KOCHI UNIVERSITY OF TECHNOLOGY

Social Design Engineering Series SDES-2014-14

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7th November, 2014

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Intergenerational Games with Dynamic Externalities and Climate Change Experiments (Running title: Intergenerational Games, Dynamic Externalities) *

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*This research was supported by the University of Hawaii College of Social Sciences research grant and the Grant-in-Aid for Scientific Research on Priority Areas from the Ministry of Education, Science and Culture of Japan. We would like to thank the Editor, two anonymous referees, Timothy Halliday, Emmanuel Vespa, Alistair Wilson, and participants of the Economic Science Association meetings for many useful comments and suggestions.

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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 intergenerational 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, increased strategic uncertainty of an intergenerational setting may lead to an increased inconsistency of own actions and beliefs about the others, making own actions more myopic. Intergenerational learning through history and advice from previous generations may improve dynamic efficiency, but may also lead to persistent myopic bias.

Key words: economic experiments; dynamic externalities; intergenerational games; climate change

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 the experimental laboratory. Experimental methods have proven extremely useful in helping to alleviate environmental problems and providing 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, or do not consider the intergenerational setting (Pevnitskaya and Ryvkin, 2013). In contrast, our research focuses on the global (international) aspects where collective action by sovereign nations is called for, and the dynamic aspects where collective action has a long-term and intergenerational dimension. We use a controlled laboratory experiment to compare games with dynamic externalities 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-temporal structure, and the implications for overall dynamic efficiency.

We focus on the following research questions in this study. Can dynamic efficiency be

[1]Extensive literature in political economy indicates that politician's actions are largely motivated by 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).

achieved in dynamic externality games? Do intergenerational games with dynamic externalities achieve the same outcomes as games with long-lived players? If not, are the differences solely due to the lack of motivation of short-lived players to care about the future? What other factors affect decision-making in an intergenerational setting? And, finally, do non-strategic instruments, such as raising player's awareness about future effects of own actions through access to information, history, and advice to the followers, make people's actions future-regarding?

The unique contribution of this paper can be summarized as follows. First, we bring to the forefront the intergenerational nature of the problem and compare, in a unified framework, dynamic-externality games across the long-lived and the intergenerational settings. This 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 intergenerational aspect. In comparison, 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); however, each generation is treated as a single player and thus strategic interactions within each generation are absent. Among experimental studies, some address the dynamic externalities problem in a long-lived setting (Herr et al. 1997; Pevnitskaya and Ryvkin 2013; Vespa 2013) while others consider the problem as an intergenerational game (Chermak and Krause 2002; Fischer et al. 2004).[2] Our

[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

contribution is to compare the two settings within a unified framework. 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.

Our second contribution is in identifying two distinct sources of difficulties brought in by the intergenerational aspect: (i) difficulties arising due to decision makers' limited caring about the future, and (ii) difficulties due to increased strategic uncertainty of the intergenerational decision-making. As an example of the latter, a decision maker may doubt the benefits of adopting a long-sighted policy because of uncertainty about whether his policy recommendations will be followed in the future. No previous study has considered the 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 use a unique experimental design that allows us to identify and disentangle distinct sources of differences, and find that both the lack of direct motivation and the lack of consistency

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 intergenerational CPR setting. They report that the subjects in their study expected others to care about the future generations, but showed little evidence of intergenerational concerns in own actions. Other studies suggest that subjects may exhibit future-regarding behavior even in an intergenerational 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.

between actions and beliefs play a role in making intergenerational 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 (non-strategic) instruments that are being discussed as possible means to help resolve the climate change mitigation problem. 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. Regarding advice, our paper builds upon the existing literature on social learning and intergenerational advice in recurring games (Schotter and Sopher, 2003; Ballinger et al. 2003; Chaudhuri et al. 2006), and extends it to arguably more complex dynamic externality 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 intergenerational settings, advice from previous generations may improve dynamic efficiency, but it may also lead to persistent myopic bias. This finding points to the danger of current myopic policies persisting into the future through social learning channels.

Section 2 below overviews the underlying theoretical model of games with dynamic externalities and defines theoretical benchmarks that are used to evaluate experimental results. Section 3 discusses our experimental design, and Section 4 presents the results. We discuss our conclusions and open questions in Section 5.

2 Theoretical model

Given that the prior evidence of cooperation in dynamic externality settings is limited, we choose a relatively simple setting with no static externalities, 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: We apply a dynamic game with $N \geq 2$ players. In each period $t = 0, 1, \ldots$, player i chooses an emission $x_{it} \in [0, \bar{x}_i]$, where $\bar{x}_i > 0$ is the maximum feasible emission level. Players' 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.

Assume that all players have the same payoff function. Player 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:

$$\pi_i(x_{it}, S_t) = B(x_{it}) - D(S_t), \tag{2}$$

where B is strictly concave, differentiable, and has a unique finite maximum $\hat{x}$ that lies between 0 and $\bar{x}$. For simplicity, we adopt a quadratic benefit function $B(x) = ax - \frac{1}{2}cx^2$. Following Dutta and Radner, we assume a linear damage function $D(S_t) = dS_t$. Parameter $d > 0$ represents the marginal damages due to the stock of pollution.

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

Benchmark solutions Consider the following three benchmark emissions allocations.

First Best solution (FB): Assume that all players' return functions are measured in terms of a common metric. Then the First Best, or the cooperative emission allocation maximizes the sum of N players' 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 (i.e, independent of stock level) and satisfies $B'(x_{it}^*) = \frac{\delta N d}{1-\delta\lambda}$, for all i, t.

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 because the assumption $\delta = 0$ implies that the decisions are made with zero weight on future returns. The quadratic benefit function implies a unique MN solution $\hat{x} = a/c$. This solution is useful as a noncooperative benchmark for players who are not explicitly motivated to care about the future, or for boundedly rational players who do not understand dynamic aspects of the game.

Markov Perfect equilibrium (MP): The above dynamic game has many subgame perfect equilibria. We consider the outcome of a Markov perfect equilibrium (MPE), where each player conditions its emission in each period solely on the current pollution stock, as a another useful noncooperative benchmark. In particular, (among many MPE) 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 player's emission is independent of the pollution stock level is given by $\tilde{x}$ such that $B'(\tilde{x}) = \frac{\delta d}{1-\lambda\delta}$.[3]

The constant-emission MPE is a useful noncooperative benchmark for players who are motivated to care about the future payoffs and who understand the dynamic nature of the game. While there are many other subgame perfect equilibria, the simple nature of this particular MPE may make it more attainable for experimental participants. Our experiment

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

allows subjects to send verbal advice to participants in succeeding rounds, therefore expanding the set of equilibria and possibly enhancing the efficiency, where FB serves as the upper bound. In fact, depending on the parameter values, FB emissions levels can be supported as an equilibrium outcome with an MPE-reversion trigger strategy (Dutta and Radner 2009). As discussed below (Section 3), with the specific parameter values used in our experiment, FB is indeed supportable as an equilibrium outcome. Hence, while we do not necessarily expect the constant-sum MPE or the FB to be the outcomes of our experiment, we consider both MP and FB as useful benchmarks.[4]

2.2 Games with multiple generations of players

To extend the above framework to a game with multiple generations of players, we assume that the set of players in 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 1. 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 his concurrent payoff and the payoff of player $(i, t+1)$ in the next generation:

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

[4]Battaglini et al. (2012) document that the MPE benchmark explains the behavior well in their dynamic setting that admits many subgame perfect equilibria; Vespa (2013) and Wilson and Vespa (2014) find a significant presence of cooperation along with behavior consistent with MPE play. This suggests both MP and FB may be useful theoretical benchmarks for our experiment.

This specification allows for intergenerational caring, where $0 \leq \delta \leq 1$ is interpreted as the weight that player i in generation t puts 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 intergenerational 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 $\delta = 0$, we have the Myopic Nash solution (MN) as defined in the previous subsection. In the context of this intergenerational game, the decisions given $\delta = 0$ are not so much myopic but rather selfish for each generation; nevertheless, we call this benchmark MN because it is behaviorally equivalent to MN for the game with infinitely lived players.

