The Role of Information and Monitoring on Collusion

1. Introduction

Firms' coordination to obtain high profits has been a continuous concern for researchers and antitrust authorities. As a consequence, there exists a large body of theoretical work on the factors that determine the likelihood of collusion. But analyzing collusion empirically is difficult because the illegal status of cartels makes field data scarcely available. Importantly, with many exogenous and unobservable factors in field data, the task of identifying and estimating the effect of different market conditions on collusion becomes problematic. One objective of this paper is to improve the understanding of the role of two factors that have been prominent in models of repeated interaction with demand uncertainty: demand information (knowledge of the demand function or schedule) and monitoring (knowledge of rivals' actions). The general strategy is to analyze the effects of these factors on collusion by generating data from controlled experiments that resemble various demand information and monitoring conditions.

The motivation comes from two models that have been highly influential in the development of the theoretical and empirical literature on cartel stability: Green and Porter (1984) and Rotemberg and Saloner (1986) [GP and RS henceforth]. Both models assume an uncertain (stochastic) demand structure, but differ on their assumption about firms' information regarding the actual demand realization (e.g. high, low). RS assume that firms have perfect foresight about demand next period (i.e. the demand realization can be anticipated) whereas GP assume that firms are always uncertain about (future and past) demand realizations. In addition, GP assume that monitoring among cartel members is imperfect (i.e. comes in the form of a noisy public signal),[2] whereas RS assume that monitoring is perfect. Our experimental design is guided by these differences in assumptions: in two of our treatments monitoring and demand information differ in the same way as GP and RS differ. In a third, 'intermediate', treatment there is uncertainty about next period's demand realization (as in GP) but monitoring is perfect (as in RS); this treatment allows us to separate the imperfect monitoring effect from the imperfect demand information effect.

[2] This assumption is needed so that uncertainty about past demand realizations persists into the future.

Interestingly, the differential treatment of demand information and monitoring assumptions by GP and RS generate theoretical predictions that appear to be “at odds” (Ellison, 1994: 38). GP show that price wars in a cartel may be triggered by unusually small demand shocks, but RS show that a cartel may experience price wars during periods of unusually large demand shocks.[3] A usual interpretation of these theories is that GP predicts more collusion during booms, while RS predicts more collusion during recessions.[4] Given the divergent predictions of these theories and our encompassing experimental design, we test each theory’s internal validity; this is the second objective of this research.

It is important to point out, however, that GP and RS are not mutually exclusive theories, and results from our second objective may well indicate that each model is valid in its own domain. Instead, our effort is to investigate the empirical plausibility of each theory. Studying each theory’s internal validity is important for at least two reasons. First, with field data there is no guarantee that firm behavior that appears to correspond to the predictions of a given theory (even if the theory’s assumptions appear to hold) is a consequence of the theory at work (e.g. Frechette, Kagel and Morelli, 2005). Second, from a practical perspective, the multiplicity of equilibria in infinitely repeated games and the large number of theories on collusion makes it important for empirical economists to identify the empirically *plausible* equilibria from the set of theoretically *possible* equilibria; experiments can be a particularly useful tool in this effort. For example, if the predictions of a collusive theory hardly emerge-0., Specifically, we test whether the collusive equilibrium path for which GP is known (finite price wars triggered by low demand) is supported by the data. For the RS theory, we test the equilibrium prediction that price wars should occur during high demand periods whereas collusion should occur otherwise. We also study strategies at the individual level to determine whether the strategies implied by each theory constitute a reasonable explanation of behavior when compared with other plausible strategies. Finally, we study how the RS and GP equilibria explain behavior with respect to other possible equilibria.

Results indicate that monitoring appears to be a critical factor in facilitating collusion. Conversely, contrary to conventional wisdom, demand information does not appear to have the expected effect on collusion: removing demand information does not decrease (and in some cases increases) collusion. The results provide some support for both the RS and the GP predictions; however, evidence appears to be stronger for permanent price wars (i.e. grim-trigger strategies) rather than the temporary reversions for which both theories are known for. This is important as one of the several GP equilibria allows for permanent price war, while the RS equilibria do not permit this possibility.

Section 2 reviews the literature while section 3 describes the model. Section 4 provides details of the experimental design and section 5 describes its implementation. Section 6 presents the results and section 7 discusses our main findings.

2. Literature Review

Friedman (1971) showed that if firms are patient enough in a non-cooperative infinitely repeated game, a trigger strategy (reversion to Cournot production levels when market price dropped below a threshold) would produce an equilibrium in which no firm has an incentive to deviate. According to this early view, the existence of price wars in oligopoly markets was interpreted as a sign of cartel breakdown. However, GP show that instead of a symptom of unsuccessful collusion, finite price wars may be part of a 'collusive' equilibrium path. GP modify Friedman's model by allowing for a stochastic demand structure and imperfect monitoring of rivals' actions.[5] As in Friedman, collusion can be sustained through the use of trigger strategies, but now switching from the collusive outcome to the competitive outcome (after an unusually low demand state) is only temporary. More importantly, the seminal result of this model is that price wars are part of the collusive equilibrium path as they constitute a self-enforcing mechanism used by successful colluders.

RS propose a model with a stochastic environment similar to that of GP. The main differences between RS and GP is that firms know next period's demand shock realization prior to setting their quantity (or price) and that firms can perfectly monitor rivals' choices. In this environment, firms' incentive to deviate from the collusive outcome is positively correlated with next period's demand shock and for unusually large (and positive) demand shocks this incentive more than offsets the expected future losses of a reversion to the competitive outcome. A cartel is thereby predicted to be less stable during "booms". To avoid the competitive outcome during large demand shock periods, firms limit the incentives to deviation by reducing (increasing) their "collusive" price (quantity) below (above) the monopoly level. The resulting collusive equilibrium path has firms pricing in a countercyclical fashion.[6]

Empirical work assessing the validity of the GP theory has been restricted to data from the 19th century Joint Executive Committee (JEC). However, limited data and an uncontrolled field environment do not allow a direct test of the GP theory. As a result most of the work with these data has been concerned with finding evidence for the existence of regime switching between high and low prices (see Ellison, 1994, and references cited therein).[7] Empirical work on the RS theory has focused on its countercyclical pricing prediction; this has been a puzzling issue as it runs counterintuitive to conventional wisdom (i.e. a rightward shift in demand should increase

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equilibrium price) but is nevertheless frequently observed in many markets (e.g. soft drinks during summer, turkey during Thanksgiving). Prior research has tried to explain this pattern against other competing models and has found little support for RS as an explanatory theory (Chevalier, Kashyap and Rossi, 2003).

On the experimental front, there has been work studying how demand information and monitoring affect collusion/cooperation in repeated games. This literature has addressed either monitoring or demand information, but not both, and in rather specific ways. The role of imperfect monitoring on collusion has been studied Holcomb and Nelson (1991, 1997), Bereby-Meyer and Roth (2006), and Aoyagi and Frechette (2008). Holcomb and Nelson study repeated duopoly games in which opponent's quantity choices are randomly changed uncertainty. In different treatments, subjects accessed information about the state of demand in different ways. The main result is that subjects generally decided to share information to reduce uncertainty, which led to output reductions. However, in treatments where subjects did not have the choice of sharing information, information itself did not increase tacit collusion. Feinberg and Snyder claim that uncertain demand shocks do interfere with collusion, although few data points and an apparent ‘group effect’ do not allow a clear interpretation of the results.

