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Bayesian analysis of deterministic and stochastic prisoner's dilemma games

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Abstract

This paper compares the behavior of individuals playing a classic two-person deterministic prisoner's dilemma (PD) game with choice data obtained from repeated interdependent security prisoner's dilemma games with varying probabilities of loss and the ability to learn (or not learn) about the actions of one's counterpart, an area of recent interest in experimental economics. This novel data set, from a series of controlled laboratory experiments, is analyzed using Bayesian hierarchical methods, the first application of such methods in this research domain.

We find that individuals are much more likely to be cooperative when payoffs are deterministic than when the outcomes are probabilistic. A key factor explaining this difference is that subjects in a stochastic PD game respond not just to what their counterparts did but also to whether or not they suffered a loss. These findings are interpreted in the context of behavioral theories of commitment, altruism and reciprocity. The work provides a linkage between Bayesian statistics, experimental economics, and consumer psychology.

Keywords: prisoner's dilemma; uncertainty; bayesian analysis; controlled experiments.

1 Introduction

Interdependent security (IDS) games are social multi-player games with stochastic payoffs where each player must decide whether or not to mitigate her own risks. More specifically, each player knows that even if she fully protects herself by investing in a risk-reducing measure, she may still be subject to indirect losses by being "contaminated" by one of the other players who chose not to invest. As Heal and Kunreuther (2005) have shown, there are a wide variety of significant current problems that fit into an IDS framework ranging from investing in airline or port security, protecting oneself against disease through vaccinations, individual users incurring software security costs when connected to a network, and divisions of firms undertaking risky investments that could cause the entire firm to become insolvent or bankrupt (as in the current financial crisis).

Kunreuther and Heal (2003) have shown that IDS games can have either multiple Nash equilibria or just a single Nash equilibrium. In a Nash equilibrium both players' strategies are the best response to each other's strategies (Gibbons, 1992). This paper presents the results and analysis of controlled laboratory experiments involving two players in an IDS game where there is a single Nash equilibrium. If both players invest in a risk-reducing measure, there is no chance that either will suffer a loss. However, if either or both players do not invest in the protective measure, then there is some likelihood (hence the stochastic part) that both individuals will suffer a loss. Furthermore the dominant strategy of both players, if they are risk neutral (i.e., neither risk averse nor risk seeking), is *not* to invest in the protective measure, despite the fact that had they taken this step, their expected values would have been higher than if they had not.

This IDS game can be viewed as a stochastic prisoner's dilemma (SPD) game, an area of increased interest

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in experimental economics (e.g., Bereby-Meyer & Roth, 2006). In the standard deterministic prisoner's dilemma game, two prisoners face the dilemma of testifying for the prosecution against each other and admitting their own crime, or remaining silent; the Nash equilibrium strategy is for each prisoner to testify against each other even though both would be better off if they agreed to cooperate with each other by remaining silent. In an IDS game, investing in a risk-mitigating measure is analogous to cooperating in the classic prisoner's dilemma game.

In our experiment, subjects were assigned to play one of three types of prisoner's dilemma games: (i) a standard deterministic prisoner's game; (ii) a full feedback stochastic prisoner's dilemma game based on an IDS model where the players receive feedback about their counterparts' actions and payoffs (each round); and (iii) a partial feedback stochastic prisoner's dilemma game where the players receive feedback only about their counterparts' payoffs but not their actions. Subjects were randomly paired to play ten prisoner's dilemma games of their assigned type against each other; this is called a repeated prisoner's dilemma game or a supergame.

In the deterministic prisoner's dilemma game, there is considerable evidence from controlled experiments that if players play repeated prisoner's dilemma games against each other, i.e., a *supergame*, cooperation can emerge, even though they would be likely to defect in a single period game (Axelrod, 1984). Each subject in our experiment played multiple (3–10) supergames of the same type (i.e., deterministic, stochastic full feedback or stochastic partial feedback) with randomly chosen counterparts. More details on our experimental design are provided in Section 3.

Our interest in this research area is both substantive and methodological. From a substantive perspective, we would like to compare the behavior of individuals in a standard deterministic prisoner's dilemma (DPD) multiperiod *supergame* with their behavior in an SPD supergame based on an IDS model. Our interest is in determining whether stochastic payoffs weaken cooperation, and how feedback affects cooperation. Specifically, we compare behavior in a full feedback stochastic game (where each player learns about both her counterpart's actions and payoffs) with behavior in a partial feedback game (where each player only learns about her counterpart's payoffs). In this partial feedback game, a player may or may not be able to infer her counterpart's action based on the payoffs received by both players, and so the ability to "pin the loss" on the counterpart may be obscured.

Behavior in a partial feedback game is of considerable interest today where each decision maker knows only what has happened to her but is unclear as to the cause. In such social dilemmas each individual receives a higher payoff for making a socially defecting choice (e.g. polluting the environment) than for pursuing a socially cooperative choice no matter what the other individuals in society do. Furthermore, all individuals are better off if they all cooperate than if they all defect (Dawes, 1980).

From a methodological perspective, we utilize a Bayesian hierarchical model to understand more fully the factors that influence individuals to invest in socially beneficial protective measures over time, and whether there are significant differences in behavior when payoffs are deterministic versus stochastic. To the best of our knowledge this is the first time that Bayesian hierarchical methods have been applied to the analysis of repeated prisoner's dilemma game experiments. (Stockard, O'Brien & Peters, 2007, applied a hierarchical mixed model to repeated prisoner's dilemma games, similar to our approach, but did not use Bayesian methods.) From a scientific perspective such an analysis enables us to understand more fully how different treatments in a controlled experimental design affect the distribution of individual-level parameters, e.g., an individual's likelihood of retaliating against a counterpart.

There are several attractive features of utilizing Bayesian hierarchical models for analyzing repeated prisoner's dilemma game experiments. They include the ability to perform exact small-sample inference where sample sizes are likely to be small, to incorporate within-person dependence with repeated-measures data, and to understand drivers of heterogeneity by tying in covariates of subjects and the context of their decisions to their individual-level parameters. These are classic advantages of Bayesian methods (Gelman, Carlin, Stern & Rubin, 2004) and ones that are particularly salient and relevant to the analysis of repeated prisoner's dilemma game experiments.

To foreshadow the results of our detailed analysis, we summarize the key findings of the paper as follows. In a two person prisoner's dilemma game, individuals are much more likely to be cooperative when payoffs are deterministic (the DPD game) than in the SPD games where the outcomes are stochastic. A key factor behind this difference is that subjects in the SPD games respond not just to what their counterparts did, but also to whether or not they suffered a loss. When a person does not invest but his or her counterpart does, the individual is less likely to reciprocate the counterpart's investment in the next period if he or she does not suffer a loss. In comparing the two aforementioned SPD games, one with full feedback on the counterpart's behavior and the other with only partial feedback on the counterpart's behavior, the overall amount of cooperation (investment) was similar. However, we found that the *pattern of cooperation* was different in the two types of games. In particular, when subjects in the partial feedback game could learn their counterpart's actions *implicitly*, they were less likely to reciprocate their counterparts' behavior than in analogous situations in the full feedback game where subjects learned their counterparts' behavior *explicitly*.

The remainder of the paper proceeds as follows. Section 2 provides a brief summary of theoretical and empirical studies on prisoners' and social dilemmas with a focus on recent experiments in a noisy or stochastic environment. In Section 3 we describe a general formulation for an interdependent security (IDS) two-player game, showing under what conditions it takes the form of a stochastic prisoner's dilemma game. After characterizing our experimental design for a set of controlled laboratory experiments (Section 4), we then specify a set of between-treatment hypotheses and test them using regression analysis (Section 5). In Section 6, we build a Bayesian hierarchical model that enables us to test hypotheses with respect to within-subject behavior. Section 7 summarizes the findings, discusses their prescriptive implications and suggests areas for future research. The Appendix provides the details of our experiments, making them reproducible by others interested in studying stochastic IDS games.

2 Background on deterministic and stochastic prisoner's dilemma games

In this section we review the literature on repeated prisoner's dilemma games and explain the contribution of our experiments to this literature.

2.1 Deterministic multi-period games and the emergence of cooperation

We first consider deterministic prisoner's dilemma (DPD) games. In a single period DPD game, defecting is the only Nash equilibrium and experiments have shown that players *learn* to play this Nash equilibrium in a series of games in which a player is matched with a different player in each period (e.g., Cooper et al., 1996). But in supergames, as we study here, in which a player is matched with the same player for repeated periods, players learn to reciprocate cooperative behavior as they gain experience (Selten & Stoecker, 1986; Andreoni & Miller, 1993; Hauk & Nagel, 2001). Cooperation tends to break down near the end of the supergame, however, due to so-called "end-game effects." In a tournament setting, Axelrod and Hamilton (1981) and Axelrod (1984) showed that the tit-for-tat (TFT) strategy, where a player cooperates on the first move and thereafter does whatever the other player did on the previous move, generates a fair amount of cooperation. Kreps et al. (1982) have addressed the theoretical issue of whether it can be rational for players to cooperate in a finitely repeated game. Our research provides further empirical tests of these theories.

2.2 Stochastic versus deterministic games

A recent paper by Bereby-Meyer and Roth (henceforth B&R) (2006) compared cooperation in a multi-period DPD to cooperation in a multi-period stochastic prisoner's dilemma game in which the payoffs were random, but the expected payoffs were that of the DPD and the players learned the action that their counterparts took (i.e., there was full feedback). B&R hypothesized that because the SPD provides only partial reinforcement for cooperating when one's counterpart cooperates, players would learn to cooperate more slowly (if at all) in the SPD compared to the DPD. B&R confirmed their hypothesis and showed that players' decisions in the SPD at time *t* are affected by the lottery that determined their random playoff at time *t-1* in addition to their counterpart's action at time *t-1*. Our results provide additional confirming evidence and insights into why players cooperate less in an SPD game.