A simple Markov Perfect equilibrium (MP) is also defined analogously. Several studies have investigated the nature of Markov perfect equilibria in games with multiple generations of players where $N = 1$ (i.e., one player in each generation). When $N = 1$, a Markov perfect equilibrium coincides with the efficient outcome with an infinitely-lived agent (provided exponential discounting as in our framework).[5] An analogous property holds when $N > 1$: a Markov perfect equilibrium given multiple generations of players coincides with a Markov perfect equilibrium given infinitely-lived players.

To see this, suppose $(\phi_1, \ldots, \phi_N)$ is a Markov perfect equilibrium of the game with infinitely-lived players. (In the Markov perfect equilibrium, ϕ_i represents a decision rule that specifies player i's choice of emissions as a function of the current stock level S.) Let

[5]This is demonstrated in Phelps and Pollak (1968) in the context of growth models and Karp (2005) in the context of a stock pollutant as in our model.

$(V_1, \ldots, V_N)$ be the associated value functions. Then we have

$$V_i(S) = \max_{x_i \geq 0} \pi(x_i, S) + \delta V_i(\lambda S + x_i + \sum_{j \neq i} \phi_j(S)) = \pi(\phi_i(S), S) + \delta V_i(\lambda S + \sum_{j=1}^{N} \phi_j(S)).$$

We observe that the same functional equations with the same decision rules characterize the payoff maximization problems of each player of the game with generations of players. Thus $(\phi_1, \ldots, \phi_N)$ for each generation constitutes a Markov perfect equilibrium of the game with generation of players.

As with the game with infinitely-lived players, while we do not necessarily expect these theoretical predictions—FB, MN and MP—to be the only likely outcomes, we consider them as useful benchmarks that would help us understand and compare the participants' actual behavior in the experiment.

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 (which corresponded to different emission levels), given information about the current payoffs from own token choices, and the effect of group token choices on future series' (generations') payoffs.[6] 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 by choosing 7 tokens (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 stock increases.[7] The payoff scenario given in Figure 1 illustrates how the payoffs would evolve across series if the total number of tokens ordered by the group

[6]In fact, each series consisted of three independent decision trials, where the subjects in each group made token choices given the same stock level. One of the trials was then chosen randomly as a paid trial, and used to determine the next series' stock for that chain. We decided to have more than one trial in a series to give the subjects an opportunity to learn faster by making more decisions. Individual decisions were consistent across trials within series; regression analysis indicates that decisions were independent of the trial number. In what follows, we therefore focus on the data analysis for the chosen (paid) trials of each series.

[7]The participant token choices τ_{it} were translated into emission levels x_{it} using the the linear transformation $x_{it} = 2\tau_{it} + 2$. 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: $a = 208$, $c = 13$, $d = 26.867$, $K = 424.4$, $\lambda = 0.3$. The constant $K = 424.4$ was added to player payoffs to ensure positive payoffs over a reasonable range of token choices. 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 (see Online Appendix B) 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."

stays at 21 in each series (corresponding to the MN outcome).

The parameter values are chosen so that the three theoretical benchmarks for individual token investments, all independent of the stock level, are distinct from each other and integer-valued: 4 tokens under First Best; 6 tokens under Markov Perfect; and 7 tokens under Myopic Nash. 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.

Each chain continued for several series (generations). To model an infinitely repeated game and eliminate end-game effects, we used the random continuation rule, a method that has been shown to induce discounting in experimental settings (Roth and Murnighan 1978; Dal Bo 2005). A randomization device (a bingo cage) was applied after each series (generation) to determine whether the chain continues to the next series. 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 $\delta = 0.75$.

Under the parameter values specified above, players can support the first-best outcome x^* using a trigger strategy with MPE reversion (as discussed in Dutta and Radner 2009).[8]

[8] Online Appendix A explains the detail.

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 intergenerational 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 provides a benchmark for comparison with intergenerational treatments.

(2) Intergenerational Selfish (IS) : A separate group of subjects makes decisions for each generation; each subject's 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 a purely selfish preference with no weight put on the next generations' welfare, thus suggesting Myopic Nash behavior. We use this treatment to assess a lower benchmark of performance in the intergenerational setting, when the decision makers are made aware of the dynamic effect of their decisions on the followers' payoffs but are not directly motivated to care about the future. This incentive structure is aimed to mimic the well-documented incentive of the politicians to improve their constituencies' current economic performance rather than invest into long-term policies (see Section 1 footnote 1).

(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. The cumulative payment in IL keeps the setup consistent with the theory in Section 2.2. This suggests that the behavior in this treatment could be theoretically the same as in the baseline

LL treatment. This treatment allows us to investigate whether the subjects restrain their emissions in the intergenerational setting as much as in the long-lived setting when they are fully motivated (by monetary incentives) to care about the future.

Example: differences in payments among treatments Suppose, in a given chain, Subject 2's concurrent payoffs are: 911 in generation 1, 296 in generation 2, 400 in generation 3, and 481 in generation 4, after which the chain ends. (This was the actual stream of Subject 2's payoffs under LL Chain 1). Under LL, the same participant makes decisions as Subject 2 in all generations, and is paid $911 + 296 + 400 + 481 = 2088$ experimental dollars. Under IS, the role of Subject 2 is taken by a different participants in each generation, and each is paid based on their concurrent payoff: Subject 2 in generation 1 gets 911, Subject 2 in generation 2 gets 296, Subject 2 in generation 3 gets 400, Subject 2 in generation 4 gets 481. Under IL, the role of Subject 2 is taken by a different participant in each generation, and each participant is paid their own concurrent payoff plus those of all their followers': Subject 2 in generation 1 gets $911 + 296 + 400 + 481 = 2088$, Subject 2 in generation 2 gets $296 + 400 + 481 = 1177$, Subject 2 in generation 3 gets $400 + 481 = 881$, and Subject 2 in generation 4 gets 481.[9]

[9] Ex-ante, the expected number of future generations is the same for each generation in a chain; this number was used to calibrate expected payments to participants. The exchange rates were also calibrated to equalize expected dollar payoffs across treatments (assuming no differences in behavior). The payment methods applied under IL is necessary to induce the objective functions given by Equation 4; alternative payment methods such as used in Chaudhuri et al. (2006) would bias the participants' objectives; for more details, see Sherstyuk et al. (2013).

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

We therefore model these features in our design. First, subjects' expectations about the others' choices in the current series are elicited, and the subjects are induced with monetary payoffs (as in Van Hyuck et al. 1990) to submit accurate predictions. Further, to enhance social learning, at the end of each series each subject is asked to send "an 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). These design features are common to all treatments. See Online Appendices B and D for 'Experimental Instructions' and 'Screenshots.'[10]

Procedures The experiments were computerized using z-tree software (Fischbacher, 2007). Several (up to three) independent groups of three subjects, with each group belonging to an independent chain, participated in each experimental session. In the baseline LL treatment,

[10]We build on Chaudhuri et al. (2006) who find that making advice available to all players in future generations enhances social learning. In our experiment, the results screen for each series contained information on the current participants' token choices and their payoffs, the payoff schedule for the next series, and a space where the participants were asked to type in numerical and verbal advice to the next series' participants. The numerical advice from the previous series, along with the history of token choices and the current payoff schedule, then appeared on the computer screen at the beginning of the next series. In addition, each participant received a handout with the whole history of token choices and numerical and verbal advices from all previous series in their chain.

the same groups of subjects made token decisions in all of the chain's decision series, carried out within the same session. In the intergenerational IS and IL treatments, each group of subjects participated in one decision series per session, 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. Decisions were inter-linked across series within a chain 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, which included examples of dynamic payoff scenarios as illustrated in Figure 1; followed by (b) Practice, consisting of six to eight 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.[11] 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. See Online Appendices B, C, and D for experimental instructions, examples of payoff scenarios, and screenshots of decision screens with payoff calculators.

Each experimental session lasted up to three hours in the LL treatment, and up to two hours in the IS and IL treatments. To equalize expected payoffs across treatments, the exchange rates were set at $100 experimental = US $0.5 in the LL and IL treatments, and

[11]Most sessions had six practice series. The first three session for the IS treatment had eight practice series, out of concern that the participants in intergenerational treatments may need more practice to learn how the experiment worked. As it became apparent from these sessions that six series were enough for practice, the practice was cut back to six series for other intergenerational sessions.