3. The Model

The model is based on the prisoner’s dilemma game. There are at least two reasons for studying collusion in an environment that is a highly simplified version of the models that motivate this research: a) we want to give collusion its best possible chance of occurrence - subjects’ coordination on the collusive outcome is less likely if a game

Table 1: Typical Payoff Table

Player 2

through a noisy signal: the market price. These two sources of uncertainty impede firms from inferring their opponents' strategies even *after* the realization of demand. GP show that finite punishment strategies (reversion to *H*) can be sustained in an equilibrium path in which no firm deviates from the collusive agreement. These finite punishment periods are triggered by a low market price: since there is imperfect monitoring of rivals' actions, a low price can either denote a negative demand shock or a rival's deviation. As with other cartel models, GP entertain a collusive equilibrium in which no firm has an and the resulting Bellman's equation is:

$$V_i(y_i) = \begin{cases} \gamma_i(L) + (1 - F_k^L)\delta V_i(L) + F_k^L \left(\sum_{t=1}^{N} \delta^t \lambda_i + \delta^{N+1} V_i(L) \right) & \text{if } y_i = L \\ \gamma_i(H) + (1 - F_k^H)\delta V_i(H) + F_k^H \left(\sum_{t=1}^{N} \delta^t \lambda_i + \delta^{N+1} V_i(H) \right) & \text{if } y_i = H \end{cases}$$

parameterization 2 the GP equilibrium is feasible with a punishment length of at least 3 periods.

Table 2: Payoff Tables for Three Demand States

Parameterization 1

High Demand (probability=0.2)

		Player 2	
		L	H
Player 1	L	26.00 , 26.00	7.50 , 43.00
	H	43.00 , 7.50	12.50, 12.50

Medium Demand (probability=0.6)

		Player 2	
		L	H
Player 1	L	7.50 , 7.50	2.10 , 12.50
	H	12.50 , 2.10	3.50 , 3.50

Low Demand (probability=0.2)

		Player 2	
		L	H
Player 1	L	2.10 , 2.10	0.60 , 3.50
	H	3.50 , 0.60	1.00 , 1.00

Parameterization 2

High Demand (probability=0.2)

		Player 2	
		L	H
Player 1	L	31.00 , 31.00	9.00 , 43.00
	H	43.00 , 9.00	12.50, 12.50

Medium Demand (probability=0.6)

		Player 2	
		L	H
	L	9.00 , 9.00	2.50 , 12.50

H 9.036 Tm -0.0005 Tc 38(9.00 , 9.00)-173Tc 72.5

Likewise, parameterization 1 is calibrated in accordance with the predictions of the RS theory (collusion is an equilibrium only in the medium and low demand states), while parameterization 2 is not (i.e. collusion is an equilibrium in all demand states). Parameterization 2 also serves to check the robustness of our other main result, namely the more prominent role of monitoring (rather than demand information) on collusion.

Instead of specifying a demand function, the payoff tables are constructed so that the percentage difference between payoffs across entries remains invariant across demand states. For example, in parameterization 1 the payoff in the collusive outcome is about 100% higher (with some rounding error) than the payoff in the Nash-Equilibrium. The reason for constructing payoff matrices in this fashion is that individuals seem to care about relative variation in payoffs rather than the absolute variation (Weber, Shafir and Blais, 2004); thus, the potential confounding effect of significant variation in relative payoffs across demand states is reduced.

strategy after a round's profit realization. Payoff tables in parameterization 1 are constructed such that the incentive to deviate in the high demand state (LHS of (3)) is their opponent's choice.[18] The motivation for adding this treatment is twofold. First, while demand uncertainty and imperfect monitoring (as assumed by GP) may be realistic sometimes, it is plausible that firms accrue information to infer rivals' past actions. Secondly, this treatment isolates one of the two factors that differentiate the FI treatment from the IM treatment.

The treatments are organized in a 2x2 matrix (Table 3). The perfect demand foresight/no monitoring treatment is unfeasible because subjects can infer the opponent's strategy. This yields a 3 (treatments) x 2 (parameterizations) experimental design.

5. Implementation

Twelve sessions with a total of 288 subjects were run. Six sessions were run with each parameterization (two sessions for each treatment). Subjects were recruited from Economics, Statistics and Management courses at the University of Massachusetts-Amherst. Demographic composition was not unusual for laboratory experiments with college students: 40% were females, 72% were white, and the combined number of freshmen and sophomores was 51% (with the remaining 49% distributed relatively evenly among juniors, seniors and graduate students). Subjects received a $5 show-up fee and earned additional money from their decisions; earnings from decisions were in experimental dollars ($1=10 experimental $). Average earnings in dollars ($) per session, as well as the corresponding dates and number of subjects are presented in table 4.

Table 3: Experimental Design

	Monitoring	**No Monitoring**
Perfect Demand Foresight	Full Information (FI)	-
Imperfect Demand Foresight	Monitoring (M)	Imperfect Monitoring (IM)

All experiments were computerized and programmed in Z-tree (Fischbacher, 1999).[19] Students were assigned a computer terminal and advised that they would be randomly paired with someone else in the room for the duration of the experiment and that communication with other participants was forbidden. Special efforts were made to achieve subjects' comprehension and familiarity with the experiment before the start of

[18] In order to keep the experimental design consistent across treatments, subjects in the IM treatment are informed of the demand state instead of their opponent's choice.

[19] Instructions and decision screens are available at: http://www.umass.edu/resec/faculty/rojas/z-tree.html

[redacted] 3 practice rounds, each with one [redacted] correctly to a question, the [redacted] explanation.[20]

[redacted] gs per Session*

[redacted]						
[redacted]	[redacted]		itoring		Imperfect Monitoring	
[redacted]	[redacted]	[redacted]	[redacted]	IV	V	VI
[redacted]	[redacted]	[redacted]	[redacted]	04/30/08	04/28/08	04/28/08
[redacted]	[redacted]	[redacted]	[redacted]	24	24	24
[redacted]	[redacted]	[redacted]	[redacted]	30.40	24.74	26.86
[redacted]						
[redacted]	[redacted]		toring		Imperfect Monitoring	
[redacted]	[redacted]	[redacted]	IX	X	XI	XII
Date	04/30/08	04/30/08	05/05/08	05/05/08	05/02/08	05/02/08

Figure 1: Decision Screen in the Full Information (FI) Treatment (Parameterization 1)

