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Unintended Consequences of Enforcement in a Fisheries Institution: Results from an Artefactual Experiment in Tanzania

Spencer MacColl
University of San Francisco, sdmaccoll@gmail.com

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Spencer MacColl

Department of Economics
University of San Francisco
2130 Fulton St.
San Francisco, CA 94117

e-mail: sdmaccoll@usfca.edu

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Abstract: Overfishing and the destruction of fishing commons in developing countries is a growing problem. Policymakers and local community leaders are looking for solutions to keep their fishing commons sustainable. Fines and enforcement mechanisms are commonly suggested to help preserve the commons. This paper discusses a novel artefactual experiment conducted throughout several fishing communities in Tanzania to determine the effect of enforcing a ban on illegal fishing gear on fishing behavior. Results indicate that the fishers in the enforcement treatment group depleted the fish stock significantly faster than the unenforced control group. One possible explanation for this result is that the players in the enforcement group responded to cheating players by increasing their fishing efforts as a grim trigger response. Alternatively, the ban and subsequent enforcement mechanism crowded out fishers' intrinsic attitudes to sustain the resource for future rounds in the game. The fishers may have been more focused on not using illegal fishing gear than they were with sustaining the resource.

1. Introduction

Managing fisheries in developing countries is notoriously difficult. Limited regulations and enforcement exposes these fisheries to overfishing which can lead to their destruction. Recent studies have shown that approximately 85 percent of the world's fish stocks are fully exploited, over exploited, depleted, or in recovery from exploitation (Food and Agriculture Organization, 2010). Moreover, fish populations in the tropic regions are expected to decline an additional 40 percent by 2050 (Cheung, 2010). Eliminating destructive fishing practices has been a main focus of natural resource economists as they attempt to find policies that can effectively reduce overfishing behavior. This becomes more difficult in developing countries where even limited enforcement is often not feasible. One common policy prescription is to place bans on certain types of fishing gear (e.g. dynamite, small mesh nets, poison) while simultaneously adding a community enforcement mechanism. Through the combination of survey and experimental data from inland and marine fishing communities in Tanzania, this study examines the impact of enforcing a ban on illegal fishing gear on overfishing behavior and compliance rates.

Although current research indicates the dire need to reduce overfishing, fisheries are very important source of employment for many in the developing world. The Food and Agriculture Organization estimates that 10 to 12 percent of the world's population depends on fisheries for their livelihood, when including both primary and secondary sectors such as trading, marketing, and processing. Within Africa, 2.1 percent of the population is directly employed in the fisheries sector either as fishers or processors (FAO, 2014). Small-scale fishers catch nearly half of all of the world's fish production, with 95 percent of them living in developing countries (FAO, 2015). As the future brings increasing population pressures and uncertain impacts from climate change, more of the world's fisheries will need to find sustainable management solutions.

The early literature about overfishing believed that without a strong centralized institution protecting the commons a "tragedy of the commons" would occur (Hardin G. , 1968; Hardin R. , 1971). However, this simple model of human behavior has not been empirically validated. Many fishers followed local regulations even when there was a low risk of being caught. Researchers also discovered that in the absence of a strong centralized enforcement, some local communities could regulate themselves in a successful manner. Local self-governing institutions are able to manage the commons, but only under the correct conditions (McCay & Acheson, 1987; Baland & Platteau, 1996; Ostrom, 1990). Not all self-governing groups are successful, and researchers are still debating what conditions lead to sustainable commons management (Ostrom, 2000)[1].

Today's economists understand that individuals often do not make decisions based on of purely self-interested motives (Fehr & Schmidt, 2000; Sobel, 2001). Instead, a variety of social factors including social preferences (Fehr & Fischbacher, 2002), reciprocity (Falk & Fischbacher, 2006), inequity aversion (Fehr & Schmidt, 1999), fairness (Frey & Pommerehne, 1993; Seidl & Traub, 2001), and general social norms determine an individual's behavior.

Current literature in this field focuses on the effects of increased monitoring on compliance rates but rarely focus on alternative consequences to monitoring. This paper adds to the current body of literature by going beyond just measuring changes in compliance rates to also examining the effects on overfishing behavior. To measure this impact, a novel artefactual experiment was conducted to examine any changes in group fishing behavior among two different institutions. The first treatment arm consisted of fishers who could use illegal nets without penalty (the unenforced treatment arm), and the second treatment included fishers who could use illegal nets but there was a chance they would be caught and punished by the group (the enforcement

[1] For example does heterogeneity within groups increase contributions to public goods or does it cause less contributions? (Reuben & Riedl, 2013).

treatment arm). This controlled dynamic common pool resource game made it easier to isolate and identify the effects of these two institutions on fishing behavior.

The results show that the enforcement treatment did not significantly reduce the number of players using illegal fishing gear, however it did reduce the frequency in the number of times players used illegal fishing gear. In regards to overfishing behavior, the enforcement treatment group had significantly higher rates of overfishing, as they were 30 percent more likely to play a highly exploitive strategy, and were 14 percent more likely deplete the fish stock before the game had ended. This is a counterintuitive result as the fishers were more likely to over-exploit the fishing resource when the ban was enforced rather than unenforced.

The rest of the paper is structured as follows. Section 2 discusses the literature review of compliance theory, including several empirical studies. Section 3 includes the setup of the artefactual experiment and the regression estimation models. Section 4 presents the results of the experiment, along with possible explanations to the findings. The final section summarizes the experiment's implications and directions for future research.

2. Literature Review

Fisheries are a common-pool-resource with open access rights, making overexploitation of fish stocks a perennial problem for policy makers. Fisheries management is therefore necessary to ensure that the resource is exploited sustainably, often by restricting the fishing gear, setting minimum fish-size laws, area closures, and implementing quotas. However, all of these efforts do little to prevent overfishing without high rates of compliance thereby demonstrating that a fisheries management strategy without sufficient compliance is ineffective.

2.1 Compliance and Deterrence Theory

Why in a fishery setting would some fishers obey a law banning small fishing nets and others ignore it? The first model that tried to explain why individuals commit crimes was introduced by Gary Becker (1968), who stated that the major determinant for deciding whether to do a legal or illegal act is based on the expected payoff from the illegal act after taking into consideration the risk of being caught. Becker applied rational choice theory to state that criminals are the same as other individuals because they are driven by self-interest to maximize income. According to Becker, an individual will commit the crime if the expected utility is greater than the utility gained by doing the legal action. The deterrence strategy in this model is to increase the punishment and/or probability of being punished.

The basic deterrence model was first applied to fishing violation behavior when Sutinen and Andersen (1985) used the Becker framework to explain why fishers would catch more than the fishing quota. They theorized that fishers would only be deterred by enforced penalties. One of the first empirical studies testing this model on deterrence and fishing showed that an increased risk of detection and conviction did reduce the violation rate the lobster fishery they studied (Sutinen & Gauvin, 1989).

2.2 Compliance Theory Conflicts with Empirical Evidence

The models presented thus far are limited in two important ways. The first weakness is that the models limit policy options to either increasing fines, increasing the number of enforcement officials, or both. This is not a practical option because it would require substantial, frequently unavailable resources to be spent on enforcement officers in order to achieve the appropriate compliance rates. If increasing the number of enforcement officials was not an option, fines would have to be increased excessively to deter violators. However, the fine needed to get the optimum level of deterrence is not politically possible, because the fine would not match the offense in a court of law.

The second limitation is that the model fails to explain why the vast majority of people act within the law even when there are low levels of detection and/or low fines (Robinson & Darley, 1997). The general odds of being detected for violating a fishing regulation are below 1 percent (Sutinen & Gauvin, 1989; Furlong, 1991), and the penalties for being caught are not sufficiently high compared to the gains made from the illegal catches. For example, it has been estimated that in the groundfish fishery in the Northeastern United States, violators grossed about $15,000 per trip from violating the mesh size regulations and fishing in closed areas (Sutinen, Rieser, & Gauvin, 1990). This resulted in illegal earnings of $225,000 during 1987. This is in contrast with typical penalties ranging from $3,000 to $15,000 for these types of violations. Thus, the basic deterrence model predicts that most fishers would not be deterred to conduct illegal fishing operations. However, it has been shown that 50 to 90 percent of fishers comply with the regulations (Sutinen & Gauvin, 1989; Sutinen, Rieser, & Gauvin, 1990).

2.3 Normative Compliance Theory

Due to these shortfalls, the deterrence literature has evolved into what is known as the Normative Compliance Theory. In this theory, (Robinson & Darley, 1997) argue that people want to do the right thing for moral reasons. People obey the law because they think it is legitimate, not because they are afraid of the punishment (Tyler, 1990). Normative theory also states that people act in accordance to their own moral compass such as abstaining from the consumption of animal products (Eisenhauer, 2004).