\$100 experimental = US \$2 in the IS treatment. 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, intergenerational IS and intergenerational 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 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

The discussion of experimental results is organized around several research questions of interest. First, can dynamic efficiency be achieved in games with long-lived decision makers? Second, can intergenerational games with dynamic externalities attain the same outcomes as games with long-lived players? If not, are the differences fully explained by the lack of motivation of short-lived players to care about the future? And, third, does raising awareness about future effects of own actions through access to information, history, and advice from the followers make people (somewhat) future-regarding, even if they are not directly motivated to care about the future?

Below are three ex-ante hypotheses that relate to the corresponding research questions, and that will guide our analysis of experimental data. The first hypothesis is based on existing experimental evidence on sustainability of cooperation when it is supportable as an equilibrium in infinitely repeated games (e.g., Dal Bo and Frechette 2011), and on the positive effect of communication on cooperation (e.g., Ledyard 1995).

Hypothesis 1 *The First Best outcome is attainable under LL treatment.*

To test this hypothesis, we will compare the group tokens under LL to the First Best (FB) level. In addition, given the evidence of MP equilibrium play in other experimental games with dynamic externalities (Battaglini et al. 2012, Vespa 2013), we also compare the group tokens to the MP benchmark as a noncooperative alternative.

The second hypothesis reflects the lack of previous experimental work comparing intergenerational and long-lived settings, and the vast experimental evidence that direct motivation (monetary incentives) matter.

Hypothesis 2 *(a) IL treatment yields the same level of token choices as LL; and*
(b) IS yields higher token choices than either LL or IL treatments.

To test the above, we perform cross-treatment comparisons of group tokens, and also compare the group tokens in each treatment to the relevant theoretical benchmarks (FB, MP and MN for LL and IL, and MN for IS).

Our third hypothesis is based on the large experimental literature on the existence of social preferences (e.g., Charness and Rabin 2002). We hypothesize that, being made aware of future effects of own actions, people do not act in a purely selfish manner:

Hypothesis 3 *Token choices in the intergenerational IS treatment are below the selfish MN equilibrium.*

To test this hypothesis, we compare the group tokens under IS to the MN prediction.

We now turn to the data analysis. The data displayed in Figure 2 and Table 1 suggest that, in LL treatment, all groups of subjects were able to avoid the Myopic Nash outcome and were approaching the FB levels for group tokens, stock and advised tokens. On average, there were 13.56 group tokens ordered under LL, which was significantly below the MP level of 18 ($p = 0.0156$, Wilcoxon signed ranks test), but also above the FB level of 12 ($p = 0.0781$).[12] Group tokens evolved differently in the other two treatments: on average, 15.28 group tokens were ordered under IL, and 18.00 group tokens under IS. Group tokens under LL were significantly lower than under IS ($p = 0.0190$, Wilcoxon Mann-Whitney, or WMW, test), and lower, although not significantly, than under IL ($p = 0.2143$). Group tokens in the IL treatment were also significantly below those in the IS treatment ($p = 0.0556$).

An analysis based exclusively on group averages may be misleading since it does not capture the dynamics. To consider the evolution of variables of interest over time, we apply the following model, adopted from Noussair et al. (1997). Let y_{it} be an outcome variable of interest (group tokens or advice[13]) in chain i and series t. Then:

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

[12] In nonparametric tests, we use chain averages, as given in Table 1, as units of observation.

[13] Stock levels may be evaluated as well. However, unlike actions (chosen tokens) and advice, stock is not a choice variable for participants, but a deterministic function of participant actions. We constrain our statistical analysis to decision variables, namely, choices and advice.

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 convergence levels, or asymptotes, for the dependent variable. Thus we allow for a different origin for each chain, but estimate common, within-treatment, asymptotes. The error term u_{it} is assumed to be distributed normally with mean zero. To allow for later comparison across different outcome variables of interest, we use seemingly unrelated estimation of group tokens and advised group tokens, clustering the standard errors on chain ID.

The results of regression estimations of convergence levels for actual and advised group tokens, by treatment, are given in Table 2. Table 3 displays p-values for the test of the equivalence of the estimated asymptotes in each treatment to the theoretical benchmarks (FB, MP and MN), and tests for their equality between treatments.

TABLES 2–3 AROUND HERE

The regression results confirm that treatments evolved very differently. The group tokens under LL were converging to 11.95, which is not significantly different from the FB level of 12 ($p = 0.9307$). In comparison, tokens in the IL treatment converge to 15.89, which is above the FB level of 12 ($p = 0.0018$) but also marginally different from (below) the MP level of 18 ($p = 0.0895$). Group tokens in the IS treatment converge to 17.56, which is significantly below the MN level of 21, $p = 0.0017$ (and accidentally is not significantly different from the MP level of 18, $p = 0.6861$). The group token asymptotes are significantly different between

LL and IS ($p < 0.0001$), and between LL and IL ($p = 0.0047$), but not between IL and IS ($p = 0.3144$).[14]

We can make the following three conclusions:

Conclusion 1 *In the Long-Lived (LL) treatment, groups of subjects are able to avoid both myopic and long-sighted inefficient outcomes, with group tokens converging to the First Best levels. Hypothesis 1 is supported by the data.*

Conclusion 2 *All three treatments display different dynamics of token choices, with group tokens converging to the FB level under the LL treatment, levels between FB and MP under the IL treatment, and higher levels under IS. The differences in token levels between the three treatments are significant. Hypothesis 2(a) is rejected by the data, whereas Hypothesis 2(b) is sustained.*

Conclusion 3 *Players in the intergenerational short-sighted (IS) treatment restrain their actions below the selfish MN prediction. Hypothesis 3 is supported by the data.*

A likely reason for Conclusion 3 is access to information about future consequences of current actions, history, and advice from the followers, which make the participants care about the future.

Another important implication of the above is that, while direct motivation plays a significant role in explaining the subject behavior, the differences between intergenerational and long-lived dynamics cannot be attributed solely to the differences in players' direct

[14]Under IL, the group tokens are highly variable across chains (the standard deviation of group tokens across chains under IL is 3.25 tokens, as compared to 1.7 tokens under LL and 0.97 tokens under IS; see Table 1 and Figure 2) which is the likely reason for lower significance of the tests.

motivation to care about the future. In particular, we observe quite different dynamics between IL and LL treatments, both of which are associated with equivalent long-term payoffs. In the next subsection, we consider a likely reason for the observed differences between intergenerational and the long-lived treatments.

4.2 Comparing actions, beliefs and advice

The above evidence suggests that achieving the efficient long-term First Best outcome in an intergenerational setting is 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 on FB actions among subjects in the intergenerational context, and therefore a higher risk of miscoordination. Coordination issues may arise both within the current generation (intra-temporal coordination), and across generations (inter-temporal coordination). The former occurs because concurrent decision makers have fewer opportunities, as compared to long-lived players, to learn about their contemporaries' likely actions and adjust own actions accordingly. The latter occurs because a decision maker in the intergenerational setting may not trust their followers to carry out the long-term FB plan of actions to the same degree as a long-lived decision maker trusts themselves. Both of these factors may increase strategic uncertainly and decrease the chance to coordinate on the First Best dynamic path, even if it is supportable as an equilibrium.[15]

We therefore investigate: Can differences in intra-temporal and inter-temporal coordination help explain the differences in outcomes between the long-lived and intergenerational

[15]See Van Hyuck et al. (1990) on how strategic uncertainly causes coordination failure in games with multiple Pareto-rankable equilibria.

treatments?

To address this question, we analyze the relationship between participants' actions, beliefs and advice across treatments. Higher inconsistency between own actions and beliefs about contemporaries' actions may suggest a higher difficulty in inter-temporal coordination, whereas higher inconsistency between own actions and advice given to the followers may indicate a bigger challenge in inter-temporal coordination. Our hypothesis is based on the challenges for both intra-temporal and inter-temporal coordination under IL as compared to LL. Regarding IS, we hypothesize no difference with IL, based on equal duration of individual interactions, and the same set of coordination instruments (intergenerational advice, in particular) available under both IS and IL.

