An Experimental Study of Compliance and Leverage in Auditing and Regulatory Enforcement*

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Abstract

Evidence suggests that a large majority of firms and individuals comply with regulations and tax laws even when fines for noncompliance are small or the frequency of inspections and audits is low. These observations are not consistent with static compliance models. Harrington (1988) developed a dynamic enforcement model in which some agents have an incentive to comply even when the cost of compliance each period is greater than the expected penalty. This paper reports a laboratory experiment based on the Harrington model framework. Subjects move between two inspection groups that differ in inspection probability and fine severity. Subjects face low, medium or high compliance costs. Enforcement leverage arises in the Harrington model from movement between the inspection groups based on previous observed compliance and noncompliance. Our results indicate that consistent with the model, violation rates increase when compliance costs become higher and as the probability of switching groups becomes lower. Behavior does not change as sharply as the model predicts, however, since violation rates do not jump from 0 to 1 as parameters vary across critical thresholds. A simple model of bounded rationality explains these deviations from optimal behavior.

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1: Introduction

Regulatory policy makers have observed that many firms and individuals comply with regulations even when both the frequency of audits and the penalty for violations are low. This is seen in areas as diverse as income tax collection, customs, antitrust laws, health and safety and environmental regulation. This phenomenon is difficult to explain using static enforcement models (for example, Linder and McCabe, 1984, Storey and McCabe, 1980, Harford, 1978) in which the penalty facing the firm depends only on the firm's performance in the current period and not on its previous compliance record.

Economists in recent years have proposed dynamic repeated game models to reconcile the low expected penalties and yet high observed compliance rates. In these models, the regulated firm and the enforcement agency can react to previous actions by the other (Landsberger and Meilijson, 1982, Greenberg, 1984, Harrington, 1988). The enforcement agency alters the expected penalty and the inspection frequency based on the firm's past performance. Harrington finds that a firm could have an incentive to comply with regulations even though the costs of compliance in individual periods exceed the expected penalty for violation. This is important in practice because political or practical considerations often limit the size of the fine that can be imposed on a firm. For example, in many states there is a restriction on the size of penalties that can be levied for violating an environmental regulation (e.g., $5000 per day).[1]

The strategy the enforcement agency uses to achieve this result divides the firms into two groups, and the firms in one group face a more severe enforcement regime than the firms in the

[1] Compliance can occur for other reasons, of course. Firms may sometimes comply with regulations to guide regulatory authorities to set higher standards for the whole industry, thereby increasing the costs of their rivals (Salop and Scheffman, 1983). Firms could also comply to obtain a reputation of being an environmentally conscious organization. Arora and Gangopadhyay (1995) show that public recognition plays a very important role in the success of voluntary environmental programs. Individuals and firms could also comply with regulations because they are honest and get disutility from violating regulations.

other group. A firm's compliance status determines which group it is in. Each firm can move from one group to the other depending on its performance. Violations discovered in the rarely inspected "good" group are punished by transfer into the more frequently inspected "bad" group and compliance discovered in the more frequently inspected group is rewarded with the chance of a return to the rarely inspected good group. This enforcement scheme poses a Markov decision problem from the firm's perspective. The firm moves from group to group according to transition probabilities that depend not only on the inspection probabilities and the current state of the system but also on the action taken (comply or not) during that period. Harrington shows that firms' optimal policies in this scheme depend upon their individual costs of compliance. Low cost firms are always in compliance, high cost firms are never in compliance and medium cost firms move in and out of compliance depending on the results of recent inspections.

This paper reports laboratory evidence on compliance behavior of decision makers when faced with enforcement conditions consistent with the Harrington model framework. We examine treatments in which the compliance costs are low, medium or high. In these within session treatments we also change the probability of the firm switching from the frequently inspected group to the rarely inspected group if inspected and found compliant, from 10 percent to 90 percent. Our results indicate that consistent with theoretical predictions, violation rates increase when compliance costs become higher and as the probability of switching groups becomes lower. Behavior does not change as sharply as the model predicts, however, since violation rates do not jump from 0 to 1 as parameters vary across critical thresholds. A simple model of bounded rationality, in which agents choose more profitable strategies with higher probability but not with probability equal to one, can explain these deviations from optimal behavior.