2.3 Partial feedback versus full feedback

In the usual DPD and B&R's SPD games, players know what actions their counterparts have taken in previous rounds. But in many real situations, decision makers are uncertain about their counterparts' actions. Motivated by this issue, Bendor, Kramer and Stout (1991) conducted a multi-period prisoner's dilemma game tournament modeled after Axelrod (1984) but with random payoffs and where players only learned about their own payoff. Players received no feedback regarding either their counterpart's action or payoff. Bendor et al. found that the TFT strategy, which outperformed other strategies in Axelrod's DPD tournament, fared rather poorly in this SPD tournament with partial feedback. Axelrod and Dion (1988) note that when there is uncertainty in outcomes, then cooperation may avoid unnecessary conflict but can invite exploitation. Axelrod (1984) and Donninger (1986) also presented results of tournaments of SPDs with partial feedback, finding that TFT could still perform well if there is only a small amount of noise in the payoffs.

Bendor (1987, 1993), Molander (1985), and Mueller (1987) studied SPDs with partial feedback from a theoretical perspective. Bendor (1993) showed that, although uncertainty about one's counterpart's actions hinders cooperation in some circumstances, there are other situations in which the uncertainty can enhance cooperation by allowing reciprocating but untrusting strategic players to begin cooperating because of unintended consequences (i.e. a random "cooperative-looking" event occurs). Our research provides further insights in this direction.

2.4 The contributions of our experiments

Our experiments are the first that we know of to compare side-by-side a DPD multi-period game, an SPD with full feedback (SPD-FF) multi-period game and an SPD with partial feedback (SPD-PF) multi-period game. The shared losses in our SPD game may affect players' psychological reaction to the outcome of the game and the other player's action. In our SPD game with partial feedback, players learn only their counterpart's *loss* and not their counterpart's *action*. For some combinations of a player's strategy and the losses of both players, it is *possible to infer* what actions one's counterpart took; for other combinations, it is impossible. To our knowledge, our experiments are the first to consider an SPD with partial feedback among live players. Furthermore, for the SPD-FF and SPD-PF games, we vary the probability of experiencing a loss so that we can decompose the direct effects of the *existence* of stochasticity from the *magnitude* (value of p) of the likelihood of the negative event.

Our first goal is to compare the overall levels of cooperation (investment in protection) in the information conditions DPD, SPD-FF and SPD-PF, which we study in Section 5. Our second goal is to understand the source of any differences in cooperation between the three information conditions in terms of how players respond to different situations, which we study in Section 6. Because individuals are endowed with a large sum of "money" at the beginning of each supergame, and because the losses in each of the rounds are relatively small (despite whether neither, one or both individuals decide to cooperate), we assume that the subjects behave as if they are *risk neutral* in determining what action to pursue in any period *t*. In future research, as we discuss in the concluding section, we will consider games in which there are small probabilities of loss yet high losses when they occur; risk aversion may play a more significant role in this context. The next three sections respectively characterize the nature of IDS games, our experimental design and hypotheses.

3 IDS games

To motivate our experiments in the context of interdependent security models we focus on two identical individuals, A_1 and A_2, each maximizing her own expected value in a one-period model and having to choose whether to invest in a protective measure. Such an investment by individual i costs c and reduces the probability of experiencing a *direct loss* to 0. Let p be the probability of a direct loss to an individual who does not invest in protection. If one individual experiences a direct loss, there is some probability $q \leq p$ that the second individual will also experience an indirect loss from the first individual even if the second individual has invested in protection. That is, q is defined to be the *unconditional* probability of an indirect loss to the second individual when the first does not invest in protection. For example, an apartment owner who has invested in a sprinkler system to prevent fire damage may still suffer a loss indirectly from a neighboring unit that does not invest in this form of protection and experiences a fire. The direct or indirect loss to each player is L.

Let Y be the assets of each individual before she incurs any expenditures for protection or suffers any losses during the period. Assume that each individual has two choices: invest in protection, I, or do not invest, NI, and makes her decision so as to maximize expected value. The four possible expected outcomes from these decisions are depicted in Table 1.

To illustrate the nature of the expected returns consider the upper left hand box where both individuals invest in security (I, I). Then each individual incurs a cost of c and faces no possible losses so that each of their net returns is $Y\text{-}c$. If A_1 invests and A_2 does not, then this outcome is captured in the upper right hand box (I, NI). Here A_1 incurs an investment cost of c but there is still a chance p that a loss will occur to A_2 so that A_1's expected loss from damage from a negative externality is pqL. The lower left box (NI, I) has payoffs which are just the mirror image of these.

Suppose that neither individual invests in protection (NI, NI) — the lower right hand box in Table 1. Then each has an expected return of $Y\text{-}\ pL\ \text{-}(1\text{-}p)pqL$. The expected losses can be characterized in the following manner. The term pL reflects the expected cost of a direct loss. The second term reflects the expected cost from an indirect loss originating from the other individual (pqL) and is multiplied by $(1\text{-}p)$ to reflect the assumption that a loss can only occur once. In other words, the risk of contamination only matters to an individual when that individual does not experience a direct loss ("you can only die once").

Assuming each individual wants to maximize her expected returns, the conditions for her to invest in protection are that $c<pL$ and $c<p(1\text{-}pq)L$. The first constraint is exactly what one would expect if the individual could not be contaminated by the other person. Adding a second individual tightens the constraint by reflecting the possibility of contamination should this person decide not to invest in protection. The resulting Nash equilibrium (NE) for this IDS model can be determined as follows:

- If $c<p(1\text{-}q)L$ then (I, I) is a NE

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Table 1: Expected returns associated with investing and not investing in protection.

		Individual 2 (A_2)	
		I	NI
Individual 1 (A_1)	I	$Y-c, Y-c$	$Y-c-pqL, Y-pL$
	NI	$Y-pL, Y-c-pqL$	$Y-[pL+(1-p)pqL], Y-[pL+(1-p)pqL]$

- If $c>pL$ then (NI, NI) is an NE
- If $p(1\text{-}pq)L<c<pL$ then both (I, I) and (NI, NI) are NE

An IDS game becomes an SPD game when $pL + (1\text{-}p)pqL> c >pL$ so that (NI, NI) is a dominant solution but both individuals would be better off if they had decided to invest in protection (I, I). For the experiments described below, we set q = 1 so that, if one individual suffers a loss, the other individual is certain to also experience this same loss. We also choose values of p and L so that the IDS game takes the form of an SPD game with only one stable equilibrium.

4 Experimental design

The experiments were carried out in the behavioral laboratory of a large, northeastern university using a web-based computer program. The pool of subjects recruited for the experiment consisted primarily of undergraduate students, though a small percentage of the 520 subjects were graduate students and students from other area colleges.[1]

The studies were run with three different experimental conditions (DPD, SPD-FF, SPD-PF). Between three and seven pairs of subjects participated in specific sessions. A session consisted of a set of supergames, each consisting of 10 periods. The computer program randomly paired the subjects before the start of each supergame.

A person played a 10-period supergame with his/her anonymous partner; and at the conclusion of the supergame the person was then told that she would be randomly paired again before the start of the next supergame. The number of supergames in each session ranged from three to ten depending on how long the session ran and how rapidly the pairs of players were able to complete each supergame. More than half the participants participated in exactly eight supergames in their given session.

Each subject was given an initial surplus of 300 "talers" (described below) at the beginning of every supergame. Before the experiment began, every subject was told that each supergame consisted of 10 periods. The number of supergames was not announced at the beginning of the experiment nor was the final supergame announced when it began. Subjects were also told that, at the end of the entire session, one supergame and one pair playing that supergame would be chosen at random, and each individual from the selected pair would receive the dollar equivalent of his/her final payoff from that 10 period game. The lucky pair received these payments in addition to the fixed fee of \$8-\$12 (depending on the length of the session) that each person received for participating in the experiment.

The initial surplus and payoffs presented to the subjects during the experiment were in an artificial currency called "talers," and these were converted to dollars (10 talers = \$1) at the end of the experiment for the randomly selected lucky pair. The average earnings per person from the game, for the pairs chosen at random to receive their final payoff, was \$25.55. Screen shots of the instruction pages for all conditions, as well as decision and payoff screens, are presented in the Appendix. We next describe each of these experimental treatment conditions in detail.

Information Condition 1: Deterministic Prisoner's Dilemma (DPD) Game. Subjects in the DPD condition were presented the payoff matrix depicted in the online appendix (Figure B1). In this condition, the cost of investing in protection is c=12 talers. A loss of L=10 talers (in addition to any investment costs) occurs for both players if exactly one player does not invest. A loss of L=16 talers occurs for both players if both players do not invest. Both individuals would be better off if they had each invested rather than not invested; however (NI, NI) is the Nash equilibrium.

Information Condition 2: Stochastic Prisoner's Dilemma Game with Full Feedback on Counterpart's Decision (SPD-FF). The stochastic conditions replicated the effect of p (the probability of a random nega-

[1] Of those who provided the information, here are the numbers in each category: Male: 226; female: 293; Asian or Pacific Islander: 205; black, not of Hispanic origin: 37; Hispanic: 24; white, not Hispanic: 229; other: 24; 17 yrs old: 6; 18: 84; 19: 101; 20: 92; 21: 71; 22: 38; 23: 20; 24: 9; 25: 7; over 25: 88; Undergraduate student, business: 164; undergraduate, arts & sciences: 158; undergraduate, engineering: 65; undergraduate, nursing: 6; graduate student, arts & sciences: 17; graduate student, engineering: 10; graduate student, other (med, law, etc.): 38; other/non-student: 63.