Hypothesis 4 *(a) The discrepancies between actions and beliefs about the contemporary's actions, and actions and advice to the followers, are higher under IL than under LL;*
(b) The actions-beliefs and actions-advice discrepancies are no different between IS and IL.

To test this hypothesis, we analyze the data on both group and individual levels. On the group level, we test if the recommended group tokens were converging to the same levels as the actual group tokens. We further use the individual data to test if the treatments vary in their differences between own actions, beliefs about others' actions, and advice to the followers.

First, consider recommended tokens and compare them to actual tokens across treatments. 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 consistent with 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) treatments.[16]

Figure 2, bottom panel, also suggests that recommended tokens in each treatment followed a trend similar to that of actual tokens. The regression analysis of dynamics of actual and recommended group tokens (Tables 2–3) confirms, for LL and IS, that the actual and recommended group tokens were converging to the same theoretical benchmarks, and to the levels not significanly different from the actual tokens. The recommended tokens asymptote in the LL treatment was 11.68, and was not different from the FB level of 12 ($p = 0.3142$). The recommended tokens asymptote in the IS treatment was 17.43, below the MN level of 21 ($p < 0.0001$). Further, the results of Wald tests reported in Table 2 indicate that the asymptotes for the group tokens and the recommended group tokens were not statistically different for either LL ($p = 0.7285$) or IS ($p = 0.8366$). For the IL treatment, however, the recommended group tokens asymptote of 14.67 is different from both FB ($p = 0.0200$) and MP ($p = 0.0036$) benchmarks, and is also marginally different from (i.e., is below) the actual group tokens asymptote of 15.89 ($p = 0.0900$). We conclude:

Conclusion 4 *Under both LL and IS the recommended tokens were converging to levels not statistically different from the actual tokens. Under IL, the recommended group tokens asymptote is marginally below the actual group tokens asymptote. This is in support of*

[16]On the individual level, 72% of recommendations under LL were at the FB level of 4 tokens per person or lower, and only 3% of advices were at 7 tokens or higher. Under IL, 40% of all recommendations were 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, 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.

Hypothesis 4(a), but not Hypothesis 4(b).

We now turn to the analysis of individual-level differences between actions and beliefs about others' actions, and actions and advice to the followers. Figure 3 plots the dynamics of the difference between own token choice and the expectation of the other subjects' mean choice (i.e., own tokens minus expectation of others) – panel A, and the difference between own token choice and the advised token level (i.e., own tokens minus advice to others) – panel B, by treatment.

FIGURE 3 AROUND HERE

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 actions relative to beliefs and advice across sequences of subjects. We classified all subject-ID-linked sequences of experimental participants (participants connected by the same subject ID within a given chain)[17] depending on whether the median deviation of their actions from their expectations of others (or advice given to others, respectively) was negative, positive or zero. Participants with a zero median deviation of their tokens form expectations did not exceed the token orders that they expected from the others at least half of the times. In comparison, participants with a positive median deviation of actions form expectations ordered more tokens than they expected the others to do at least half of the times. Likewise, regarding own actions and advice to the future, we classified all subject-ID-linked sequences of participants into those with median non-positive and those with positive deviations of own token choices from advice given to followers. The results are presented in Figure 4.

FIGURE 4 AROUND HERE

Under LL, the majority (72%) of the long-lived subjects mostly (in half of the cases or more) chose tokens that were at or below the levels that they expected the other subjects to choose; moreover, 33% of subjects mostly chose tokens strictly below what they believed the others would do. Under IS, 75% of short-lived subject sequences mostly chose tokens that were at or below their expectations of others, but fewer (25% of subjects) chose tokens strictly below their beliefs. This contrasts with IL, where the majority (53%) of sequences of short-lived

[17] That is, a unit of observations here is an individual participant in the LL treatment, or a sequence of participants sharing the same subject ID in a given chain in IL or IS treatment. Alternatively, we could consider the behavior of each individual participant separately. However, such analysis would be misguided, as the essence of the intergenerational setting is that sequences of short-lived individuals make decisions for the same long-lived entity (represented by a given subject ID in the experiment).

subjects mostly chose tokens above their expectations of others, and only 7% of sequences mostly chose tokens below what they expected of the others. Aggregating to chain averages for independence of observations, the median difference between own actions and beliefs about others' actions is significantly higher in the IL treatment than in the LL treatment ($p = 0.0152$, WMW test); the difference is also higher, at 10% level, in the IL than the IS treatment ($p = 0.0952$), while it is insignificant between LL and IS treatments. Similarly, the majority of participants under LL and of sequences of participants under IS (72% and 58%, respectively) mostly chose tokens that were at or below what they advised their followers to choose. The opposite is the case under IL, where 53% of sequences of participants mostly chose tokens above the levels they advised to the followers. Although the differences between the treatments are not statistically significant ($p = 0.1237$ for the difference between LL and IL treatments), it is again suggestive of a higher divergence between actions and advices under IL as compared to those under LL or IS treatments.

Table 4 lists examples of verbal advice for LL (Chain 2), IS (Chain 4) and IL (Chain 4) treatments.[18]

TABLE 4 AROUND HERE

These examples together with the above analysis, suggest that under LL, many participants were willing to be the first to cut down their tokens, in the hope that they will be followed by others in later series. Under IS, attempts by individual subjects to convince the followers to cut down their tokens were scarce and largely unsuccessful, as evident from Table 4. Overall, under IS, participants' own actions, expectations of others, and advice to the followers closely

[18]Complete scripts of advices given in these chains are presented in Online Appendix E.

matched each other; the subjects expected the others to choose tokens at noncooperative levels, and did so themselves. In contrast, under the IL treatment, participants often exhibited "optimistic free-riding" (Fischer et al 2004), when they chose higher tokens than what they believed their contemporaries would choose, and what they advised to their followers (see, for example, Table 4, IL Chain 4, Series 7, advice by Subject 3.)[19] We conclude:

Conclusion 5 *Under LL, some people are willing to "take a lead" and choose fewer tokens than they expect others to choose. Under IS, most people's actions, beliefs and recommendations closely match each other. In contrast, under IL, many people expect others, and recommend to the followers, to choose fewer tokens than they do themselves. The inconsistency of actions and beliefs is significantly higher under IL than under either LL or IS, but is not significantly different between LL and IS. Hypotheses 4(a) is sustained, whereas Hypothesis 4(b) is rejected.*

The above suggests, in particular, that advice served as an effective coordination device under both LL and IS, but was less effective under IL. To provide further insights about the reasons behind actions and advice, we analyze the verbal content of advices across treatments. We inquire, first, are there differences between treatments in stated reasons behind advised actions? Second, given the same reason, are advised tokens levels different between long-

[19]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), most likely due to across-series advice that was made known to all participants.

lived LL and intergenerational IL treatments? For the latter, we are particularly interested in comparing advised tokens for sophisticated subjects who explicitly say that they take their long-term interest into account.[20]

The verbal contents of advice were classified by two independent decoders into the following broad categories by reason: pursuing "Own long-term interest," "Own short-term interest," "Best for self and others," along with "No reason specified." We hypothesize that, due to the monetary motivation, long-term reason will appear more prominently under LL and IL than under IS; further, given the evidence that people under IS choose and advise less than selfish MN token levels, "Best for self and others" reason should appear in advices under IS. Second, increased strategic uncertainly could result in advising higher token levels under IL as compared to LL even for those who appeal to "Own long-term interest."

Hypothesis 5 *Regarding stated reasons for advised tokens,*

(a) "Best for self and others" appears frequently under IS, whereas "Own long-term interest" is more frequent under LL and IL than under IS;

(b) Participants stating "Own long-term interest" reason advise higher token levels under IL than under LL.

To test these hypotheses, consider the composition of advices by reason, and level of token advice given reason, by treatment. As Figure 5 indicates, "Own short-term interest" is hardly used as a reason, except in rare cases under IS. Consistent with Hypothesis 5a) "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

[20]Some subjects may not care about the long-term prospect due to bounded rationality.

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 noncooperative 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).