In addition to moral reasons, community norms can act as a deterrent for harming a social good because the community will apply social sanctions against violators (Tyran & Feld, 2006). An example of a community norm is littering in a society where this is looked down upon. The chance of getting a fine for littering is relatively small, yet most people in that community will not litter due to the social norm against littering (Korobkin & Ulen, 2000). Controlled field studies have shown that people tend to litter significantly less in a clean environment than in a littered environment, showing the effects of deterrence through social norms (Cialdini, 1990).

Another critical component of Normative Compliance Theory is having important parties involved in the rulemaking process. Bardhan (2000) conducted a study that found that when individuals and communities helped create the laws instead of having a government top-down approach to the law, compliance for the law was higher. In this study, researchers interviewed farmers in India and found that they had a more positive attitude about the water resource allocation rules when they were involved in crafting the laws, and they subsequently maintained the water irrigation systems at a more responsible level. In line with this finding, within the fishing literature, it has been found that laws perceived as violating a citizen's moral rights tend to provoke noncompliance (Hauck, 2009a; Hauck, 2009b; Jentoft, 2000). Similarly, laws perceived as promoting citizen's shared values have triggered compliance (Acheson & Gardner, 2004; Gezelius, 2004; Jentoft & Kristoffersen, 1989; Scholz & Lubell, 1998).

2.4 Crowding Out Theory

A subset of this literature has more recently focused on the "crowding out" hypothesis, which is based on Titmuss' (1971) argument that blood donors are typically motivated by moral concerns rather than money, and if monetary compensation is introduced it could decrease the supply of blood donations. As Rode, Gomez-Baggethun, and Krause (2013) write,

> Motivational crowding theory is based on the psychological notions of intrinsic vs. extrinsic motivation. Intrinsic motivation refers to doing an activity for its inherent satisfaction…Counter to a common assumption in economics, motivation crowding suggests that the effects of extrinsic motivators such as

monetary incentives do not necessarily complement intrinsic motivations. Instead they may undermine ("crowd out") …intrinsic motivation.(p.2)

As policy makers design institutions to improve management of the fishing commons they must ensure that the institutions change behavior for a Pareto-superior outcome. As the results indicate in Section 3, one theory to explain the results is that the enforcement game crowded out cooperative strategies by focusing group strategies on avoiding using illegal gear. By focusing the game on penalizing those who use illegal gear, it distracted players from sustaining the game's fishing resource.

3. The Experiment

3.1 Experimental Design

This study is based on the results of a dynamic common pool resource game. The game is conducted at beach management units (BMUs) within two fishing regions of Tanzania. BMUs are village-level organizations that elect community leaders to oversee the fishing activities of the village. The first research site is on Ukerewe Island, located in Lake Victoria, and the second site is Mafia Island, located in the Indian Ocean. Each treatment arm of the experiment was played with five different players at each of the BMUs.

Once each group is organized the participants are presented with a bin of beans in the middle of the group, and each participant is given a spoon and a personal bucket[2]. The bin in the middle of the group represents the common pool water resource, such as Lake Victoria, and the beans in the bin represent fish in the resource. Instructions are read by trained game moderators and two practice rounds are conducted so the players can understand how the game works. The game starts with 2,000 grams (4.4 lbs) of beans in the bin. The game is played three times, with each

[2] See Appendix D for image of experiment

cycle randomly lasting between seven and ten rounds. Each round lasts for 30 seconds where participants can scoop the beans out of the bin and into their own personal buckets. Each of the participants personal buckets are weighed to record the amount of beans they harvested each round. The amount of beans left in the bin is then calculated and a logistic growth function[3] is applied to add new beans to the bin. This simulates the natural reproduction cycle that occurs each year in the fisheries and causes endogenous, dynamic changes in payoffs as the game progressives.

The participants are allowed to communicate freely throughout the game and due to playing the game all at the same time, some general observation of how much the other players are harvesting occurs. Every player's individual harvest is kept secret by the game moderators. The participants are told that the game will end randomly between 5 and 15 rounds. In reality the game randomly ends sometime between 7 and 10 rounds to save time during the experiment, as each round can take several minutes. The game does not have a definite end-round to prevent end-game effects. The game can also prematurely if the stock of the beans drops to zero.

The payout function is 2,000 Tanzanian Shillings ($1.17 USD) per 1,000 grams harvested in the games. Average player payouts for the three cycles were about $2.00 USD. The players are not told any goal for the game. Participants sometimes asked if they were trying to preserve the resource or make as much money as possible but the moderator said there was no explicit goal. The moderators were trained to not prime the players in any way such as complimenting the players when they preserve the harvest or showing dissatisfaction when the players over harvest.

[3] The logistic growth function is: $X(t+1) - X(t) = rX(t)[1 - (1/K)X(t)] - H(t)$
Where $X(t)$ is the weight of beans at the beginning of round t and $H(t)$ is the total group harvest (and spillage) in round t - $K=10{,}000$g and $r = 0.25$

3.2 Treatment Arms

As mentioned in Section 1, there are two treatment arms in this experiment. The first is the unenforced treatment arm which allows players to privately decide before the start of each round if they are going to use illegal nets to harvest the beans. If a player decides to use illegal nets, the amount they harvest in that round it is doubled in their payout. The consequence to using the illegal nets is that the fish stock also decreases faster as the harvest is doubled. The participants have cards that signal legal or illegal nets on them. As the game moderator walks behind them, the players reveal their card decision to them privately. At the end of each round the group will know that someone used illegal nets – but will not know the violator's identities.

The second treatment arm is the enforcement game. This game is the same as the unenforced game however there is a 50 percent chance at the end of each round that one of the players will be randomly caught by a "patrol". The game moderator will then announce if that player used illegal gear during that particular round. If the player is revealed to have used illegal gear in that round, the group will vote on three possible options: to forgive the player and waive any penalty, fine the player 1,000 grams off of their harvest, or to make them sit out from playing the next round.

3.3 Contribution

This experiment is inspired in part by the novel artefactual experiment by Knapp and Murphy (2010), which also used beans and a common bin on a table where participants had to scoop the "fish" out of the bowl with kitchen measuring cups to measure spillage effects. This study adds to the literature by using an artefactual experiment to measure overfishing behavior. Additionally, this common pool resource game is played in a developing country context with participants that deal with fisheries issues daily, making them an ideal sample group for testing the effects of institutions on fishing behavior. Rather than playing the game in a static environment where each round of the game is independent of the past round, this experiment is dynamic and is much closer to the real fishing environment. If a group overharvests in the first round of the game it has severe consequences for the remainder of the game. Similar to overfishing in the real world, it takes years for the fish stocks to return to pre-existing levels. Lastly, this experiment is not conducted completely anonymously because in the fisheries, fishers get a sense about the kind of nets the other fishers are using and how much fish they are catching. To make the game completely anonymous is not in line with the real world.

3.4 Estimation Method

The participants were randomly assigned to each treatment arm so it is assumed that there is no selection bias between groups. Section 4.1 confirms there are no statistically significant differences between the two treatment groups when comparing observable characteristics. Ordinary least squares regression is used to measure the impacts of the enforcement game, however, when binary dependent variables are being measured, marginal effects logit estimation is used.

To measure the effects of the enforcement game on illegal gear use (hereafter referred to as cheating) the model looks to see if the number of players that cheated at least once during the experiment is different between the two treatments. The model also looks to see if the number of times players cheated per game increased in order to measure a change in cheating frequency. Three dependent variables will measure the impact of the enforcement game on fishing behavior: harvest rate, relative harvest rate, and the stock remaining. The harvest rate is the average weight of beans harvested per player in each group. The higher the harvest rate is, the more intense the group is harvesting the stock. The relative harvest rate is the percent above or below the constant-stock harvest rate. The constant-stock rate is the rate that the group can harvest and the total stock will be unaffected after the growth is added. For example, the game starts with 2,000 grams of beans and if the group harvests collectively 508 grams, the growth will also be 508 grams, making the next round's stock 2,000 grams again. Therefore the five players can harvest just over 100 grams each in the round in order for the relative harvest rate to be zero. If the players harvest more/less than 100 grams each, the relative harvest rate will be greater/less than zero. This relative harvest measure is used to compare harvest rates when the stock levels are at different levels across groups.

The stock remaining variable is the total grams left in the bin at the end of each round. If a group harvested 800 grams the first round, the stock remaining is 1,200 grams (2,000 grams to start – 800 grams = 1,200 grams). If a group has an aggressive harvest rate the stock remaining will be lower than those groups that limit their harvest rates.