Table 2: Scenarios related to Decisions in Period t and whether or not it is possible to infer the decision of one's counterpart in the Stochastic Partial-Feedback Condition.

Scen-ario	Player 1 decision	Player 2 decision	Color	Loss or No loss?	Player 1 can infer decision of Player 2?
1	I	I	Red	No loss	Yes
2	I	I	Orange	No loss	No
3	I	I	Green	No loss	No
4	I	NI	Red	Loss	Yes
5	I	NI	Orange	No loss	No
6	I	NI	Green	No loss	No
7	NI	I	Red	Loss	No
8	NI	I	Orange	No loss	Yes
9	NI	I	Green	No loss	No
10	NI	NI	Red	Loss	No
11	NI	NI	Orange	Loss	Yes
12	NI	NI	Green	No loss	No

tive event each period as described in Table 1) by means of a random number. In order to understand the impact of the probability and magnitude of a loss on behavior in the SPD game, we ran sessions where *p=.2, p=.4* and *p=.6*. The cost of investing in protection remained at *c=12* (as in condition 1 above) for each of these cases; however the respective losses were set at *L*=50, 25 and 19 so that the expected payoff matrices were essentially equivalent across the three experimental conditions.[2] This was done so that we could isolate the impact of the change in loss probability on one's decision to invest and not have it be confounded by the magnitude of the expected loss.

The exact payoff matrix presented to subjects in the SPD-FF condition, sub-treatment *p=0.2*, is depicted in the online appendix (Figure B5); the payoff matrix for sub-treatment *p=0.4* is depicted in (Figure B8); and the payoff matrix for sub-treatment *p=0.6* is depicted in (Figure B9).

At the end of each period *t,* each player was told whether his/her counterpart had chosen I or NI (hence full feedback). If either (or both) players had chosen NI, then the computer would draw a random number from 1 to 100 and highlight this number on a table on each subject's screen indicating whether or not a loss had occurred.[3] Each player was then shown her cumulative balance in talers and her counterpart's cumulative balance for period *t* and all previous periods in the supergame (see the example in the online appendix).

Information Condition 3: Stochastic Prisoner's Dilemma Game with Partial Feedback on Counterpart's Decision (SPD-PF). This game is identical to the SPD-FF game except that after each period *t* the random number generates an outcome even if both players invested in protection (i.e. (I,I)). Each player is then told whether or not she suffered a loss but not what action her counterpart had taken. Each player is reported only her own cumulative balance in talers for period *t* and all the previous periods. For some outcomes in period *t* it is *possible* for a player to infer what action her counterpart had taken that period. For example, if Player 1 invests in protection (I) but still suffers a loss, then she can deduce that Player 2 must not have invested (NI). In other cases it is impossible for the other player to infer what her counterpart has done. For example, if a green (no-loss) random number is drawn, then there is no loss whether or not either player invested in protection. Table 2 summarizes the twelve combinations of investment-color configurations that could arise each period, and whether Player 1 can infer whether or not her counterpart has invested in that period (a symmetric table exists for Player 2).

4.1 General overview of the data collected for all conditions

Table 3 indicates the number of individuals who participated in experiments in each of the three treatment conditions and as a function of *p* for the SPD experiments

Each individual played several supergames in the same treatment condition. (e.g. SPD-FF, p=.4). Thus for each subject there exists a vector of person-level covariate data about that subject (age, gender, race, etc.), plus a vector of

[2]Note that it is impossible for the expected payoffs to be *exactly* equal in all of the risk treatments. The expected value of your loss is pL in the (NI, I) case and $L(1-(1-p)^2)$ in the (NI, NI) case. To match the deterministic matrix (where your outcomes of (NI, I) and (NI, NI) are 10 and 16 respectively), it is necessary to find values of p and L such that both pL=10 and $L(1-(1-p)^2)$=16. For p=.4, we find L=25 holds for both equations. But for p=.2 and p=.6, no value of L will satisfy both equations simultaneously. For instance, for p=.2 and L=50, your expected loss in (NI, NI) is 18 (slightly higher). We are assuming the differences in expected value are so small that they shouldn't affect individuals' behavior.

[3]A single three-color probability table was used for *both* (1) the case where one player invests and the other doesn't, and (2) the case where both players do not invest. In the first case, the red area represents the probability that a negative event occurs to the player who does not invest (p); in the second case, the red and orange squares combined represent the probability that a negative event occurs to either or both players ($p(1-p) + (1-p)p + p^2 = 1-(1-p)^2$). We could not use *two* different tables (i.e. one table for the first case which would indicate p in red and $1-p$ in green, and another table for the second case which would indicate $1-(1-p)^2$ in red and $(1-p)^2$ in green) because then the choice of table would immediately reveal the counterpart's decision, a situation which needs to be avoided in the partial feedback treatment (Information Condition 3).

Table 3: Number of individuals in each experimental condition.

Condition	Number of Supergames	Number of Individuals
DPD	84	104
SPD-FF (all)	140	210
p=0.2	40	54
p=0.4	40	76
p=0.6	60	80
SPD-PF (all)	140	206
p=0.2	40	52
p=0.4	50	96
p=0.6	50	58
TOTAL	324	520

Table 4: Percentage of individuals investing in protection in the three conditions.

Condition (Loss)	Total Decisions	Total I Decisions	I/Total
DPD (L=10)	8800	5039	0.57
SPD-FF (all)	14800	4626	0.31
P=0.2 (L=50)	4320	1094	0.25
P=0.4 (L=25)	4440	1211	0.27
P=0.6 (L=19)	6040	2321	0.38
SPD-PF (all)	13600	4753	0.35
P=0.2 (L=50)	4140	1092	0.26
P=0.4 (L=25)	5400	1809	0.34
P=0.6 (L=19)	4060	1852	0.46
All P=0.2 (L=50)	8460	2186	0.26
All P=0.4 (L=25)	9840	3020	0.31
All P=0.6 (L=19)	10100	4173	0.41

treatment-level covariate data for the subject (deterministic condition vs. stochastic full-feedback vs. stochastic partial-feedback, and p=0.2 vs. p=0.4 vs. p=0.6), plus a series of 10-period supergame vectors, each of which contain the data about (a) the decision the subject made in each period (I or NI), (b) the decision her counterpart made in each period (I or NI), (c) the color that appeared on the random-number grid for that round (red, orange, or green), and (d) the number of points (talers) deducted from the subject's account each period. In addition to these four decision-level pieces of information collected during the experiment, we also added a binary variable indicating whether or not the subject was *able to infer* the decision of her counterpart; this "infer" indicator can be calculated based on Table 2.

5 Analyses of between-treatment hypotheses

We first postulate between treatment hypotheses that can be tested with marginal analyses and simple regressions. These include (a) how levels of investment differ between the DPD, SPD-FF and SPD-PF conditions and (b) how levels of investment differ as the probability of a negative random event (p) increases from 0.2 to 0.4 to 0.6.

5.1 Specific between-treatment hypotheses

H1: The probability of investment will be greater in the DPD game than in either of the SPD games. Bereby-Meyer and Roth (2006), (B&R) found evidence that there was less cooperation in an SPD-FF game than in a DPD game. They ascribe this finding to the fact that stochastic games provide only partial reinforcement for cooperation. We expect to find similar results.

H2: The probability of investment will be greater in the SPD-FF game than in the SPD-PF game. We hypothesize that the lack of complete information in the SPD-PF game and hence the inability to infer what one's counterpart has done in many scenarios (see Table 2) will limit the emergence of stable cooperation between the two players.

H3: For either SPD-FF or SPD-PF, the probability of investment will be greater in the p=0.4 treatment than in the p=0.2 treatment, and will be greater in the p=0.6 treatment than in the p=0.4 treatment. As p increases, the likelihood that a non-investing subject will experience a loss increases. There is considerable evidence from other studies that experiencing a loss increases the incentive to invest in protection. Kunreuther (2006) has shown that homeowners are likely to purchase earthquake or flood insurance after a recent disaster even when they indicate that the probability has not increased (flood) or may even be lower in the immediate future (earthquake). Because subjects who do not invest in the previous period are more likely to experience a loss as p increases, this would lead them to invest in the next period, other things being equal.

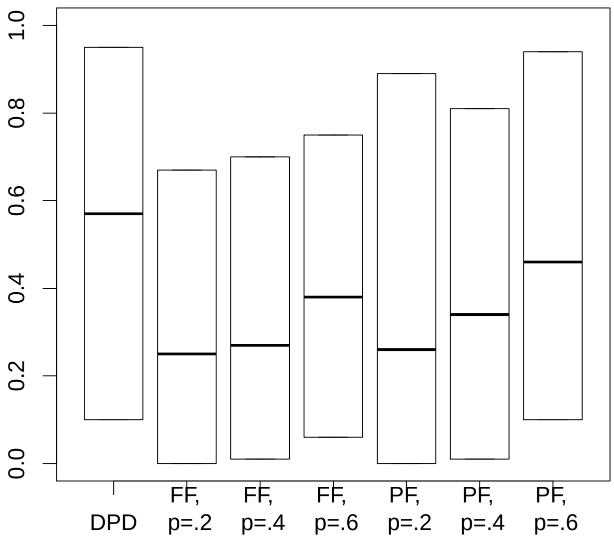

Figure 1: Mean, .05 and .95 quantiles of investment in different conditions. The ends of the boxes show the .05 and .95 quantiles of the distribution of subject investment proportions in a condition, where the investment proportion for a given subject is computed using all supergames the subject played. The dark line in the middle of the box shows the mean investment across subjects in the condition.