Although these conditional audit rules have received significant attention in the theoretical literature, direct empirical evidence on their performance is scarce. Empirical research using field data exists (e.g., Helland, 1998, Oljaca et al., 1998, Eckert, 2004), but it is hampered by the absence of reliable information regarding individual reporting behavior and unknown compliance decisions for uninspected firms.[2] Laboratory experiments, however, are well suited to study the different features of compliance schemes and individual behavior within these schemes. Most of the existing experimental literature on compliance and auditing has focused on static models, where different policy changes like an increase in tax rate, a change in penalty rates, tax amnesties or changes in audit probabilities are introduced to determine the impact on compliance behavior. Alm and McKee (1998) provide a survey of this literature. Torgler (2002) surveys the experimental findings on the tax compliance literature with a focus on social norms and institutional factors, which are seen to encourage compliance.

Alm, Cronshaw and McKee (1993) examine dynamic audit rules and compare these to a 5 percent inspection probability random audit rule. The auditor's discovery of non-compliant behavior in a random audit scheme could lead to audits of previous or future years with certainty. Alm et al. find that the forward looking rules achieve lower compliance rates, since in this scheme an individual can cheat until audited in the current period and can then avoid any additional penalties by reporting honestly for the next two periods. On the other hand, under the backward looking audit policy, an individual found to be non-compliant in the current period has no chance of avoiding penalties on previous periods' records. This increases the incentive for individuals to comply under backward looking policies and might be more attractive from the

[2] Helland (1998) uses data from the American pulp and paper industry to test whether environmental regulators audit and fine according to the model described in Harrington (1988). He finds that firms who are discovered in violation experience a one or two quarter penalty period during which they are inspected more frequently. Eckert's (2004) data on Canadian petroleum storage facilities is also consistent with the Harrington framework. She finds that inspections deter future violations, although the effect is small.

viewpoint of regulators, particularly in the area of tax reporting. Backward looking schemes however would typically not be feasible in others kinds of regulatory areas like environmental and natural resource management when the data (for example, for actual emissions rates) from previous periods cannot be checked. Therefore, forward-looking conditional audit rules like those studied here are practical for a wider range of applications.

The previous research most closely related to the present study is Clark, Friesen and Muller (2004), which compares two dynamic audit rules: Harrington's (1988) scheme and another proposed by Friesen (2003) that is designed to minimize the inspections regulators must make to achieve a target rate of compliance. Both the rules use the current audit record of the firm to assign them to different audit groups in future periods, but in Friesen's scheme all of the transitions between audit groups can be probabilistic, while in Harrington's scheme all transitions are deterministic except for the movement of an inspected, compliant firm from the bad group to the good group. In Friesen's optimal targeting scheme the firms face a fixed probability of moving from the good group to the bad group which is independent of compliance status in the current period. There are no inspections conducted of firms in the first group. Clark et al. find an enforcement possibility frontier between compliance and minimizing inspections, with the Friesen rule requiring slightly lower inspection rates. Their experiment focuses on a comparison of the two conditional audit rules against simple random auditing for a single compliance cost and one set of enforcement parameters in each rule. Harrington's rule performs well on certain measures, such as for the rate of compliance per inspection. This suggests that further exploration of the performance of this enforcement policy is warranted, and in the present study we consider seven different enforcement parameter and compliance cost combinations to more fully examine its empirical properties. These multiple treatments allow us to study how compliance choices respond to different enforcement rules, and estimate a boundedly rational choice model to characterize behavioral responses for this type of probabilistic enforcement.

2: Theoretical Framework

We are interested in the relationship between the firm's compliance cost, its compliance decisions, and the conditional audit scheme chosen by the regulator. Our experiment is structured by Harrington's (1988) model, which determines for a two-state model the level of compliance that can be achieved when both enforcement budgets and the maximum feasible penalty are limited. Let G_1 and G_2 denote the two "inspection" groups of firms and denote the inspection probability in G_i as p_i and the penalty for violation as F_i, with $p_1 < p_2$ and $F_1 < F_2$. Firms can avoid a violation by incurring the compliance cost c. If a firm is inspected its compliance status is observed perfectly.[3] Firms found to be in violation in G_1 are punished by a transfer into G_2 and firms found to be in compliance in G_2 are rewarded with a chance of a return to G_1. The probability that a firm found in compliance in G_2 is returned to G_1 is denoted by u. Table 1 presents the payoffs to the firm in this game. For future reference, this table also includes the parameters chosen for the experiment.

