL	2	5	15	48.93	13.4
			(4.24)	(8.08)	(2.30)
LL	3	5	11.6	41.57	11.2
			(3.05)	(5.81)	(1.10)
LL	4	9	11.89	42.69	11.44
			(2.15)	(3.79)	(1.51)
LL	5	8	13.63	47.96	13.63
			(2.50)	(4.94)	(1.92)
LL	6	8	14.38	48.71	11.38
			(2.88)	(3.15)	(0.74)
LL all	**mean**	**7**	**13.56**	**46.83**	**12.55**
	(stddv)	**(1.67)**	**(1.87)**	**(3.81)**	**(1.36)**
IS	1	5	14.4	48.4	13
			(2.88)	(5.97)	(4.76)
IS	2	4	20	58.96	1.67
			(1.41)	(11.02)	(1.53)
IS	3	5	18.2	55.44	15.8
			(1.48)	(7.52)	(1.92)
IS	4	5	19.4	57.67	18
			(0.55)	(8.77)	(1.87)
IS all	**mean**	**4.75**	**18**	**55.12**	**16.62**
	(stddv)	**(0.50)**	**(0.97)**	**(4.71)**	**(1.50)**
IL	1	6	17.67	56.3	16.17
			(2.42)	(7.43)	(2.56)
IL	2	6	17.5	55.85	15.17
			(2.35)	(8.14)	(1.60)
IL	3	7	13	44.6	11.29
			(1.83)	(3.41)	(2.06)
IL	4	7	17.57	54.96	16.71
			(1.27)	(6.29)	(1.60)
IL	5	3	10.67	37.39	9
			(3.79)	(4.74)	(4.58)
IL all	**mean**	**5.8**	**15.28**	**49.82**	**13.63**
	(stddv)	**(1.64)**	**(3.25)**	**(8.46)**	**(3.33)**

*Benchmark predictions are: Group Tokens: Sus=9, FB=12, MP=18, and MN=21;
Stock: Sus=34.3, FB=42.9, MP=60.0, and MN=68.6.

Table 2: Group tokens, stock and recommended group tokens: Convergence by treatment

Cross-sectional time-series generalized least squares estimation

	Group Tokens		Stock		Advised Group Tokens	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
Origin			42.57	(1.08)		
LL chain 1 origin	21.22	(1.63)			18.84	(0.99)
LL chain 2 origin	19.92	(2.26)			14.05	(1.93)
LL chain 3 origin	10.22	(2.33)			10.78	(0.74)
LL chain 4 origin	12.18	(1.83)			12.16	(1.10)
LL chain 5 origin	17.72	(1.22)			17.38	(0.93)
LL chain 6 origin	16.04	(1.46)			11.06	(0.58)
IS chain 1 origin	12.39	(2.76)			9.34	(3.10)
IS chain 2 origin	21.33	(0.92)			21.14	(0.49)
IS chain 3 origin	18.38	(1.23)			13.56	(1.02)
IS chain 4 origin	19.60	(1.15)			18.03	(1.40)
LL chain 1 origin	21.74	(0.71)			18.22	(1.65)
LL chain 2 origin	18.43	(2.09)			16.70	(1.04)
LL chain 3 origin	18.08	(1.60)			17.35	(1.87)
IL chain 4 origin	7.69	(1.83)			4.94	(1.44)
LL chain 5 origin	12.04	(2.15)			8.02	(1.97)
LL asymptote	11.98	(0.48)	49.91	(1.55)	11.55	(0.25)
IS asymptote	18.48	(0.63)	69.29	(1.59)	17.51	(0.53)
IL asymptote	15.27	(0.47)	59.03	(2.26)	14.51	(0.57)
Number of observations:	*90*		*90*		*90*	
AR(1) coefficient:	*0.0906*		*0.6029*		*-0.0874*	

Heteroskedastic Panels; Common autocorrelation AR(1) coefficient for all panels

*p-values for H0: Asymptote==Theoretical prediction**

IL asymptotes	Group Tokens	Stock	Advised Group Tokens
p-value: Asymptote=(Sus)	0.0000	0.0000	0.0000
p-value: Asymptote=(FB)	0.9613	0.0000	0.0720
p-value: Asymptote=(MP)	0.0000	0.0000	0.0000
p-value: Asymptote=(MN)	0.0000	0.0000	0.0000
IS asymptotes	**Group Tokens**	**Stock**	**Advised Group Tokens**
p-value: Asymptote=(Sus)	0.0000	0.0000	0.0000
p-value: Asymptote=(FB)	0.0000	0.0000	0.0000
p-value: Asymptote=(MP)	0.4454	0.0000	0.3575
p-value: Asymptote=(MN)	0.0001	0.8062	0.0000
IL asymptotes	**Group Tokens**	**Stock**	**Advised Group Tokens**
p-value: Asymptote=(Sus)	0.0000	0.0000	0.0000
p-value: Asymptote=(FB)	0.0000	0.0000	0.0000
p-value: Asymptote=(MP)	0.0000	0.6662	0.0000
p-value: Asymptote=(MN)	0.0000	0.0000	0.0000