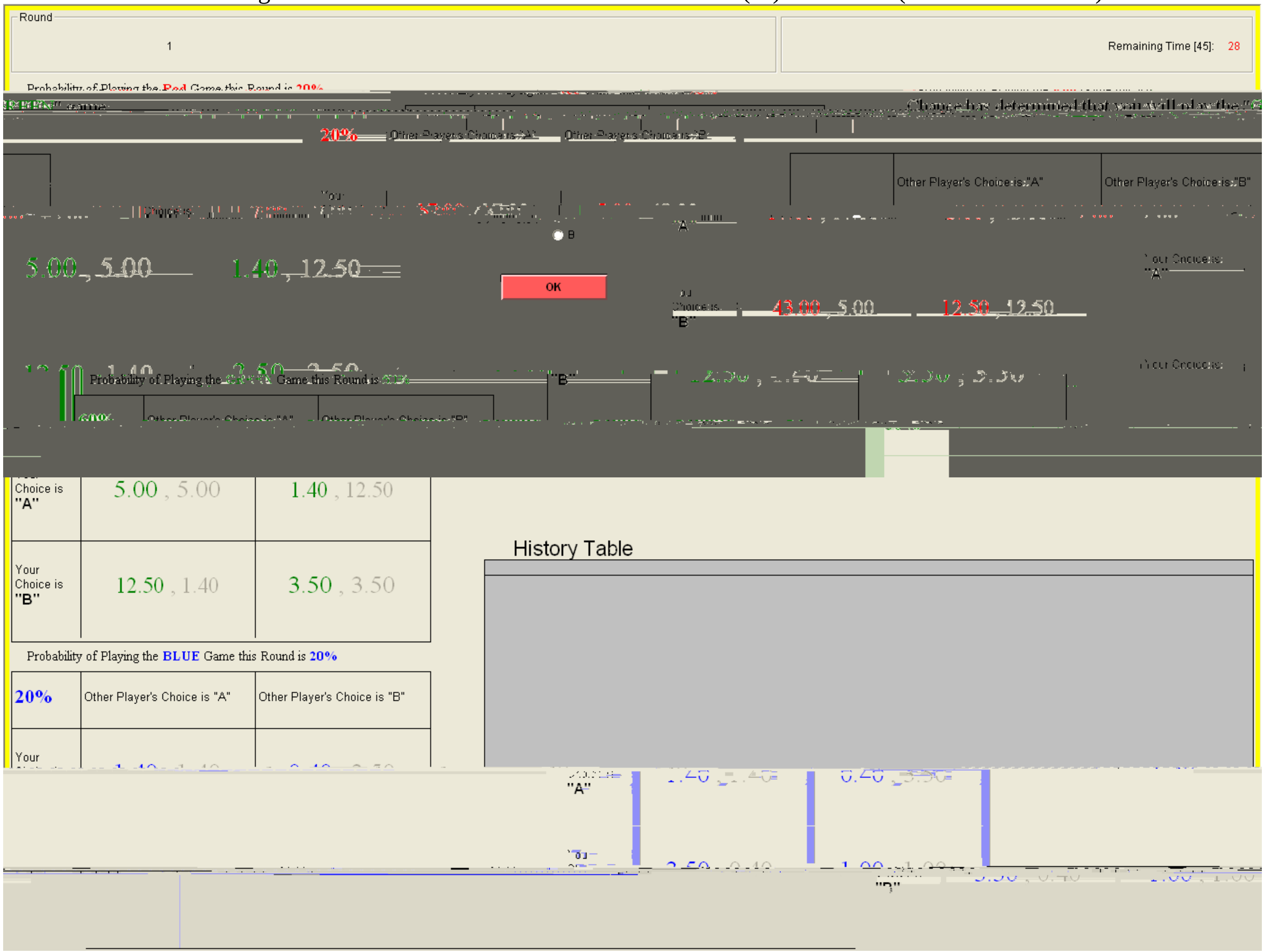


Figure 2: Decision Screen in the Monitoring (M) and Imperfect Monitoring (IM) Treatments (Parameterization 1)