5.2 Marginal analyses

Before formally testing the between-treatment hypotheses, we first explore the data at its marginal level. Table 4 describes the proportion of times individuals invested in protection (cooperated) in the different conditions of our experiment. Figure 1 displays these mean investment levels along with the .05 and .95 quantiles of the distribution of subject investment levels in a condition, where the subject investment level for a given subject is the proportion of times the subject invested across the subject's supergames. The investment proportions were highest in the DPD game, with roughly similar investment proportions in SPD-FF and SPD-PF games.

Nonparametric Wilcoxon tests for differences in the investment proportions among subjects in the different conditions show that there is strong evidence for a difference between the DPD and SPD-FF conditions ($p < 0.0001$) and between the DPD and SPD-PF conditions ($p < 0.0001$), but there is not strong evidence for a difference between the SPD-FF and SPD-PF conditions (p-value = 0.23). The analysis described in Section 6 will demonstrate that, although there is not a large difference in *overall* investment between individuals in the SPD-FF and SPD-PF conditions, there are systematic differences in investment behavior between subjects in these two conditions when the ability (or not) to infer what one's counterpart has done in the previous round is taken into account. A Bayesian statistical model applied to these data will help uncover these patterns, controlling for individual differences.

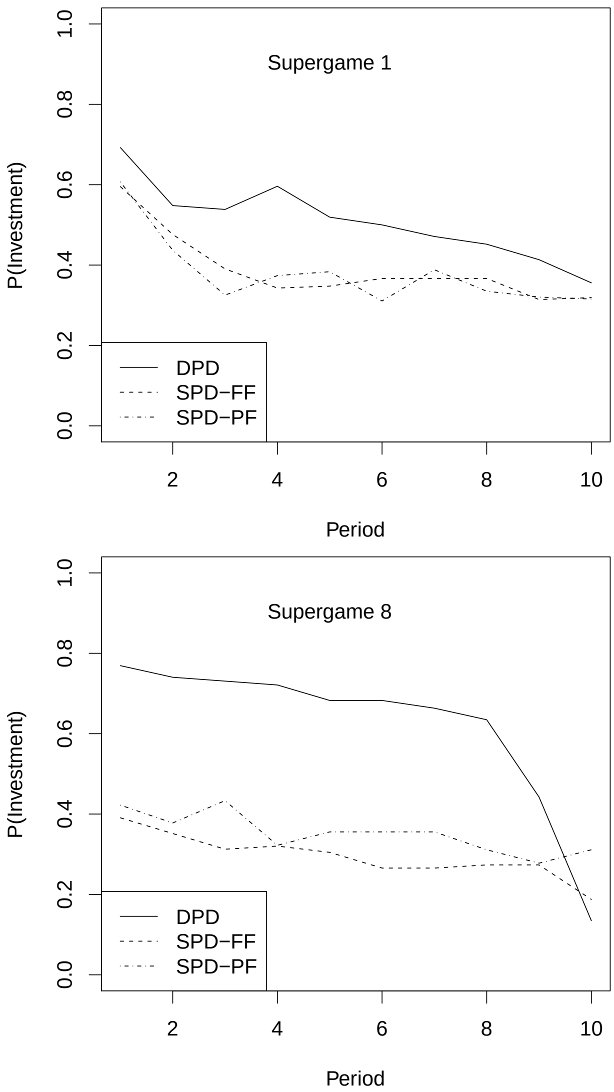

Figure 2: Estimated probability of investment in supergame 1 (top) and 8 (bottom).

In the SPD conditions, the investment proportion increases with the probability of loss. There is a substantial amount of heterogeneity of investment among different individuals within a given condition; for example for DPD, the 5%-quantile of investment proportion is 0.10 and the 95%-quantile of investment proportion is .95. Although there is substantial heterogeneity among individuals within a condition, there are clear patterns of different mean investment levels across conditions.

We now explore how the probabilities of investment change as the period increases from 1 to 10. We show

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Table 5: Confidence intervals for contrasts in proportion of investment between.

Contrast	Estimated difference	95% CI	
(SPD-FF, p=.2) — DPD	−0.34	(−0.41,-0.27)	R1
(SPD-PF, p=.2) — DPD	−0.30	(−0.37,-0.23)	R2
(SPD-FF, p=.4) — DPD	−0.29	(−0.40,-0.18)	R3
(SPD-PF, p=.4) — DPD	−0.25	(−0.36,-0.14)	R4
(SPD-FF, p=.6) — DPD	−0.18	(−0.29,-0.07)	R5
(SPD-PF, p=.6) — DPD	−0.13	(−0.02,-0.25)	R6
(SPD-FF,p=p*) — (SPD-PF,p=p*) for p*=(.2,.4,.6)	−0.04	(−0.09,0.00)	R7
p=.6 — p=.2 for fixed SPD game	0.16	(0.10,0.22)	R8
p=.6 — p=.4 for fixed SPD game	0.12	(0.06,0.17)	R9
p=.4 — p=.2 for fixed SPD game	0.05	(−0.01,0.10)	R10

these probabilities in Figure 2 for the first and last supergames, 1 and 8.

For the DPD in supergame 1, investment generally declines gradually as the periods increase. For the DPD in supergame 8, investment declines gradually from periods 1 to 8 and then declines sharply in periods 9 and 10. This behavior of declining investment as a function of period mirrors the findings of Selten and Stoecker (1986), Andreoni and Miller (1993), Hauk and Nagel (2001) and B&R (2006). For the SPDs in supergame 1, investment declines from period 1 to 3 and then stays relatively flat. For the SPDs in supergame 8, investment generally declines gradually. This is similar to B&R's finding that in an SPD, investment declines gradually as the period increases. In other words there is less of a drop in investment from period 1 to period 10 for the SPD than the DPD game.

5.3 Regression analyses

To more formally test the between treatment hypotheses H1-H4, we fit a regression of the proportion of times each subject invested as a function of the subject's information condition (DPD, SPD-FF or SPD-PF), the subject's probability of loss condition if in one of the stochastic information conditions SPD-FF or SPD-PF ((p=.2)*stochastic, (p=.4)*stochastic and (p=.6)*stochastic, where stochastic = 1 if in a stochastic condition and 0 otherwise) and interactions between the information condition and the probability of loss condition.[4] The interaction terms in the regression were not significant (*p-value* for F-test = 0.63) and hence were dropped from the regression. Table 5 shows confidence intervals for a variety of interesting contrasts in the proportion of investment between conditions.

[4]We recognize that taking logits would yield a dependent variable more in line with the assumptions of ordinary regression, however, we wanted to provide exploratory results using the original scale. Model-based analyses, presented at the end of Section 5 and in Section 6, are based on logistic regressions, more appropriate to the 0/1 nature of the data.

The data in Table 5, R1-R6 provide strong evidence for H1. There was a higher mean investment proportion in the deterministic information condition than in either of the two stochastic information conditions for each of the three probability of loss levels. In some cases there is substantially more investment in the DPD condition than in the SPD cases. For example, the estimated difference is 0.29 between the DPD and (SPD-FF, p=.4) (R3), and 0.25 between the DPD and (SPD-PF, p=.4), (R4).

The data do not support H2, as there was slightly *less* investment in the full feedback SPD than the partial feedback SPD. The estimated difference is 0.04 [95% confidence interval: (0.00, 0.09)] and the sign of the difference between full feedback and partial feedback SPD is the opposite of what we hypothesized in H2, albeit the effect is quite small.

We now consider hypothesis H3, that subjects' mean investment level increases as the probability of loss increases. Comparing the probability of loss conditions among subjects playing a given SPD game, there was substantially more investment when the probability of loss was .6 than when it was .4 or .2; the estimated difference in mean investment proportion is 0.16 for p=.6 compared to p=.2 (R8) and 0.12 for p=.6 compared to p=.4 (R9), and both differences are statistically significant ($p<0.05$). There was slightly more investment for p=.4 compared to p=.2 — the estimated difference is .05, but the difference is not statistically significant. Thus, there is evidence for part of H3 that the subjects' mean investment level increases as the probability of loss increases from p=.2 or p=.4 to p=.6, but there is no strong evidence that the mean investment level increases as p increases from .2 to .4.

6 Bayesian analyses of within-treatment hypotheses

In order to gain further insight into the reasons for the differences in investment across the treatment conditions, we formulated a set of within treatment hypotheses that could be tested using Bayesian analyses.

6.1 Specific hypotheses

H4: There will be substantial variability between subjects in their tendency to invest, holding other factors fixed. This hypothesis characterizes how subjects within the same experimental treatment differ among each other in their aggregate investment levels, holding other factors fixed. It is supported by the findings of Andreoni and Miller (1993) who showed that some individuals were naturally cooperative even if they knew their counterpart was non-cooperative while others were non-cooperative even if they were aware their counterpart was cooperative.

The next set of hypotheses examine within-subject comparisons on how individuals change their investment decision in period *t* as a function of their decision to invest or not invest in period *t-1,* their counterpart's decision to invest or not invest in period *t-1* (when this can be learned) and the interaction between investment decisions in period *t-1* and whether or not an individual experienced a loss in period *t-1*.