A policy for the firm is a map $f:\{1, 2\} \rightarrow \{0, 1\}$ of states 1 and 2 into decisions to comply with (0) or violate (1) the regulations. The firm's goal is to choose the policy that minimizes the present value of its expected costs over an infinite horizon. The firm has four available policies: f_{00}, f_{01}, f_{10} and f_{11}, where f_{00} is the policy that the firm would comply in both state 1 and 2 and f_{01} is the policy of complying when in G_1 and violating when in G_2 and so on. The expected present

[3] This is not a critical assumption for Harrington's two-state model, but it is for other models. Greenberg (1984) showed that a three-state model, in which transitions out of a third, "habitual offender" group were impossible, can dramatically reduce the rate of violations compared to a two-state model. However if false positives are possible (i.e, situations where compliant firms are wrongly classified as violators with some positive probability), every firm eventually moves into the third group and all firms are inspected every period.

value of the policy would be the cost this period plus the expected present value discounted one period. This leads to four sets of simultaneous equations which can be solved to obtain the present values of the four policies. For example, the expected cost of policy f_{10} in state 1 is:

$$(1) \qquad \frac{cp_1\beta + p_1F_1(1-\beta + p_2u\beta)}{(1-\beta)(1-\beta + p_1\beta + p_2u\beta)}$$

and the expected cost of f_{10} in state 2 is:

$$(2) \qquad \frac{c(1-(1-p_1)\beta) + \beta p_2 u p_1 F_1}{(1-\beta)(1-\beta + p_1\beta + p_2u\beta)},$$

where β is the discount factor.

Harrington shows (his Lemma 1) that in this framework, f_{01} is never an optimal policy as it is dominated by f_{00} when the cost of compliance $c < p_2F_2$ and by f_{11} when $c \geq p_2F_2$. Hence the firm chooses between three policies f_{00}, f_{10}, f_{11} and the optimal policy depends on the compliance costs facing the firm and the enforcement parameters chosen by the regulatory agency. Table 2 presents the expected payoff for each policy, based on an exogenous per-period revenue of R. Firms with compliance costs below a particular threshold (p_1F_1) always comply, and those with costs above a higher threshold never comply. For an intermediate range of costs the firm chooses policy f_{10}, and it cheats when in G_1 and complies in G_2. Ironically, for these intermediate compliance costs the "good guys" in G_1 can afford to cheat, whereas the "bad guys" in G_2 comply until they are moved back into G_1. Compared to a static model, in this dynamic model compliance is achieved in G_2 even though the expected penalty is not large, because firms in G_2 may be allowed to return to G_1 depending on their compliance record.

The enforcement agency in this model wants to minimize the resources spent on monitoring and enforcement subject to achieving a target compliance rate Z. The agency has five parameters that can be changed to achieve desired compliance rates: the probability of inspections, p_1 and p_2, the two penalties F_1 and F_2 and the probability u of the firm moving back into G_1 if found compliant. We manipulate u as well as the compliance cost c as exogenous treatment variables in the experiment. For certain parameters—specifically the u=0.9, compliance cost=200 treatment described below—firms have an incentive to comply even though the expected penalty (p_2F_2=0.5×300=150) is less than the single period compliance cost. This property is termed leverage in the literature.

In the optimal combination of enforcement parameters characterized by Harrington, marginal firms that adopt policy f_{10} just slightly prefer to comply rather than violate in G_2. In our choice of parameters described in the next section, we avoid these optimal parameter cases in which individuals are nearly indifferent between two strategies. This design choice is guided by experience with previous experiments, which demonstrate that more than marginal incentives are necessary for subjects to learn optimal behavior. This is confirmed by the noisy choice model results reported in Section 4.3.

3: Experimental Design

We conducted 13 sessions with 8 or 9 subjects in each session. All 114 subjects were undergraduate students at Purdue University and were inexperienced in the sense that they had not participated in a similar experiment. The University of Zurich's z-tree program was employed to conduct all sessions (Fischbacher, 1999). Each session lasted about 45 minutes, including instruction time. Payoffs in the experiment were converted using an exchange rate of 1500 experimental dollars = 1 U.S. dollar and subject earnings ranged from 6.75 to 15.25 U.S. dollars, with median earnings of $12.75. These sessions constituted the first half of a longer session that trained subjects to make compliance choices in a study of emissions permit trading with imperfect enforcement (Cason and Gangadharan, 2005). Each subject made 61 separate compliance choices over seven different period sequences, one for each treatment variable combination.[4]