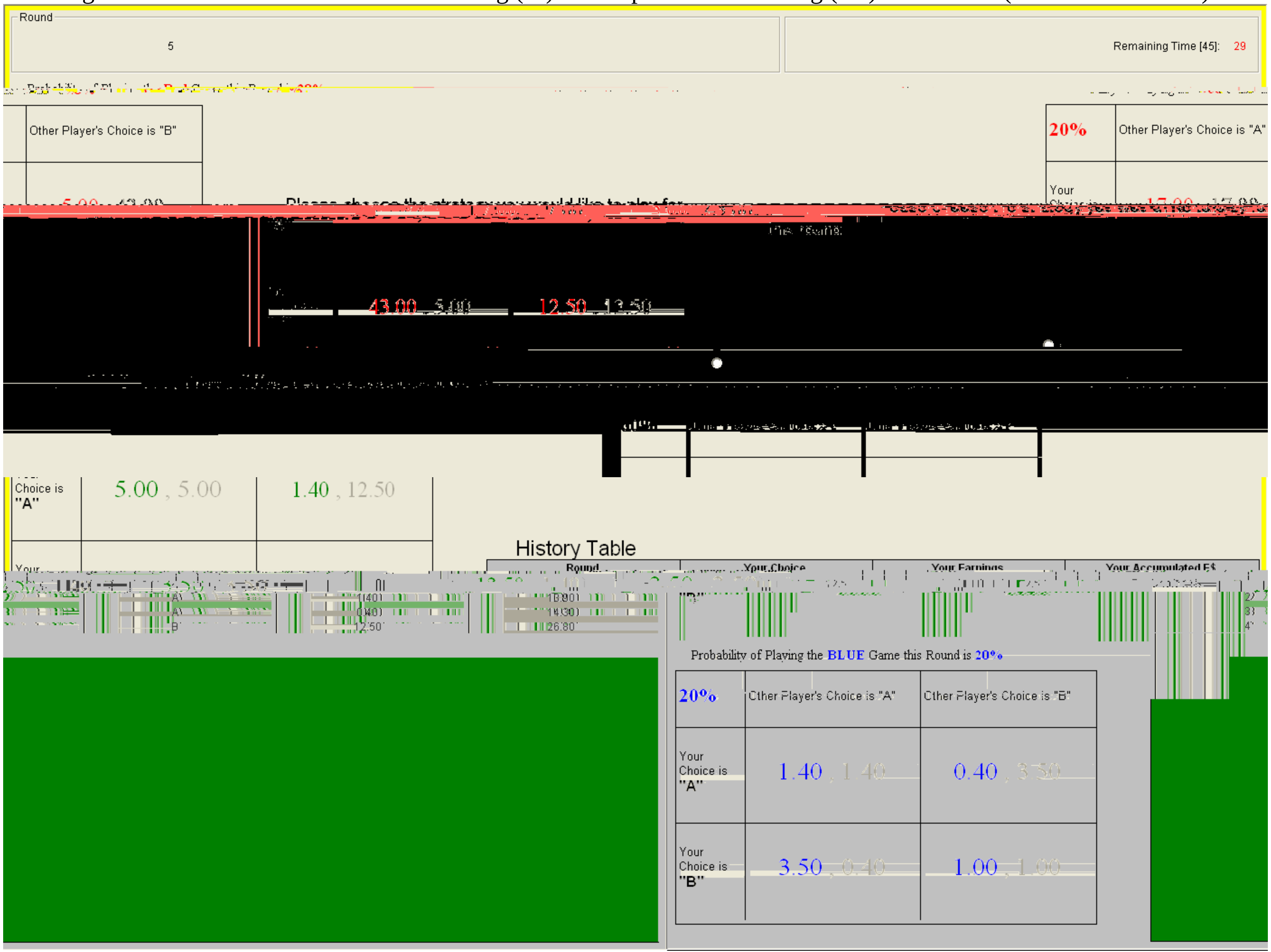
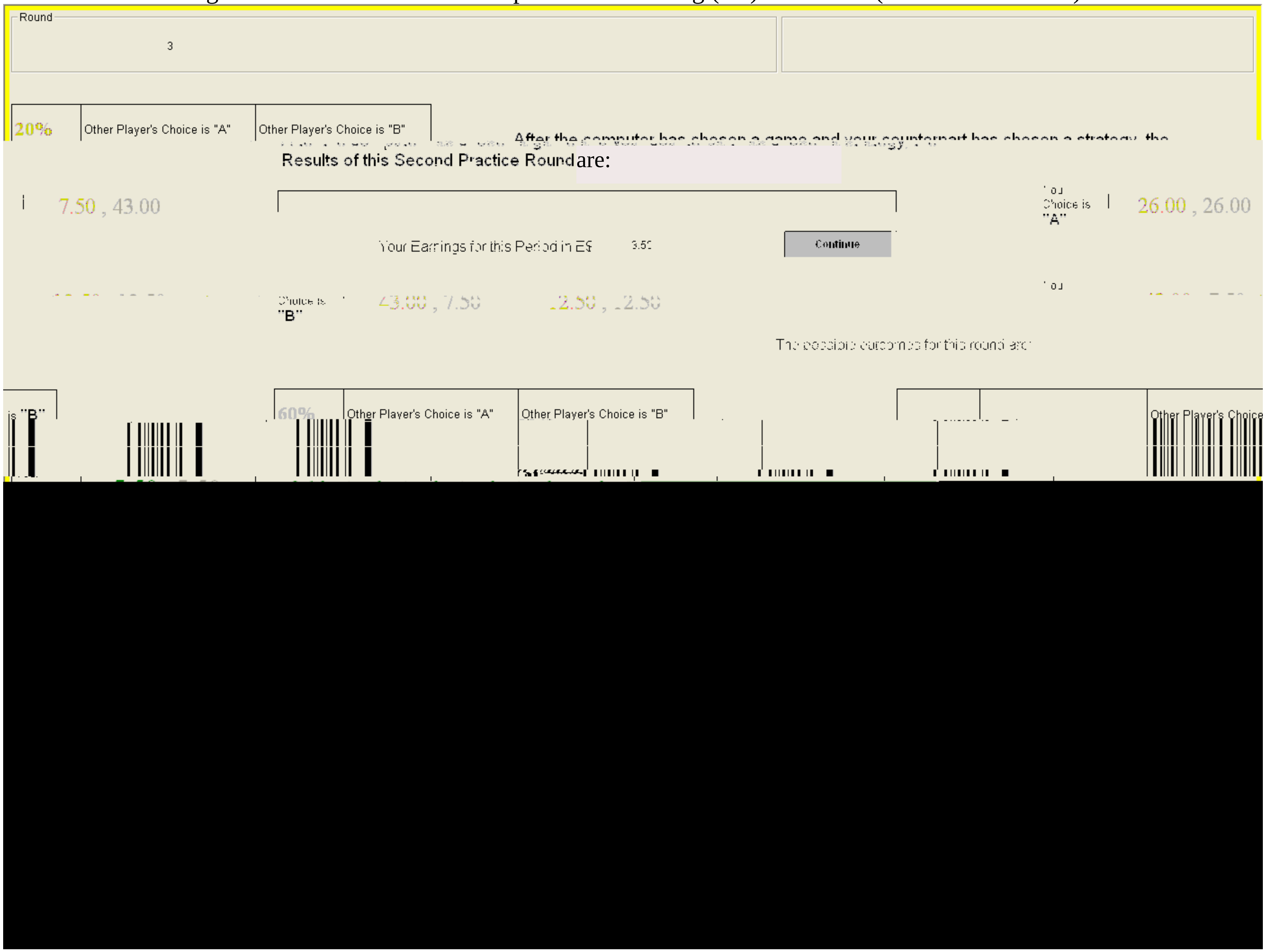


Figure 3: Profit Screen in the Full Information (FI) and Monitoring (M) Treatments (Parameterization 1)

Figure 4: Profit Screen in the Imperfect Monitoring (IM) Treatment (Parameterization 1)



All subjects in all treatments were informed about the probability of appearance of each payoff table. Subjects played 30 rounds with certainty; after round 30, the computer terminated the game with 20% probability. To keep treatments comparable, the same draw was used to terminate the game in all treatments; the total number of periods turned out to be 33. To determine the demand state (high, medium or low), 33 random draws from a uniform distribution were taken once, and the same set of demand states implied by these draws was used in all treatments to preserve comparability.

A round consisted of subjects making a simultaneous decision between low output (*L*) and high output (*H*) (decision screen, figures 1 and 2); after a decision, subjects were informed of profits and the round ended (profit screen, figures 3 and 4). In the FI treatment, the decision screen presented subjects with the payoff matrix that they would play (figure 1). Conversely, in the IM and M treatments the decision screen only reminded subjects of the probability with which each payoff table will be chosen for play (figure 2).

In the M treatment, the profit screen reveals the chosen demand state. Also, this screen highlighted the cell in the chosen payoff table that determined the subject's profit. Because the FI and M treatments imply perfect monitoring and demand information *after* the round is played (ex-post), the profit screen for both of these treatments was the same (figure 3). In the IM treatment, the profit screen presented subjects with the *possible* outcomes that might have occurred (figure 4), effectively implementing the desired imperfect monitoring.

As depicted in the figures above, the program also contains a history table where subjects can see their cumulative earnings. In addition to the experiment on collusion, subjects completed a risk task (see Appendix B) and a small survey that contained questions on demographics, and on the subjects' assessment of the clarity of the experiment (97% of the subjects believed that the instructions were clear).[23] All sessions lasted approximately one and a half hours, including instructions. A total of 9,504

[23] Answers to the statement "The instructions for th

observations were collected (33 rounds x 288 participants). At the end of the experiment, subjects were individually called in private and were paid their cumulative earnings from the task in cash.

6. Results

6.1 Effect of Demand Information and Monitoring

For each of the three treatments, table 5 presents the frequency of individual cooperation (at least one player chooses the collusive outcome - *L*)[24] as well as the frequency of collusion (both players choose *L*) for the two parameterizations considered. Contrary to a stylized fact in industrial organization, when demand information is removed (from Full Information to Monitoring), cooperation and collusion increase in parameterization 1 and appear unchanged in parameterization 2. Conversely, cooperation and collusion diminish in both parameterizations when imperfect monitoring is introduced (from Monitoring to Imperfect Monitoring).