Conclusion 6 *"Best for self and others" is a popular reasons for the given advice in all treatments and the most frequently-stated reason under IS. "Own long-term interest" is the most frequent reason under both LL and IL; the subjects stating this reason advise the FB cooperative actions to their followers under LL, but higher noncooperative actions under the intergenerational IL treatment. Hypotheses 5(a) and (b) are both supported.*

The above evidence suggests the following. While both the cooperative First Best and the noncooperative Markov Perfect (along with many other) action paths can be supported as equilibria under LL and IL, the two treatment result in quite different outcomes. A likely explanation for the observed differences is higher strategic uncertainty under the intergenerational setting. As the subjects under the LL treatment interact with the same group of people in every series, they can rely on more consistent actions across generations, and give advice to follow the First Best path. This allows the groups under LL to coordinate successfully on a payoff-superior First Best action path. In contrast, new groups of subjects make choices in each series of the IL treatment, and these subjects are less certain about their contemporaries' and the followers' behavior. As one may not trust the others to make long-sighted decisions, one oneself may take (and often recommend) a safer, more myopic action. Conclusions 5 and 6 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. This often results in a path of actions that are less risky than FB but associated with lower payoffs.

An interesting note can be made regarding the IS treatment. Although the same coordination instruments (intergenerational advice, in particular) are available under both IS and IL, consistency between own actions, beliefs and advice is higher under IS than under IL. To understand why, observe that, unlike LL or IL, playing the selfish MN equilibrium strategy is both (monetary) payoff-dominant and risk-free under IS. This lack of tension between payoffs and risk results in a lesser need for coordination and a higher degree of consistency between own actions, beliefs and advice. Interestingly, concerns for the followers do not reduce this consistency, with levels of own actions, beliefs and advice all settling somewhat below the selfish MN level.

5 Discussion

While several aspects of the climate change problem—the public good and the long-term nature of emission reductions, in particular—have been well known and extensively researched, the intergenerational aspect has been under-investigated. Our research brings the latter to attention, and investigates how strategic interactions among players evolve in an intergenerational setting as compared to an infinitely-lived setting in an experimental game with dynamic externalities. We find that the games evolve very differently in the long-lived and in intergenerational setting, and further identify and disentangle two sources of inefficiency brought in by the intergenerational aspect: one due to a possible lack of motivations to care about the future generations, and the other due to the difficulties in intergenerational coordination—in particular, increased strategic uncertainty that arises because the players change across generations.

In the Long-Lived treatment of our experiment, the subjects are 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.[21] In contrast, in our Intergenerational Selfish treatment, noncooperative behavior evolves and persists across generations; participants choose noncooperative 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 noncooperative 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

[21] Of course, cooperation is not guaranteed even with long-lived governments; as explained in Section 3 above, we employ a setting favorable for cooperation in this experiment. More realistic settings—in particular, with static externalities and a higher retention rate of GHG emissions—may create extra challenges for cooperation even with long-lived decision makers.

treatments. Some chains in the IL treatment were converging to cooperative emission levels, while others stayed at noncooperative levels. Thus, if the governments are short-lived but long-sighted, 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 intergenerational 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 is the case in our Intergenerational Long-sighted treatment.[22] 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 emissions and advices that are higher on average than under the LL treatment average levels, 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

[22]We are grateful to the anonymous referee for the following note. Another difference between the IL and LL treatments may exist because discounting was introduced via risk, through random continuation; hence subject decisions may depend on their risk attitudes. This could be a problem if the different settings induced different responses to risk among the subjects, and this was not controlled or randomized. We acknowledge this possible confounding factor but also believe that factors other than nature-induced uncertainty—strategic uncertainly in particular—played an important role in inducing differences in outcomes.

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 that future-regarding behavior can be induced, to some extent, through non-strategic instruments, such as information, advice, and access to history, even in the absence of direct monetary incentives to care about the future. While token choices and advices in the Intergenerational Selfish (IS) treatment were significantly above those in the other two treatments, the behavior did not evolve all the way towards the selfish Myopic Nash prediction.[23] This suggests that making the decision makers (and the general public who may influence the decision makers' actions) aware of the long-term consequences of their actions, and exposing them to the history of previous actions and outcomes, may reduce emissions.

Finally, our experiments once again demonstrate the role of intergenerational 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 intergenerational treatments. However, as evidenced by the Intergenerational Selfish treatment, in the absence of direct incentives to care about the future, the intergenerational advice often led the participants to coordinate on noncooperative 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, in the presence of advice, the subjects coordinated on cooperative First

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

Best emission levels, the intergenerational setting 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 investigate such mechanisms for intergenerational 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: Actual and Advised Group tokens: Convergence by treatment

Seemingly unrelated estimation, with standard errors adjusted for clusters in chain ID

	Group Tokens		Advised Group Tokens		p-value: Tokens == Advised Tokens
	Coef.	Robust Std. Err.	Coef.	Robust Std. Err.	
LL chain 1 origin	21.33	(0.45)	18.65	(0.23)	
LL chain 2 origin	19.58	(0.35)	14.03	(0.18)	
LL chain 3 origin	10.24	(0.35)	10.73	(0.18)	
LL chain 4 origin	12.27	(0.53)	12.12	(0.26)	
LL chain 5 origin	17.72	(0.49)	17.14	(0.25)	
LL chain 6 origin	16.29	(0.49)	10.95	(0.25)	
IS chain 1 origin	12.59	(0.61)	9.72	(0.24)	
IS chain 2 origin	21.83	(0.51)	21.14	(0.18)	
IS chain 3 origin	18.82	(0.61)	13.67	(0.29)	
IS chain 4 origin	20.17	(0.61)	18.10	(0.29)	
LL chain 1 origin	21.32	(0.80)	18.33	(0.74)	
LL chain 2 origin	18.18	(0.80)	16.62	(0.74)	
LL chain 3 origin	7.34	(0.43)	4.95	(0.40)	
IL chain 4 origin	11.19	(0.89)	8.19	(0.82)	
LL chain 5 origin	17.86	(0.89)	17.17	(0.82)	
LL asymptote	11.95	(0.63)	11.68	(0.32)	0.7285
IS asymptote	17.56	(1.10)	17.43	(0.51)	0.8366
IL asymptote	15.89	(1.24)	14.67	(1.15)	0.0900
Number of observations:	*90*				

Benchmark predictions are: Group Tokens:FB=12, MP=18, and MN=21

Table 3: Tests for equality of group tokens and advice asymptotes between treatments

*p-values for Ho: Asymptote==Theoretical prediction**		
H0:	Group Tokens	Advised Group Tokens
LL asymptote==FB	0.9307	0.3142
LL asymptote==MP	0.0000	0.0000
LL asymptote==MN	0.0000	0.0000
H0:	Group Tokens	Advised Group Tokens
IS asymptote==FB	0.0000	0.0000
IS asymptote==MP	0.6861	0.2663
IS asymptote==MN	0.0017	0.0000
H0:	Group Tokens	Advised Group Tokens
IL asymptote==FB	0.0018	0.0200
IL asymptote==MP	0.0895	0.0036
IL asymptote==MN	0.0000	0.0000
p-values for Ho of Equality of Asymptotes between treatments		
H0:	Group Tokens	Advised Group Tokens
LL==IS	0.0000	0.0000
LL==IL	0.0047	0.0121
IS==IL	0.3144	0.0277

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

Table 4: Evolution of verbal advice, by treatment: extracts from participant advice

