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Abstract

We examine whether optimization incentives --- incentives to best-respond --- have an effect on behavior in finitely repeated two-player dilemma games with strategic complements. We run an experiment in which we increase optimization incentives in two different ways compared to a baseline treatment. In the first treatment, the increase in optimization incentives is created by an increase in payoffs on the best-response curve, while its slope remains unchanged. In the second treatment, the increase in optimization incentives takes the form of an increase in the slope of the best-response curve, while best-response payoffs remain unchanged. We find that the impact of optimization incentives is overshadowed by the effect of the slope of the best-response curve. Although an increase in optimization incentives leads subjects to best-respond more frequently when the best-response curve is relatively flat, it leads to more cooperative behavior if it is accompanied by an increase in the slope of the best-response function.

JEL Classification: C91, D01, D74

Keywords: optimization incentives, strategic complementarity, repeated game, Cooperation, Experiments

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Optimization incentives in dilemma games with strategic complementarity

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March 2020

Abstract

We examine whether optimization incentives — incentives to best-respond — have an effect on behavior in finitely repeated two-player dilemma games with strategic complements. We run an experiment in which we increase optimization incentives in two different ways compared to a baseline treatment. In the first treatment, the increase in optimization incentives is created by an increase in payoffs on the best-response curve, while its slope remains unchanged. In the second treatment, the increase in optimization incentives takes the form of an increase in the slope of the best-response curve, while best-response payoffs remain unchanged. We find that the impact of optimization incentives is overshadowed by the effect of the slope of the best-response curve. Although an increase in optimization incentives leads subjects to best-respond more frequently when the best-response curve is relatively flat, it leads to more cooperative behavior if it is accompanied by an increase in the slope of the best-response function.

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1 Introduction

If a payoff function is flat in the neighborhood of the optimum, little is lost by not choosing that optimum. The more quickly payoffs decrease when moving away from the optimum, the higher the incentive to choose that optimum *ceteris paribus*. In the class of twice-continuously-differentiable payoff functions with an interior optimum, the (monetary) incentive to optimize a certain payoff function manifests itself in the concavity of that function.[1] This logic underlies models that incorporate decision costs (e.g., Wilcox, 1993), as well as probabilistic choice models in which the probability that an action is chosen increases with the payoff from that action relative to the payoff from other actions (e.g., McFadden, 1976; McKelvey and Palfrey, 1995, for individual and strategic choice, respectively). In line with the logic, laboratory experiments using games that fit within the above class of payoff functions have shown that higher concavity of the payoff function leads to play closer to or faster converging to the equilibrium (Harrison, 1989; Chen and Plott, 1996; Davis, Reilly, and Wilson, 2003; Chen and Gazzale, 2004). This paper presents novel results on the role of concavity of payoffs in the context of repeated dilemma games which fit within the class of games with a twice-continuously-differentiable payoff function.

Dilemma games are characterized by a tension between individual and joint payoff maximization, and are in their continuous form a paradigm for interactions like, for example, team production and behavior of firms in oligopoly. If repeated, even finitely, dilemma games are theoretically conducive to cooperation; cooperation until almost the end can be supported in a Nash equilibrium, in a subgame perfect Nash equilibrium if noise is allowed for, or in a sequential equilibrium in the case there is incomplete information about the partner's type (Kreps, Milgrom, Roberts, and Wilson, 1982; Fudenberg and Maskin, 1986; Benoit and Krishna, 1986; Radner, 1984). Behaviorally, dilemma games are particularly conducive to cooperation if played among pairs of players (Andreoni and Miller, 1993; Dufwenberg and Gneezy, 2000; Huck, Normann, and Oechssler, 2004). Increasing the concavity of a player's payoff function in these games not only affects the player's incentives near the payoff maximum of the stage game, it also affects marginal incentives at all other points in the strategy space. For example, incentives near the joint-payoff maximum are affected as well; the joint-payoff function also becomes more concave. A possible consequence is that a cooperative equilibrium is reached more easily, and it is not obvious that a more concave payoff function will lead to more frequent play of the stage-game equilibrium. Our experiment is designed to explore the effect of an increase in concavity (optimization incentives)

[1] Twice continuously differentiable payoff functions are commonly used in economics.

on behavior in a long finitely repeated dilemma game.

The main challenge is to study the effect of optimization incentives in a *ceteris paribus* manner. By changing optimization incentives, other important features of the game change as well. To illustrate, consider a two-player team-production game in which effort levels are complements and effort costs are convex. With z_i denoting the effort of player i the payoff function is, for example, equal to $z_i(A + \theta z_j) - dz_i^2$. In this setting optimization incentives are captured by d: the higher d, the higher is the second derivative, and the more costly it is to move away from the optimal effort level. It would seem natural to vary d in order to study the effects of a change in optimization incentives. However, doing so would not give a 'clean' test of the effect of the optimization incentive, as other important features of the game change with d as well. For example, as d changes, equilibrium effort levels and Pareto-optimal effort levels change as do the corresponding payoffs. Also the slope of the best-response (BR) curve changes with d. Given that such changes potentially affect behavior, it could be misleading to attribute an effect of a change in d on observed effort levels exclusively to a change in optimization incentives. Our design prevents such confounds as much as possible.

We compare behavior across games which vary in optimization incentives, but which have the same benchmark outcomes. We use two-player dilemma games with strategic complements.[2] We run treatments that have the same (interior) stage-game Nash equilibrium (SNE), the same joint-payoff-maximizing choice, the same SNE payoffs, and the same payoffs from joint-payoff maximization (i.e. mutual cooperation).[3] Two additional features of the payoff function that may affect behavior are *payoffs on* the BR curve and the *slope of* the BR curve. Payoffs on the BR curve potentially affect behavior because they influence the incentive to defect from mutual cooperation. The slope of the BR curve can also affect behavior because its absolute value influences the number of steps of iterated deletion of dominated strategies needed to arrive at the SNE (Van Huyck, Wildenthal, and Battalio, 2002), and, potentially, how easy players find it to cooperate in repeated games (Rotemberg, 1994; Bester and Güth, 1998; Boone, Declerck, and Suetens, 2008; Potters and Suetens, 2009; Davis, 2011; Embrey, Mengel, and Peeters, 2018).

[2]Games characterized by strategic complementarity constitute an important class of social dilemmas (Milgrom and Roberts, 1990; Eaton, 2004; Vives, 2005). Examples include team production with complementarity in skills, price competition with substitute goods, quantity competition with complementary goods, public goods with economies of scale, tax competition with mobile capital, R&D competition with spillovers, and arms races between enemy countries.

[3]Payoffs along the diagonal (i.e., payoffs associated with symmetric strategies) do not differ between the different treatments either.

If one implements a linear BR curve (which we do), it is impossible to control for these two features at the same time. As we show in the next section, increasing optimization incentives while keeping the slope of the BR curve constant, changes the payoffs on the BR curve, and thus increases the incentive to deviate from mutual cooperation. Increasing optimization incentives keeping constant the payoffs on the BR curve, increases the slope of the BR curve. The first effect, an increase in incentive to deviate from mutual cooperation, may weaken the scope for cooperation and thus confound the effect of optimization incentives. The second effect, a higher degree of strategic complementarity, may increase cooperation and overshadow a potential effect of optimization incentives on cooperation. That is why in our design we vary optimization incentives in both ways.

We find that an increase in optimization incentives accompanied by an increase in the incentive to deviate from mutual cooperation does not have effect on the average choice nor on the mutual cooperation rate. It does lead to more frequent myopic best-response play and stage-game equilibrium play though. If the increase in optimization incentives is accompanied by an increase in the degree of strategic complementarity, we find that average choices and mutual cooperation rates increase, and that there is no effect on myopic best-response play or stage-game equilibrium play. These results suggest that an increase in optimization incentives can help to coordinate on a non-cooperative equilibrium (i.e. the stage-game equilibrium) as well as on a cooperative equilibrium (i.e. a repeated-game equilibrium).

The remainder of the paper is organized as follows. section 2 introduces dilemma games with strategic complementarity. section 3 presents the experimental design, procedures, and research questions. section 4 talks about the results. section 6 concludes.

2 Dilemma Games with Strategic Complementarity

We employ a two-player game with a Pareto-dominated SNE. The stage game is characterized by the following general quadratic payoff function:

$$\pi_i(x_i, x_j) = a + bx_i + cx_j - dx_i^2 + ex_j^2 + fx_ix_j \qquad i, j = 1, 2, j \neq i, \tag{1}$$

with $x_i, x_j \geq 0$. From the first-order condition the following BR function is obtained for player i:

$$x_i^{BR}(x_j) = \frac{b}{2d} + \frac{f}{2d}x_j \qquad i, j = 1, 2, j \neq i. \tag{2}$$

The second-order condition specifies that $\frac{\partial^2 \pi_i}{\partial x_i^2} = -2d < 0$, i.e., $d > 0$. A necessary condition for the game to be a dilemma game is that the BR curve represented by $x_i^{BR}(x_j)$ has a slope strictly smaller than one: $\frac{f}{2d} < 1$, or $2d > f$. A necessary condition for the game to be characterized by strategic complementarities is that $f \geq 0$.[4]

Solving the first-order condition for $i, j = 1, 2, j \neq i$ leads to a SNE action equal to $x^{\mathrm{N}} = \frac{b}{2d - f}$ with associated payoff $\pi(x^{\mathrm{N}}, x^{\mathrm{N}}) = a + \frac{b^2(d + e) + bc(2d - f)}{(2d - f)^2}$. Maximizing the sum of payoffs of both players for $i, j = 1, 2, j \neq i$ leads to a mutually cooperative action of $x^{\mathrm{C}} = \frac{b + c}{2(d - e - f)}$ with associated payoff $\pi(x^{\mathrm{C}}, x^{\mathrm{C}}) = a + \frac{(b + c)^2}{4(d - e - f)}$.[5]

We define the optimization incentives as the absolute value of $\frac{\partial^2 \pi_i}{\partial x_i^2}$. Optimization incentives fully hinge on parameter d, measuring the concavity of the payoff function. It can be seen that the SNE (x^{N}) and the joint-payoff-maximizing choice (x^{C}) as well as payoffs change as d changes. In order to come as close as possible to a *ceteris paribus* change in optimization incentives, we vary d across treatments while keeping the values of x^{N} and x^{C} as well as corresponding payoffs $\pi(x^{\mathrm{N}}, x^{\mathrm{N}})$ and $\pi(x^{\mathrm{C}}, x^{\mathrm{C}})$ constant.