3.5 Model

To estimate the effects of the enforcement game on fishing behavior there are a set of models that each display the impact in a different way. Due to randomization of the players across treatment groups not many controls are needed in the models except to control for village level characteristics and exogenous group characteristics like age.

Effect of enforcement on number of illegal players:

$$logit: Illegal_i = \alpha + \beta_1 Enf_i + \epsilon_i$$

Illegal is a dummy variable indicating if player *i* cheated at least once during the game. *Enf* is a dummy variable to indicate that player *i* was in the enforcement treatment arm of the experiment. Logit estimation is conducted because the dependent variable is binary and marginal effects are reported.

Effect of enforcement on number of times a player uses illegal gear per game:

$$Illegal\,Total_i = \alpha + \beta_1 Enf_i + \epsilon_i$$

Illegal Total is the number of times a player cheated during each cycle of the game. This specification is run with BMU level controls.

Effect of enforcement on number of rounds a group has a cheating player:

$$logit: Illegal_{jt} = \alpha + \beta_1 Enf_{jt} + \gamma_2 Controls_{jt}(cycle, ppr, stock, round) + \epsilon_{jt}$$

This specification is at the group level *j* and counts each round as an observation *t* – analyzing 303 rounds. If the group has at least one player that cheats the variable *Illegal* is a 1 and a 0 otherwise. This measures the probability that the enforcement group will have at least one cheater at any given round when compared to the unenforced treatment group. The controls are the cycle of the game (*cycle)*, the number of players in the group (*ppr*), the stock remaining at the end of the round (*stock*), and the round that is being played (*round*).

Effects of enforcement on stock levels:

$$S4_j = \alpha + \beta_1 Enf_j + \gamma_2 Controls_j + \epsilon_j$$

$$StockRem_{jt} = \alpha + \beta_1 Enf_{jt} + \gamma_2 Controls_{jt}(cycle, ppr, round) + \epsilon_{jt}$$

Where *S4* is a group level variable representing the stock remaining after the 4th round in the game, *Enf* is a dummy variable to indicate that the player was in the enforcement treatment arm of the experiment. The controls are run in both standard deviations and group averages because the regression is looking to see both how the variation and mean level of group characteristics effects group decisions. For example, does greater variation in the education of the group result in more cooperative or exploitive strategies? The controls are the within group variation and the within group average of: age, education, married, captain, BMU satisfaction, BMU illegal fishing prevalence, weekly income (USD), and opinion of fish stocks.

StockRem is a group level variable measuring the average stock level that a group has at any given round, *t*. This estimation treats every round as an observation and the controls are: the cycle of the game, the number of players in the group (ppr), the stock remaining at the end of the round, and the round that is being played.

Effects of enforcement on harvest rates:

$$Harvest_{jt} = \alpha + \beta_1 Enf_{jt} + \gamma_2 Controls_{jt}(cycle, ppr, stock\ rem) + \epsilon_{jt}$$

$$RelativeHarvest_{jt} = \alpha + \beta_1 Enf_{jt} + \gamma_2 Controls_{jt}(cycle, ppr, stock\ rem) + \epsilon_{jt}$$

Harvest is a group level variable representing the average harvest rate (in grams) per player throughout the game. *RelativeHarvest* is a group level variable measuring the percent difference from a constant-stock rate as was explained in Section 3.4. The controls are as in the 3.54 specifications.

Effects of enforcement on group strategies:

$$logit: Exploit\_Exploit_j = \alpha + \beta_1 Enf_j + Controls\ (standard\ deviations) + \epsilon_i$$

$$logit: Save\_Save_j = \alpha + \beta_1 Enf_j + Controls\ (standard\ deviations) + \epsilon_i$$

There are nine strategies that each group could potentially play:

1) Exploit - exploit
2) Exploit - steady
3) Exploit - save
4) Moderate - exploit
5) Moderate - steady
6) Moderate - save
7) Save - exploit
8) Save - moderate
9) Save - save

Each strategy is determined by the amount of stock remaining at the end of round 4 and at the end of round 7. This strategy assumes that the group has three harvest options when the game begins – harvest a lot, moderate, or a little. After the 4^{th} round (mid-point of the game), the groups again decide their harvest strategy for the remainder of the game – harvest a lot, moderate, or a little. The 4^{th} round acts like an inflection point in group strategy. Therefore there are nine possible strategies. See Appendix A for a complete explanation of these strategies. A logit estimation is used here to look at the probability that a group will play an "exploit-exploit" strategy, or a "save-save" strategy.

4. Results

4.1 Summary Statistics

The first table (Table A) shows the descriptive statistics between the unenforced and enforcement games. None of the variables are statistically significantly different between the two groups.

TABLE A:

Individual Variables	Unenforced	Enforcement	T-value	N(U)	N(Enf.)
Total Participants	-	-	-	48	48
Age (yrs)	39.47	41.77	0.81	45	43
Education (yrs)	7.22	7.65	0.78	45	43
Married (1,0)	0.91	0.88	0.38	44	43
Captain (1,0)	0.32	0.33	0.07	44	43
BMU Satisfaction	2.7	2.56	1.11	44	41
BMU Illegal Fishing	2.18	2.51	1.39	44	43
Weekly Income (USD)	44.91	36.47	0.49	44	41
Catch Same Fish?	0.22	0.32	1.1	46	47

Group Variables (mean)	Unenforced	Enforcement	T-value	N(U)	N(Enf.)
Total Groups	-	-	-	10	10
Age (yrs)	39.89	40.91	0.24	10	10
Education (yrs)	7.255	8	1.11	10	10
Married (1,0)	0.91	0.9	0.2	10	10
Captain (1,0)	0.295	0.38	0.68	10	10
BMU Satisfaction	2.675	2.58	0.53	10	10
BMU Illegal Fishing	2.205	2.48	0.79	10	10
Weekly Income (USD)	44.25	32.4	0.69	9	10
Catch Same Fish?	0.21	0.32	1.43	10	10

Group Variables (sd)	Unenforced	Enforcement	T-value	N(U)	N(Enf.)
Total Groups	-	-	-	10	10
Age (yrs)	9.7	12.06	0.96	10	9
Education (yrs)	2.04	2.06	0.03	10	9
Married (1,0)	0.19	0.17	0.2	10	9
Captain (1,0)	0.36	0.46	0.9	9	9
BMU Satisfaction	0.49	0.37	0.59	10	9
BMU Illegal Fishing	0.87	0.83	0.25	9	9
Weekly Income (USD)	65.43	29.09	1.16	8	9
Catch Same Fish?	0.35	0.47	1.29	10	10

Married is a dummy variable, 1 if married or widowed, 0 if never married. Captain is a dummy variable if the participant is a captain of their fishing vessel. BMU Satisfaction is a variable 1, 2, or 3, where 3 indicates the participant is satisfied with the job the BMU is doing, 2 is neither satisfied nor unsatisfied, and 1 is unsatisfied. BMU Illegal Fishing is a scale 1 – 5, where a participant responds 1 if they think no one in their community uses illegal gear when fishing and 5 when they believe everyone in their community uses illegal gear. Responding 2, 3 or 4 are, "a small amount", "about half", and "most", respectively. Weekly Income is self-reported weekly income in US dollars, and "Catch Same Fish" is a binary response to the question, "Compared to five years ago, do you catch the same amount of fish today?"

4.2 Estimation Results

The results show that the enforcement treatment did not reduce the number of players that cheated during the game, but it did reduce the frequency of cheating. The enforcement arm is also associated with significantly higher harvest rates and higher probabilities of depleting the common resource when compared to the unenforced treatment group (control).

4.21 Enforcement Game Effect on Number of Illegal Gear Players:

Chart A below shows the effect of the enforcement game on the number of players that use illegal gear. The bar chart shows the percentage of players that used the illegal gear for the first, second and third cycles of the game. In the first cycle of the game, 22.9 percent of the players cheated in the illegal game (no penalty for using illegal gear), and 20.8 percent of players in the enforcement game cheated at least once. In the second cycle of the game, cheating dropped in half for both groups with 10.4 percent of the players cheating at least once in the unenforced treatment arm, and 8.3 percent of the players cheated in the enforcement game. In the third (and last) cycle of the game more players in the enforcement game cheated than those in the control group – 12.5 percent to 8.3 percent respectively.