*Benchmark predictions are: Group Tokens: Sus=9, FB=12, MP=18, and MN=21; Stock: Sus=34.3, FB=42.9, MP=60.0, and MN=68.6.

Table 3: Evolution of verbal advice, by treatment: extracts from participant advices

LL, Chain 2

Series	Subject	Advice
1	2	we started out really high this past one. maybe we can go lower for the next trials.
		…
2	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.
		…
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
4	3	The benefit from 4 to 5 is only a 100 point difference (50 cents) so let's stay with 4.
		…
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! …
5	2	...I don't know what to say now. We seem to be doing whats best.

IS, Chain 4

Series	Subject	Advice
1	4	For me I try to choose the tokens which has the highest payoff. My two friend choose the tokens are quite the same as me.
1	6	the next set you should choose a low amount of tokens so your payoff level will increase....
		…
2	5	The greatest payoff calculated against the results for the subsequent group is 6
2	6	for maxmin payoff for your series, but the payoff decreases for the later series
		…
3	6	choose 7
		…
4	4	never go beyond 5 to save your future generations
		…
5	5	for your own benefit, choose the maximal payoff, ie 7; the rest is not worth considering, it's just a diversion.
5	6	Get the most out of it NOW!

IL, Chain 4

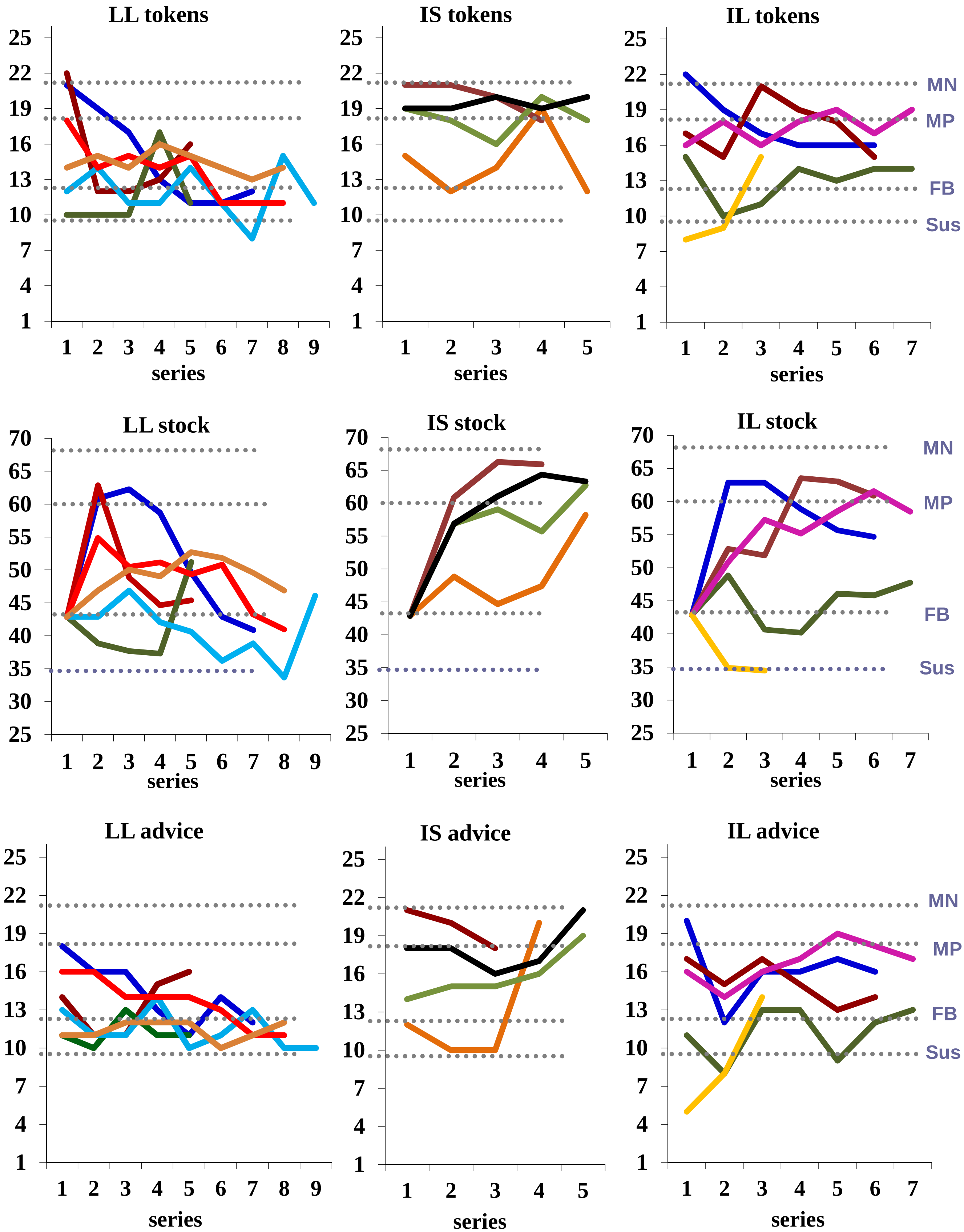
Series	Subject	Advice
1	1	PLEASE try either try 3 or 4...dont kill the group payoff, which will affect all of you when it continues further it will affect your individual payoff too…
	3	the lower the numbers, the higher the payoff in the later series
…		…
5	1	keep it at 3 or 4 please! if people get greedy, 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.
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.
		…
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)