Define the payoff function of player i in game k as

$$\pi_i^k(x_i, x_j) = a_k + b_k x_i + c_k x_j - d_k x_i^2 + e_k x_j^2 + f_k x_i x_j, \tag{3}$$

with $x_i, x_j \geq 0$, $i, j = 1, 2$, $j \neq i$, and $k \in (\mathrm{F}, \mathrm{S})$ where F and S refer to 'flat' and 'steep', respectively. The function is of the type of eq. 1 and we assume that the necessary requirements to guarantee that the game is a twice-continuously-differentiable dilemma game with strategic complementarity are fulfilled. In order to ensure that the payoff function in game 'steep' is steeper than the one in game 'flat', we take that $d_{\mathrm{S}} = l d_{\mathrm{F}}$ with $l > 1$.

The payoff function has six free parameters and holding constant the above-mentioned theoretical benchmarks as well as the requirement that $d_{\mathrm{S}} = l d_{\mathrm{F}}$ leads to five requirements that need to be satisfied when varying parameters between games with a flat and a steep payoff function. The sixth degree of freedom can be used to vary optimization incentives in one of the following ways: (1) by holding constant the BR curve's slope and varying payoffs on the BR curve,

[4] A game exhibits strategic complementarity (or increasing differences) if the marginal returns to increases in one's action increase with increases in the other players' actions, that is if in the two-player case $\frac{\partial^2 \pi_i}{\partial x_i x_j} \geq 0$ with $i, j = 1, 2$ and $j \neq i$ (Fudenberg and Tirole, 1984; Bulow, Geanakoplos, and Klemperer, 1985). This condition is satisfied if $f \geq 0$.

[5] The mutually cooperative action is unique and symmetric if and only if $d > e - f$ (see Appendix A.3).

and (2) by holding constant the payoffs on the BR curve and varying its slope. Variation (1) leads to the following parameters in the 'steep' game as a function of those in the 'flat' game: $a_S = a_F; b_S = lb_F; c_S = (1-l)b_F + c_F; d_S = ld_F; e_S = e_F - (1-l)(d_F - f_F); f_S = lf_F$. Variation (2) leads to the following parameters in the 'steep' game as a function of those in the 'flat' game: $a_S = a_F; b_S = \sqrt{l}b_F; c_S = (1-\sqrt{l})b_F + c_F; d_S = ld_F; e_S = -(1+l)d_F + e_F + f_F + \sqrt{l}(2d_F - f_F); f_S = 2ld_F - \sqrt{l}(2d_F - f_F)$. Variation (1) increases the temptation payoff (that is, the payoff when best-responding to mutual cooperation) keeping constant the degree of strategic complementarity. Variation (2) increases the degree of strategic complementarity keeping constant the temptation payoff.

3 Experimental design, procedures, and research questions

3.1 Experimental design

The key treatments in our experiment are a treatment with a flat payoff function (Flat) and two treatments with a steep payoff function (SteepTemp and SteepComp). The parameters of the payoff function in Flat are $a_F = 45, b_F = 3.2, c_F = 14.88, d_F = 1, e_F = -0.53$, and $f_F = 0.4$. The parameters of the payoff function in SteepTemp are calculated from those in Flat using variation (1), and the parameters in SteepComp are calculated from those in Flat using variation (2). So in both Steep treatments, the payoff function is four times steeper than the payoff function in Flat ($l = 4$). In SteepTemp the BR curve has the same slope (equal to 0.2) as in Flat, but the payoffs on the BR curve (including the temptation payoff) are different. To illustrate, the temptation payoff $\pi(x_i^{BR}(x_j^C), x_j^C)$ is 209.5 in SteepTemp as compared to 140.4 in Flat. In SteepComp the degree of strategic complementarity is higher—the slope of the BR curve is equal to 0.6 compared to 0.2 in Flat and SteepTemp—but the payoffs on the BR curve are the same. Table 1 gives an overview of the theoretical benchmarks in the three treatments.As shown in the table, all treatments have the same SNE and the same joint-payoff-maximizing choice, and associated payoffs. The table includes the payoff if one chooses the joint-payoff maximizing choice and the partner best-responds to it, denoted as $\pi(x_i^C, x_j^{BR}(x_i^C))$, similar to the 'sucker' payoff in a prisoner's dilemma. This payoff is substantially lower in SteepTemp than in the other treatments, and is almost equal in Flat and SteepComp. Figure A3 in the Appendix illustrates the BR curves and the iso-payoff contours calculated at the SNE for each of the treatments. As can be seen in the figure, the range of outcomes that Pareto-dominate the SNE is much larger in Flat than in the other two treatments.[6]

Table 1: Treatments and parameters

	Flat	SteepTemp	SteepComp
$x_{\min}$	0.0	0.0	0.0
$x_{\max}$	10.0	10.0	10.0
x^{N}	2.0	2.0	2.0
x^{C}	8.0	8.0	8.0
$\pi(x^{\mathrm{N}}, x^{\mathrm{N}})$	76.6	76.6	76.6
$\pi(x^{\mathrm{C}}, x^{\mathrm{C}})$	117.3	117.3	117.3
concavity payoff function ($2d$)	2	8	8
slope BR curve ($\frac{f}{2d}$)	0.20	0.20	0.60
$x_i^{\mathrm{BR}}(x_j^{\mathrm{C}})$	3.2	3.2	5.6
$\pi(x_i^{\mathrm{BR}}(x_j^{\mathrm{C}}), x_j^{\mathrm{C}})$	140.4	209.5	140.4
$\pi(x_i^{\mathrm{C}}, x_j^{\mathrm{BR}}(x_i^{\mathrm{C}}))$	59.0	-37.7	60.1

Notes: $x_{\min}$ and $x_{\max}$ respectively refer to the lower and upper bound of the stage-game strategy space, x^{N} ($\pi(x^{\mathrm{N}}, x^{\mathrm{N}})$) and x^{C} ($\pi(x^{\mathrm{C}}, x^{\mathrm{C}})$) to the stage-game NE and the fully cooperative choice (payoff), $\pi(x_i^{\mathrm{BR}}(x_j^{\mathrm{C}}), x_j^{\mathrm{C}})$ to the payoff from best-responding to full cooperation (temptation payoff), and $\pi(x_i^{\mathrm{C}}, x_j^{\mathrm{BR}}(x_i^{\mathrm{C}}))$ to the payoff from fully cooperating with a partner who best-responds to full cooperation (sucker payoff).

3.2 Experimental Procedures

The experiment has been conducted at the Laboratory for Experimental Economics of the University of Copenhagen.[7] The three treatments were run in three sessions covering 74 participants in total. The numbers of participants per treatment are 26 in Flat, 20 in SteepTemp, and 28 in SteepComp.

All participants received the same instructions (see section A.1 of the Appendix). The treatments differed only with respect to the payoff function. The subjects were explained that their earnings depended on their own choices and on the choices of one other participant in the session,

[6] In an experiment that studies the effect of strategic complementarity on imitation of best-performers, Gazzale (2009) includes treatments that control for the number of Pareto-superior outcomes. In his experiment the frequency of Pareto-superior outcomes is not influenced by the theoretical range of such outcomes, but rather by the extent to which the range includes best-responses.

[7] The experimental software toolkit *z-Tree* was used to program the experiment (see Fischbacher, 2007) and ORSEE to recruit participants (see Greiner, 2015).

which remained the same during the entire experiment. They were asked to choose a number between 0.0 and 10.0 in each round.[8] Subjects could calculate their earnings in points by means of a payoff table and by means of an earnings calculator on the computer screen for any combination of hypothetical choices.[9]

The same (static) game was repeated 30 times with the same pairs of players excluding a trial round which did not count to calculate earnings. After each round, subjects were informed about the choice of the paired participant and their own and the opponent's payoff. Earnings were denoted in points and transferred to cash at a rate of 250 points = 10 DKK. Subjects were informed about the number of rounds. The sessions lasted about 50 minutes including the reading of instructions. Average earnings were 120.3 DKK (16.2 EUR).[10]

3.3 Hypotheses

We start from the premise that the repeated games in our experiment may be conducive to behavior that is more cooperative than the SNE prescribes. The question is thus one of identifying conditions under which cooperation is more likely to occur. Given that optimization incentives are basically the marginal costs of a deviation from a best-response, it is intuitive to expect that players are more inclined to best-respond and less likely to stay in a cooperative equilibrium as these increase. The intuition can be formalized by appealing to quantal-response equilibrium, which assumes that the likelihood of deviating from the payoff-maximizing choice is inversely related to the cost of doing so (McKelvey and Palfrey, 1995).[11] We therefore formulate our research hypothesis as follows:

Main hypothesis. *An increase in optimization incentives leads to a decrease in cooperation:* $\mathsf{Flat} > \mathsf{SteepTemp} \approx \mathsf{SteepComp}$.