H5: Subjects will tend to maintain the same investment behavior over time, holding their counterparts' decisions fixed. There is a large body of empirical and experimental evidence suggesting that individuals maintain the status quo even though they may be able to improve their expected profits by modifying their behavior (Samuelson & Zeckhauser, 1988; Kahneman, Knetsch & Thaler 1991).

H6: A subject will be more likely to invest in period t if she learns that her counterpart invested in period t-1. In spite of people's tendency to persist in their actions (as stated in H5), there is evidence that people can learn to cooperate in repeated prisoner's dilemma games (Axelrod, 1984). A theoretical model as to how cooperation can emerge in repeated prisoner's dilemma games was presented by Kreps et al. (1982). Such cooperation is expected to emerge here.

H7: If a subject experienced a loss in period t-1, she will be more likely to invest period t than if she had not experienced a loss in period t-1, holding all other conditions fixed. We can further divide H7 into four (interaction) sub-hypotheses.

H7A: In the SPD-FF, when a subject invested and her counterpart did not invest in period t-1.

H7B: In the SPD-FF, when a subject did not invest and her counterpart invested in period t-1.

H7C: In the SPD-FF, when a subject did not invest and her counterpart also did not invest in period t-1.

H7D: In the SPD-PF, when a subject did not invest in period t-1 and could not infer her counterpart's investment decision.

The reasoning behind hypothesis H7 was discussed in the context of H3. There is considerable evidence from other studies that experiencing a loss increases the incentive to invest in protection. Note that the situation described in H7D is the only situation in the SPD-PF when a subject's response to a loss holding all other conditions fixed can be studied (see Table 2). Specifically, Scenarios 7 and 10 in Table 2 are the two cases where a subject has not invested in the previous period, experiences a loss, and cannot infer what her counterpart has done. These two scenarios can be compared with Scenarios 9 and 12 where the individual has not invested, has not suffered a loss, and has no idea what her counterpart has done.

H8: A subject who experienced a loss and did not invest in period t-1 is more likely to invest in period t if she knows that her counterpart invested in period t-1. We hypothesize that a subject experiencing a loss in period *t-1* is likely to feel more regret if she knows she is fully responsible for the loss because she did not invest and her counterpart did. Note that H8 can be tested only in the SPD-FF.

6.2 A Bayesian hierarchical model for individual investment decisions

To examine these hypotheses we build a Bayesian hierarchical model for how subjects make investment decisions as a function of their previous experience and the treatment condition they are in. We recognize that a more general modeling framework would look at the entire path of investment decisions an individual participant made within a supergame. There is some empirical basis for focusing on just the previous round's decision. In examining experiments on coordination games, Crawford (1995) and Crawford and Broseta (1998) found that, in making a decision in period t, there was a much higher weight

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placed on the decision in period t than in periods $t-j$; $j \geq 2$. Bostian, Holt and Smith (2007) obtained a similar result for laboratory experiments on the newsvendor problem. It is important to note that our Bayesian modeling framework is completely general and could easily incorporate decisions over a more complex set of past variables.

The following notation characterizes a model of individual (investment) choice:

Let $i = 1, \ldots, I$ index subjects participating in the experiment ($I = 936$);

$t = 1, \ldots, T$ index periods in a supergame ($T = 10$);

$r = 1, \ldots, R$ index the round of the supergame played in one participant session (e.g., $r = 1, \ldots, 8$) with differing opponents;

g = the information condition associated with the game [1 = deterministic prisoner's dilemma (DPD), 2 = stochastic prisoner's dilemma with full feedback (SPD-FF), 3 = stochastic prisoner's dilemma with partial feedback (SPD-PF)]; and

$z = 1, \ldots, Z$ index the probability of loss level ($z = 1, p = 0.2$); ($z = 2, p = 0.4$); ($z = 3, p = 0.6$).

The outcomes of the experiments are characterized as follows:

Y_{itrgz} = 1 if participant *i* in period *t* of supergame *r* in information condition *g* and in probability of loss level *z* chooses to invest in protection; 0 otherwise.

L_{itrgz} = 1 if participant *i* in period *t* of supergame *r* in information condition *g* and in probability of loss level *z* experiences a stochastic loss; 0 otherwise.

M_{itrgz} = 1 if participant *i* in period *t* of supergame *r* in information condition *g* and in probability of loss level *z* *could* have learned his or her counterpart's choice and 0 otherwise.

Y_{itrgz}^{c}= 1 if the counterpart *c* of participant *i* in period *t* of supergame *r* in information condition *g* and in probability of loss level *z* chooses to invest and 0 otherwise.

6.3 Analyzing the prisoner's dilemma games using the Bayesian model

We model the probability of investing in protection in period *t* as a function of a set of independent variables that includes: (i) one's loss experience in period *t*-1, *(ii)* one's own behavior in period *t*-1, (iii) whether one can learn whether one's counterpart has invested in period *t*-1, (iv) the decision made by one's counterpart *c* in period *t*-1 if it can be learned, all varying by the different information conditions *g*, supergames r, and probability of loss conditions *z*. More formally we are interested in estimating the parameters of the following general model:

$$Probability(Y_{itrgz} = 1) = f(L_{it-1rgz}, M_{it-1rgz}, Y_{it-1rgz}, Y_{it-1rgz}^{c}) \quad (1)$$

We can examine the relative importance of the variables specified in (1) using the data from our experiments and "running that data" through the lens of a Bayesian hierarchical model. The coefficients associated with each of the variables are modeled as differing from subject-to-subject (reflecting heterogeneity, e.g., some subjects are more or less influenced by their counterpart's choices), and are assumed to be drawn from a multivariate normal distribution with general covariance matrix. By allowing for a covariance matrix among the individual-level parameters[5], we can further assess, whether an individual who is influenced more by his or her counterpart's non-investment decision is also more likely to invest following a loss.

We also model the expected value of a subject's coefficients as a function of both *person-level covariates* such as age, gender, race, and undergraduate major and *treatment-level covariates* such as the probability of a loss, *z*, and whether the subject is playing a DPD, SPD-FF or SPD-PF game, *g*. In this manner, we can answer the question of "why" certain individuals respond in the way they do (based on individual-level characteristics) and maybe, more importantly, as a function of the treatments (probability and information condition, and their interaction) that are imposed upon them.

Before laying out the model, we note that an advantage of building a Bayesian hierarchical model for our data is that we can control for confounding variables in assessing the importance of certain factors on investment decisions. As an example, a marginal analysis might show that subjects are more likely to invest after having invested in the previous round. However, suppose that investment propensity declines as the period in the game increases. Then, the effect of period is confounded with the effect of previous investment decisions. Our Bayesian hierarchical model enables us to assess the effect of previous investment decisions, holding the period fixed.

In particular, we model the log odds of the probability of a participant investing (i.e., $logit(P_{itrgz}) = ln(P_{itrgz}/(1-P_{itrgz}))$) as a function of fixed and random effects as shown in Table 6. The random effects ($\beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}, \beta_{i6}, \beta_{i7}$) are modeled as coming from a multivariate normal distribution with a mean that depends linearly on the following observed covariates:

(1) *person-level covariates*: age, gender, race, dummy variable for undergraduate, dummy variable for business major and interaction between business major and undergraduate,

(2) *treatment-level covariates*: information condition (dummy variables for deterministic condition and stochastic partial feedback condition), probability of a

[5] Since the model is Bayesian, we put a prior on the covariance matrix of the multivariate normal distribution; the prior is reasonably noninformative.

Table 6: Explanation of model.

Term $logit(P_{\text{itrgz}}) =$	Explanation	Random/Fixed
$\beta_{i1}+$	Participant-level propensity	Random
δ_t+	Varying propensity by period	Fixed
$\kappa_{tg}+$	Interactions between period and information condition	Fixed
γ_r+	Varying propensity by supergame	Fixed
$\kappa_{rg}+$	Interactions between supergame and information condition	Fixed
$\beta_{i2} * Y_{it-1,rgz}+$	Effect of subject's own decision in previous period	Random
$\beta_{i3} * M_{i,t-1,rgz} * Y^c_{i,t-1,rgz}+$	Effect of counterpart investing in previous period when subject is able to learn this	Random
$\beta_{i4} * M_{i,t-1,rgz} * Y_{i,t-1,rgz} * Y^c_{i,t-1,rgz}+$	Interaction between subject's decision and counterpart's decision when subject is able to learn counterpart's decision	Random
$\beta_{i5} * L_{i,t-1,rgz} * (1 - Y_{i,t-1,rgz})+$	Effect of experiencing a loss when subject did not invest in previous round	Random
$\beta_{i6} * L_{i,t-1,rgz} * Y_{i,t-1,rgz}+$	Effect of experiencing a loss when subject did not invest in previous round	Random
$\beta_{i7} * L_{i,t-1,rgz} * (1 - Y_{i,t-1,rgz}) * Y^c_{i,t-1,rgz} * M_{i,t-1,rgz}$	Interaction between experiencing a loss, subject's investment decision and counterpart's investment decision for when subject is able to learn counterpart's decision	Random
$\psi * \beta_{i1} * Period\ dummy$	Additional effect of participant level propensity in period 1 to account for there being no $Y_{i,t-1,rgz}$ in period 1	Fixed

loss level (dummy variables for p=0.2 and p=0.6) and interactions between the information condition and the probability of a loss level (dummy variables for the combinations of deterministic condition and p=.2, deterministic condition and p=.6, stochastic partial feedback condition and p=.2 and stochastic partial feedback condition and p=.6).