At the start of each period sequence, subjects were initially randomly assigned into inspection group 1 or 2, which differ in the probability of inspections and severity of fine. Each subject had a binary choice: whether to comply or violate in each period. If they decided to comply they paid a compliance cost, which remained unchanged within a period sequence but varied across period sequences. Subjects were inspected with a certain probability that depended on which group they were in. Group 1 subjects were inspected with a probability of 20 percent and group 2 subjects were inspected with a probability of 50 percent. Subjects were required to pay a fine if they did not comply in a particular period and they were inspected. The fine for violation was 50 experimental dollars in group 1 and 300 experimental dollars in group 2. In addition, subjects in group 1 were moved to group 2 when they were caught violating. If subjects were in group 2 and they are observed to comply on inspection, then they were moved back into group 1 with a low or a high probability. The instructions were framed using the terminology of this paragraph (i.e., "comply," "violate," "inspection," "fine," and so on). Comparison of our results with the more neutrally-framed terminology employed in Clark et al. (2004) suggests that framing does not have a substantial impact on the results.[5]

Each subject participated in a random number of periods in seven separate period sequences. The number of periods in each period sequence was determined before the session

[4] Experiment instructions are available at http://www.krannert.purdue.edu/faculty/cason/papers/leverage-instr.pdf.

[5] For example, Clark et al. (2004) use "Option A" and "Option B" instead of "Comply" and "Violate." Our leverage treatment with compliance cost=200 and u=0.9 is most similar to the one treatment Clark et al. study, in that violation is optimal in group 1 and compliance is optimal in group 2, even though the compliance cost exceeds the expected fine in group 2. Clark et al. observe overall compliance rates of 12 percent in group 1 and 75 percent in group 2, whereas in our similar treatment we observe overall compliance rates of 11 percent in group 1 and 63 percent in group 2. While obviously not identical, these rates are similar—especially considering the many other procedural, training and payment design differences between our and Clark et al.'s experiment.

and was unknown to the subjects. Subjects in the same session faced the different treatments in different orders, which implies that our treatment comparisons control for sequencing effects. The random ordering also leads to an approximately equal number of decisions in each treatment. As explained in the instructions, each period there was a 90 percent chance that the same period sequence continued for an additional period. This implements a discount factor β=0.9. Subjects were only told at the end of the last period in a sequence that a new period sequence would now begin.

The period sequences were a combination of two treatment variables, both varied within sessions, in a three-by-two factorial design. For one treatment variable we vary the compliance costs (c) across three levels from low to medium to high to determine whether subjects change their compliance decisions in the presence of different levels of compliance costs. The compliance costs are 100 in the low cost scenario, 200 in the medium cost and 375 in the high cost case. For the other treatment variable we manipulate at two levels the probability (u) of subjects moving from group 2 to group 1 to determine whether subjects comply more when the probability of switching groups is higher. Subjects face a switching probability of 0.1 in some period sequences and 0.9 in others. As noted above, these enforcement parameters do not represent the "optimal" parameters derived in the Harrington model; instead, they reflect our design goal to explore a variety of compliance conditions with strong and weak incentives to comply or violate in the different inspection groups. We also employ a seventh period sequence that served as a baseline with very low compliance costs (7) and u=0.9, for which compliance is always optimal. All subjects made compliance decisions in all treatment variable combinations.

Although it is obviously quite stylized, several features of the experimental design increase its parallelism with the field or were chosen specifically to explore the range of possible behavioral responses to a variety of enforcement conditions. As already noted, we employ natural, non-neutral terminology, in which subjects choose to "violate" or "comply". Second, subjects make individual rather than group compliance decisions. This may limit the range of application of the behavioral results since some decisions in response to regulations are made by groups; however, a large proportion are made by individuals in the field, including many individual decisions when reporting personal taxable income. Third, subjects are exposed to different compliance costs in different period sequences, helping us determine how individual behavior changes with changes in the costs. Fourth, subjects are moved from the low intensity audit group to the high intensity group with different switching probabilities. This dynamic audit rule is similar to what often happens in income tax auditing and health and environmental auditing. Moreover, as already noted the forward looking conditional audit rule that we study can apply in cases where past compliance cannot be assessed, which makes it relevant and applicable for a more general and broader class of regulatory issues.

4: Results

4.1 Overall Violation Rates

Figure 1 presents the average violation rate for later periods in the period sequences, along with the steady state predicted violation rates, for each of the seven treatments. The predicted violation rate is 0 when compliance policy f_{00} is optimal, and it is 1 when compliance policy f_{11} is optimal. When policy f_{10} is optimal, the predicted violation rate is the stationary probability of being in inspection group 1, $p_2u/(p_1+p_2u)$. The figure shows that violations usually increase when they are predicted to increase, but that they do not reach the corner solution rates of 0 or 1 when policies f_{00} or f_{11} are optimal.