If we take into account other forces that have been identified to play a role in repeated dilemma games predictions are different. A factor that may be particularly relevant is the degree of

[8]The number of possible decimal points was limited to one.

[9]Earnings in points were rounded at one decimal. Payoff tables are in section A.2 of the Appendix.

[10]In the context of another study, subjects played a one-shot prisoner's dilemma with a different partner before they played the repeated dilemma game. This part had between-subjects treatment variation in terms of 'sucker' payoff, and no differences in cooperation rates were found between the treatments. The outcomes were only communicated to the subjects after they had finished the repeated dilemma games. It is thus highly unlikely that including this first part has had a systematic effect on behavior in the dilemma games.

[11]See section A.3 of the Appendix.

strategic complementarity, measured by the (absolute value of the) slope of the BR curve. More steps of iterated dominance are required, the higher the (absolute value of the) slope of the BR curve, and Van Huyck, Wildenthal, and Battalio (2002) have shown that players are less likely to play the SNE in dilemma games, the higher the number of steps of iterated dominance. Moreover, given that repeated games with strategic complementarity have been found to be more conducive to cooperation than games with strategic substitutability if opportunities to revise repeated-game strategies are flexible (Potters and Suetens, 2009; Embrey, Mengel, and Peeters, 2018), it may very well be that the degree of strategic complementarity could have a positive effect on the degree of cooperation (see also Davis, 2011).

Both of these mechanisms can be formalized by a level-k model that assumes players differ in the level of strategic sophistication (Stahl and Wilson, 1984; Nagel, 1995): level-0 players select a choice that is more cooperative than the SNE strategy because they randomize (or naively cooperate), level-1 players best-respond to the belief that the other player is a level-0 player, level-2 players best-respond to the belief that the other player is a level-1 player, and so on. Since the BR curves are upward sloping, if a level-k player selects a choice above the SNE, all players with a higher level will also do so. Responses by higher-level players deviate more from the SNE the steeper the BR curve.[12] An alternative prediction is thus that there is more cooperation in SteepComp than in Flat and SteepTemp. This leads to the first alternative hypothesis:

Alternative hypothesis 1. *An increase in the degree of strategic complementarity leads to an increase in cooperation:* SteepComp $>$ Flat $\approx$ SteepTemp.

A second set of possible determinants of behavior are the incentive to best-respond to mutual cooperation, equivalent to the temptation payoff in a prisoner's dilemma game, and the payoff from mutual cooperation being best-responded to, equivalent to the sucker payoff.It has been shown that an increase in the temptation payoff decreases the cooperation rate in finitely repeated prisoner's dilemma games (Mengel, 2018). If this force is dominant, no difference should be seen in cooperation between Flat and SteepComp, and in line with the above-included hypothesis, less cooperation should be seen in SteepTemp than in Flat. The same comparative-static prediction holds if one considers the sucker payoff, which influences the riskiness of cooperation. Both predictions can be integrated by appealing to the basin of attraction of repeated-game strategies,

[12] section A.3 of the Appendix provides an application of the level-k model. A cognitive hierarchy model à la Camerer, Ho, and Chong (2004) gives the same comparative-static predictions.

which has been shown to be helpful for organizing much of the empirical evidence on finitely repeated prisoner's dilemma games (see Embrey, Fréchette, and Yuksel, 2018). The general prediction is that a player prefers to use a cooperative strategy in the repeated game instead of a defective strategy for a wider range of beliefs about the strategy of the partner if the temptation payoff is relatively low or the sucker payoff relatively high. For example, it can be shown that if strategies are defined so that payoffs on the BR curve influence the trade-off, a cooperative strategy is least attractive in SteepTemp, and basically equally attractive in Flat and SteepComp (see section A.3 of the Appendix). We formulate the second alternative hypothesis as follows:

Alternative hypothesis 2. *An increase in the temptation payoff or a decrease in the sucker payoff lead to a decrease in cooperation:* SteepComp $\approx$ Flat $>$ SteepTemp.

4 Main results

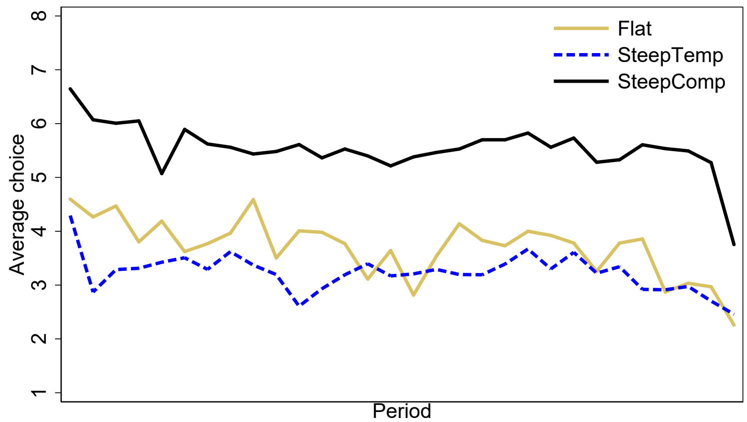
We focus on studying treatment effects on cooperation. In Subsection 4.1 we report average choices and payoffs because they indicate whether play in the repeated games is cooperative and how cooperative it is. Average choices, however, are a rough measure of behavior and may hide different types of behavioral tendencies. Different underlying distributions of choices may result in the same average. For example, averages do not provide direct information on the extent to which pairs succeed in mutually cooperating or on the extent to which subjects best-respond. Subsections 4.2 and 4.3 report results on the latter two types of behavior.

4.1 Aggregate Choices

Figure 1 depicts the evolution of average choices by treatment. Figure 1 shows that, overall, average choices are higher than 2 (the SNE) and lower than 8 (the joint-payoff-maximizing choice). More importantly, the average choice is clearly higher in SteepComp than in Flat, and, abstracting from end-game effects, this difference does not reduce over time. Overall, the effect is statistically significant ($p = 0.002$, $N = 27$) and the difference already appears in the first period ($p = 0.002$, $N = 54$).[13] The average choice in SteepTemp, on the other hand, is close to that in Flat ($p = 0.480$, $N = 25$ across all periods and $p = 0.440$, $N = 50$ across first periods) and well

[13]The statistical tests reported throughout the results section are Mann-Whitney-U tests based on independent observations. If averages across periods are compared, each pair of players is taken as an independent observation. If choices in period 1 are compared, each subject is counted as an independent observation.

Figure 1: Average Choice by Treatment



Notes: The figure shows the evolution of the average choice across subjects by treatment.

below that in SteepComp ($p = 0.001$, $N = 26$ across all periods and $p = 0.001$, $N = 52$ across first periods).[14] Significant treatment effects in the action space do not necessarily translate into significant differences in payoffs (Harrison, 1989). However, if we look at treatment effects on payoffs, then a similar picture emerges. To illustrate, the average payoff in SteepComp is about 11% higher than that in Flat ($p = 0.065$, $N = 27$) and about 16% higher than that in SteepTemp ($p = 0.006$, $N = 26$).

The patterns in the data are generally supportive of alternative hypothesis 1. If an increase in the optimization incentive is combined with an increase in the slope of the BR curve, behavior gets more cooperative. An increase in the optimization incentive combined with a change in payoffs on the BR curve does not have much of an effect on the average choice. These results are a first indication that the positive effect of the degree of strategic complementarity on cooperation tends to dominate the negative effect of payoffs on the BR curve.

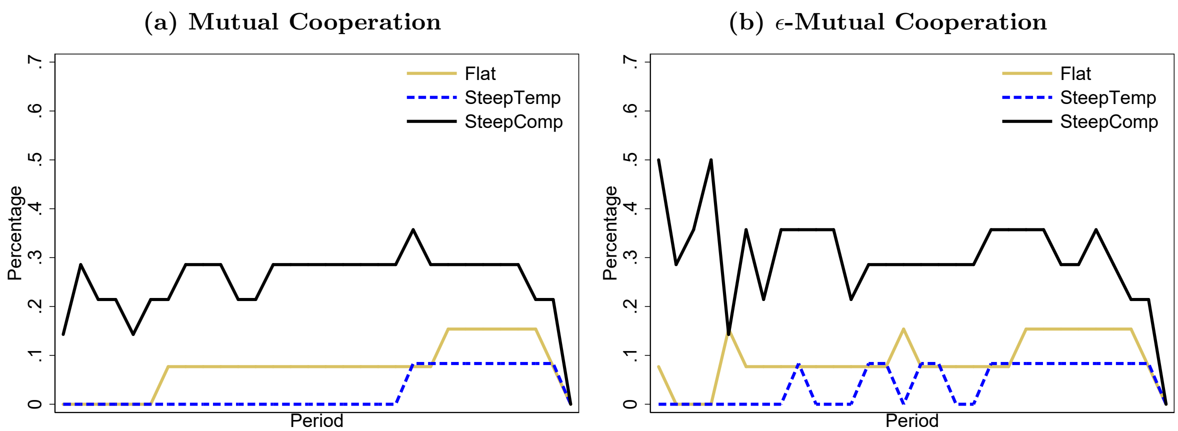
4.2 Mutual Cooperation

Figure 2 depicts the evolution of the percentage of mutual cooperation and ϵ-mutual cooperation of pairs by treatment, where ϵ-mutual cooperation refers to the average choice of a pair being in the interval $[7, 9]$ (so $\epsilon = \pm 1$).[15] The figure shows that subjects are more successful in

[14] A detailed overview of choices and other outcome variables averaged across all periods and across first periods is shown in Table A6 in the Appendix.