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

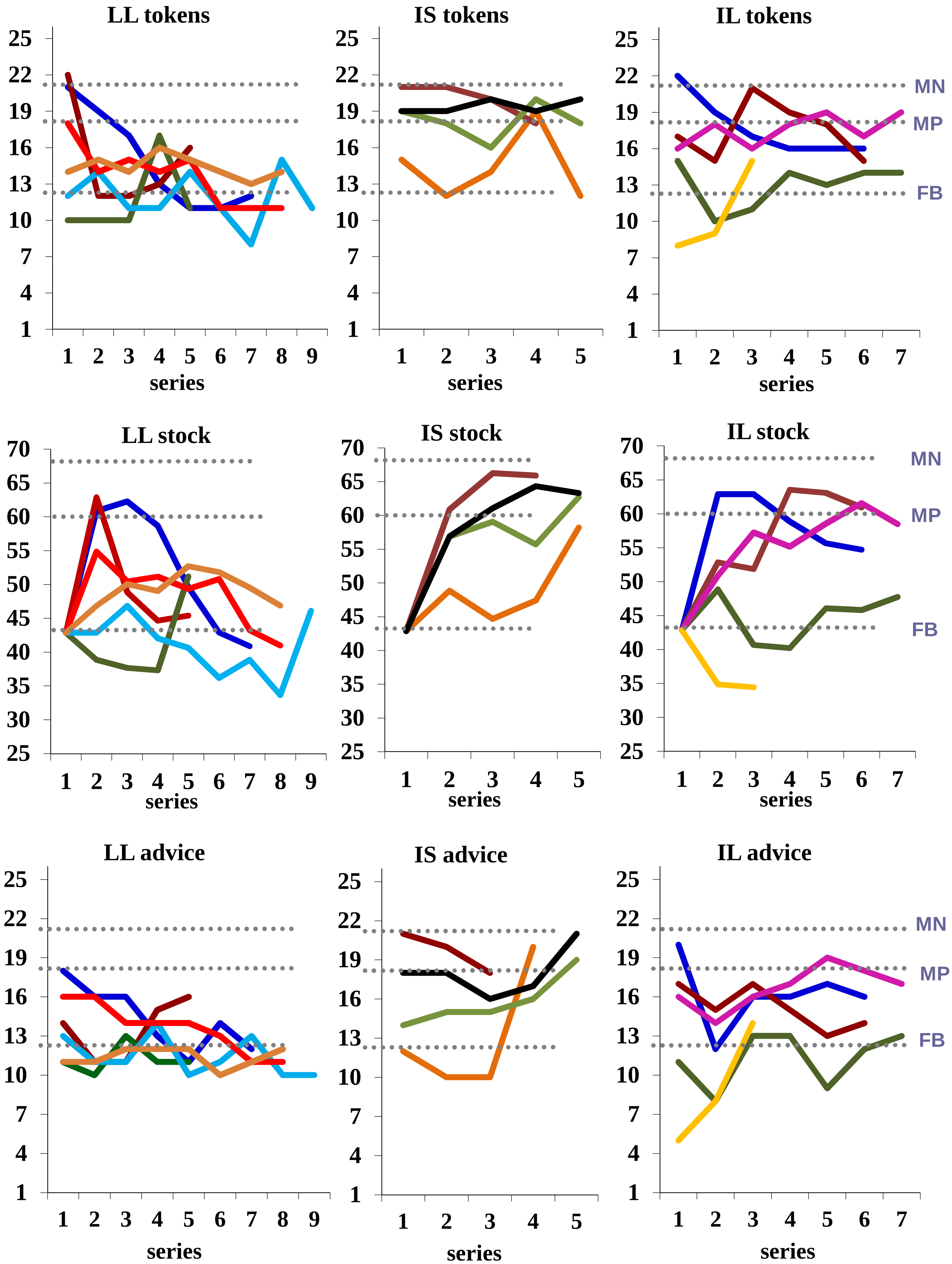
Series	Subject	Advice
1	1	PLEASE try either try 3 or 4...dont kill the group payoff, which will affect all of you when it continues further it will affect your individual payoff too…
	3	the lower the numbers, the higher the payoff in the later series
…		…
5	1	keep it at 3 or 4 please! if people get greedy,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

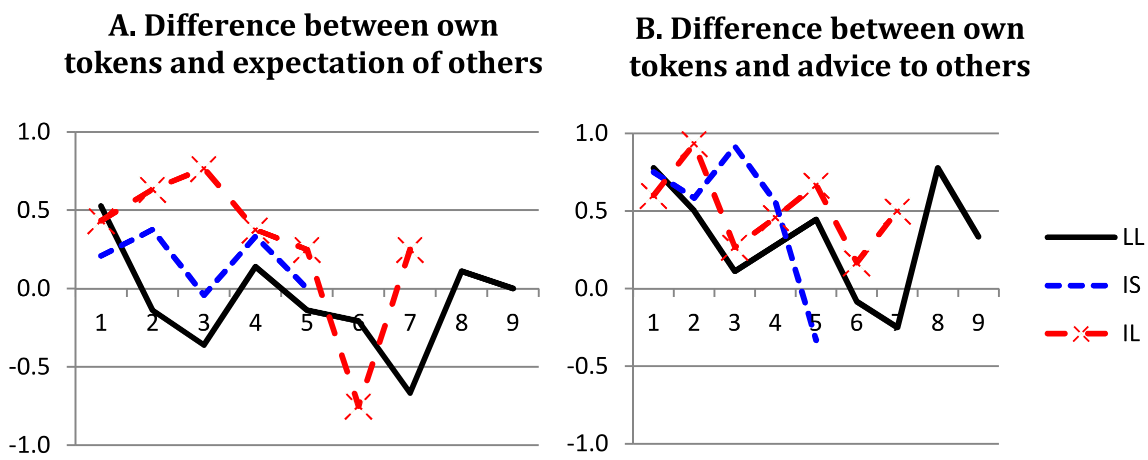
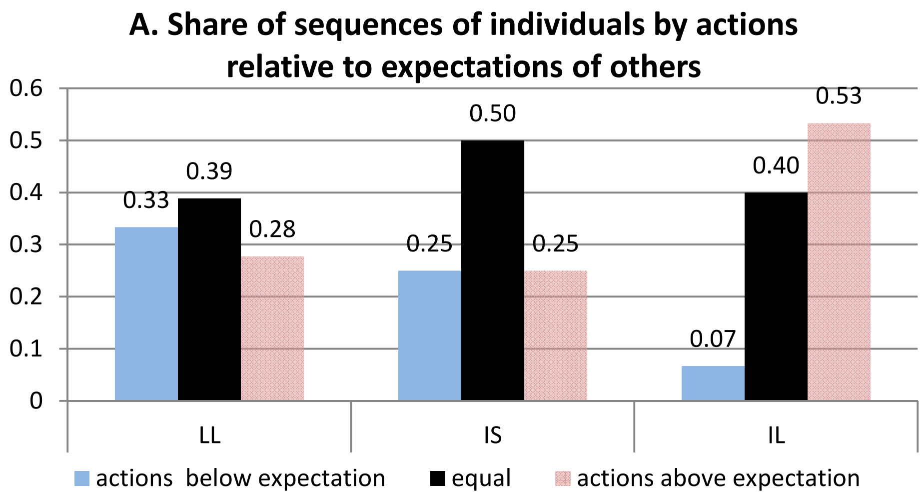


FIGURE 4: Percentage of individual sequences with positive, negative and zero median differences between actions and (A) expectations or (B) advice, by treatment