Table 3 presents the overall violation rates separately for the compliance cost (*c*), switching probability (*u*) and inspection group combinations. The model predicts that for our experimental parameters, subjects will violate whenever they are in inspection group 1 except for the baseline treatment with a very low compliance cost of 7. Table 3a shows that this prediction is broadly supported, with observed violation rates of subjects in group 1 between 73 and 93 percent when violation is predicted. These rates typically increase for the later sequences 5-7 when subjects have more experience across treatments, as shown in parentheses in the table. The violation rate is 17 percent in the baseline treatment, for which violation is not predicted.

For the parameters employed in the experiment, the model predicts violation in only 3 of the 7 treatment cells when subjects are in inspection group 2. Subjects should not violate in the low compliance cost (7 and 100) case and should violate in the high compliance cost (375) case, irrespective of the value of the switching probability *u*. In the medium compliance cost (200) case they should violate only when they are unlikely to escape from inspection group 2 (u=0.1). Table 3b indicates that violations are more common when they are predicted, but that in all 7 cases the violation rates differ from the predicted rates by at least 13 percentage points, even when considering only the late sequences 5-7. Violations also rise when moving to the right or upward in Table 3b.[6]

Table 3b clearly shows that subjects do not dramatically switch from never violating to always violating when the expected return from violating exceeds the expected return from compliance. Figure 2 illustrates the contrast between the sharp never/always violate prediction of

[6] These deviations from the optimal compliance choices are not explained by individual subjects who were "chronic" violators or by subjects who may derive utility from being "honest" and comply constantly even when violation is more profitable. Indeed, we find no evidence that such extreme behaviors were present, based on our analysis of individual subjects' play. All subjects violated at least one-third of the time and complied at least 15 percent of the time. As shown below, most individual subjects' compliance choices changed in response to the different incentives generated by the different enforcement treatments.

the model and the smoothly monotonically increasing violation rate observed in the experiment. This figure is based on choices in inspection group 2 only, and it also displays the ratio of expected profits from violating to the expected profits from compliance. These expected profits are based on the discounted, infinitely repeated compliance choice problem with the optimal compliance policy followed in all subsequent periods. The model predicts a violation rate of 1 if and only if this ratio exceeds 1. The observed violation rate, however, is merely higher whenever this ratio indicates a higher return to violation. (An exception to this occurs for one transition: compliance cost=200 and u=0.1 to compliance cost=375 and u=0.9.) In other words, subjects' choices appear to be sensitive to the relative payoffs from violation and compliance, but the overall averages do not switch from one corner solution prediction to the other at the sharp threshold when the ratio passes through one. We return to this issue in Section 4.3 where we explain this behavior using a simple model of boundedly-rational, or "noisy," decision-making.

Clearly the data do not support the point predictions of the model, but they are consistent with many of the comparative static predictions about how the compliance rates differ in the various treatment cells. For formal tests we do not use the overall averages displayed in Table 3, since individual subjects made multiple compliance choices and therefore the data points in this table are not statistically independent. Fortunately, we can conduct rather powerful tests based on statistically independent observations of individual subjects' compliance rates and compliance rate differences across treatment cells. Recall that 114 individual subjects participated in this study, and they did not interact at all so each provides statistically independent observations. Therefore, for example, to test whether the violation rate in inspection group 2 for u=0.9 is significantly higher when compliance cost=375 than when compliance cost=200, we first calculate the violation rate for each individual subject within those two treatment cells. We then calculate the difference in these rates for the 70 individual subjects who made choices in both treatment cells, and employ a nonparametric Wilcoxon Signed Rank test to determine whether these differences are significantly different from zero. The test statistics for all the comparisons are presented in Tables A1-A3 in the Appendix.

This statistically conservative and yet powerful (due to our sample size) procedure yields the following conclusions. All statements are based on a five-percent significance threshold.

First, violation rates are significantly higher when in inspection group 1 than when in inspection group 2 for all 7 treatment cells. Note that the model predicts a significant difference in only 3 of the treatment cells (i.e., for both u=0.1 and 0.9 when compliance cost=100 and when u=0.9 and compliance cost=200).