[15] We keep ϵ fixed across treatments for simplicity. Because optimization incentives differ between the treatment, one may argue that ϵ should depend on the treatment. Given that patterns of mutual cooperation and ϵ-mutual

Figure 2: Percentage of (ϵ-)Mutual Cooperation by Treatment



Notes: The figure shows the evolution of the percentage of (ϵ-)mutual cooperation by treatment.

reaching mutual cooperation in SteepComp than in Flat ($p = 0.060$, $N = 27$) and than in SteepTemp ($p = 0.060$, $N = 26$), and that there is not much of a difference between Flat and SteepTemp ($p = 1$, $N = 27$). To illustrate, 25% of the subjects in SteepComp earn the joint-payoff-maximizing payoff of about 117 points whereas in Flat and SteepTemp only 7% and 3% respectively earn such payoff. Comparative statics in ϵ-mutual cooperation are qualitatively similar and generally reach higher statistical significance (e.g. $p = 0.015$ for SteepComp versus Flat and $p = 0.018$ for SteepTemp versus Flat). The results show that a high degree of strategic complementarity is a catalyst for a high level of cooperation.

The higher tendency to cooperate already appears in the first round. In SteepComp 32% of the subjects choose the joint-payoff-maximizing choice of 8 versus 12% in Flat and 4% in SteepTemp ($p = 0.018$ in a χ^2-test, $N = 78$). The percentages for ϵ-cooperation are equal to 54%, 23%, and 13%, respectively ($p = 0.003$ in a χ^2-test, $N = 78$).[16] We conclude that games with high optimization incentives are not by definition less conducive to cooperation. If high optimization incentives imply a high degree of complementarity, they are instead more conducive to cooperation, as summarized in alternative hypothesis 1.

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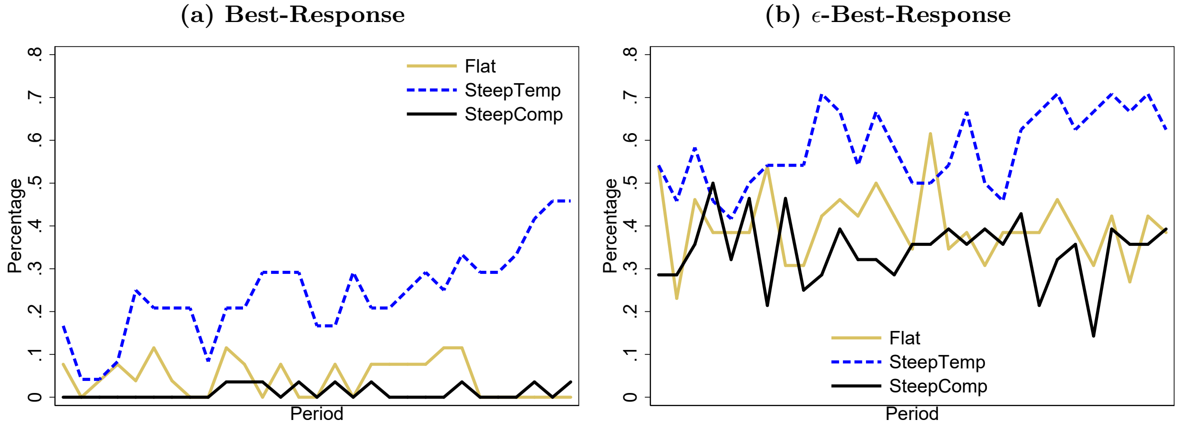
cooperation are largely similar across treatments, we do not consider this a problem.

[16]Relatedly, if we classify initial choices into ϵ-cooperation, ϵ-SNE, ϵ-best-response-to-cooperation and other, we find that the distribution is significantly different between treatments ($p = 0.008$ in a χ^2-test, $N = 78$).

Figure 3: Percentage of (ϵ-)Best-Response Play by Treatment



Notes: The figure shows the evolution of the percentage of (ϵ-)best-response play by treatment.

4.3 Best-Response and Static Nash Play

We study whether there are treatment effects on the extent to which subjects play BR. As a proxy for BR play we use the percentage of times subjects choose a BR to the matched partner's choice from the previous period (cf. myopic BR). Figure 3 depicts the percentages of BR and ϵ-BR play by treatment. We say that a subject plays an ϵ-BR if he/she plays a BR $\pm$ 1.

Figure 3 shows that there is more BR and ϵ-BR play in SteepTemp than in the two other treatments, and that the percentage of BR and ϵ-BR play increases over the course of the experiment in SteepTemp. The differences in BR and ϵ-BR play between SteepTemp and Flat are marginally significant if all periods are taken into consideration (resp. $p = 0.082$ and 0.057, $N = 25$ for BR and ϵ-BR play), and are strongly significant if only the last five periods are considered (resp. $p = 0.005$ and 0.025, $N = 25$). If we compare SteepTemp and SteepComp, we get p-values of resp. $p = 0.007$ and 0.045 across all periods and p-values of resp. $p = 0.023$ and 0.027 across the last five rounds ($N = 26$).[17]

In our games this adjusted dynamic converges to the SNE, and the speed of convergence is higher the higher the slope of the BR curve (Milgrom and Roberts, 1991). With respect to (ϵ-)SNE play we find that the (ϵ-)SNE is played most frequently in SteepTemp and least frequently in SteepComp (see Figure A4 in the Appendix). Flat lies in between the two.

We conclude from the results that although optimization incentives do not have an effect on

[17] With respect to the comparison between SteepComp and Flat we find that $p = 0.056$ for BR-play and $p = 0.544$ for ϵ-BR play ($N = 27$).

the rate of cooperation, they have some influence on the extent of BR and SNE play. Provided that the degree of strategic complementarity is low, higher optimization incentives lead to more BR and SNE play.

5 High complementarity and low optimization incentives

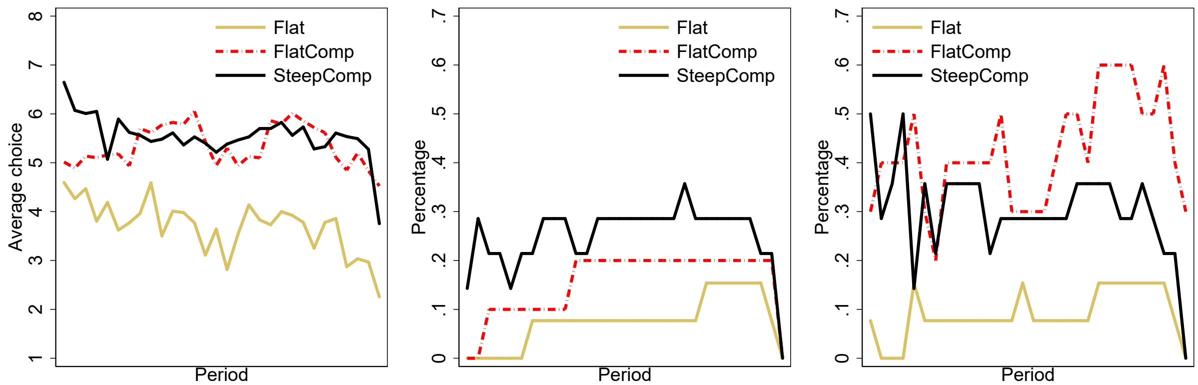
In order to further study the role of strategic complementarity on cooperative behavior in a repeated game, we ran another treatment with a high degree of complementarity. In this treatment, which we label FlatComp, the SNE, the joint-payoff-maximizing choice and associated payoffs are the same as in the other treatments, the slope of the best-response curve is as high as in SteepComp ($\frac{f}{2d} = 0.6$) and optimization incentives (i.e. costs of deviation from best-response play) are as low as in Flat ($d = 1$). In the payoff function there are no free parameters left to also control to what we have referred to as the temptation payoff and the sucker payoff. Consequently, the temptation payoff in FlatComp and other payoffs on the BR curve are lower than in any of the other treatments (equal to 123.1), and the sucker payoff is higher (equal to 98.1), leading to a higher basin of attraction of a grim trigger strategy. FlatComp thus differs from the other treatments in at least two respects. Since FlatComp and SteepTemp differ in *three* respects — different optimization incentives, different degree of strategic complementarity and different basin of attraction of a grim trigger strategy — we focus in what follows on comparing FlatComp to Flat and SteepComp.

The main hypothesis, which predicts that an increase in optimization incentives leads to a decrease in cooperation, still stands. Consistent with optimization incentives having most influence, a QRE model predicts that choices in FlatComp are of the same order of magnitude as in Flat, and substantially higher than in SteepComp (see section A.3 in the Appendix). Consequently, comparative statics in terms of cooperativeness are predicted to be as follows: FlatComp $\approx$ Flat $>$ SteepComp. Alternative hypothesis 1 states that strategic complementarity drives cooperation so that FlatComp $\approx$ SteepComp $>$ Flat. Alternative hypothesis 2 builds upon the basin of attraction of a cooperative strategy, and implies that FlatComp $>$ Flat $\approx$ SteepComp.