Even though the two treatment arms had similar numbers of cheating players, the frequency of cheating was higher for the unenforced group as the dotted lines show. Players who cheated in the unenforced group used illegal gear 3.4 times per cycle. Players who cheated in the enforcement group used illegal gear only 1.2 times per cycle:

CHART A:

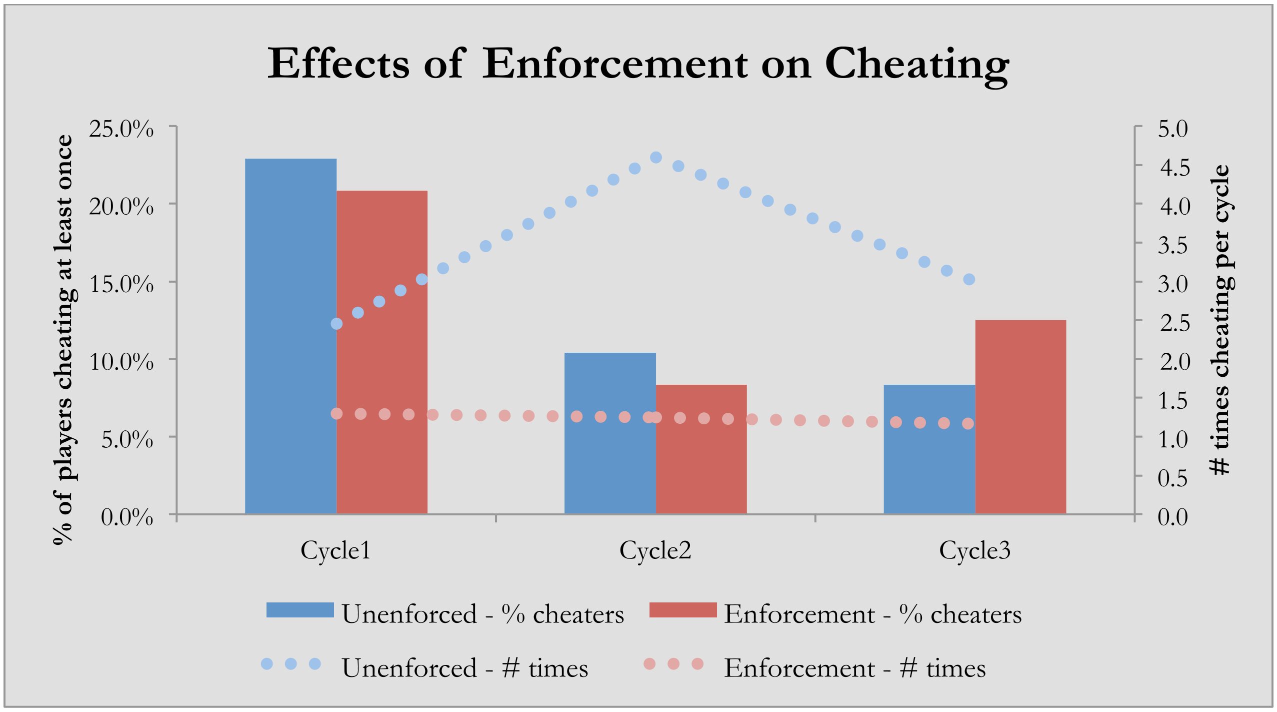


Table B shows the three estimation models from Section 3.51. The number of cheaters per treatment arm is about the same and the first specification is insignificant. Specification two is just outside the ten percent significance level and it shows that of the players that cheated, being in the enforcement group decreased the frequency of cheating per game cycle by 4.1 times. The third specification shows that being in the enforcement group decreases the chances that there will be a cheater in any given round of the game by 10 percent and is significant at the five percent level.

TABLE B:

Effects of Enforcement on Cheating

VARIABLES	(1) Cheating Once per Game	(2) Num. Times Cheating	(3) Cheating Once per Round
Enforcement	-0.041	-4.11**	-0.102**
	(0.090)	(1.92)	(0.041)
Cycle			-0.069***
			(0.025)
People Per Group			0.064
			(0.056)
Stock Remaining			-0.000
			(0.00)
Round			-.036***
			(0.011)
Constant		4.82**	
		(1.18)	
Observations	96	26	303
R-squared		0.407	

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
(1) uses a marginal effects logit estimation. (2) is a OLS estimation with robust standard errors and BMU constant effects. (3) is a marginal effects logit estimation at the group level and treats every round as an observation looking at the probability of having at least one cheating player in the group during that round.

3.22 Effects of Enforcement on Stock Levels:

It can be clearer to see the difference in harvest strategies for these two treatment arms graphically. The first graph (Chart B) shows the harvest paths of the ten enforcement groups with the optimum harvest path for payout maximization overlaid on top. The second graph (Chart C) shows the same thing for the ten unenforced groups. Notice that none of the groups matched the shape of the payout-maximizing path and that the unenforced groups have more BMUs ending with at least 1000 grams remaining after round seven:

CHART B:

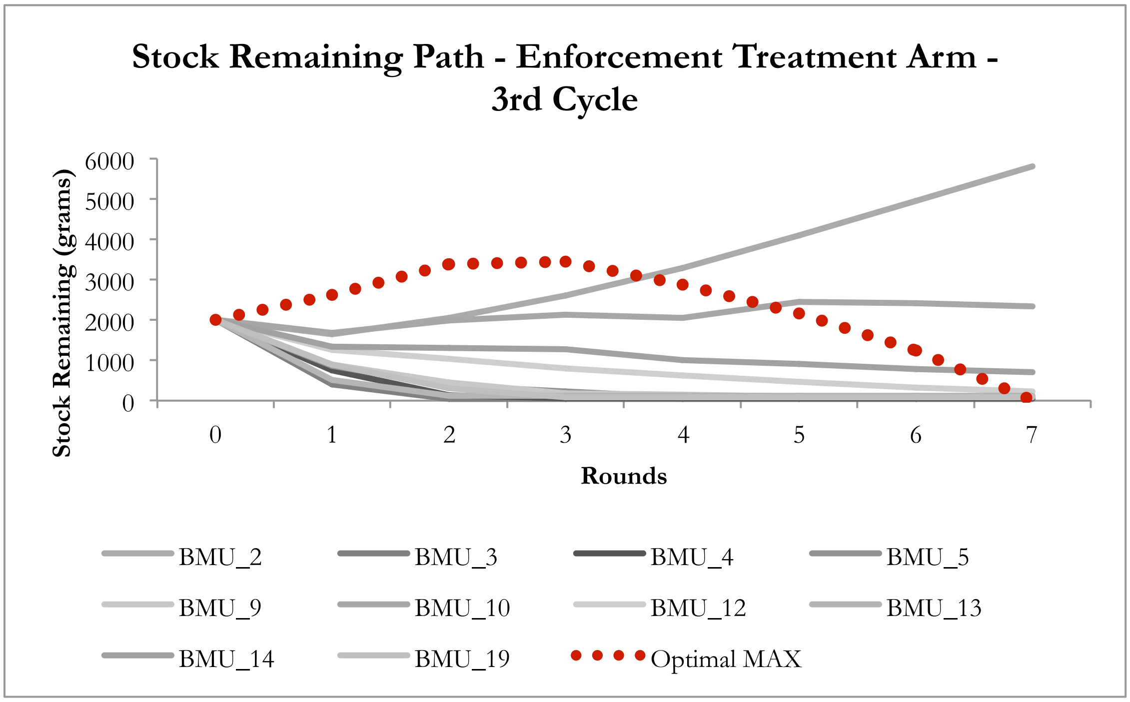
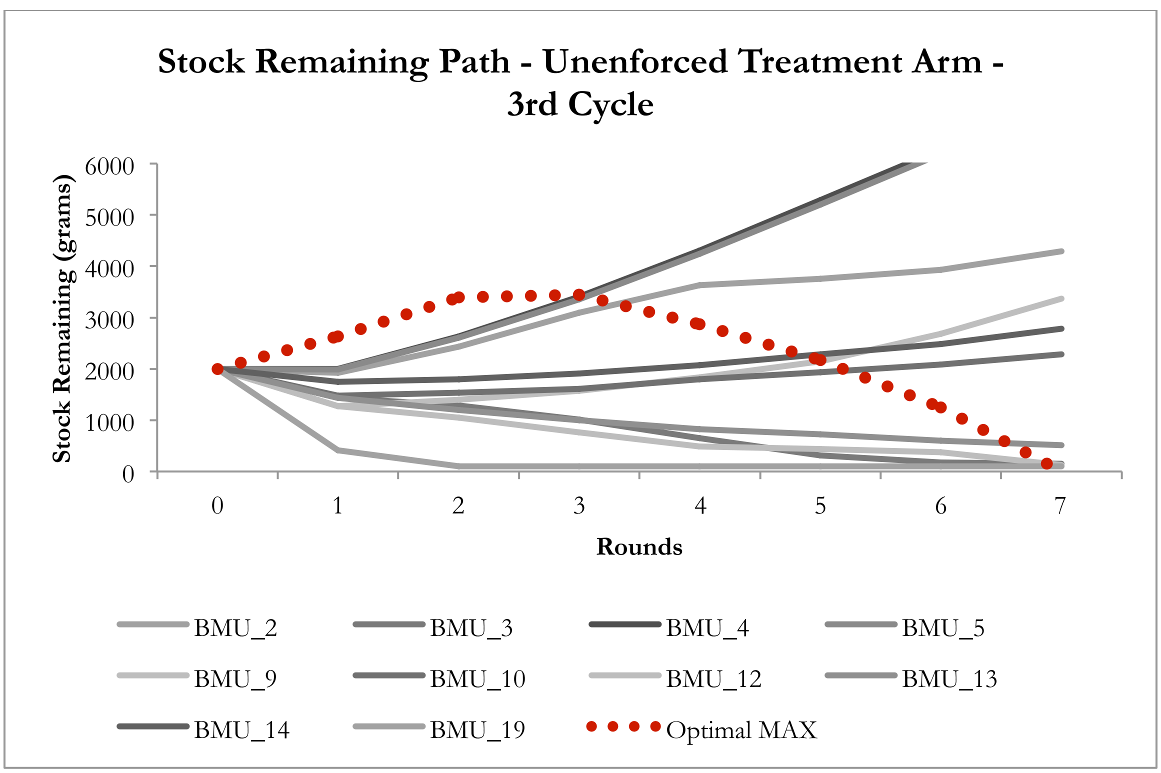
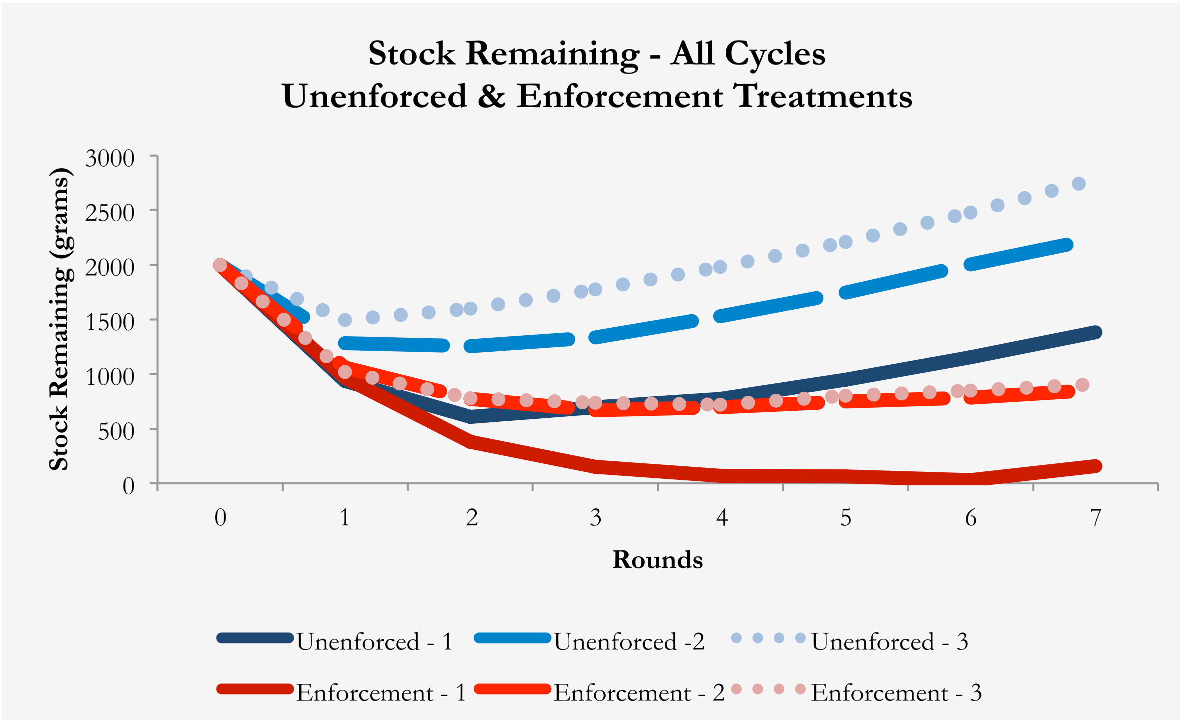


CHART C:



The graph (Chart D) below shows the average harvest path for both treatment arms, covering all three cycles. The gap between these two groups is widest in the third cycle:

CHART D:



To measure these changes using regression analysis the dependent variable is the stock remaining. Stock level is measured here because the lower a stock level is at any given round, the more intensely the group has harvested the beans. The enforcement game had a significant impact on groups' average stock levels. The first specification of Table C shows that after the 4th round of the cycle 3[4], the groups in the enforcement treatment arm had 1,263 less grams remaining in their bin that those in the unenforced treatment arm. This is a large result considering the game begins with 2,000 grams of beans. This result is significant at the five percent level. This goes against the assumptions that introducing an enforcement mechanism

[4] The results look at third cycle of the game because this is considered the "true" strategy of the groups. The first cycle could be a learning game where the parameters of the game are still being understood. Groups shift strategies in the second cycle and finally the third cycle is considered the best result to analyze.

would help to preserve the resource as less fishers would use illegal gear. However, the opposite has occurred here.

In specifications two and three, controls are added. When controlling for average group characteristics such as group age and education level, the significance falls out, however when controlling for group variation, the effect on the stock remaining is significant again, and at the ten percent level. These regressions are run with robust standard errors, controlled at the BMU level, and weighted by group size. The last regression aggregates the stock remaining at each round throughout all three cycles to determine the overall effect that the enforcement game had on average stock levels. The results show that on average, the groups in the enforcement treatment arm had 865 fewer grams of beans in the bin than the unenforced groups for any given round. This is significant at the one percent level. The variable Cycle is positive and significant indicating a learning effect because for each cycle that the game was played, groups had more stock in their bins at any given round in the game:

TABLE C:

Effects of Enforcement on Stock Remaining

VARIABLES	(1) Stock Rem. 4th Rd	(2) Stock Rem. 4th Rd	(3) Stock Rem. 4th Rd	(4) Stock Rem. Avg. Rd
Enforcement	-1,263.252**	-1,316.559	-1,503.104*	-865.344***
	(541.107)	(1,247.039)	(170.301)	(120.258)
Age (mean)		44.750		
		(120.429)		
Education Yrs (mean)		1,119.921		
		(1,222.716)		
Married (mean)		-2,074.101		
		(3,484.123)		
Captain (mean)		1,074.994		
		(4,575.314)		
Catch Same Fish (mean)		-3,907.190		
		(5,266.775)		
Weekly Income (USD) (mean)		11.416		
		(35.245)		
Age (std dev)			431.658**	
			(21.549)	
Education Yrs (std dev)			-1,034.049*	
			(157.329)	
Married (std dev)			808.906	
			(538.071)	
Captain (std dev)			-153.160	
			(737.339)	
Catch Same Fish (std dev)			-6,591.462*	
			(649.166)	
Weekly Income (USD) (std dev)			7.659*	
			(0.843)	
Players Per Group				-221.295
				(268.904)
Cycle				307.402***
				(73.642)
Round				14.357
				(30.064)
Constant	2,034.352***	-6,240.804	2,225.131*	1,997.786
	(382.319)	(8,175.851)	(204.260)	(1,307.438)
Observations	20	19	17	420
R-squared	0.693	0.816	0.999	0.344

Robust standard errors in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$
All regression are with BMU level controls. (4) uses each round as an observation and measures the average stock remaining after per game controlling for the cycle, round and players per group

A surprising result from Table C was that standard deviation of group age and group income is positive. Past literature has suggested that greater heterogeneity within groups results in less cooperative behavior. However these results suggest that greater heterogeneity in age and income results in *more* cooperative behavior. Groups that exploit the resource faster play more individual, self-interested strategies, and therefore having *more* stock left in the bin can be interpreted as greater cooperative behavior.

3.23 Effects of Enforcement on Harvest Rates:

This regression looks to see if groups that are in the enforcement game have higher or lower harvest rates per average group player. Similar to the results from Table C, the enforcement treatment groups had more aggressive harvest rates. For any given round, players in the enforcement treatment groups will harvest 27 grams more than those players in the unenforced groups. This is a large result because the average harvest rate is almost 100 grams meaning the enforcement treatment arm increased harvest rates close to 30 percent.