In other words,

$$
\begin{aligned}
&E(\beta_{ij}|i,g,z) = \\
&\quad \pi_{0j} + \pi_{1j}\text{age}_i + \pi_{2j}\text{gender}_i + \pi_{3j}\text{race}_i + \\
&\quad \pi_{4j}I(i \text{ is undergraduate}) + \\
&\quad \pi_{5j}I(i \text{ is business major}) + \\
&\quad \pi_{6j}I(i \text{ is undergraduate and business major}) + \\
&\quad \pi_{7j}I(g\text{=Deterministic(Det)}) + \\
&\quad \pi_{8j}I(g\text{=Stochastic Partial Feedback (SPF)}) + \\
&\quad \pi_{9j}I(z = 0.2) + \pi_{10,j}I(z = 0.6) + \\
&\quad \pi_{11,j}I(g\text{=Det}, z = 0.2) + \\
&\quad \pi_{12,j}I(g\text{=SPF}, z = 0.2) + \\
&\quad \pi_{13,j}I(g\text{=Det}, z = 0.6) + \\
&\quad \pi_{14,j}I(g\text{=SPF}, z = 0.6)
\end{aligned}
$$

where I(x) = 1 if condition x is true, 0 otherwise. We note, as previously mentioned, the "scientific importance" of equation (2) as it allows us to answer 'whys', i.e. what is the impact of the treatment on people's investment propensities?

We put the following relatively non-informative prior distributions on the parameters. For the period and supergame round effects, we used independent standard normal priors. For the covariance matrix of $(\beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}, \beta_{i6}, \beta_{i7})$, we used an inverse-Wishart prior with 7 degrees of freedom and scale matrix $10 * I_7$, where I_7 denotes the 7x7 identity matrix. For the coefficients on the covariates that affect the mean of $(\beta_{i1}, \beta_{i2}, \beta_{i3}, \beta_{i4}, \beta_{i5}, \beta_{i6}, \beta_{i7})$, we used independent standard normals.

We used the WinBUGS software (http://www.mrc-bsu.cam.ac.uk/bugs/) to obtain draws from the posterior

Table 7: Median (across respondent) posterior odds of investing given ones counterpart invested in the previous period.

Information Condition	Posterior Median of β_{i3}	95% Credibility Interval for β_{i3}
DPD	1.37	(0.99, 1.82)
SPD-FF	0.87	(0.58, 1.12)
SPD-PF	0.03	(−0.45, 0.43)

distribution using Markov chain Monte Carlo (MCMC). We ran three chains of 25,000 draws each, taking the first 20,000 draws of each chain as burn-in and the last 5,000 draws of each chain as draws from the posterior distribution. We assessed convergence of the MCMC chains using Gelman-Rubin's (1992) potential scale reduction statistic. The code and further computational details are available from the authors upon request.

6.4 Experimental findings

We now use the Bayesian hierarchical model to test H4 through H8. For each of the hypotheses, we indicate the coefficient in the logit model that is used to test whether or not the experimental data provide support for it, holding all the other factors fixed. It is through the direct mapping of parameters to hypotheses that inference under the Bayesian model is made straightforward.

6.4.1 Testing H4

There is strong support that some individuals are much more likely (i.e., over 5 times) to invest than others, holding other factors fixed. In our model, the parameter β_{i1} measures subject *i*'s propensity to invest. H4 says that there is substantial variability in β_{i1}. The posterior mean of the standard deviation of β_{i1} is 0.79 with a 95% credibility interval of (0.67, 0.92). This means that if we consider two subjects, subject 1 with β_{i1} one standard deviation above the mean and subject 2 with β_{i1} one standard deviation below the mean, then when all previous investments, losses and learning are held fixed, the odds ratio for subject 1 to invest compared to subject 2 to invest is estimated to be exp(2*0.79)=4.85, a large effect.

6.4.2 Testing H5

There is strong evidence that there is persistence in investment behavior. The parameter β_{i2} measures persistence since it reflects the effect on investment in period *t* of having invested in period *t-1*, holding other factors fixed. We have thus hypothesized that the mean of β_{i2} is positive. The posterior median (across subjects) for the mean of β_{i2} across the information conditions is 2.05 with a 95% credibility interval of (1.83, 2.25). This means that, for the average subject, the odds ratio for the subject to invest if he or she invested in the previous round compared to if he or she did not invest, holding all other factors fixed, is estimated to be exp(2.05)=7.78 with a 95% credibility interval of (exp(1.83), exp(2.25))=(6.23,9.49).

6.4.3 Testing H6

The parameter β_{i3} reflects how an individual's likelihood of investing in period *t* is impacted by learning that her counterpart invested in period *t-1*, holding other factors fixed. H6 says that the mean of β_{i3} is positive. Table 7 shows the posterior median for the mean of β_{i3} (across subjects) in the three information conditions.

There is strong evidence that for the DPD and the SPD-FF, the average subject is more likely to invest if his or her counterpart invested in the previous round than if his or her counterpart did not. For the DPD, the median of the odds ratios among different subjects for the subject to invest if his or her counterpart invested in the previous period compared to if his or her counterpart did not is estimated to be exp(1.37)=3.94; for the SPD-FF, the median odds ratio is estimated to be somewhat smaller, exp(0.87)=2.39, but still significant. For the SPD-PF, there is not strong evidence that a subject is more likely to invest if his or her counterpart invested in the previous round than if his or her counterpart did not; the median odds ratio is estimated to be only exp(0.03)=1.03. The differences in the impact of learning about one's counterpart investing between SPD-FF and SPD-PF might be explained by the implicit learning in SPD-PF not being as effective as the explicit learning in DPD and SPD-FF. The explicit learning of the SPD-FF compared to the implicit learning of the SPD-PF will make subjects more likely to reciprocate if their counterparts cooperate. As shown in Table 2 a subject can only learn that his or her counterpart has invested in an SPD-PF game when the subject has not experienced a loss (Scenarios 1 and 8).

6.4.4 Testing the four versions of H7

For the most part, we found support that experiencing a loss makes subjects more likely to invest in the future, holding all other conditions fixed. The only situation in which we did not find strong support for H7 was when a subject invested but his or her counterpart did not invest (H7A).

H7A: There is only moderate evidence that the mean of β_{i6} is positive for subjects in SPD-FF. The posterior median for the mean of β_{i6} for subjects in SPD-FF is 0.28

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with a 95% credibility interval of (-0.02, 0.58).

H7B: There is strong evidence that the mean of $\beta_{i5} + \beta_{i7}$ is positive for subjects in SPD-FF. The posterior median for the mean of $\beta_{i5} + \beta_{i7}$ for subjects in SPD-FF is 0.51 with a 95% credibility interval of (0.28,0.85). The estimated median odds ratio for the effect of a loss in the situation of H8B is exp(0.51)=1.67, a 67% increase.

H7C: There is strong evidence that the mean of β_{i5} is positive for subjects in SPD-FF. The posterior median for the mean of β_{i5} is 0.39 with a 95% credibility interval of (0.16, 0.59). The estimated median odds ratio for the effect of a loss in the situation of H8C is exp(0.39)=1.48, a 48% increase.

H7D: There is strong evidence that the mean of β_{i5} is positive for subjects in SPD-PF. The posterior median for the mean of β_{i5} for subjects in SPD-PF is 0.33 with a 95% credibility interval of (0.12, 0.54). The estimated median odds ratio for the effect of a loss in the situation of H8D is exp(0.33)=1.39, a 39% increase. Although we cannot determine why an individual chose to invest in period *t* after not investing and suffering a loss in *t–1,* one plausible reason would be that the person wanted to avoid the regret next period that she experienced at having not taking an action that could have prevented the loss in the previous period. This has been demonstrated in some recent neuroimaging studies of choice behavior between two gambles (Coricelli et al., 2005).

6.4.5 Testing H8

We did not find strong evidence that the effect of a loss was greater when the subject's failure to invest was the sole cause of the loss as compared to when both players share some blame for the loss. This hypothesis can be tested only for subjects in SPD-FF. The odds ratio for a subject to invest in the current period if the subject did not invest in the previous period, experienced a loss and the counterpart invested compared to the same conditions but the subject did not experience a loss is $\exp(\beta_{i5}+\beta_{i7})$. The odds ratio for a subject in SPD-FF to invest in the current period if the subject did not invest in the previous period, experienced a loss and the counterpart did not invest compared to the same conditions but the subject did not experience a loss is $\exp(\beta_{i5})$. H8 is hypothesizing that the former odds ratio is larger than the latter odds ratio on average. Thus, H8 is hypothesizing that the mean of β_{i7} is greater than zero for subjects in SPD-FF. The posterior median for the mean of β_{i7} for subjects in SPD-FF is 0.13 with a 95% credibility interval of (-0.17, 0.49). Thus, although the point estimate supports H8, there is not strong evidence for H8.

6.4.6 Effects of person-level covariates

We now describe for each of the random subject coefficients $\beta_{i1}, \ldots, \beta_{i7}$ which of the six person level covariates (age, gender, race, undergraduate, business major and the interaction between undergraduate and business major), if any, had statistically significant effects on the mean of the random coefficient at a 95% confidence level.

1. β_{i1} (propensity to invest): None of the person level covariates had a significant effect.

2. β_{i2} (persistence of investment): Age had a positive effect on persistence. The mean of β_{i2} was estimated to increase by 0.03 for each year of age with a 95% credibility interval for this effect of (0.01, 0.06). Men were more persistent than women on average. The mean of β_{i2} was estimated to be 0.35 higher for men than women with a 95% credibility interval of (0.03, 0.66).