Table 5: Frequencies of Cooperation and Collusion (standard deviation)

Treatment	Parameterization	Frequency of Cooperation*	Frequency of Collusion**
Full Information	1	0.72 (0.45)	0.51 (0.50)
	2	*0.83 (0.38)*	*0.71 (0.46)*
Monitoring	1	0.76 (0.42)	0.59 (0.49)
	2	*0.84 (0.37)*	*0.71 (0.46)*
Imperfect Monitoring	1	0.63 (0.48)	0.31 (0.46)
	2	*0.66 (0.47)*	*0.41 (0.49)*

* At least one player chooses *L*. ** Both players choose *L*. # of observations in all treatments is 1,584

We test and confirm these observations using several non-parametric tests (Wilcoxon, Kolmogorov-Smirnov, Pearson's Chi-square and Epps-Singleton) as well as the parametric *t*-test: frequencies (for both cooperation and collusion) in parameterization 1 are statistically larger in the M treatment than in the FI treatment (all p-values<0.01), but frequencies from these two treatments are not statistically different from each other in parameterization 2 (p-values>0.39); frequencies (for both collusion and cooperation) in both parameterizations are statistically larger in the M and FI treatments when (individually) compared with the IM treatment (all p-values<0.01). Finally, using the

[24] Alternatively, one can define cooperation as the number of "*L*" choices (a smaller number). The results in the paper are invariant to either definition.

same battery of parametric and non-parametric tests, the level of cooperation and collusion in a given treatment is statistically larger in parameterization 2 (p-values<0.01), except for cooperation in the IM treatment (p-values tests range from 0.05 to 0.39). It important to note that the described results support theoretical predictions:

a) As noted earlier, the incentives to collude are stronger in parameterization 1, regardless of the treatment. Further, in the FI treatment, parameterization 2 implies that the left hand side of (2) is smaller than its right hand side *for all* three demand states, whereas in parameterization 1 this is true only for the medium and low demand states (deliberately, to test the RS theory); this reinforces the fact that a larger amount of collusion should be observed in parameterization 2 in the FI treatment.

b) In the M treatment, collusion is an equilibrium if the following condition (a modified version of equation (1)) is met:

$$E(\Pi_s^D - \Pi_s^{NE}) < \frac{\delta}{1-\delta}[E(\Pi_s^C - \Pi_s^{NE})]$$

$$0.2(\Pi_h^D - \Pi_h^{NE}) + 0.6(\Pi_m^D - \Pi_m^{NE}) + 0.2(\Pi_l^D - \Pi_l^{NE}) < \frac{\delta}{1-\delta} 0.2(\Pi_h^C - \Pi_h^{NE}) + 0.6(\Pi_m^C - \Pi_m^{NE}) + 0.2(\Pi_l^C - \Pi_l^{NE}) \quad (5)$$

where $E(\Pi_s^C - \Pi_s^{NE}) = 0.2(\Pi_h^C - \Pi_h^{NE}) + 0.6(\Pi_m^C - \Pi_m^{NE}) + 0.2(\Pi_l^C - \Pi_l^{NE})$. In parameterization 1, the left hand size of equation (5) is equal to 6.68 and the right hand side is equal to 15.96; this inequality is even more pronounced in parameterization 2: the left hand size of equation (5) is equal to 4.70 and the right hand side is equal to 21.90.[25] Assuming no mistakes by subjects, we should rarely observe deviations from cooperation/collusion in this treatment (especially in parameterization 2).

c) Theoretically, if the GP equilibrium were supported by the data, larger levels of collusion and cooperation should be expected in parameterization 2 as the collusive scheme predicted by GP can not be an equilibrium in parameterization 1. This only holds for collusion, however.

[25] These numbers correspond to the case of risk neutrality. After adjusting for the level of risk aversion observed in our sample (see Appendix B), the inequalities remain unchanged: 1.89 (left hand side) and 5.99 (right hand side) for parameterization 1 and 1.28 and 7.82 for parameterization 2.

Figures 5A and 5B show the frequency of cooperation throughout the 33 periods of the experiment, in both parameterizations. The figures confirm the higher level of cooperation in the FI and M treatments (with respect to the IM treatment) in both parameterizations. Also, the figures confirm the higher cooperation rate in the M treatment than in the FI treatment in parameterization 1 (5A), and the similar cooperation

Figure 5: Frequency of Cooperation over 33 Periods of Stochastic Demand: h=high [---], m=medium or l=low [—]; by Parameterization (in parenthesis)