An alternative measurement to the average harvest rate is the average relative harvest rate. The null hypothesis is that the harvest rate will not increase as fewer players use illegal gear and the group will work more cooperatively to save the resource for later extraction. However, when looking at the average relative harvest rate between the two treatment groups, those in the enforcement groups harvest 71 percent over the sustainable rate compared to 2 percent over the sustainable rate for unenforced groups. The results below (Table D) show that the enforcement game increases the average relative harvest rate by 64 percentage points and is significant at the one percent level. The *Cycle* variable is significant and negative indicating that a learning effect also occurs as groups reduce their relative harvest rate each new game cycle.

Table E looks at the difference in the average harvest and relative harvest rates between the enforcement treatment and the unenforced treatment arm:

TABLE D:

Effects of Enforcement on Harvest Rates

VARIABLES	(1) Harvest Rate Avg. Round	(2) Relative Harvest Rate Avg. Round
Enforcement	27.356***	0.646***
	(7.107)	(0.082)
Players Per Round	-34.279**	0.052
	(16.940)	(0.196)
Round	-18.188***	-0.112***
	(1.823)	(0.021)
Cycle	-1.605	-0.188***
	(4.278)	(0.049)
Constant	312.940***	0.577
	(81.466)	(0.940)
Observations	303	303
R-squared	0.453	0.526

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Both regressions have BMU level controls and robust standard errors. (1) has the dependent variable of the average harvest rate per player and (2) has the dependent variable of the relative harvest rate per player

3.24 Enforcement on Individual Harvest Variance

It seems clear that the enforcement game causes players to harvest more aggressively. Is the increase in harvest rates due to all the players in the group harvesting more, or is it from one outlier? The following heat graph examines each individual's harvest for each group in the enforcement treatment. It only looks at the harvest for the first round of the third cycle. Most of players choose close to the same strategy. "Over exploit" is the most aggressive harvest rate and "over save" is the most conservative harvest rate.[5] The number in each box represents the number of players in the group that played that strategy:

CHART E:

Enforcement Game – 1st Round Harvest Strategy Per Player

BMU	over exploit	exploit	steady	save	over save
2	1	0	0	3	1
3	4	1	0	0	0
4	5	0	0	0	0
5	4	0	1	0	0
9	4	0	0	0	0
10	0	1	1	1	2
12	2	0	3	0	0
13	5	0	0	0	0
14	1	1	2	1	0
19	4	0	0	0	0

There are four groups in the enforcement game that had all of their players play the "over exploit" strategy and none groups had all of their players play the "over save" strategy. The unenforced groups have the opposite results: Three out of the ten groups had all of their players play the "over save" strategy and no groups had all of their players play the "over exploit" strategy. When compared to the illegal game strategies by the players in each group, the enforcement game has many more players over exploiting the resource. It was not the case that a few outliers were responsible for the differences in the harvest rates – rather the groups acted as a unitary group.

[5] The five strategies (over exploit, exploit, steady, save, over save) are explained in Appendix B

CHART F:

Unenforced Game – 1st Round Harvest Strategy Per Player

BMU	over exploit	exploit	steady	save	over save
2	0	0	0	0	5
3	0	1	4	0	0
4	0	0	0	0	5
5	0	0	0	0	5
9	2	1	0	1	0
10	0	0	4	1	0
12	1	2	1	0	0
13	1	2	1	0	1
14	0	0	1	3	1
19	5	0	0	0	0

3.25 Effects of Enforcement on Group Strategies:

In order to analyze the harvest decisions of each treatment group on a continuous level each group's harvest path are categorized into one of nine strategies (as explained in Section 3.56). Rather than looking at the stock remaining at just the 4th round, this harvest path looks at the entire harvest path by analyzing the percent change in the stock remaining at the 4th and 7th rounds. The results show that the enforcement treatment arm played the most exploitative strategy 65 percent of the time compared to 35 percent for the unenforced treatment arm. Below are the strategies that each of the treatment arms played during their second and third cycles:

CHART G:

Strategy	Unenforced	Enforcement
exploit-exploit	35%	65%
exploit-steady	0%	10%
exploit-save	10%	0%
moderate-exploit	5%	0%
moderate-steady	10%	5%
moderate-save	5%	0%
save-exploit	0%	0%
save-steady	5%	10%
save-save	30%	10%

The marginal effects logit estimation below (Table G) shows that enforcement treatment groups are 30 percent more likely than the unenforced groups to play an "exploit-exploit" strategy[6] in their second and third cycles; this is significant at the five percent level. This shows that after looking at the harvest path of each treatment group, the enforcement again are playing more aggressive harvesting strategies.

TABLE E:

Effects of Enforcement on Exploit-Exploit Harvest Strategy

VARIABLES	(1) Cycle 2	(2) Cycle 3	(3) Cycle 2 & 3
Enforcement	0.4*	0.2	0.3**
	(0.21)	(0.22)	(0.15)
Observations	20	20	40
R-squared	0.11	0.02	0.06

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All regressions run with logit estimation marginal effects and robust standard errors.

It is important to note the exploit-exploit strategy is not the optimal strategy to maximize payouts. The optimum group payout at the 7th round is 5,752 grams or 1,150 grams per player (with 5 players to a group). The closest any group got to this was 63% of the optimum total. Chart H below shows the strategies that the groups played along with the percentage of the optimum total:

[6] In-depth descriptions of the group strategies are listed in Appendix A

CHART H:

Strategy	Avg. Percent of Optimal
exploit-exploit	48%
exploit-steady	44%
moderate-steady	59%
moderate-save	37%
save-steady	56%
save-save	18%

3.3 Discussion

After playing a unique common pool resource game with 96 players the results show that the groups in the enforcement treatment harvest the resource more aggressively than the unenforced control group. This is an unintended consequence of the enforcement. Additionally, the enforcement treatment did not lower the number of cheating players but it did reduce the frequency of cheating. The most interesting result is that the enforcement game causes players to exploit the resource at a faster rate. This section explores explanations for these results.

3.31 Theory 1 - Enforcement Increased Frustration - Grim Trigger Response

It may have been that when it is shown that a player cheated, the players in the enforcement treatment responded differently than those in the control group. In the enforcement group cheating is designed as an action that is punishable and monitored. This could potentially raise the stigma associated with someone cheating. If it was announced someone had cheated in a group, the group will respond by harvesting more beans as a revenge tactic (known in game theory as the grim trigger response). In the unenforced game the revenge, grim trigger response is not seen.

Table F shows the effect of having a player in the group cheat on the next round's relative harvest rate. The first column shows the effect for those in the unenforced treatment and the second column shows the effect for those in the enforcement treatment. The direction of the effect is opposite; the unenforced groups see a decrease in their relative harvest rate and the enforcement groups see an increase in their relative harvest rates. Those in the enforcement group increased their relative harvest rates by 21 percentage points and this is significant at the five percent level. This implies that the enforcement groups increased their harvest intensity after it was revealed that someone had cheated:

TABLE F:

Effect of Cheating in the Previous Round on Relative Harvest Rates

VARIABLES	(1) Unenforced	(2) Enforced
Cheat Previous Round	-0.152	0.212**
	(0.171)	(0.089)
Round	-0.080***	-0.051*
	(0.020)	(0.029)
Cycle	-0.264***	-0.148**
	(0.052)	(0.064)
Constant	0.908***	1.162***
	(0.165)	(0.207)
Observations	172	131
R-squared	0.716	0.666

Robust standard errors in parentheses, and all regressions run with BMU-level controls
*** p<0.01, ** p<0.05, * p<0.1

3.32 Theory 2 – Moderator Effects

One concern in reaching this surprising result was that there was a game moderator effect. Perhaps the game moderators had a way of explaining the game instructions so that they inadvertently primed the participants to either save or exploit the resource. This study did not use rotating game moderators, so the same moderator was used for each treatment arm throughout the entire experiment. In addition to the experiment for this study, a different concurrent experiment was conducted with the same game moderators but they were all to play the same game. The moderators were given the exact same instructions so if there is any significant difference between the groups harvest rates it may be because of a moderator priming effect. After controlling for group age, education, and weekly income, there should be no statistically significant difference in the group harvest rates and/or individual harvest rates between the groups. Below (Table G) are the regression results from the four groups where all groups played the same game. The unenforced moderator is left out of the regression as the baseline:

TABLE G:

Effects of Moderators on Harvesting Behavior

VARIABLES	(1) Harvest 1st Rd	(2) Rel. Harvest 1st Rd	(3) Stock Remaining 4th Rd.	(4) Stock Remaining 7th Rd.
Enforcement Moderator	10.770	-0.026	-623.574	-1,286.539
	(60.622)	(0.561)	(550.241)	(1,019.518)
Moderator 1	-11.860	-0.138	95.292	146.756
	(54.550)	(0.550)	(596.898)	(1,094.169)
Moderator 2	-59.957	-0.676	433.777	820.086
	(57.591)	(0.615)	(748.541)	(1,351.697)
Age	0.194	-0.020	2.011	26.313
	(3.077)	(0.032)	(38.411)	(75.452)
Education	23.859	0.218	-1.622	210.176
	(28.853)	(0.311)	(352.363)	(644.109)
Married	169.313	1.785	-464.738	-481.502
	(120.355)	(1.224)	(1,825.242)	(3,394.317)
Weekly Income (USD)	0.435	0.005	6.071	8.782
	(1.041)	(0.010)	(12.977)	(23.726)
Constant	-160.253	-1.590	1,137.405	-1,108.724
	(302.358)	(3.227)	(4,096.697)	(7,634.528)
Observations	24	24	24	24
R-squared	0.571	0.569	0.540	0.514

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The moderator for the unenforced game is left out to be the baseline on the regressions. All regressions are conducted with BMU-level controls.