Second, when in inspection group 1 the violation rate increases significantly when the compliance cost increases in 3 of the 5 pairwise comparisons: for u=0.1 when moving from compliance cost=100 to 200, and for u=0.9 when moving from compliance cost=7 to 100 and when moving from 100 to 200. When in inspection group 2 the violation rate increases significantly when the compliance cost increases in 4 of the 5 pairwise comparisons: all cases *except* for u=0.9 when moving from compliance cost=7 to 100. Note that the data support all 3 compliance cost treatment effects predicted by the model (for u=0.1, when moving from compliance cost=100 to 200 in inspection group 2, and for u=0.9, when moving from compliance cost=200 to 375 in inspection group 2 and when moving from compliance cost=7 to 100 in inspection group 1). However, also note that 4 additional differences are also significant (these are, for u=0.1, when moving from compliance cost=100 to 200 in inspection group 1 and from compliance cost=200 to 375 in inspection group 2; and for u=0.9, when moving from compliance cost=100 to 200 in both inspection groups).

Third, the violation rate is significantly higher when u=0.1 than when u=0.9 for all 3 pairwise comparisons when subjects are in inspection group 2. This is predicted only for the medium compliance cost=200 case, where the leverage of the two inspection groups is greatest. The violation rate is not significantly different for any of the 3 pairwise u comparisons when subjects are in inspection group 1, as predicted by the model.

These statistical conclusions generally hold for alternative subsets of the data, including for compliance choices based on only the initial inspection group that subjects are randomly assigned to, or compliance rates based only on subjects who have at least three compliance choices for a particular treatment cell. They are also robust to alternative statistical tests such as a simple nonparametric sign test or the standard parametric t-test.

4.2 Classification of Strategies

The violation rates just analyzed separately for each compliance cost (c), switching probability (u) and inspection group combination employ a state-by-state perspective of this choice problem that differs from the strategy specification of Harrington's model. Recall that agents in the model adopt an entire compliance policy; for example, if they adopt strategy f_{10} they violate when in inspection group 1 and comply when in inspection group 2. Therefore, in this section we examine the entire sequence of compliance choices within treatment cells to classify individual subjects' compliance policies. The main difficulty we encounter in this classification is that some subjects do not make choices in both inspection groups and so their observed choices are consistent with multiple policies. Table 4 presents the classification for only those subjects who can be perfectly classified into a specific strategy for a particular treatment, and Table 5 classifies every subject based on her "best-fitting" strategy.

Table 4 classifies an individual subject as choosing compliance policy f_{11} for a particular treatment cell if they always violate in that cell, regardless of which inspection group they are in. We classify an individual in compliance policy f_{10} for a cell if they always violate when in inspection group 1 and never violate when in inspection group 2. The classifications for f_{01} and f_{00} are defined analogously. Some subjects never make choices in one of the inspection groups for some treatment cells, so we have no data to classify their behavior in that group. These cases are denoted with question marks. For example, $f_{1?}$ indicates that a subject always violated in inspection group 1, but never made decisions in inspection group 2. This individual's behavior is consistent with both f_{10} and f_{11}. In the summary sections in Table 4 we count observations as consistent with f_{10}, for example, if they are identified in the "frequency (rate)" section as $f_{1?}$, $f_{?0}$ or f_{10}. Likewise, we count observations as consistent with f_{11} if they are identified in the "frequency (rate)" section as $f_{1?}$, $f_{?1}$ or f_{11}, and we count observations as consistent with f_{00} if they are identified in the "frequency (rate)" section as $f_{0?}$, $f_{?0}$ or f_{00}. The percentage of individuals who are classifiable as consistent with each policy does not sum to 100 percent because of the "question mark" subjects whose choices are consistent with two policies.

Clearly we have a large number of subjects who are not classifiable into any policy, ranging from 37 to 70 percent of the individuals depending on the treatment cell. In Table 5 we therefore present an alternative classification based on the policy that provides a best-fit to each individual subject's choices. This simple procedure counts the number of "errors" assuming subjects follow a particular strategy, and yields a strategy classification for every subject that minimizes the number of errors in classification. For some subjects, however, two policies are equally best-fitting. This occurs most frequently when subjects do not make choices in both inspection groups.