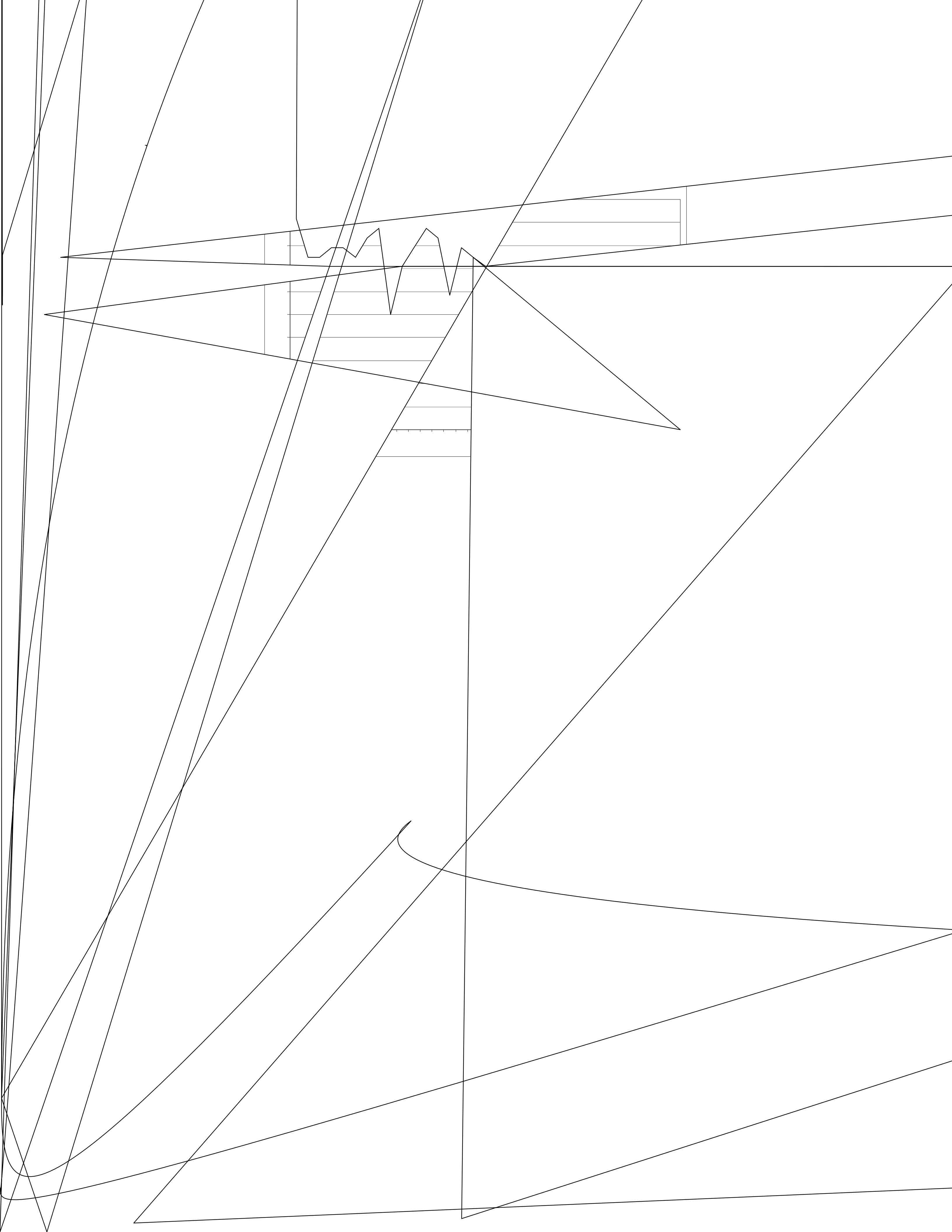


Table 6: Frequencies of Cooperation and Collusion in FI Treatment (St. Dev.)

Demand State	Parameterization	All Observations (Periods 1-33)			Periods 1-25		
		# Obs.	Freq. Coop.*	Freq. Collusion**	# Obs.	Freq. Coop.*	Freq. Collusion**
High	1	288	0.58 (0.49)	0.42 (0.49)	240	0.58 (0.49)	0.43 (0.50)
(*h*)	*2*	*288*	*0.78 (0.42)*	*0.65 (0.48)*	*240*	*0.80 (0.40)*	*0.67 (0.47)*
	1	1,008	0.73 (0.44)	0.52 (0.50)	720	0.78 (0.42)	0.56 (0.50)

Note that all these strategies can be defined as trigger strategies, each with three characteristics: a) the type of trigger, b) the duration of reversion to the non-cooperative outcome, and c) the rule for returning to the collusive outcome. It is important to note, however, that while s_t^{RS} is a trigger-like strategy, it tests whether subjects are on the *equilibrium path* predicted by RS; that is, the trigger strategy upon which the RS prediction is based (i.e. reversion to the NE forever if deviation occurs in the medium and low demand states) is not observed. Put differently, s_t^{RS} tests whether the equilibrium outcome predicted by RS occurs, whereas s_{it}^{∞}, for example, tests whether subjects use a strategy that is *consistent* with the conditions needed to obtain the RS equilibrium (i.e. the grim-trigger strategy). In a sense, then, s_t^{RS} entails a demanding test of the RS theory.

While searching for patterns that may explain subjects' strategies better than the RS theory alone, informal inspection of the data revealed that subjects may appear to be basing their strategies on both the demand state (high or not) as well as on their opponent's choice; the last column presents the estimates of this "combined" strategy.

In all specifications, the statistical significance of

Table 8: Probit Estimates of Different Strategies in the FI treatment, Parameterization 1, Rounds 1-25

Parameter	**Random**	**RS**	**tt**	**P-1**	**P-2**	**P-3**	**P-4**	**P-5**	**P-6**	**P-**	**RS + tt**
	-0.80***	-0.66	-0.97*	-0.88**	-0.93**	-0.85**	-0.90**	-0.88**	-0.86**	-0.69*	-0.86**
	(0.43)	(0.46)	(0.36)	(0.42)	(0.39)	(0.39)	(0.36)	(0.36)	(0.35)	(0.16)	(0.38)
$_1$		0.92*									0.99*
		(0.14)									(0.14)
$_2$			0.56*								0.68*
			(0.12)								(0.12)
$_3$				0.17	0.37*	0.23**	0.51*	0.49*	0.53*	2.39*	
				(0.11)	(0.11)	(0.12)	(0.12)	(0.13)	(0.14)	(0.24)	
	2.40*	2.56*	2.03*	2.31*	2.20*	2.20*	2.02*	2.03*	1.98*	0.69*	2.14*
	(0.52)	(0.53)	(0.43)	(0.48)	(0.46)	(0.45)	(0.41)	(0.42)	(0.41)	(0.23)	(0.44)
ρ	0.69*	0.72*	0.60*	0.67*	0.65*	0.65*	0.60*	0.61*	0.59*	0.69*	0.63*
LL	-450.84	-427.84	-440.41	-449.80	-445.30	-449.17	-443.37	-444.33	-444.16	-422.07	-413.77
LR Test	N/A	46.00	20.85	2.07	11.08	3.34	14.94	13.01	13.35	57.53	74.13
(p-value)†		(<0.01)	(<0.01)	(0.15)	(<0.01)	(0.07)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)

* Significant at 1%. ** Significant at 5%. *** Significant at 10%. †

Equilibrium Outcomes

As opposed to the econometric model presented above, the focus of the analysis here is on *equilibrium outcomes* rather than on individual strategies. Specifically, we analyze how the data lends support to the different feasible equilibria presented in Appendix A (table A.1). Table 9 displays the frequencies of the outcomes observed in each of the three demand states; the bold numbers indicate that the cell is a feasible equilibria. There are several patterns worth noting. First, collusion (*L*,*L*) is the most frequently observed outcome, except when theory predicts it is not an equilibrium (high demand, parameterization 1). Second, (*H*,*L*)/ (*L*,*H*) is the least frequently observed outcome, except in one case (low demand, parameterization 2). Third, within a parameterization, collusion appears a more likely outcome during "bad times" (i.e. its frequency decreases as demand becomes larger), whereas the one-shot NE becomes more likely during "good times"; the frequency of the (*H*,*L*)/(*L*,*H*) equilbria, on the other hand, is relatively stable within a parameterization.

Table 9: Frequencies of Observed Outcomes

Demand State (outcomes)		**Parameterization 1**	**Parameterization 2**
High (*h*)	(*L*,*L*)	41.67%	**65.28%**
	(*H*,*H*)	**42.36%**	**22.22%**
	(*H*,*L*)/(*L*,*H*)	**15.97%**	**12.50%**
Medium (*m*)	(*L*,*L*)	**51.79%**	**70.44%**
	(*H*,*H*)	**26.59%**	**17.46%**
	(*H*,*L*)/(*L*,*H*)	**21.63%**	**12.10%**
Low (*l*)	(*L*,*L*)	**57.64%**	**75.69%**
	(*H*,*H*)	**21.53%**	**11.11%**
	(*H*,*L*)/(*L*,*H*)	**20.83%**	**13.19%**

Notes: Bold numbers indicate that entry is a feasible equilibrium (see Appendix A for details)

To contrast the predictive power of the RS equilibrium with that of other feasible)/(

indicator variable predicts collusion (C) and compare them with the frequencies of cooperation and collusion when the indicator variable predicts a price war (R).