3. β_{i3} (increase in investment when counterpart invests): Whites increase their investment when the counterpart invests less (are less cooperative) than non-whites on average. The mean of β_{i3} was estimated to be 0.46 lower for whites than non-whites with a 95% credibility interval of (0.18, 0.75).

4. β_{i4} (interaction between subject's and counterpart's decision to invest): Whites have more of an interaction between subject's and counterpart's decision to invest than minorities on average. The mean of β_{i4} was estimated to be 0.44 higher for whites than minorities with a 95% credibility interval of (0.11, 0.79).

5. β_{i5} (effect of loss when subject does not invest): Undergrads respond less to losses than graduate students and non-students on average. The mean of β_{i5} was estimated to be 0.34 lower for undergrads with a 95% credibility interval of (0.09,0.59).

6. β_{i6} (effect of loss when subject does invest): None of the person level covariates had a significant effect.

7. β_{i7} (additional effect of loss when subject does not invest and counterpart invests): None of the person level covariates had a significant effect.

While these covariate effects are quite suggestive, we believe that further study with a broader population is necessary, and also presents a possibility for public policy implications in the future.

7 Interpretation of key findings

This paper provides evidence that, in a two person prisoner's dilemma game, individuals are much more likely to be cooperative when payoffs are deterministic (the DPD game) than when there is some chance that one will not suffer a loss, even if one does *not* invest in protection (the SPD games).

There are several reasons why individuals may decide to undertake cooperative action in some period *t* of a DPD

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or SPD game even though non-cooperative behavior with its inferior payoffs is the Nash equilibrium. An individual might decide to choose actions that she would most like the other person to choose so that both parties gain in the process. This *commitment* theory implies that in a two person DPD or SPD game individual *A* will choose to cooperate under the assumption that individual *B* will do the same; the expected payoffs to *A* and *B* of this action is higher than if both persons did not cooperate (Laffont, 1975; Harsanyi, 1980). This may be the principal reason why there was more cooperative behavior in the DPD game than in the SPD games and why there is more cooperation in an SPD game with full feedback than in one with partial feedback. (See H1 and H4). Commitment theories are consistent with voluntary behavior in social dilemmas such as water conservation (Laffont, 1975), tax evasion (Baldry, 1987) and voting (Struthers & Young, 1989).

An alternative view of such behavior is that an individual will be altruistic by being concerned with her counterpart's welfare and trying to enhance it. In a two person game, individual A might be *altruistic* so that a higher return obtained by individual B is treated positively as an attribute in A's utility function (Becker, 1974; Andreoni, 1989, 1990). Altruistic behavior has been used by economists to explain intergenerational bequests and social security (Coate, 1995) as well helping others employees in a workplace setting (Rotemberg, 1994).

A more self-interested view of behavior would be anticipated by *reciprocity* whereby individual A decides to cooperate in period *t-1* with the expectation that B will then cooperate in period *t*. Models of reciprocity have been used to explain helping in the work place (Frey, 1993) and labor markets (Akerlof, 1982) as well as voluntary contributions to public goods (Sugden, 1982). The above theory of reciprocity might also imply retaliation, so that if individual A learned that B did not cooperate in period *t* then A would also decide not to cooperate in period *t+1*. One reason that there may have been more cooperation in a DPD world than in an SPD environment (H1) is that individuals knew that if they followed such a tit-for-tat (TFT) strategy they could hurt the other opponent. In an SPD game if one learned that an opponent had not cooperated, a TFT strategy may not punish the other player since there is some chance of not suffering a loss even if both players do not cooperate (i.e. do not invest in protection).

8 Suggestions for Future Research

An IDS setting with two equilibria opens up the possibility of tipping behavior in the spirit of Schelling (1978) and others. Future experiments could study when tipping is likely to occur if all players in the group are identical or when there is heterogeneity among the players. In either situation one could force one or more of the players to make a decision as to whether or not to invest, as Hess, Holt and Smith (2007) did this in their sequential model where the probability of suffering an indirect loss is uncertain (i.e. $q<1$). One could then determine whether tipping occurs because other players follow suit. A related line of experiments would examine individual behavior in either a simultaneous or sequential game when the probability of a loss is very low (i.e. $p, q < .1$) and the loss L is very high. One could also vary the size of the loss depending on whether the cause is due to one's own failure to invest or from the counterpart's decision not to protect herself.

At a prescriptive level one could also design experiments that induced one or more players to invest in protection by imposing positive economic incentives (e.g. subsidies) to encourage this actions or negative sanctions (e.g. fines) for failure to do so. Given the much larger proportion of pairs of individuals who failed to invest in protection when outcomes were uncertain than when they were deterministic, it may be necessary to intervene in these ways to improve both individual and social welfare in the many IDS-like situations that we are facing in today's interdependent world.

This research represents only one data point in the large "hypercube" of possible IDS games. We expect very soon to complete a web-based IDS tool that will allow researchers from other universities and research institutions to run IDS games with differing values of p, q, c, L, vary the number of players, examine context effects as well as undertake other analyses. We would also add process survey questions to understand why individuals behaved as they did. This promises to provide additional clarity as to individuals' decision processes when there are uncertain outcomes and use these findings to suggest ways of inducing cooperation among agents, thus improving both individual and social welfare.

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Appendix. Instructions to subjects

1. Instructions Presented to Subjects in the Deterministic Prisoner's Dilemma Condition

[Opening Instruction Page:]

This is a game in which the outcomes of your decisions depend not only on what *you* do, but also on what your *counterpart* does.

You will be paired with another person in the room whose identity is not known to you. In each of 10 rounds, you and your counterpart will independently make a decision about whether or not to invest funds to avoid a financial loss from a negative event.

• If both of you choose to INVEST then it will cost each of you 12 talers, but neither of you will experience a financial loss from a negative event.

• If one of you INVESTS and the other does NOT INVEST, it will cost the one who INVESTS 12 Talers. In addition, both people will suffer an equal financial loss of 10 Talers from a negative event.

• If both of you choose to NOT INVEST, then each of you suffers an equal financial loss of 16 Talers from a negative event.

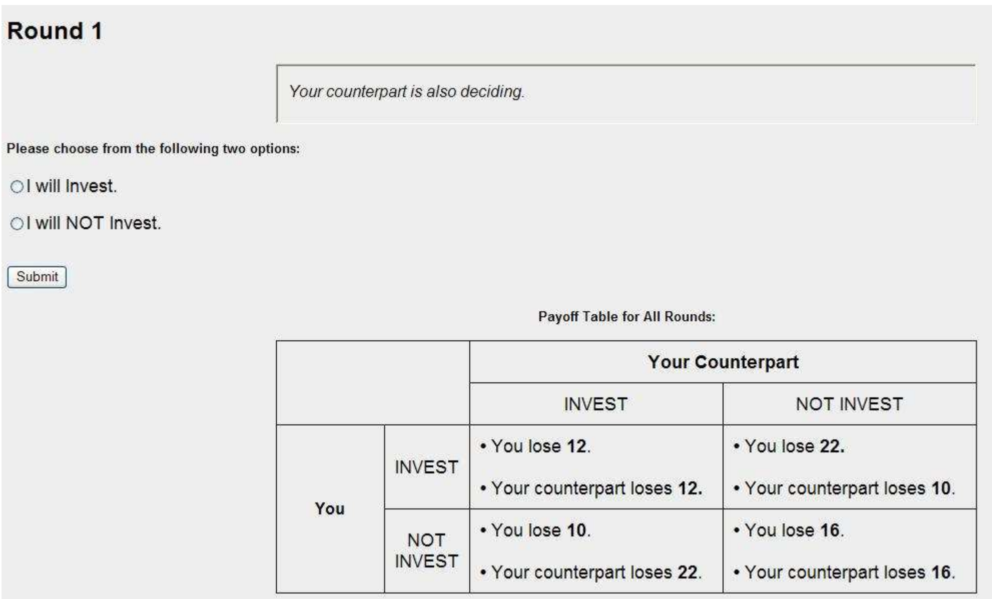
Below is the summary of the possible outcomes:

		Your Counterpart	
		INVEST	NOT INVEST
You	INVEST	• You lose **12**. • Your counterpart loses **12.**	• You lose **22.** • Your counterpart loses **10**.
	NOT INVEST	• You lose **10**. • Your counterpart loses **22**.	• You lose **16**. • Your counterpart loses **16**.

You and your counterpart are each given 300 Talers (10 talers = $1) before you start making decisions. You will not know the decision your counterpart has made until the end of the round. Before the start of the next round you will be given feedback on what each of you did and the status of your assets.

One pair will be chosen at random to receive the dollar equivalent of the talers they have at the end of the game (10 talers = $1).

[Each subject sees the following screen before making his/her decision for the first round:]



[After each person in the pair has made a decision, subjects see their decisions and payoffs highlighted in a table:]

Round 1

You have chosen to Invest, but your counterpart has chosen to Not Invest, as indicated in blue in the table below.

		Your Counterpart	
		Invest	Not Invest
You	Invest	• You lose 12 talers. • Your counterpart loses 12 talers.	• You lose 22 talers. • Your counterpart loses 10 talers.
	Not Invest	• You lose 10 talers. • Your counterpart loses 22 talers.	• You lose 16 talers. • Your counterpart loses 16 talers.

You Lose 22 Talers and your counterpart loses 10 Talers.