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, stock and recommended group tokens, by treatment



Note: Each trajectory represents a different chain.

FIGURE 3: Actions relative to beliefs and advice

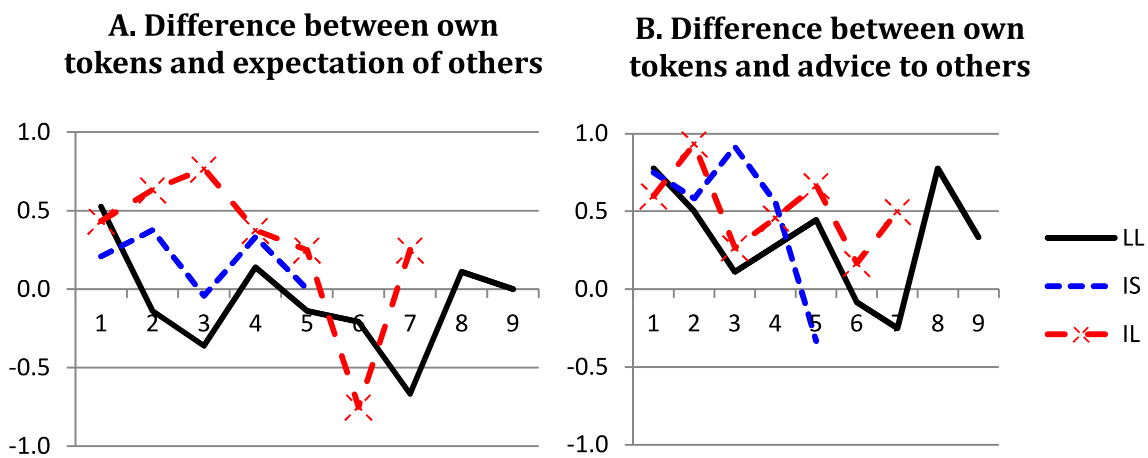


FIGURE 4: Percentage of individuals with 50% or more actions above or below (A) expectations and (B) advice, by treatment