Table 10 reports the cooperation and collusion frequencies during the two regimes, as predicted by the different lengths of punishment after price drops to p_2 (or

Subjects' Strategies

Recall that the basis for the GP equilibriu

Table 11: Strategies Considered and Corresponding Variables, IM treatment

Strategy	γz_{it}	Definition
Random	N/A	N/A
GP, with: N = 1,…,	${}_1 s_t^{GP_N}$	For t = 1: $s_1^{GP_N}$ = 1 $s_t^{GP_L}$ = 1 if $s_{t-1}^{GP_N}$ =1 and demand=high or medium or $s_{t-1}^{GP_N}$ =0 and $s_{t-(N+1)}^{GP_N}$ =1 0 otherwise
One Threshold Strategy (T1), with: k =f(p) N = 1,…,	${}_2 s_{it}^{T1_N}$	For 1: $_{i1}^{T1_N}$ 1 For 1 1 if $_{it\ 1}^{T1_N}$ =1 and $_{t\ 1}$ $_{it}^{T1_N}$ or $_{it\ 1}^{T1_N}$ =0 and $^{T1_N}_{(\ \ 1)}$ =1 0 otherwise

These strategies allow several possibilitie

Table 12: Probit Estimates of Different Strategies in the IM treatment, Rounds 1-25

Random	GP_N	$T1_N$ $\{N\}$	$TT1_N$ $\{N\}$	$T2$	$TT2$

Parameterization 1

$k \quad p_1$ 2 $\qquad k \quad p_2$ 2 $\qquad k(L) \quad p_1$ / $k(H) \quad p_0$ 3 $\qquad ^{up}(\quad)$ 4

The evidence presented in table 12 is interpreted as providing support for the existence of trigger strategies in general, a in our design. Appendix D reports the results of the estimations, which strongly confirm the latter finding. Conversely, the evidence for the RS theory still exists but is not as strong as in parameterization 1. In particular, the tit-for-tat and the grim strategies now appear to describe data better than the RS strategy.

Table 13: Fraction of Times the Equilibrium Path Correctly Predicts Outcomes

Equilibrium Path	**Parameterization 1**	**Parameterization 2**
(*H*,*H*) every period	**36.87%**	**33.59%**
GP_3	50.00%	**50.63%**
GP_4	56.82%	**53.91%**
GP_5	48.48%	**48.36%**
GP_6	52.27%	**51.14%**
GP_{15}	66.16%	**60.48%**
GP_{16}	67.68%	**60.73%**
GP_{17}	68.69%	**61.74%**
GP_{18}	70.20%	**61.74%**
GP	71.72%	**62.25%**

Notes: Bold numbers indicate a theoretically feasible equilibrium (see Appendix A for details). The GP_N path takes a value of 1 when collusion is predicted and 0 when a price war is predicted; a price war is assumed to be triggered by a low signal (price p_2) which lasts *N* periods.

With the observed level of risk aversion, the set of GP equilibria gets larger (see Appendix B). Specifically, the GP equilibrium becomes feasible in parameterization 1 for punishment lengths that range from 6 periods to . Another possible equilibrium emerges for parameterization 2: with threshold level p_1, the feasible range of punishment lengths for the GP equilibrium is [6,..,]; in addition, the punishment length for a threshold of p_2 increases its range to [2,..,]. This attenuates our interpretation of the results regarding the similar behavior across parameterizations being construed as lack of evidence for the incentives implied by the GP equilibrium. In addition, since p_1 is now a threshold level that yields feasible GP equilibria, the estimation results for strategy *T1* are no longer inconsistent with the GP predictions.

We still note, however, that the finite punishment behavior for which GP is known does not describe the data as well as the infinite punishment strategy. To be sure, we carried out an additional check: we varied the random draws that determine the demand states and conducted additional sessions with parameterization 2. Our main results are robust (Appendix D).

8. Discussion

In this paper we focus on two factors (demand information and monitoring) that

The traditional (or simple) interpretation of the RS model is that it is a theory of countercyclical pricing (*temporary* low price during high demand), whereas the GP theory is usually attributed with

In general, we find that the RS environm

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APPENDIX A: Equilibrium Set

A.2 The Imperfect Monitoring Treatment (GP theory)

As with the FI treatment, it is easy to show that the playing the one shot NE (*H*,*H*) in every period is an equilibrium of this game. Collusion, on the other hand, can be sustained through the use of trigger strategies; but, as opposed to the RS equilibrium, collusion here refers to a "collusive path" rather than observing (*L*,*L*) every period: reversion to the NE play is part of the equilibrium path for some period of time (finite or infinite). This is an important difference because observing reversion to the NE play in the RS model may be consistent with RS strategies but inconsistent with the RS equilibrium path, whereas in the GP model reversion is consistent with both equilibrium strategies and the equilibrium path.[ii]

Table A.1: Feasible Equilibria by Demand State and Parameterization in the FI Treatment, (strategy pair), [range of feasible punishment lengths "*N*"]

Demand State	**Par[redacted]meterizatio[redacted]**	**Parameterization 2**	**Parameterization 3**
High (*h*)	(*H*,[redacted] (*H*,[redacted](*L*,*H*) [2- [redacted]	(*L*,*L*) [3-]* (*H*,*H*) (*H*,*L*)/(*L*,*H*) [1-]	(*H*,*H*)
Medium (*m*)	([redacted]		

Table A.2: Feasible Equilibria in the IM Treatment, (choices),[range of feasible punishment lengths “*N*”]

Equilibrium Path	**Parameterization 1**	**Parameterization 2**
(*H*,*H*) every period	Yes	Yes
Trigger: (*L*,*L*) as long as observed *p* greater than:		
p_0	No	No
p_1	No	No**
p_2	No*	Yes [3-]***
p_3	No	No
p_4	No	No

Notes: Parameterization 3 is not considered as it does not have the imperfect .0013i imperfect cb

Appendix B: Risk Aversion Estimate and Parameterization Details

B.1. Risk Aversion Estimate

The underlying assumption of the theories studied in this paper is that subjects are risk neutral, or that utility is of the form $u(x) = x$, where x is the monetary payoff. To allow for the possibility of risk averse (or risk seeking) behavior, we adopt the widely used constant relative risk aversion (CRRA) utility specification:

APPENDIX C: Imperfect Public Monitoring

Consider parameterization 1. Without loss of generality, let'

APPENDIX D: Results of Robustness Checks

First, we constructed an additional parameterization (table D.1), to address the potential drawback caused by subjects' risk aversion in the analysis of the evidence for the RS theory (see appendix A). To achieve the desired critical discount factors in the presence of risk aversion, however, the imperfect monitoring characteristic could no longer be maintained; thus, sessions were run only for the FI and M treatments.[i] A total of 102 subjects from the University of Massachusetts participated in 3 sessions (2 for treatment FI and 1 for treatment M); mean earnings (excluding show up fee and risk task payments) were $19.12 for the FI treatment and $19.40 for the M treatment. Further, parameterization 3 also serves as a robustness check for our other main finding (demand information removal does not decrease collusion).