Figure 4 shows the evolution of the average choice in FlatComp as compared to the relevant benchmark treatments as well as that of the mutual cooperation rate and the ϵ-mutual cooperation rate. It can clearly be seen that the average choice and the ϵ-mutual cooperation rate are at a similar level in SteepComp (resp. $P = 0.907$ and $P = 0.217$, $N = 23$) and substantially higher than in Flat (resp. $P = 0.047$ and $P = 0.004$, $N = 24$). A similar conclusion holds for the mutual

Figure 4: Behavior in FlatComp

(a) Average choice **(b) Mutual Cooperation** **(c) ϵ-Mutual Cooperation**



cooperation rate, albeit less pronounced and without statistical significance ($P > 0.325$). With respect to (ϵ-)BR play and (ϵ-)SNE play, levels are not significantly different between treatments and patterns over time are very similar in the three treatments (see Figure A5 and Figure A6 in the Appendix). We conclude that data from FlatComp confirm that the degree of strategic complementarity is the main driving force of cooperativeness, which implies that we reject the main hypothesis in favor of alternative hypothesis 1.

6 Conclusion and discussion

We have studied whether and how optimization incentives influence behavior in repeated dilemma games with strategic complementarity characterized by a twice-continuously-differentiable payoff function. To do so, we varied the concavity of the payoff function. The steeper the payoff function, the higher the penalty for not playing a static best response; hence the lower the extent of cooperation one should observe. Our aim was to test this prediction in a *ceteris paribus* manner, that is, by controlling for the location and payoff of several benchmark outcomes. It turns out that this can be done only by allowing either the *payoffs on the best-response function* or the *slope of the best-response function* to vary alongside the optimization incentives. In particular, in terms of a quadratic model, if one would increase concavity, one either increases the payoffs on the best-response curve (including the temptation payoff) or the slope of the best-response function. Our experiment varies both components, which allows us to disentangle their effect.

The results show that stronger optimization incentives do not generally decrease cooperation.

In the case that payoffs on the best-response curve increase alongside the optimization incentives, we find that although the frequency of best-response play increases, and so does the frequency of static equilibrium play, the effect does not reveal itself in the aggregate level of cooperation. In the case that the slope of the best-response curve increases alongside the optimization incentives, the results reveal an *increase* in the degree of cooperation rather than a decrease. The stronger incentives to best-respond are overshadowed by the best-response curve's slope being higher, which has a facilitating effect on cooperation. The results fit well in a literature that shows that strategic complementarity generates an amplifying effect of boundedly rational behavior (Haltiwanger and Waldman, 1989; Fehr and Tyran, 2005). A move in a certain (e.g., cooperative) direction by one player induces a move in the same direction by a best-responding other player. The amplifying effect is stronger, the steeper is the best-response function. Unlike equilibrium notions such as static Nash or quantal-response equilibrium, recursive models of bounded rationality like level-k and cognitive hierarchy predict that this affects the final outcome (Camerer and Fehr, 2006).

The results have implications for the design of incentive schemes in the context of team production in long relationships. In particular, if the aim is to increase cooperation among the team members, then this can be achieved by increasing the degree of strategic complementarity between team members, even if this goes along with a sharpening of the individual incentives to best-respond. For practical purposes, it would be relevant to have information about the boundaries of the effect of strategic complementarity, that is, about the sensitivity of the effect to a further increase in payoffs on the best-response curve.[18] It is an open question whether at some point the incentive to be on the best-response curve starts to dominate so that the cooperation-inducing effect of a high slope is reduced. Another interesting question is whether strategic complementarity would have a similarly strong effect if there would be no scope for repeated-game effects. The result that an increase in strategic complementarity not only increases the average choice but also the rate of mutual cooperation suggests that such effects may be important.

[18]This can for example be studied by adding a treatment in which the slope of the BR curve is the same as in SteepComp and the temptation payoff and other payoffs on the best-response curve are as in SteepTemp.

References

Andreoni, J. and J. H. Miller (1993). Rational cooperation in the finitely repeated prisoner's dilemma: Experimental evidence. *The Economic Journal 103*, 570–585.

Benoit, J.-P. and V. Krishna (1986). Finitely repeated games. *Econometrica 53*, 905–922.

Bester, H. and W. Güth (1998). Is altruism evolutionary stable? *Journal of Economic Behavior and Organization 34*, 193–2092.

Boone, C., C. Declerck, and S. Suetens (2008). Subtle social cues, explicit incentives and cooperation in social dilemmas. *Evolution and Human Behavior 29*, 179–188.

Bulow, J., J. Geanakoplos, and P. Klemperer (1985). Multimarket oligopoly: strategic substitutes and complements. *Journal of Political Economy 93*, 488–511.

Camerer, C. and E. Fehr (2006). When does "economic man" dominate social behavior? *Science 711*, 47–52.

Camerer, C. F., T. H. Ho, and J. K. Chong (2004). A cognitive hierarchy model of games. *Quarterly Journal of Economics 119*(3), 861–898.

Chen, Y. and R. Gazzale (2004). When does learning in games generate convergence to Nash equilibria? The role of supermodularity in an experimental setting. *American Economic Review 94*, 1505–35.

Chen, Y. and C. Plott (1996). The Groves-Ledyard mechanism: an experimental study of institutional design. *Journal of Public Economics 59*, 335–64.

Davis, D. (2011). Behavioral convergence properties of Cournot and Bertrand markets: an experimental analysis. *Journal of Economic Behavior & Organization 80*, 443–458.

Davis, D., R. Reilly, and B. Wilson (2003). Cost structures and Nash play in repeated Cournot games. *Experimental Economics 6*(2), 209–226.

Dufwenberg, M. and U. Gneezy (2000). Price competition and market concentration: An experimental study. *International Journal of Industrial Organization 18*(1), 7–22.

Eaton, B. (2004). The elementary economics of social dilemmas. *Canadian Journal of Economics 37*, 805–29.

Embrey, M., G. R. Fréchette, and S. Yuksel (2018). Cooperation in the finitely repeated prisoner's dilemma. *Quarterly Journal of Economics 133*(1), 211–224.

Embrey, M., F. Mengel, and R. Peeters (2018). Strategy revision opportunities and collusion. *Experimental Economics forthcoming.*

Fehr, E. and J. Tyran (2005). Individual irrationality and aggregate outcomes. *Journal of*

Economic Perspectives 19, 43–66.

Fischbacher, U. (2007). z-Tree: Zurich toolbox for ready-made economic experiments. *Experimental Economics 10*, 171–178.

Fudenberg, D. and E. Maskin (1986). The folk theorem in repeated games with discounting or with incomplete information. *Econometrica 54*(3), 533–554.

Fudenberg, D. and J. Tirole (1984). The fat-cat effect, the puppy-dog ploy, and the lean and hungry look. *American Economic Review 74*, 361–6.

Gazzale, R. (2009). Learning to play Nash from the best.

Greiner, B. (2015). Subject pool recruitment procedures: Organizing experiments with ORSEE. *Journal of the Economic Science Association 1*, 114–125.

Haltiwanger, J. and M. Waldman (1989). Limited rationality and strategic complements: the implications for macroeconomics. *Quarterly Journal of Economics 104*, 463–83.

Harrison, G. (1989). Theory and misbehavior of first-price auctions. *American Economic Review 79*, 749–62.

Huck, S., H. Normann, and J. Oechssler (2004). Two are few and four are many: number effects in experimental oligopolies. *Journal of Economic Behavior and Organization 53*, 435–46.

Kreps, D., P. Milgrom, J. Roberts, and R. Wilson (1982). Rational cooperation in the finitely repeated prisoners' dilemma. *Journal of Economic Theory 27*, 245–52.

McFadden, D. (1976). Quantal choice analysis: A survey. *Annals of Economic and Social Measurement 5*, 363–390.

McKelvey, R. and T. Palfrey (1995). Quantal response equilibria for normal form games. *Games and Economic Behavior 10*, 6–38.

McKelvey, R. D., A. M. McLennan, and T. L. Turocy (2014). Gambit: Software tools for game theory, version 15.1.1. http://www.gambit-project.org.

Mengel, F. (2018). Risk and temptation: A meta-study on social dilemma games. *The Economic Journal 128*, 3182–3209.

Mermer, A., W. Müller, and S. Suetens (2019). Cooperation in infinitely repeated games of strategic complements and substitutes. Working paper.

Milgrom, P. and J. Roberts (1990). Rationalizability, learning, and equilibrium in games with strategic complementarities. *Econometrica 58*, 1255–77.

Milgrom, P. and J. Roberts (1991). Adaptive and sophisticated learning in normal form games. *Games and Economic Behavior 3*, 82–100.

Nagel, R. (1995). Unraveling in guessing games: An experimental study. *American Economic*

Review 85(5), 1313–1326.

Potters, J. and S. Suetens (2009). Cooperation in games of strategic complements and substitutes. *Review of Economic Studies 76*, 1125–47.

Radner, R. (1984). Can bounded rationality resolve the prisoner's dilemma? In A. Mas-Colell and W. Hildenbrand (Eds.), *Contributions to mathematical economics*, pp. 387–399. Amsterdam: North-Holland.

Rotemberg, J. (1994). Human relations in the workplace. *Journal of Political Economy 102*, 684–717.