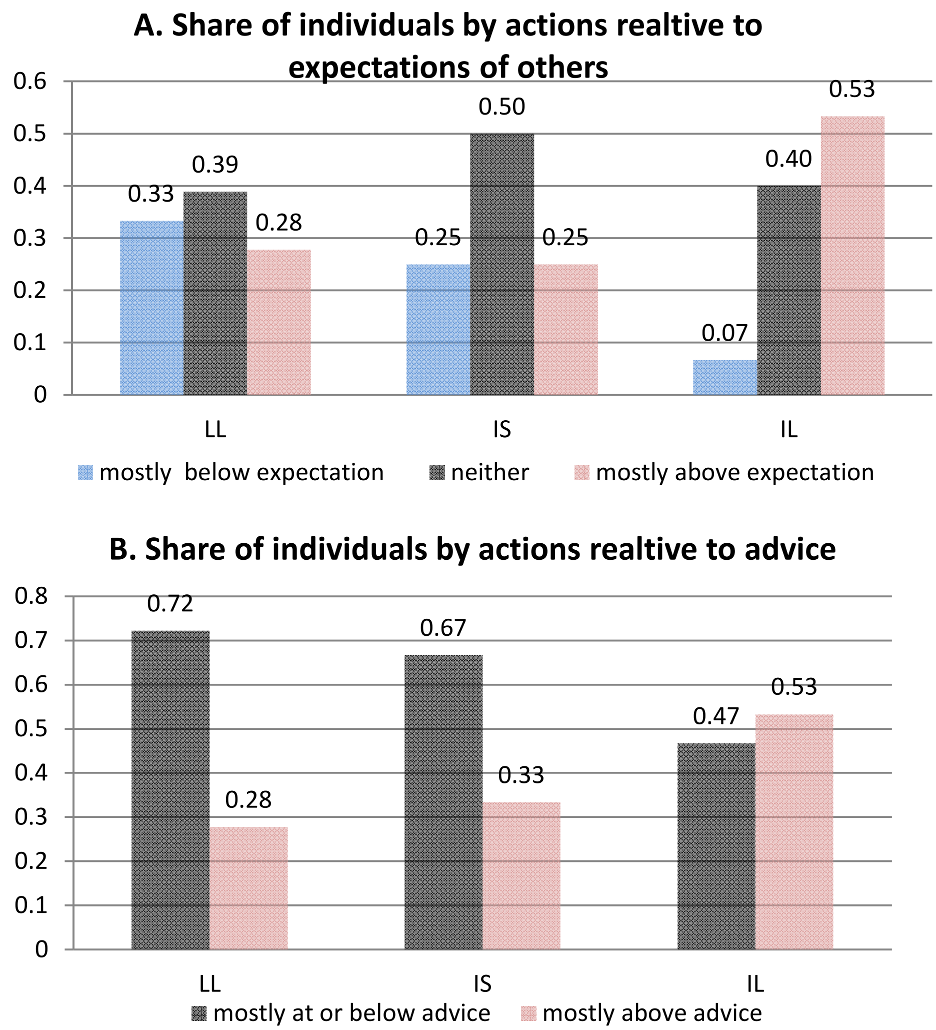


FIGURE 5: Share of verbal advice by reason

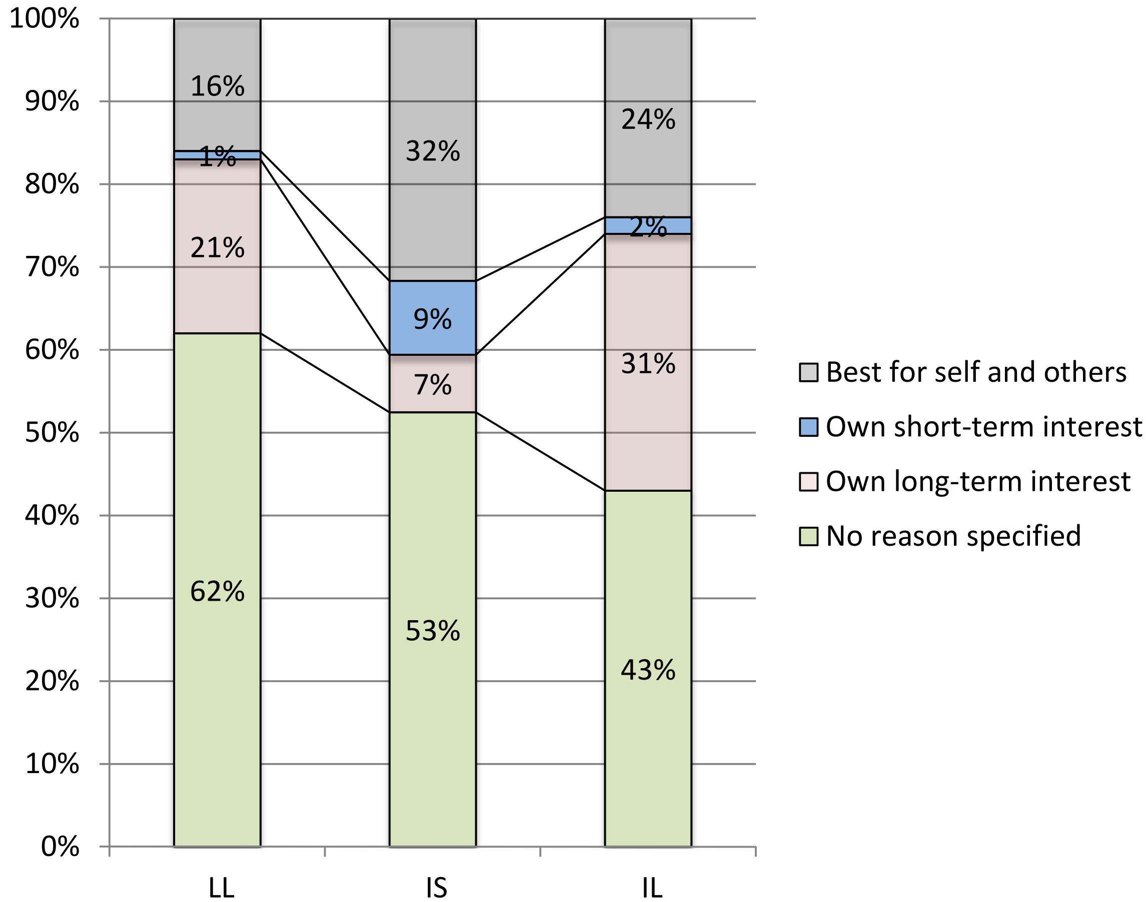
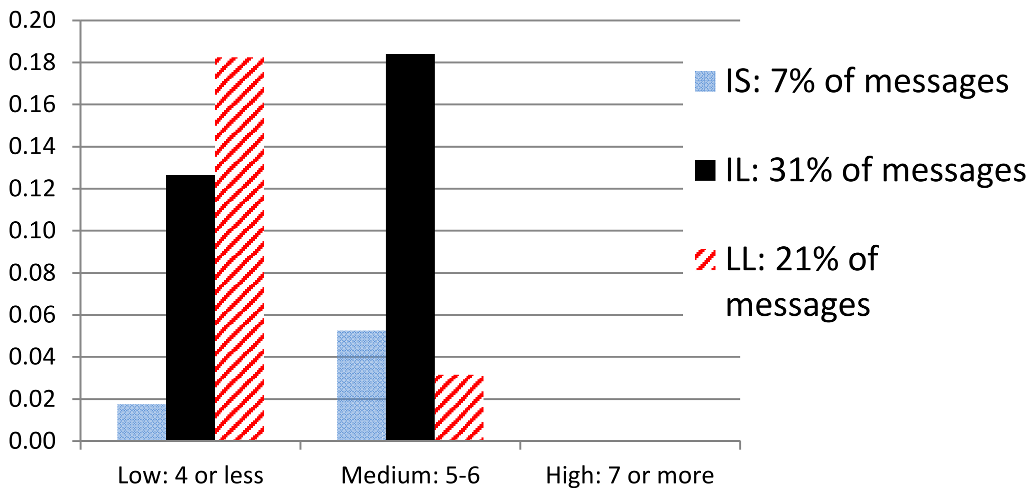


Figure 6: Distribution of token advice for subjects with "own long-term interest" reason.



Supplementary Materials

Appendix A: Experimental Instructions

Appendix B: Payoff Scenarios