The results are largely consistent across the two classification methods in the two tables. Both indicate that more subjects are consistent with the optimal policy (shown in bold on the tables) than any other policy for 6 treatment cells, with the exception being the cell where compliance cost is medium and u = 0.1. In this cell, for example, Table 5 shows that 60 percent are consistent with policy f_{10} and 54 percent are consistent with the optimal policy f_{11}. For all other conditions, at least two-thirds of the subjects' strategies are consistent with the optimal policy. The switching probability u can be an important determinant in the individual's decision making, particularly so when the compliance costs are high. When the compliance costs = 375, more subjects are consistent with f_{10} when u = 0.9 than when u = 0.1, although the optimal policy f_{11} is still played by a larger percentage of the subjects. For these high compliance costs—which are more than double the single period expected penalty—apparently some individuals increase their compliance rates because of the greater opportunity of moving back to the good group 1 as u increases. This suggests that leverage works to some degree even when it is not predicted to work by the model.

Taken together, these points concerning the classification rates suggest that (1) some subjects' behavior is either confused or consistent with some alternative model we have yet to consider; and (2) a large portion of subjects choose the compliance policy predicted by the Harrington model. The next subsection presents an alternative choice model in an attempt to make sense of some of the systematic deviations from this model.

4.3 A Noisy Choice Model

The Harrington model predicts that subjects choose the optimal compliance policy with probability one, regardless of whether this policy provides a return that is, for example, 331 percent higher or 10 percent higher than the next best alternative. Figure 2, however, shows that although subjects are more likely to make choices that provide greater expected profits, their likelihood of making the optimal choice increases when its return is greater relative to its alternatives. This suggests that a model that permits errors in decision-making might be useful to understand our experimental outcomes. In what follows we employ a “quantal choice” model that accounts for boundedly-rational decision-making. This model allows subjects to make errors, but it accounts, in an intuitive way, for the fact that subjects are less likely to make errors that are more costly.[7] In particular, it provides some structure for the distribution of errors that agents make, by relating the errors to their expected payoff consequences.

We use the logit form of the quantal choice model first introduced by Luce (1959) and popularized more recently by McKelvey and Palfrey (1995) in a game-theoretic context as a quantal response equilibrium. In our study subjects are not playing a strategic game—just a game against nature since the inspector is not strategic. The idea is therefore quite simple: If strategy i has expected utility U_i, it is played with probability

$$q_i = \frac{\exp(U_i / \mu)}{\sum_{\text{all } j} \exp(U_j / \mu)} \tag{3}$$

The parameter μ is estimated from the data and scales the sensitivity that subjects have to the relative payoffs (in terms of utility) of the various choices. As μ decreases the subjects put less probability weight on choices that yield suboptimal payoffs, and the probability that they make the optimal choice approaches one as μ approaches zero. As μ approaches infinity, subjects choose their available strategies with equal probability, independent of the relative expected payoffs.

[7] Figure 2 clearly shows how deviations from the optimal choice depend on the relative profitability of the different choices, and thus rejects alternative choice error models like the Noisy Nash model that do not account for relative payoffs. In the Noisy Nash model the agent makes his optimal choice with probability γ and randomizes (uniformly) over all choices, independent of their relative payoffs, with probability $1-\gamma$ (McKelvey and Palfrey, 1998).

This framework also allows us to determine if risk aversion, either as a competing or a complementary explanation to this type of boundedly rational decision making, might also explain the deviations from optimal choices. Risk aversion is sometimes argued to lead to higher compliance rates than is predicted as risk averse subjects could be very sensitive to the probability of being caught (Alm, Jackson and McKee, 1992). The greater risk of a fine increases the cost of violating while leaving unchanged the returns from complying. To introduce risk aversion in a simple way we posit a constant relative risk averse utility function for each subject of the form $U(\pi) = \pi^{1-\alpha} / (1-\alpha)$, where π is the dollar payoff for the choice and α is the index of relative risk aversion. We can estimate both μ and α by maximum likelihood techniques within the same model. If α is significantly positive while μ is near zero, this would suggest that risk aversion rather than bounded rationality is a primary cause of the deviations from the optimal choice. We obtain the opposite result, however. In all of our estimates, whether looking at only late periods, only early periods, or all decisions, we find the maximum likelihood estimate of α to be 0 but μ to be positive and highly significant. Therefore, we reject risk aversion as a main explanation of our results and focus on the bounded rationality term μ.