Stahl, D. O. and P. W. Wilson (1984). Experimental evidence on players' models of other players. *Journal of Economic Behavior and Organization 25*(3), 309–327.

Van Huyck, J., J. Wildenthal, and R. Battalio (2002). Tacit cooperation, strategic uncertainty, and coordination failure: Evidence from repeated dominance solvable games. *Games and Economic Behavior 38*, 156–175.

Vives, X. (2005). Games with strategic complementarities: new applications to industrial organization. *International Journal of Industrial Organization 23*, 625–37.

Wilcox, N. (1993). Lottery choice: Incentives, complexity and decision time. *Economic Journal 103*, 1397–1417.

A Appendix (for online publication)

A.1 Instructions

You are participating in an experiment on economic decision making and will be asked to make a number of decisions. If you follow the instructions carefully, you can earn a considerable amount of money. At the end of the experiment, you will be paid your earnings in private and in cash.

During the experiment you are not allowed to talk to other participants. If something is not clear, please raise your hand and one of us will help you.

Your earnings depend on your own decisions and on the decisions of one other participant, different from the matched participant from experiment 1. The identity of the other participant will not be revealed. The other participant remains the same during the experiment and will be referred to by 'the other' in what follows.

The experiment consists of 30 periods. In each period you have to choose a number between 0.0 and 10.0. The other also chooses a number between 0.0 and 10.0 (one digit behind the comma is allowed). Your earnings in points depend on your choice and the other's choice. The table attached to these instructions gives information about your earnings for integer combinations of your choice and the other's choice. The other gets the same table.

By using the EARNINGS CALCULATOR on your screen, you can calculate your and the other's earnings for all possible combinations of choices. By filling in a hypothetical value for your own choice and a hypothetical value for the other's choice you can calculate your and the other's earnings for this combination of choices.

You enter your decision under DECISION ENTRY by clicking on 'Enter'.

After each period you are informed about the other's choice and your and the other's earnings in that period. A history of your and the other's past choices and earnings is available at the bottom right of your computer screen.

You receive 250 points and the number of points you earn on top of that is equal to the sum of your earnings in points over the 30 periods. Your total earnings in points will be converted into DKK according to the following rate: 250 points = 10 DKK.

The first period is a trial period and does not count when calculating your earnings. It is intended for you to try out the earnings calculator and to see how the computer screen works.

A.2 Payoff tables

Table A1: Payoff table in Flat

		The other's choice →										
		0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
	0.0	45.0	59.4	72.6	84.9	96.0	106.2	115.2	123.2	130.1	136.0	140.8
	1.0	47.2	62.0	75.6	88.3	99.8	110.4	119.8	128.2	135.5	141.8	147.0
	2.0	47.4	62.6	76.6	89.7	101.6	112.6	122.4	131.2	138.9	145.6	151.2
Your	3.0	45.6	61.2	75.6	89.1	101.4	112.8	123.0	132.2	140.3	147.4	153.4
Choice	4.0	41.8	57.8	72.6	86.5	99.2	111.0	121.6	131.2	139.7	147.2	153.6
↓	5.0	36.0	52.4	67.6	81.9	95.0	107.2	118.2	128.2	137.1	145.0	151.8
	6.0	28.2	45.0	60.6	75.3	88.8	101.4	112.8	123.2	132.5	140.8	148.0
	7.0	18.4	35.6	51.6	66.7	80.6	93.6	105.4	116.2	125.9	134.6	142.2
	8.0	6.6	24.2	40.6	56.1	70.4	83.8	96.0	107.2	117.3	126.4	134.4
	9.0	-7.2	10.8	27.6	43.5	58.2	72.0	84.6	96.2	106.7	116.2	124.6
	10.0	-23.0	-4.7	12.6	28.9	44.0	58.2	71.2	83.2	94.1	104.0	112.8

Table A2: Payoff table in SteepTemp

		The other's choice →										
		0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
	0.0	45.0	51.6	60.6	72.3	86.4	103.2	122.4	144.2	168.5	195.4	224.8
	1.0	53.8	62.0	72.6	85.9	101.6	120.0	140.8	164.2	190.1	218.6	249.6
	2.0	54.6	64.4	76.6	91.5	108.8	128.8	151.2	176.2	203.7	233.8	266.4
Your	3.0	47.4	58.8	72.6	89.1	108.0	129.6	153.6	180.2	209.3	241.0	275.2
Choice	4.0	32.2	45.2	60.6	78.7	99.2	122.4	148.0	176.2	206.9	240.2	276.0
↓	5.0	9.0	23.6	40.6	60.3	82.4	107.2	134.4	164.2	196.5	231.4	268.8
	6.0	-22.2	-6.0	12.6	33.9	57.6	84.0	112.8	144.2	178.1	214.6	253.6
	7.0	-61.4	-43.7	-23.4	-0.5	24.8	52.8	83.2	116.2	151.7	189.8	230.4
	8.0	-108.6	-89.3	-67.4	-42.9	-16.0	13.6	45.6	80.2	117.3	157.0	199.2
	9.0	-163.8	-142.9	-119.4	-93.3	-64.8	-33.7	0.0	36.2	74.9	116.2	160.0
	10.0	-227.0	-204.5	-179.4	-151.7	-121.6	-88.9	-53.6	-15.8	24.5	67.4	112.8

Table A3: Payoff table in SteepComp

		The other's choice →										
		0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
	0.0	45.0	54.8	60.6	62.7	60.8	55.2	45.6	32.2	14.9	-6.2	-31.2
	1.0	47.4	62.0	72.6	79.5	82.4	81.6	76.8	68.2	55.7	39.4	19.2
	2.0	41.8	61.2	76.6	88.3	96.0	100.0	100.0	96.2	88.5	77.0	61.6
Your	3.0	28.2	52.4	72.6	89.1	101.6	110.4	115.2	116.2	113.3	106.6	96.0
Choice	4.0	6.6	35.6	60.6	81.9	99.2	112.8	122.4	128.2	130.1	128.2	122.4
↓	5.0	-23.0	10.8	40.6	66.7	88.8	107.2	121.6	132.2	138.9	141.8	140.8
	6.0	-60.6	-22.1	12.6	43.5	70.4	93.6	112.8	128.2	139.7	147.4	151.2
	7.0	-106.2	-62.9	-23.4	12.3	44.0	72.0	96.0	116.2	132.5	145.0	153.6
	8.0	-159.8	-111.7	-67.4	-26.9	9.6	42.4	71.2	96.2	117.3	134.6	148.0
	9.0	-221.4	-168.5	-119.4	-74.1	-32.8	4.7	38.4	68.2	94.1	116.2	134.4
	10.0	-291.0	-233.3	-179.4	-129.3	-83.2	-40.9	-2.4	32.2	62.9	89.8	112.8

Table A4: Payoff table in FlatComp

		The other's choice →										
		0.0	1.0	2.0	3.0	4.0	5.0	6.0	7.0	8.0	9.0	10.0
	0.0	45.0	60.2	72.6	82.5	89.6	94.2	96.0	95.2	91.7	85.6	76.8
	1.0	45.6	62.0	75.6	86.7	95.0	100.8	103.8	104.2	101.9	97.0	89.4
	2.0	44.2	61.8	76.6	88.9	98.4	105.4	109.6	111.2	110.1	106.4	100.0
Your	3.0	40.8	59.6	75.6	89.1	99.8	108.0	113.4	116.2	116.3	113.8	108.6
Choice	4.0	35.4	55.4	72.6	87.3	99.2	108.6	115.2	119.2	120.5	119.2	115.2
↓	5.0	28.0	49.2	67.6	83.5	96.6	107.2	115.0	120.2	122.7	122.6	119.8
	6.0	18.6	41.0	60.6	77.7	92.0	103.8	112.8	119.2	122.9	124.0	122.4
	7.0	7.2	30.8	51.6	69.9	85.4	98.4	108.6	116.2	121.1	123.4	123.0
	8.0	-6.2	18.6	40.6	60.1	76.8	91.0	102.4	111.2	117.3	120.8	121.6
	9.0	-21.6	4.3	27.6	48.3	66.2	81.6	94.2	104.2	111.5	116.2	118.2
	10.0	-39.0	-11.9	12.6	34.5	53.6	70.2	84.0	95.2	103.7	109.6	112.8

A.3 Supplement on theory

Proof that x^C is unique and symmetric

We show that x^C that maximizes $\sum_i \pi_i(x_i, x_j)$ with $\pi_i(x_i, x_j)$ defined according to eq. 1 and $i, j = 1, 2$ and $i \neq j$ is unique and symmetric. If in the expression for joint payoffs $\sum_i \pi_i\ x_j$ is replaced by $m - x_i$ where $l > 0$, the following expression is obtained for joint payoffs:

$$m^2(e-d) + m\,(b + c + 2x_i(d - e + f)) + 2\left(a - x_i^2(d - e + f)\right). \tag{4}$$

The second derivative of this expression with respect to x_i is equal to $-4(d - e + f)$, and is strictly negative when $d > e - f$. Under this condition joint payoffs are thus strictly concave in the action of one player if the choice of the other player is changed so as to obtain the same sum of payoffs. Hence, x^C is unique and symmetric if $d > e - f$.