Appendix C: Evolution of advice by treatment

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 between 1 and 6, then the experiment continues to the next series. If the die shows number 7 or 8, 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 10 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.

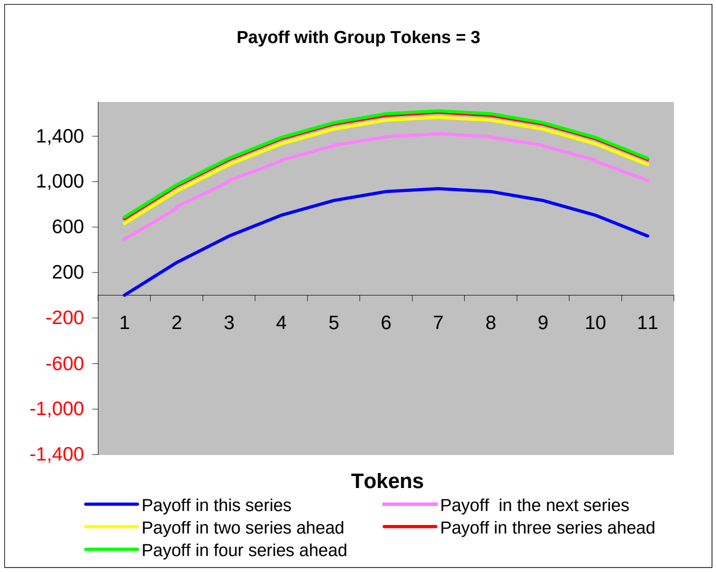
- How many series are there in this experiment?