In three of the four specifications, the direction of the enforcement game moderator's effect indicates more aggressive harvesting. None of the specifications are significant, however, the stock remaining after the 4th and 7th rounds are very low when compared to the unenforced moderator. Even when the unenforced and enforcement moderators are playing the same game with the same instructions the enforcement groups harvest more.

Another experimental procedural worry is that local fisheries patrol officers were responsible for introducing the research team to the BMU participants. This may have influenced players decisions to use illegal gear. As noted in Section 4.21, the percentage of players that cheated in the unenforced group was never higher than 22 percent.. The presence of patrol officers may have altered fisher's behavior in the game as participants may have not fully trusted that their actions would not have consequences. If the participants believed the patrol officers would punish those that used illegal gear in the game, then the overall cheating results may not be valid. However the difference in cheating levels between the two treatment groups is still valid, it just may be that cheating rates would be higher without the presence of a fisheries patrol officer.

3.33 Theory 3 – Crowding Out Effect

As policy makers design institutions to improve management of the fishing commons they must make sure that the institutions change behavior for a Pareto-superior outcome. These results could have occurred because the enforcement game crowded out cooperative strategies by focusing their strategy on avoiding using illegal gear. By focusing the game on penalizing those who use illegal gear, it distracted players from sustaining the resource.

In a similar study by Cardenas, Stranlund and Willis (2000), participants from rural Columbia played a static common pool resource game with and without an enforcement mechanism. According to the authors:

> After the subjects faced the external regulation…they made choices that were significantly closer to their purely self-interested Nash responses. Thus it appears

> that the pressure of an external control crowded out the other-regarding behavior in favor of greater self-interest." (p. 1729)

The results from this experiment show similar conclusions to those found in the current/our study, primarily that the enforcement mechanism crowded out cooperative harvesting behavior in favor of more aggressive individual harvesting behavior.

5. Conclusion

Does enforcing illegal fishing net bans have unintended consequnces? The results from this unique artefactual experiment show that there is a significant reduction in cooperative behavior when an enforcement mechanism is present. Players in the enforcement treatment groups depleted the fish stocks significantly faster than the control groups. This surprising result indicates that players may be frustrated with those that cheat and harvest more because the social norm to not cheat is broken. There also may have been a crowding out effect among participants. As local policy makers seek to design mechanisms and incentives to prevent communities from over-harvesting fishing commons, they must consider all of the unintended consequences of their actions.

When policy members implement enforcement policies they may work as intended, as this experiment showed that cheating decreased in the enforcement treatment groups. However, there are many dimensions of cooperation within common-pool-resources and cheating is just one of those dimensions. When focusing on harvest levels, this study shows that the cooperation breaks down under enforcement rather that increasing cooperation. Future studies should measure the participants frustration levels with their fellow group members and post-experiment surveys should be conducted to better understand the participants harvesting behavior. While the results from this experiment indicate enforcement increased over-harvesting behavior, there may be other explanations for this behavior and further research should address this.

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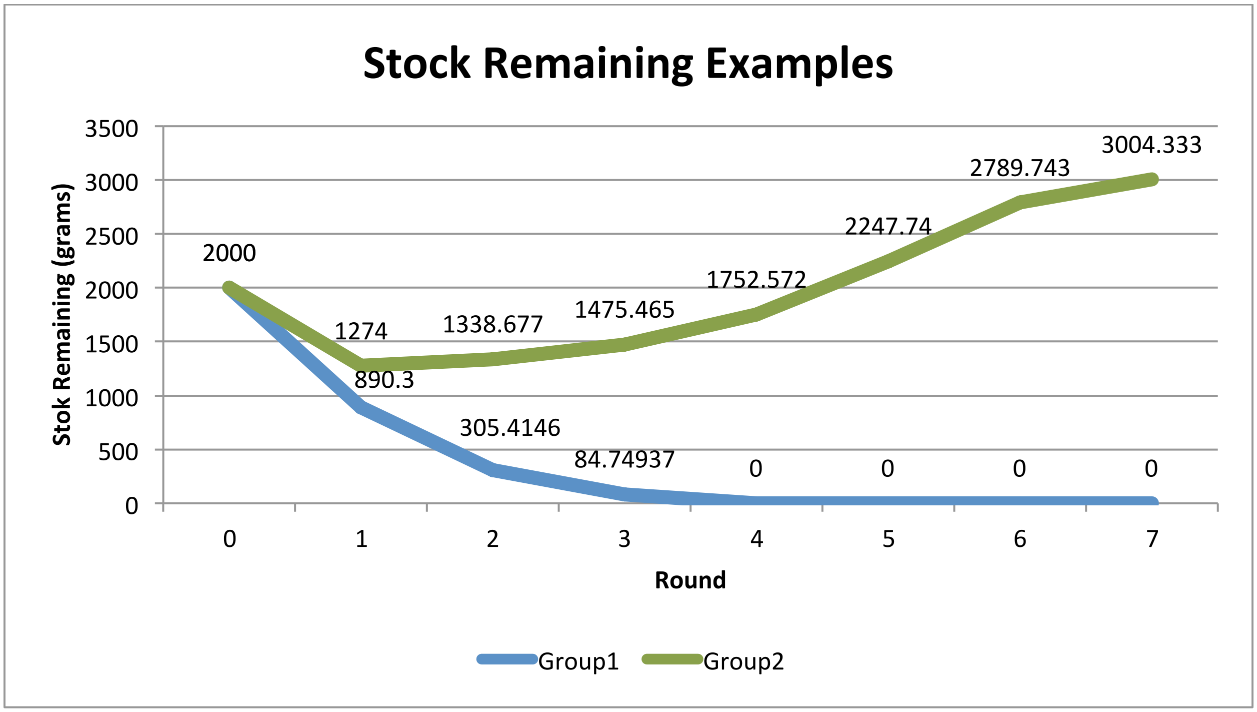
Appendix A:

<u>Nine Strategies Defined:</u>

All the games started with 2,000 grams of beans in the bins. By tracking the level of the stock at the end of each round in the game, it is clear to see the harvesting strategy of each group. For example here is the stock trend of two different groups from the sample:



It is clear to see that Group1 (blue) had a more aggressive harvesting strategy and ended up depleting the resource after three rounds, whereas Group2 (green) ultimately let the resource grow to more than 3000 grams by the end of the seventh round.