Predictions quantal-response equilibrium

In a quantal-response equilibrium (QRE) it is assumed that the probability that a player chooses k is equal to $P_k = \dfrac{e^{\lambda} E\pi_k}{\sum_k e^{\lambda} E\pi_k}$ with expected payoff $E\pi_k$ calculated on the basis of choice probability P_k. Parameter $\lambda \in (0, \infty)$ stands for the degree of precision of decision-making, so is inversely related to the degree of noise. We calculate the QRE predictions in Gambit using the payoff tables given in section A.2 of the Appendix, so $k \in [1, 10]$ (McKelvey, McLennan, and Turocy, 2014). Figure A1 shows the choice predicted in QRE as a function of λ for the three main treatments. Figure A2 adds the additional treatment.

Figure A1: Choice predicted in QRE

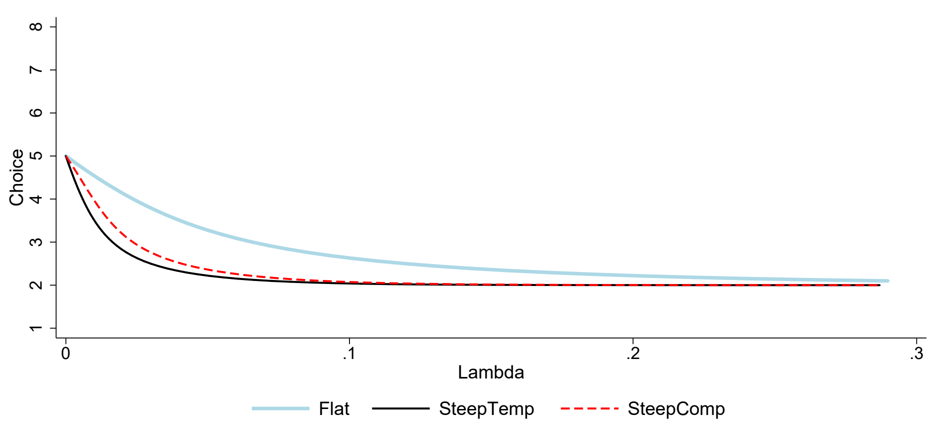
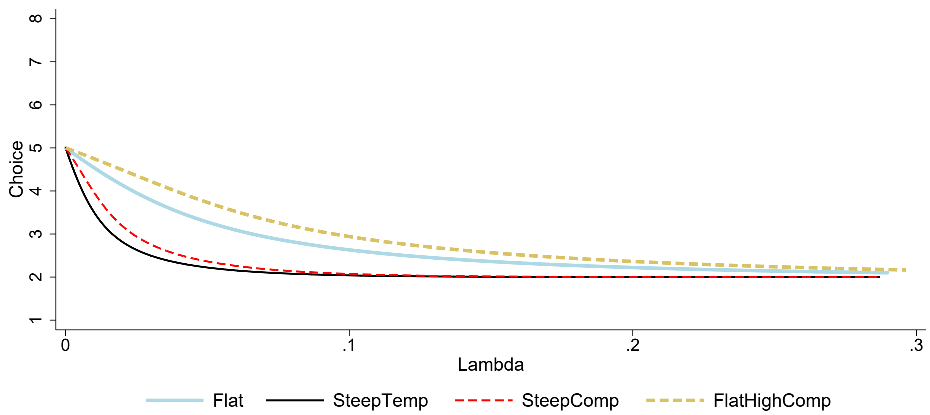


Figure A2: Choice predicted in QRE including additional treatment



Predictions level-k model

The level-k model assumes that players are heterogeneous and can be classified into different types (cognition levels): $L0$, $L1$, $L2$, $L3$, etc. A player of type Lk (with $k > 0$) plays a best response to the belief that the other player is of type $Lk-1$. Type $L0$ acts non-strategically and is typically assumed to play randomly.

Here we show that the level-k model predicts higher actions (i.e., more cooperative choices) in SteepComp than in Flat and SteepTemp. This follows from the following two features of our design:

- the Nash equilibrium is the same in each treatment and located in the lower half of the strategy space: $x^N = 2 < x_{min} + 0.5(x_{max} - x_{min}) = 5$;
- the best response functions have a constant positive slope which is larger in SteepComp than in Flat and SteepTemp: $\partial BR_i^{Comp}(x_j)/\partial x_j > \partial BR_i^{\mathsf{Flat}}(x_j)/\partial x_j = \partial BR_i^{Temp}(x_j)/\partial x_j$.

These two features imply that the best response to a given choice above the Nash Equilibrium is higher in SteepComp than in Flat and SteepTemp:

$$BR_i^{Comp}(x_j) > BR_i^{\mathsf{Flat}}(x_j) = BR_i^{Temp}(x_j) \quad \text{for any } x_j > x^N. \tag{5}$$

Assuming a player of type $L0$ chooses randomly the expected choice will be in the middle of the strategy space ($x = 5$) which is above the Nash equilibrium ($x^N = 2$). A player of type $L1$ best responds to this choice and this best response will be higher in SteepComp ($x = 3.8$)

than in Flat ($x = 2.6$) and SteepTemp ($x = 2.6$). Type $L2$ best responds to the strategy of type $L1$, and again this best response will be higher in SteepComp ($x = 3.1$) than in Flat ($x = 1.9$) and SteepTemp ($x = 1.9$). This pattern repeats itself for higher types Lk ($k > 2$). Hence, the strategies of all types above $L0$ are higher in SteepComp than in Flat and SteepTemp.

Two remarks are in order. First, note that it is not necessary that type $L0$ chooses randomly. Any choice above the Nash equilibrium will lead to the predicted ordering. For instance, if a type $L0$ chooses the fully cooperative strategy ($x^C = 8$) the same ordering of the treatments is predicted by the level-k model. Second, the Cognitive Hierarchy (CH) model predicts the same ordering of the treatments as the level-k model. The CH model assumes that a player of type Ck best responds to the belief that the other player is a mixture of types of lower levels: $C0$, $C1$, ..., $Ck-1$. Since type $C0$ is assumed to choose randomly and type $C1$ best responds to $C0$, the strategies of $C0$ and $C1$ correspond to those of $L0$ and $L1$ in the level-k model. Since type $C1$ chooses a higher action in SteepComp than in Flat and in SteepTemp, all higher types ($C2$, $C3$, ...) inherit this ordering.

Basin of attraction of repeated-game strategies

We analyze the repeated game as a game in which players choose between a cooperative strategy (CS) and a defective strategy (DS) at the start of the game. There are several ways in which the strategies can be defined and focus on an approach that occurs to us as most natural because it allows for a role for payoffs on the best-response curve (see also Mermer, Müller, and Suetens, 2019). We define CS as 'start and stay with the joint-profit maximizing choice as long as the partner does the same, and if the partner chooses something else switch to the SNE forever after'. DS is defined as 'start with best-responding to joint-profit maximization by the partner and switch to the static NE forever after'. A player needs to determine which of these two strategies generates the higher expected payoff given the belief that with probability p the other player plays CS and with probability $1 - p$ he plays DS. The basin of attraction of CS is the set of beliefs p for which playing this strategy gives a higher expected payoff than playing DS. Given that the joint-profit maximizing choice and the SNE are respectively 8 and 2 and associated payoffs are 117.3 and 76.6 in all treatments, the expected payoff of CS in a 30-periods repeated game is equal to

$$p\,[30 \times 117.3] + (1-p)\left[\pi(8, x_j^{\mathrm{BR}}(8)) + 29 \times 76.6\right], \tag{6}$$

and the expected payoff of DS is equal to

$$p\left[\pi(x_i^{\mathrm{BR}}(8),8)+29\times 76.6\right]+(1-p)\left[\pi(x_i^{\mathrm{BR}}(8),x_j^{\mathrm{BR}}(8))+29\times 76.6\right]. \tag{7}$$

Expression 6 is larger than expression 7 if

$$p>\frac{\pi(x_i^{\mathrm{BR}}(8),x_j^{\mathrm{BR}}(8))-\pi(8,x_j^{\mathrm{BR}}(8))}{30\times 117.3-\pi(BR,x_j^{\mathrm{BR}}(8))-29\times 76.6-\pi(8,x_j^{\mathrm{BR}}(8))-\pi(x_i^{\mathrm{BR}}(8),8)}\equiv\hat{p}. \tag{8}$$

If we look at how $\hat{p}$ compares between the treatment, we find that $\hat{p}$ in Flat and SteepComp are of a similar order of magnitude (equal to 0.03 and 0.05 respectively) and substantially higher in SteepTemp (equal to 0.12). This leads to the following predicted ordering of the treatments in terms of cooperativeness: Flat $\approx$ SteepComp $>$ SteepTemp. In the additional treatment FlatComp it holds that $\hat{p}=0.01$, making it most attractive to use a cooperative strategy in this treatment.

A.4 Additional treatment

The additional treatment, which we refer to as FlatComp has the same *low* curvature as in Flat and the same *high* degree of strategic complementarity as in SteepComp. Specifically, in FlatComp it holds that d in the payoff function is equal to 1, as in Flat, and the slope of the best-response curve $\frac{f}{2d}$ = is equal to 0.6, as in SteepComp, resulting in $f = 1.2$. The parameters are further calculated so as to keep constant the values of x^N and x^C, as well as the corresponding payoffs, $\pi(x^N, x^N)$ and $\pi(x^C, x^C)$. The values for the remaining parameters are as follows: $a = 45, b = 1.6, c = 16.48$, and $e = -1.33$. Table A5 gives a full overview of the main variables in all treatments. As can be seen, the 'temptation' payoff is lower than in the other treatments (see also payoffs shown in Table A4).