  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

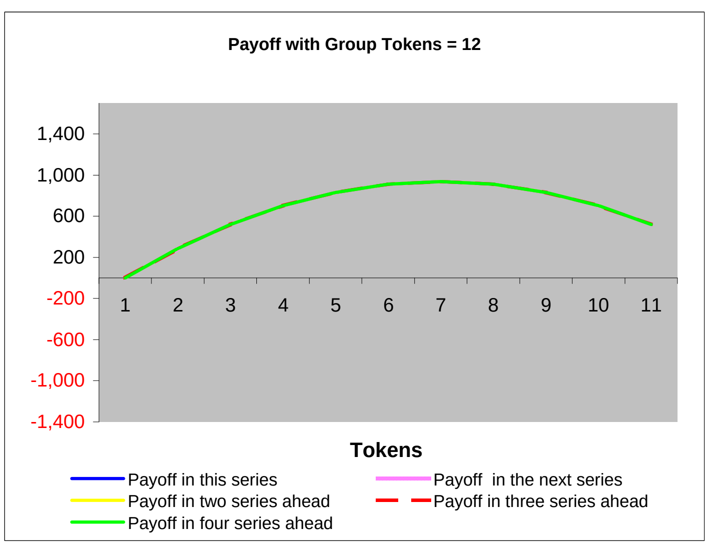
A1. Payoff with Group Tokens = 3 in each series

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

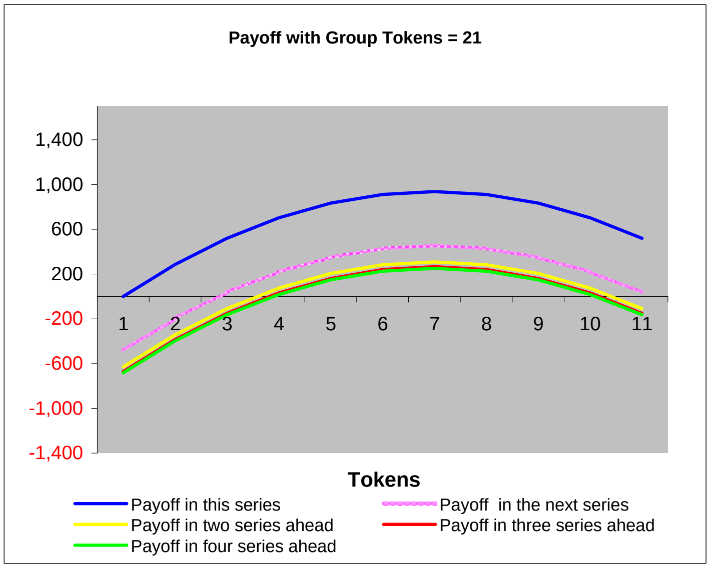
Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in two series ahead	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in three series ahead	1394	1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

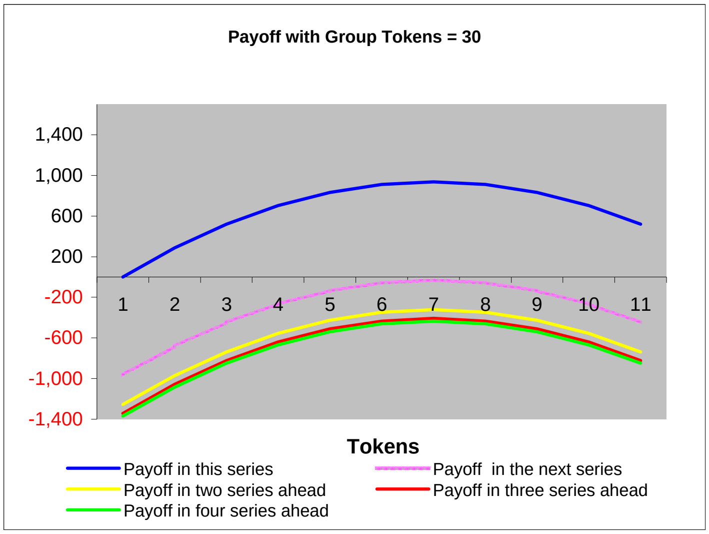
A3. Payoff with Group Tokens = 21 in each series

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



Appendix C: Evolution of advice by treatment

C1: 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.

C2: 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!

C3: 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)