Continue

[In subsequent rounds each subject sees a history report of past decisions in the supergame. The subject sees this on the decision screen:]

Round 5

Amounts lost in previous rounds:

Round	Your Decision	Your Outcome	Your Ending Balance	Counterpart's Decision	Counterpart's Outcome	Counterpart's Ending Balance
1	Invest	-22	278	Not Invest	-10	290
2	Not Invest	-16	262	Not Invest	-16	274
3	Not Invest	-16	246	Not Invest	-16	258
4	Invest	-22	224	Not Invest	-10	248

Your counterpart is also deciding.

Please choose from the following two options:

○ I will Invest.

○ I will NOT Invest.

Submit

Payoff Table for All Rounds:

		Your Counterpart	
		INVEST	NOT INVEST
You	INVEST	• You lose 12. • Your counterpart loses 12.	• You lose 22. • Your counterpart loses 10.
	NOT INVEST	• You lose 10. • Your counterpart loses 22.	• You lose 16. • Your counterpart loses 16.

2a. Instructions Presented to Subjects in the Stochastic Full-Feedback Condition (for p=0.2):[6]

[Opening Instruction Page:]

[6] For the L=50, p=0.2 condition it is possible for a subject to more than deplete her entire surplus after 10 rounds. In this case the subject's final cumulative balance would be set to zero. This situation never occurred in any of the games played

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This is a game in which the outcomes of your decisions depend not only on what *you* do, but also on what your *counterpart* does.

You will be paired with another person in the room whose identity is not known to you. In each of 10 rounds, you and your counterpart will independently make a decision about whether or not to invest funds to avoid a financial loss from a random negative event.

Financial losses will be measured in a fictitious currency called "Talers."

• If both you and your counterpart choose to INVEST, then the investment cost to each of you is 12 talers.

• If you INVEST and your counterpart does NOT INVEST, then there is a 20% chance that your counterpart will lose 50 talers and you will lose 62 talers; and there is an 80% chance that your counterpart will lose 0 talers and you will lose 12 talers.

• If you do NOT INVEST and your counterpart INVESTS, then there is a 20% chance that your counterpart will lose 62 talers and you will lose 50 talers; and there is an 80% chance that your counterpart will lose 12 talers and you will lose 0 talers.

• If both you and your counterpart choose to NOT INVEST, then each of you has an 36% chance of losing 50 talers, and a 64% chance of losing 0 talers.

Probabilistic outcomes will be determined by the following Random Number Generator, where it is equally likely that any number between 1 and 100 is chosen.

For Example: If the Random Number generated is 6, then 6 will flash as follows:

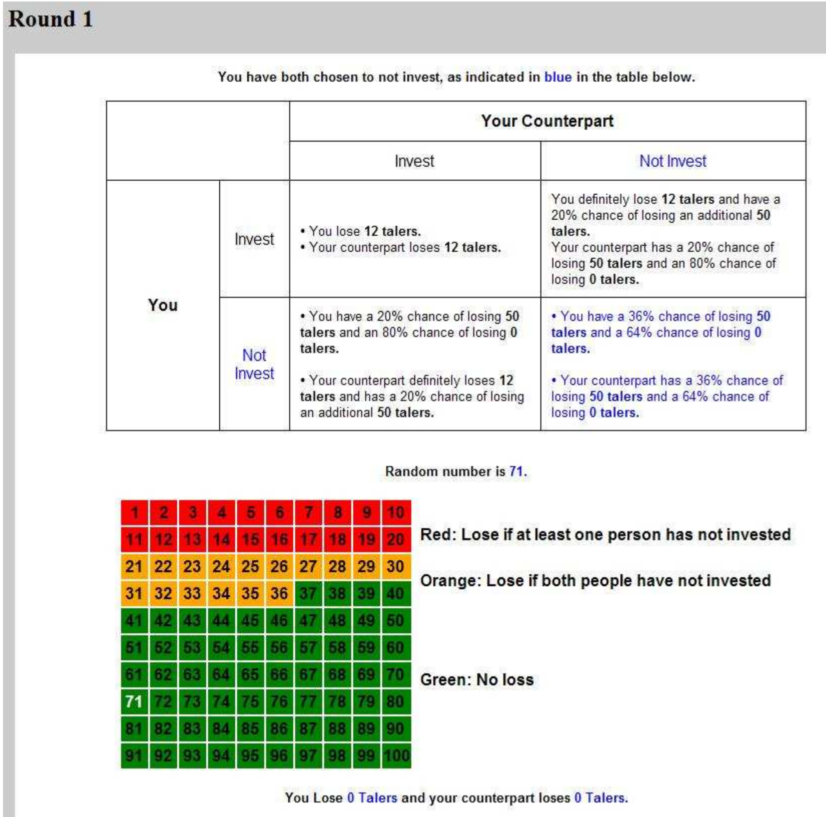
Below is a summary of the possible outcomes:

		Your Counterpart	
		INVEST	NOT INVEST
You	INVEST	• You lose **12 talers**. • Your counterpart loses **12 talers**.	• You definitely lose **12 talers** and have a 20% chance of losing an additional **50 talers**. • Your counterpart has a 20% chance of losing **50 talers** and an 80% chance of losing **0 talers**.
	NOT INVEST	• You have a 20% chance of losing **50 talers** and an 80% chance of losing **0 talers**. • Your counterpart definitely loses **12 talers** and has a 20% chance of losing an additional **50 talers**.	• You have a 36% chance of losing **50 talers** and a 64% chance of losing **0 talers**. • Your counterpart has a 36% chance of losing **50 talers** and a 64% chance of losing **0 talers**.

You and your counterpart are each given 300 Talers before you start making decisions. You will not know the decision your counterpart has made until the end of each round. Before the start of the next round you will be given feedback on what each of you did, whether or not a negative event occurred and the status of your assets.

One pair will be chosen at random to receive the dollar equivalent of the talers they have at the end of the game (10 talers = $1).

[The payoff screen (what each pair sees after making their decisions for a round) looks like this:]



[The "Results of previous rounds" history table on the decision screen looks like this:]

Round	Negative Event	Your Decision	Your Outcome	Your Ending Balance	Counterpart's Decision	Counterpart's Outcome	Counterpart's Ending Balance
1	No	Not Invest	-0	300	Not Invest	-0	300
2	Yes	Invest	-62	238	Not Invest	-50	250
3	No	Not Invest	-0	238	Invest	-12	238
4	No	Not Invest	-0	238	Not Invest	-0	238

2b. Instructions Presented to Subjects in the Stochastic Full-Feedback Condition (for p=0.4):

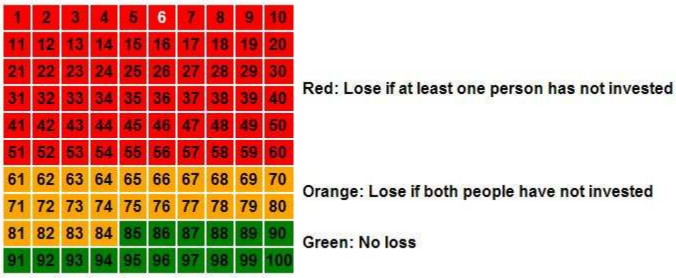
[Opening Instruction Page is analogous to the p=0.2 condition, but with the following changes to the color-grid and the payoff matrix:]

		Your Counterpart	
		INVEST	NOT INVEST
You	INVEST	• You lose **12 talers**. • Your counterpart loses **12 talers**.	• You definitely lose **12 talers** and have a 40% chance of losing an additional **25 talers**. • Your counterpart has a 40% chance of losing **25 talers** and a 60% chance of losing **0 talers**.
	NOT INVEST	• You have a 40% chance of losing **25 talers** and a 60% chance of losing **0 talers**. • Your counterpart definitely loses **12 talers** and has a 40% chance of losing an additional **25 talers**.	• You have a 64% chance of losing **25 talers** and a 36% chance of losing **0 talers**. • Your counterpart has a 64% chance of losing **25 talers** and a 36% chance of losing **0 talers**.

[Other screens are formatted analogously to those shown above for p=0.2.]

2c. Instructions Presented to Subjects in the Stochastic Full-Feedback Condition (for p=0.6):

[Opening Instruction Page is analogous to the p=0.2 and p=0.4 conditions, but with the following changes to the color-grid and the payoff matrix:]



		Your Counterpart	
		INVEST	NOT INVEST
You	INVEST	• You lose **12 talers**. • Your counterpart loses **12 talers**.	• You definitely lose **12 talers** and have a 60% chance of losing an additional **19 talers**. • Your counterpart has a 60% chance of losing **19 talers** and a 40% chance of losing **0 talers**.
	NOT INVEST	• You have a 60% chance of losing **12 talers** and a 40% chance of losing **0 talers**. • Your counterpart definitely loses **12 talers** and has a 60% chance of losing an additional **19 talers**.	• You have an 84% chance of losing **19 talers** and a 16% chance of losing **0 talers**. • Your counterpart has an 84% chance of losing **19 talers** and a 16% chance of losing **0 talers**.

[Other screens are formatted analogously to those shown above for p=0.2.]

3. Instructions Presented to Subjects in the Stochastic Partial-Feedback Condition:

[The Stochastic Partial-Feedback condition differs from the Full-Feedback as follows:]

[1. Opening Instructions in the Partial-Feedback condition are the same as in the Full-Feedback condition except that the penultimate paragraph reads as follows:]

You and your counterpart are each given 300 Talers before you start making decisions. You will not know the decision your counterpart has made. Before the start of the next round you will be given feedback on what you did and the status of your assets.

[2. The payoff screen does not indicate counterpart's decision or counterpart's talers lost.]

[3. The history table ("Results of previous rounds") does not show columns relating to counterpart information.]