Table A5: Treatments and parameters with additional treatment added

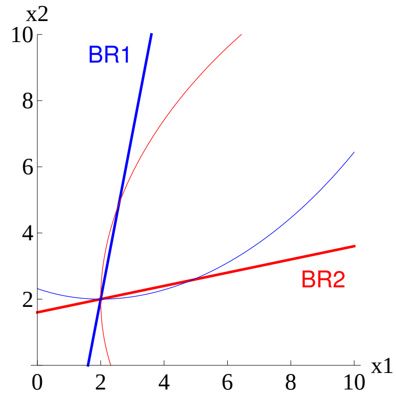
	Flat	SteepTemp	SteepComp	FlatComp
$x_{\min}$	0.0	0.0	0.0	0.0
$x_{\max}$	10.0	10.0	10.0	10.0
x^{N}	2.0	2.0	2.0	2.0
x^{C}	8.0	8.0	8.0	8.0
$\pi(x^{\mathrm{N}}, x^{\mathrm{N}})$	76.6	76.6	76.6	76.6
$\pi(x^{\mathrm{C}}, x^{\mathrm{C}})$	117.3	117.3	117.3	117.3
concavity payoff function ($2d$)	2	8	8	2
slope BR curve ($\frac{f}{2d}$)	0.20	0.20	0.60	0.60
$x_i^{\mathrm{BR}}(x_j^{\mathrm{C}})$	3.2	3.2	5.6	5.6
$\pi(x_i^{\mathrm{BR}}(x_j^{\mathrm{C}}), x_j^{\mathrm{C}})$	140.4	209.5	140.4	123.1
$\pi(x_i^{\mathrm{C}}, x_j^{\mathrm{BR}}(x_i^{\mathrm{C}}))$	59.0	-37.7	60.1	98.1

Notes: $x_{\min}$ and $x_{\max}$ respectively refer to the lower and upper bound of the stage-game strategy space, x^{N} ($\pi(x^{\mathrm{N}}, x^{\mathrm{N}})$) and x^{C} ($\pi(x^{\mathrm{C}}, x^{\mathrm{C}})$) to the stage-game NE and the fully cooperative choice (payoff), and $\pi(x^{\mathrm{Temp}}, x^{\mathrm{C}})$ to the payoff from best-responding to full cooperation (temptation payoff).

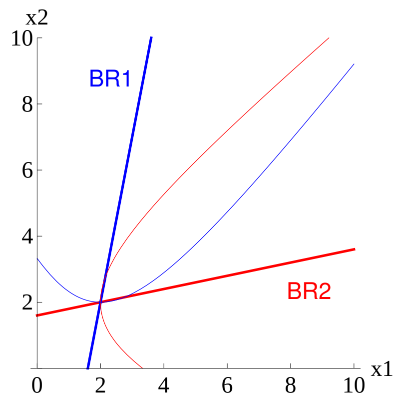
A.5 Additional figures and tables

Figure A3: Iso-payoff contours

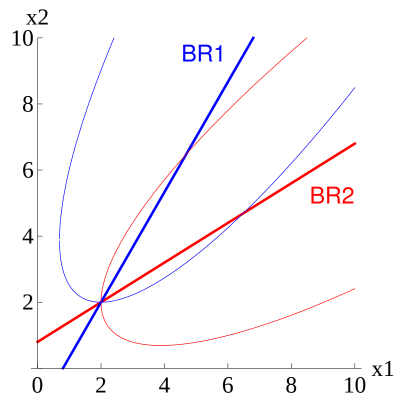
(a) Flat



(b) SteepHighTemp



(c) SteepHighComp



Notes: The figure depicts the best-response curves and the iso-payoff contours calculated at the stage-game Nash equilibrium for the four treatments. Best-response curves or iso-payoff contours in blue (red) color refer to player 1 (player 2).

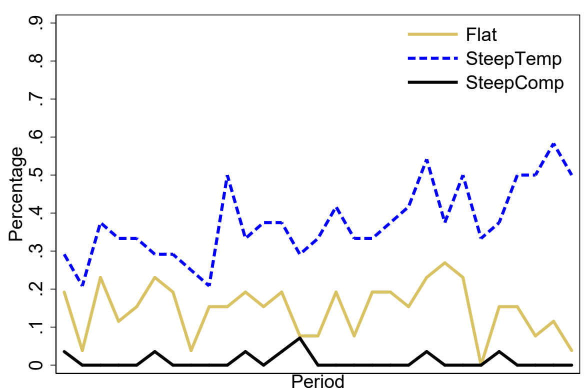
Table A6: Overview of outcome variables by treatment

	Flat	SteepTemp	SteepComp	FlatComp
Average choice round 1	4.6 (0.45)	4.3 (0.51)	6.6 (0.42)	5.0 (0.61)
Average choice all rounds	3.7 (0.36)	3.3 (0.31)	5.6 (0.43)	5.4 (0.60)
Average payoff round 1	96.1 (6.22)	82.4 (20.05)	91.5 (10.61)	93.4 (6.18)
Average payoff all rounds	88.5 (2.96)	83.9 (3.00)	97.9 (3.15)	97.3 (5.54)
Cooperation round 1	0.12 (0.06)	0.04 (0.04)	0.32 (0.09)	0.15 (0.08)
ϵ-Cooperation round 1	0.23 (0.08)	0.13 (0.07)	0.40 (0.11)	0.54 (0.10)
Mutual cooperation all rounds	0.07 (0.06)	0.03 (0.02)	0.25 (0.10)	0.15 (0.10)
ϵ-Mutual cooperation all rounds	0.09 (0.06)	0.05 (0.03)	0.31 (0.10)	0.42 (0.12)
Best-response play round 1	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
ϵ-Best-response play round 1	0.42 (0.10)	0.25 (0.09)	0.21 (0.08)	0.20 (0.09)
Best-response play all rounds	0.04 (0.01)	0.24 (0.09)	0.01 (0.00)	0.03 (0.01)
ϵ-Best-response play all rounds	0.40 (0.06)	0.58 (0.08)	0.34 (0.06)	0.28 (0.06)
SNE play round 1	0.04 (0.04)	0.25 (0.09)	0.00 (0.00)	0.10 (0.07)
ϵ-SNE play round 1	0.23 (0.08)	0.38 (0.10)	0.11 (0.06)	0.30 (0.11)
SNE play all rounds	0.14 (0.03)	0.36 (0.09)	0.01 (0.00)	0.05 (0.02)
ϵ-SNE play all rounds	0.42 (0.06)	0.57 (0.08)	0.13 (0.04)	0.18 (0.05)

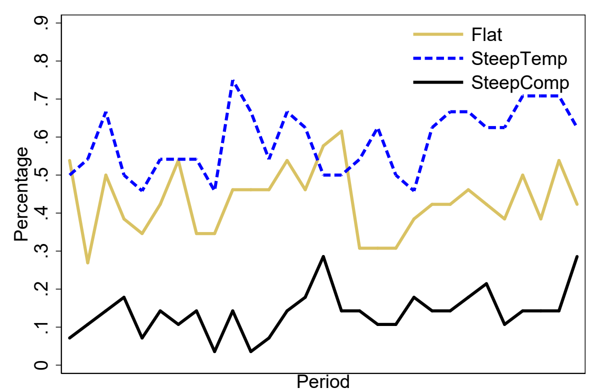
Notes: Standard errors in parentheses. Best-response play in round 1 refers to best-response to a cooperative choice of 8 and best-response play in other rounds refers to myopic best-response.

Figure A4: Percentage of (ϵ-)SNE Play by Treatment

(a) SNE



(b) ϵ-SNE



Notes: The figure shows the evolution of the percentage of (ϵ-)SNE play by treatment.

Figure A5: Percentage of (ϵ-)Best-Response Play in FlatComp

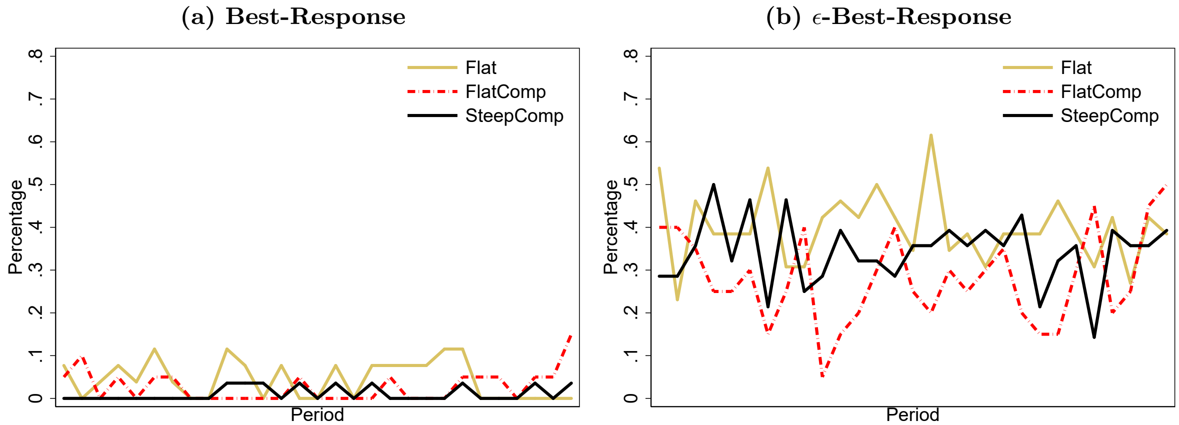


Figure A6: Percentage of (ϵ-)SNE Play in FlatComp