Second, to check the robustness of the GP results, we ran additional sessions with parameterization 2 but varied the random draws that determine the demand states. These draws can be seen in figure D.1 below; we call it parameterization 2b. A total of 74 subjects from the University of Massachusetts participated in 4 sessions (2 for the IM treatment and 1 for each of the other two treatments). Average earnings were $31.06, $33.42 and $24.73 for the FI, M and IM treatments, respectively. In addition, parameterization 2b also allows us to further check the results obtained in the analysis of evidence for the RS treatment.

Table D.1: Parameterization 3

		High Demand		**Medium Demand**		**High Demand**	
		Player 2		Player 2		Player 2	
		L	H	L	H	L	H
Player 1	L	17.00, 17.00	2.00, 31.00	5.00, 5.00	0.50, 9.00	1.40, 1.40	0.20, 2.50

Table D.2: Frequencies of Cooperation and Collusion (standard deviation)

Treatment	**Parameterization**	**# Obs.**	**Frequency of Cooperation***	**Frequency of Collusion****
	2b	660	0.87 (0.33)	0.62 (0.49)

frequency of collusion in the medium demand state is not statistically different than that observed in the low demand state.

Turning to the analysis of individual strategies, the regressions reported in table D.4 still provide support for the RS strategy, but this evidence is not as strong as in parameterization 1. In particular, the TT strategy has a higher explanatory power than the RS strategy; the grim strategy continues to be the most significant (single) strategy and it can even explain data better than the combined RS+TT strategy.

Table D.3: Frequencies of Cooperation and Collusion in Full Information Treatment (St. Dev.)

Demand State	Param.	All Observations (Periods 1-33)		Periods 1-25	
		# Obs.	Freq. Collusion**	# Obs.	Freq. Collusion**

medium state). When compared with parameterization 2, observed outcomes for parameterization 2b are somewhat different, however; the main difference is that here the collusive outcome is observed less frequently (especially in the high demand state), while the (*H*,*L*)/(*L*,*H*) outcome is now observed much more frequently. This is our least strong robustness result.

The non-parametric tests are, however, consistent with what was reported in the paper. The best fit in parameterization 3 is given by the RS equilibrium (51%) followed by the "always collude" outcome (48%), the "always defect" outcome (35.61%), and the (*H*,*L*)/(*L*,*H*) outcome (16.11%). On the other hand, the best fit in parameterization 2b is given by the "always collude" outcome (65%), the RS equilibrium (64%), the (*H*,*L*)/(*L*,*H*) outcome (25.76%), and the "always defect" outcome (12.73%). Again, the evidence from parameterzation 2b is not as conclusive as that of parameterization 2.[iii]

Table D.5: Frequencies of Observed Outcomes

Demand State (outcomes)		**Parameterization 2b**	**Parameterization 3**
High (*h*)	(*L*,*L*)	**44.00%**	41.67%
	(*H*,*H*)	**24.00%**	**46.88%**
	(*H*,*L*)/(*L*,*H*)	**32.00%**	**11.46%**
Medium (*m*)	(*L*,*L*)	**64.76%**	**49.11%**
	(*H*,*H*)	**11.43%**	**36.01%**
	(*H*,*L*)/(*L*,*H*)	**23.81%**	**14.88%**
Low (*l*)	(*L*,*L*)	**64.29%**	**52.08%**
	(*H*,*H*)	**8.57%**	**22.92%**
	(*H*,*L*)/(*L*,*H*)	**27.14%**	**25.00%**

Notes: Bold numbers indicate that entry is a feasible equilibrium (see Appendix B, table B.1 for details)

D.3 Evidence for the GP theory

Table D.6 is consistent with the results obtained for parameterization 2 (reported in table 10 of the paper): large punishment lengths tend to explain cooperation and collusion

Table D.6: Frequencies of Cooperation and Collusion in Collusive (C) and Reversionary (R) Regimes in IM treatment, Various Punishment Lengths, Rounds 1-25, Parameterization 2b

Punishment Length (*N*)	**Cooperation**			**Collusion**		
	R	C	*p-value**	R	C	*p-value**
2	0.68	0.67	*0.73*	0.18	0.24	*0.11*
3	0.69	0.67	*0.60*	**0.21**	**0.23**	***0.46***
4	0.66	0.70	*0.25*	**0.19**	**0.26**	***0.01***
14	0.66	0.78	*0.02*	**0.19**	**0.44**	***<0.01***
15	0.66	0.78	*0.02*	**0.19**	**0.44**	***<0.01***
	0.65	0.94	*0.02*	**0.19**	**0.44**	***<0.01***

Note: Bold numbers indicate that the entry entails a feasible punishment length in the GP equilibrium. The results are qualitatively similar if all rounds (1-33) are considered. Consistent with theory, the public signal assumed to trigger a price war is p_2.
* Pearson's Chi-Square statistic; p-values of other non-parametric tests (Wilcoxon, Kolmogorov-Smirnov, and Epps-Singleton) and the parametric t-test produce similar p-values.

Table D.8: Fraction of Times the Equilibrium Path Correctly Predicts Outcomes (Predictive Power)

Equilibrium Path	**Parameterization 2**
(*H*,*H*) every period	**37.98%**
GP_3	**40.40%**
GP_4	**50.51%**
GP_5	**60.61%**
GP_{14}	**75.96%**
GP_{15}	**78.18%**
GP	**81.21%**

Notes: Bold numbers indicate a theoretically feasible equilibrium (see Appendix B, table B.1 for details). The GP_N path takes a value of 1 when collusion is predicted and 0 when a price war is predicted; a price war is assumed to be triggered by a low signal (price p_2) which lasts *N* periods.

Table D.7: Probit Estimates of Different Strategies in the IM treatment, Rounds 1-25, Parameterization 2b

	Random	GP_N			$T1_N$ $\{N\}$			$TT1_N$ $\{N\}$	$T2$		$TT2$	
		N=5[1]	N=13	N=∞	k p_1 [2] {5}	{ }	k p_0 [2] { }	$k(L)$ p_1 $k(H)$ p_0 [3] { }	k^{down} p_1 k^{up} p_3	k^{down} p_1 k^{up} p_4	$k^{down}(L)$ p_1, $k^{down}(H)$ p_0; $k^{up}(L)$ p_4 $k^{up}(H)$ p_2	$k^{down}(L)$ p_1, $k^{down}(H)$ p_0; $k^{up}(L)$ p_4 $k^{up}(H)$ p_3
	N/A	0.39*	0.50*	0.61*	0.63*	0.92*	0.48*	0.60*	0.90*	0.92*	0.55*	0.62*
LL	-437.66	-431.13	-431.1	-430.0	-420.4	-415.9	-430.98	-425.8	-416.0	-415.9	-426.90	-424.89
LR†	N/A	13.04	13.15	15.28	34.38	43.35	13.35	23.68	43.23	43.35	21.52	25.54
p-value		<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01

Notes: Estimates of , and are significant at the 1% level in all specifications (not shown). Number of observations: 1,200 in both parameterizations.