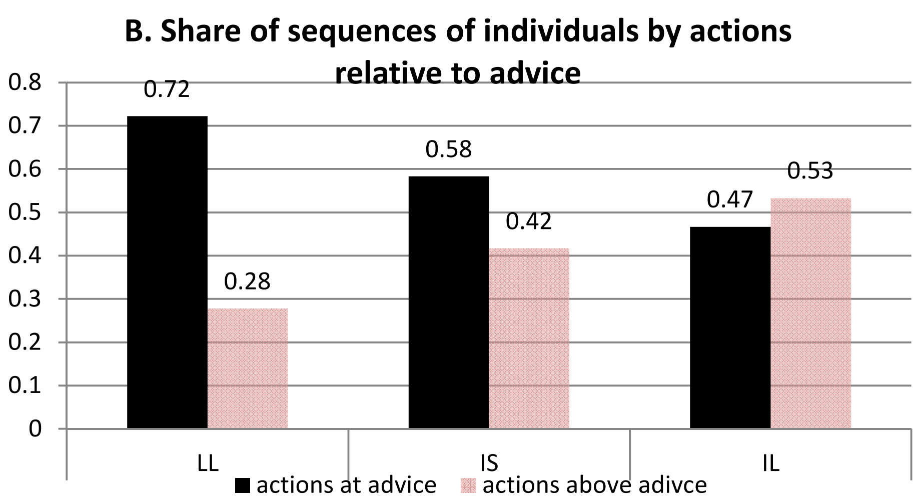


FIGURE 5: Share of verbal advice by reason

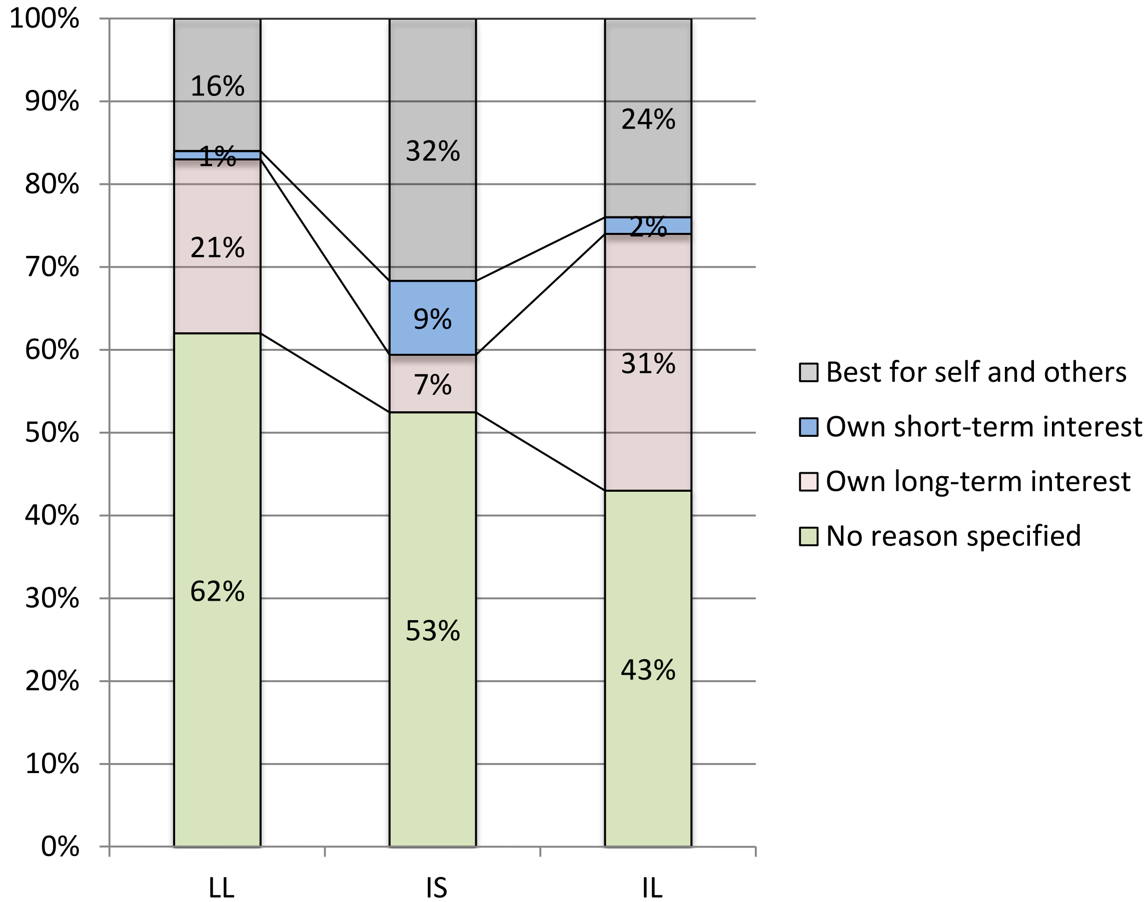
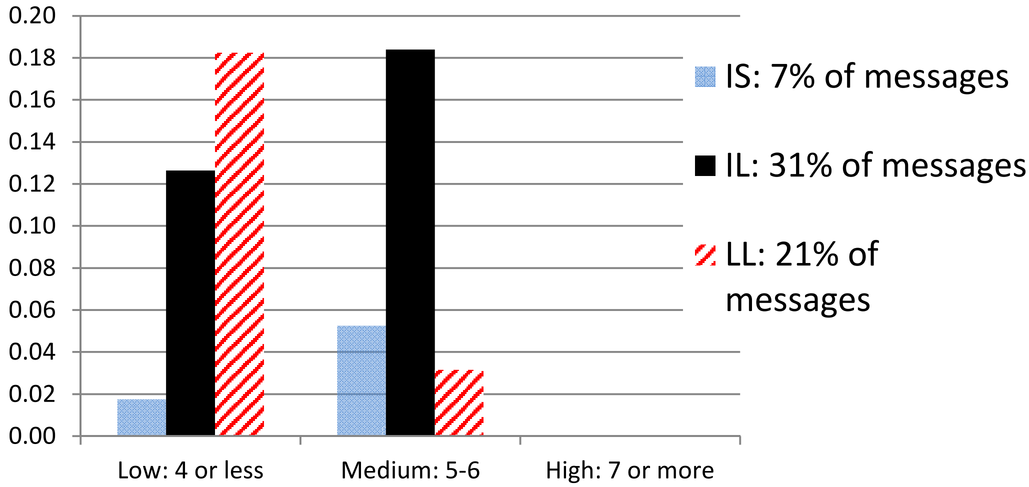


Figure 6: Distribution of token advice for subjects with "own long-term interest" reason.



Supplementary Materials

Appendix A: On supporting the first-best outcome with Nash reversion

Appendix B: Experimental Instructions

Appendix C: Payoff Scenarios

Appendix D: Screenshots

Appendix E: Evolution of advice by treatment

Appendix A: On supporting the first-best outcome with Nash reversion

Consider a trigger strategy with MPE reversion. Here we show that such a strategy supports the first-best outcome.

Let $S \geq 0$ be the current stock level. Suppose all players other than i choose the trigger strategy. Upon cooperation (i.e., by choosing the FB emission level x_i^*), player i earns $V_i(S)$ where V_i is the value function under FB:

$$\begin{aligned} V_i(S) &= ax^* - \frac{c}{2}x^* - dS + \delta V_i(\lambda S + Nx^*) \\ &= \frac{1}{1-\delta}\left(ax^* - \frac{c}{2}x^*\right) - d\left(\frac{S}{1-\delta\lambda} + \frac{\delta}{1-\delta}\frac{1}{1-\delta\lambda}x^*\right). \end{aligned}$$

(Recall that x^* represends the FB emission level.) Let W_i be the value function for player i under the constant MPE:

$$\begin{aligned} W_i(S) &= a\tilde{x} - \frac{c}{2}\tilde{x} - dS + \delta V_i(\lambda S + N\tilde{x}) \\ &= \frac{1}{1-\delta}\left(a\tilde{x} - \frac{c}{2}\tilde{x}\right) - d\left(\frac{S}{1-\delta\lambda} + \frac{\delta}{1-\delta}\frac{1}{1-\delta\lambda}\tilde{x}\right). \end{aligned}$$

(Recall that $\tilde{x}$ is the constant MPE emissions level as defined in the main text.) Because the damage function is linear in the pollution stock, the optimal deviation coincides with the MPE emissions:

$$\arg\max_{x_i} ax_i - \frac{c}{2}x_i - dS + \delta W_i(\lambda S + (N-1)x^* + x_i) = \tilde{x}.$$

Thefore, player i's payoff upon optimal deviation is given by

$$V_i^d(S) \equiv a\tilde{x} - \frac{c}{2}\tilde{x} - dS + \delta W_i(\lambda S + (N-1)x^* + \tilde{x}).$$

In the experiment, we assumed $S_0 = S^* \equiv \frac{Nx^*}{1-\lambda}$, the steady-state level under FB. Under the given parameter values ($\delta = 3/4$, $a = 208$, $c = 13$, $d = 26.876$, $K = 424.4$, $\lambda = 0.3$), the payoff upon cooperation is thus

$$V_i(S^*) \approx 1{,}114.2,$$

while the payoff upon optimal deviation is

$$V_i^d(S^*) \approx 906.2.$$

Hence, the trigger strategy with MPE reversion supports the first-best outcome. (The payoffs in experimental dollars are affine transformation of the model above. Therefore, the above conclusion holds in the experiment as well.)