The first step in determining the strategy is look at the stock remaining after the fourth round and see how different it is from the steady stock level of 1500. 1500 grams is the steady level because the stock will grow about 500 grams bringing the new stock level to the original starting level of 2000 grams. Looking at the example above, Group2 (green) has a stock level of 1752 grams after the fourth round. This is a 16.8 percent increase from the steady level [(1752-1500)/1500]. The percent cut-off rates are:

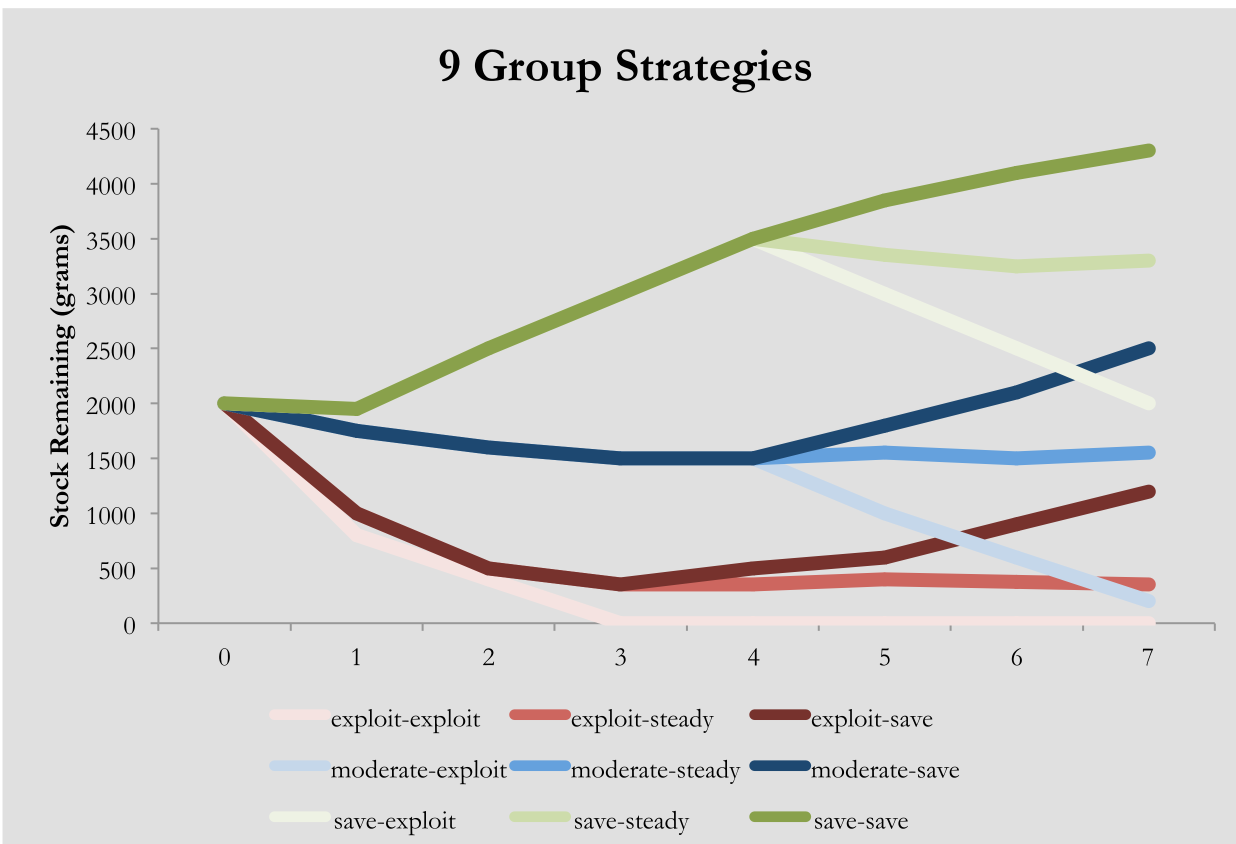
Over 33 % - "Save" strategy
Plus/Minus 33 % - "Moderate" strategy
Under 33% - "Exploit" strategy

After identifying the strategy after the fourth round, the strategy is determined again after the seventh round to see if the group had changed its strategy from the fourth round. Again using

Group2 (green) above as an example, the difference in the seventh round compared to the fourth round is 71 percent [(3004-1752)/1752]. Therefore the nine strategies are:

1) Exploit - exploit (-33%; -33%)
2) Exploit - steady (-33%; between +/- 33%)
3) Exploit - save (-33%; +33%)
4) Moderate - exploit (between +/- 33%; -33%)
5) Moderate - steady (between +/- 33%; between +/- 33%)
6) Moderate - save (between +/- 33%; +33%)
7) Save - exploit (+33%; -33%)
8) Save - moderate (+33%; between +/- 33%)
9) Save - save (+33%; -33%)

Graphically it looks like:



Appendix B:

Relative Harvest Rate and the Five Individual Harvest Strategies per Round

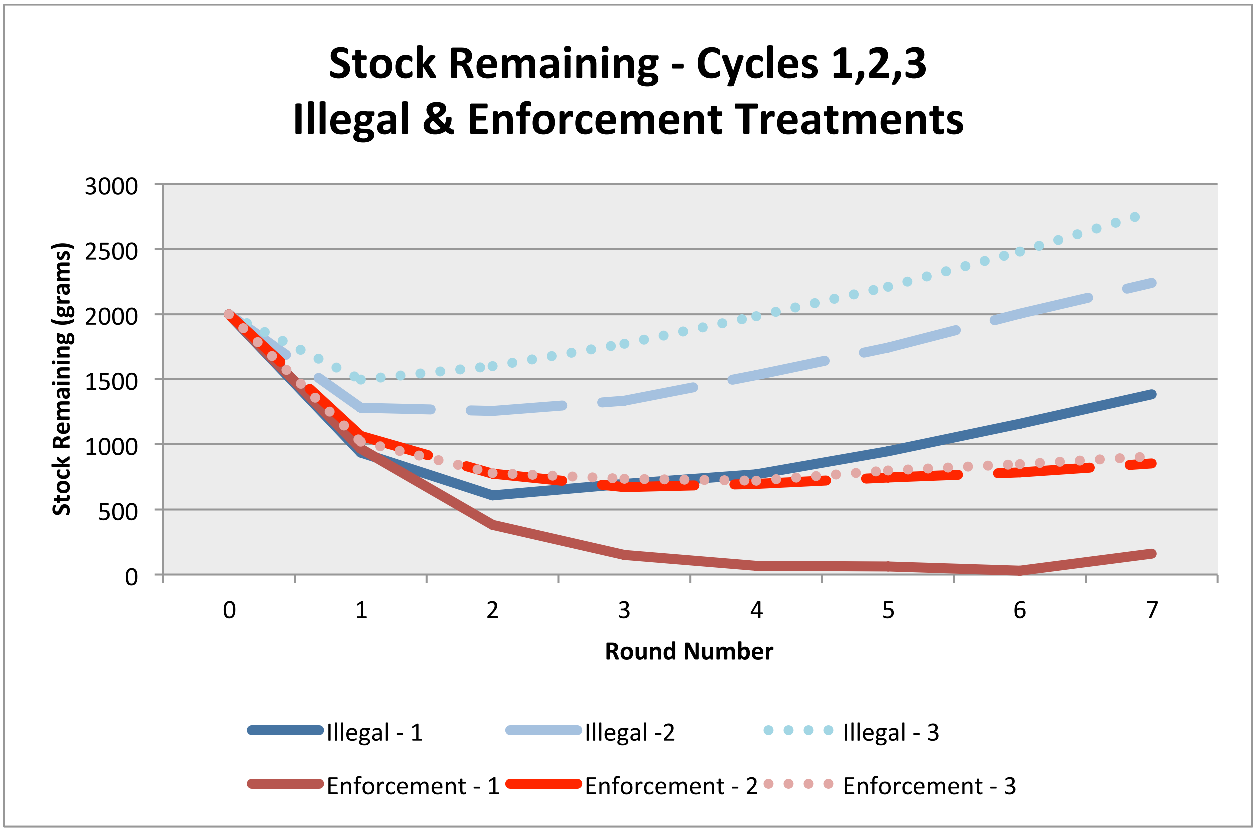
The relative harvest rate is calculated by dividing the difference between a players harvest rate and the sustainable harvest rate over the sustainable harvest rate. In the first round of each game there are 2,000 grams of beans. In order for the group to maintain the stock of beans at 2,000 grams for the next round they can collectively harvest 50 Each round an individual can choose five possible strategies. If the group wants to keep the stock at the same level as the previous round then they must not collectively harvest more than growth that it takes to get to the previous level. For example, all groups start with 2000 grams in the big bin. If they harvest 500 grams, then the growth rate will be about 500 grams and at the beginning of round 2, the group will be back again to 2000 grams in the big bin. Therefore in round 1 on average for a group of five, each player must not harvest more than 100 grams. If the player instead harvests 150 grams their harvest ratio is +50% [(150-100)/100]. Based on that growth rate as the "steady" rate, there are five individual strategies along with the harvest ratios that define them:

1) over exploit (+66.6%)
2) exploit (between 33.3% and 66.6%)
3) steady (between +/- 33.3%)
4) save (between -33.3% and -66.6%)
5) over save (-66.6%)

Appendix C:

<u>Harvest Paths for all 3 Cycles</u>

This paper only analyzes the third cycle of the games because they are most likely to portray the true strategies of the groups because the groups will have understood the instructions and parameters of the game the best by then. Below are the harvest paths between the illegal and enforcement groups for cycles one, two and three – looking at the average stock level remaining by each treatment group:



On average, the illegal treatment groups conserved more and more stock as the cycles went from 1 to 3. In the enforcement treatment groups, cycles 2 and 3 had on average the same harvest path.

Appendix D:

Images of the experiment:

Participants harvesting from the bin (above). Classroom being used as experiment site (below).