B. 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.

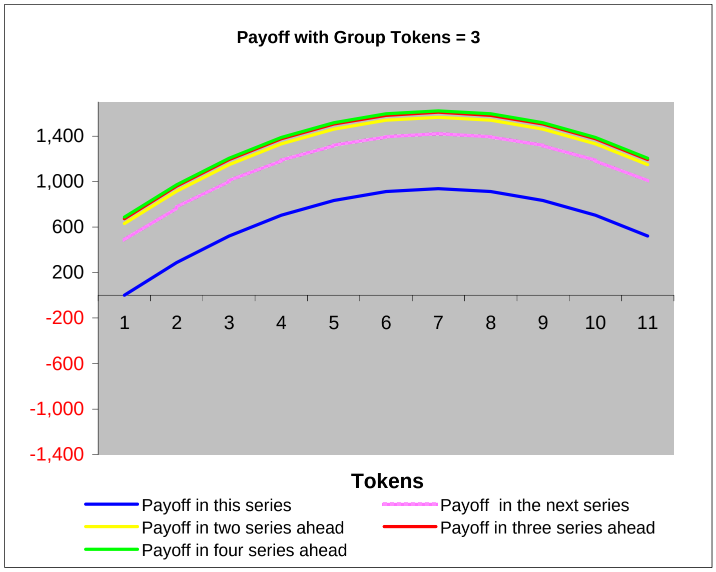
- How many series are there in this experiment?

  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.

C. Example 1 Scenarios

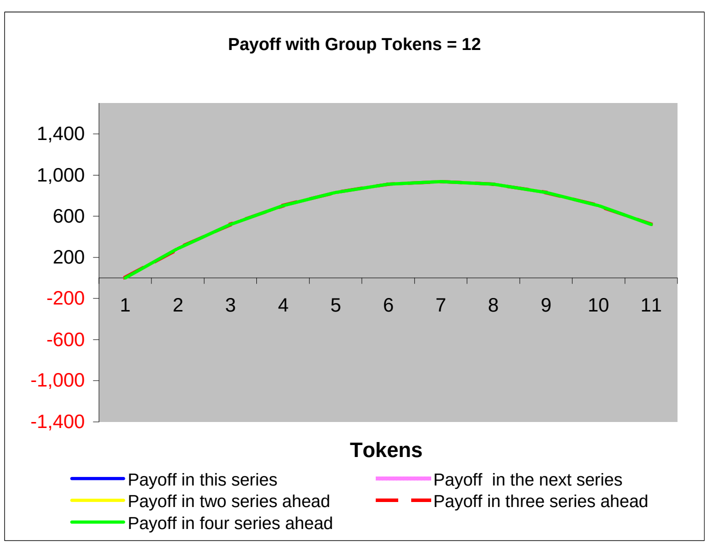
A1. Payoff with Group Tokens = 3 in each series

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

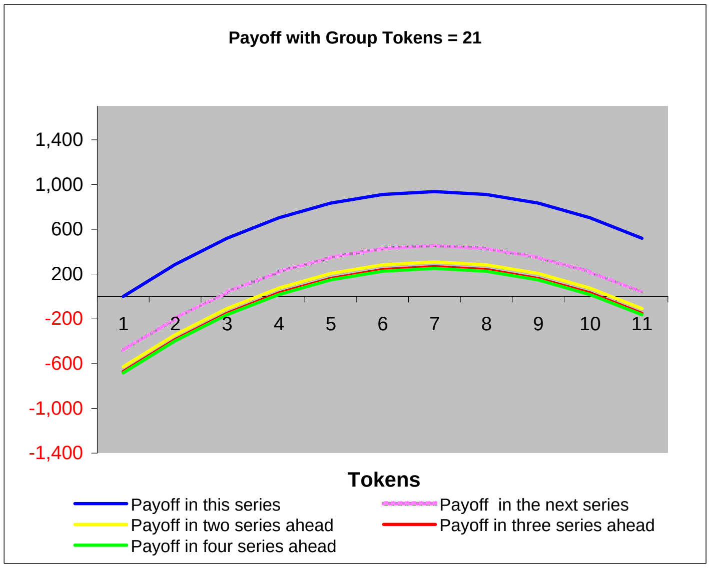
Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in this series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in the next series	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in two series ahead	1394	1	287	521	703	833	911	937	911	833	703	521
Payoff in three series ahead	1394	1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

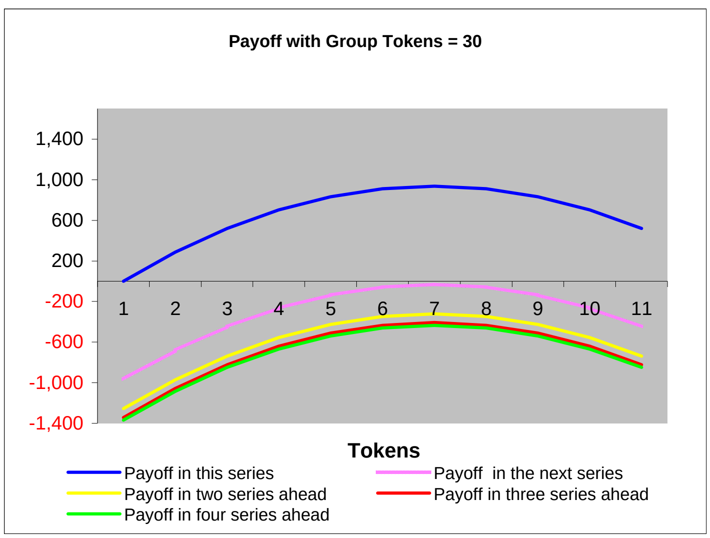
A3. Payoff with Group Tokens = 21 in each series

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



Decision Screen

Trial 3 of 3

Remaining time [sec]: 0

Please order your token now!

Series: 1

Group **1**

ID 3

Payoff schedule in this series with Payoff Level 1394

Tokens	1	2	3	4	5	6	7	8	9	10	11
Payoff	1	287	521	703	833	911	937	911	833	703	521

Calculator outcomes assuming the same token order in the future series

Your Tokens	Total Group Tokens	Current Payoff Level	Payoff Level in the next series	Payoff Level in 2 series ahead	Payoff Level in 3 series ahead	Payoff Level in 4 series ahead	Your Payoff	Payoff in the next series	Payoff in 2 series ahead	Payoff in 3 series ahead	Payoff in 4 series ahead
1	4	1394	1824	1953	1991	2003	1	431	560	599	610
11	30	1394	427	137	50	23	521	-446	-736	-823	-850

Calculator

Your tokens 11

Sum of the others' tokens 19

Test it!

History of outcomes

Trial	Your tokens	Your predicted sum of others' tokens	Actual sum of others' tokens	Group Tokens	Your payoff from token	Your payoff from prediction	Your total payoff
1	6	12	13	19	911	49.87	961
2	6	6	13	19	911	43.87	955

Please make sure that you test your decision in the calculator before placing your order!

Order Box

Payoff Level in this series 1394

Your token order 7

Your predicted sum of the others' order 12

Order now!

Series Results Screen

Series: 1

Group 1

ID 1

Trial 1 is randomly chosen as the paid trial for this series.

RESULTS IN THIS SERIES

Your tokens	Your predicted sum of others' tokens	Actual sum of others' tokens	Total group tokens	Your payoff from token	Your payoff from prediction	YOUR TOTAL PAYOFF
6	7	13	19	911	48	959

Payoff schedule in this 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 schedule in the next series

Your Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff in the next series	1018	-375	-89	145	327	457	535	561	535	457	327	145

Please give advice on token order for each participant: 4

Please leave your advice to the next series' participants here:

ID# 1: lowering it for one series might make it go up in the next

Note: Make sure to hit "ENTER" in the keyboard to register your advice on the UNshaded box.

READY

Advice from Previous Series

Series: 2

Group 1

ID 1

Payoff schedule in Previous Series

Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff	1394	1	287	521	703	833	911	937	911	833	703	521

Payoff schedule in this series

Tokens	Payoff Level	1	2	3	4	5	6	7	8	9	10	11
Payoff	1018	-375	-89	145	327	457	535	561	535	457	327	145

Token orders of participants in your group and their advice in Series 1

ID #	Token Orders	Recommended Token Orders
1	6	4
2	7	6
3	6	6
Total Token Orders	19	

Please refer to the handouts given to you for verbal advice.

Ready

Appendix E: Evolution of advice by treatment

E1: 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.

E2: 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!

E3: 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)