To evaluate this model we look at individual choices within an inspection group, similar to the analysis in Section 4.1 above (and Table 3). We consider 3 strategies for the subjects: compliance policies f_{00}, f_{10} and f_{11}, but not policy f_{01} since f_{01} is never optimal and is always played less frequently than other policies (as documented in Tables 4 and 5). Each of these three policies has an expected present value for the agent when in each inspection group, for every treatment variable combination employed in the experiment, as shown in Table 2. For example, when the compliance cost is 100 and the transition probability u=0.1, if the agent is in inspection group 2 his expected payoff from policy f_{00} (always comply) is 3000; his expected payoff from policy f_{11} (always violate) is 2500; and his expected payoff from policy f_{10} (comply only in group 2) is 3124.62. We use these expected payoffs to calculate the probability of adopting each policy using equation (3), and then translate the rates at which subjects choose these compliance policies into observed violation rates for each inspection group. For example, if μ=976 then the probability of adopting f_{11} based on the expected payoffs just described is

$$\frac{\exp(2500/976)}{\exp(3000/976)+\exp(2500/976)+\exp(3124.62/976)} = 0.219\,.$$

This is the probability of a violation in inspection group 2 implied by μ =976, since the other two policies (f_{00} and f_{10}) prescribe compliance when in inspection group 2.

We make a similar transformation for all treatment configurations, inspection groups and all possible μ, and then compare the actual compliance decisions to determine the μ most consistent with the data. Table 6 presents the maximum likelihood estimate for μ, pooling across all 6 main treatment cells (i.e., all treatments except the baseline compliance cost=7). We present results for all periods pooled, as well as results separating the early session treatment sequences from the late session treatment sequences. Consistent with previous research that employs this quantal choice approach (e.g., McKelvey and Palfrey, 1995), the choice errors decline as subjects gain experience. This is reflected in the significantly lower μ estimate for the late period sequences.

Figure 3 illustrates the remarkable success that this simple, one-parameter model has in explaining the deviations from the optimal choices, based on the pooled estimate for the entire dataset.[8] It is important to keep in mind that the noise parameter does not provide freedom to explain any deviations; instead, each particular value of μ is consistent with only one specific

[8] We could obviously fit the observed rates more accurately with treatment cell-specific μ estimates. As Haile et al. (2003) have recently emphasized, however, it is important to leave the estimated parameter unchanged across treatments to make comparative statics exercises informative.

combination of deviations across our treatments. Nevertheless, all of the observed violation rates are accurately predicted by the model, with the greatest deviation only 14 percent. Moreover, the model accurately captures the qualitative differences across treatments, such as the higher group 1 violation rates when the compliance cost is greater.

5: Discussion

Enforcement and monitoring of regulatory compliance policies can incur substantial resource costs. Dynamic audit models help us in understanding how individuals and firms might behave when faced with enforcement and compliance rules that are conditional on actions in previous and current periods. Harrington's (1988) important model demonstrates how a regulator could use multiple inspection groups to increase enforcement leverage when political or other practical considerations limit the size of fines. While there is a body of theoretical research in this area, empirical analysis of the compliance strategies of individuals in this dynamic framework is limited by a lack of observability for key variables in the theories.

Laboratory evidence presented in this paper shows that in a broad sense many subjects' behavior is consistent with the theoretical predictions of this dynamic enforcement model. Overall violation rates are significantly higher in group 1 than in group 2. When compliance costs are higher then the violation rates increase significantly. We also obtain clear support for the more subtle prediction that compliance increases in the "bad" group 2 if it is more likely to be rewarded with a transition back to the "good" group 1. That is, our results support the general idea of enforcement leverage through transitions across multiple groups.

An examination of the compliance policies chosen by the subjects reveals that a large proportion of the subjects choose the strategy predicted by the Harrington model. Subjects in our experiments do not, however, follow the sharp predictions of the model. The deviations are more pronounced when the model makes corner solution predictions even though the differences in expected profits are marginal for alternative policies or actions. To account for this we consider a quantal choice model where subjects are assumed to be boundedly rational. The standard rational choice model assumes that firms and individuals respond to regulatory policies by choosing strategies that increase their payoffs. They might however not choose the exact optimal strategy at all times; i.e., they may make some mistakes, although it seems sensible that they would tend to make fewer mistakes when the mistakes are more costly. This aspect of bounded rationality is often neglected in a policy setting.

To understand individual and firm behavior and formulate policies that provide incentives for better regulatory enforcement, our results suggest that more attention can be paid to models that incorporate noisy decision making. The quantal choice model accurately accounts for the boundedly rational behavior of our laboratory subjects, and it may also be useful for describing compliance choices of agents in the field. When faced with decisions like reporting income for taxation purposes and environmental regulation, often agents might be boundedly rational. Though they would choose strategies that increase their earnings, they might be prone to errors at the margin, where the incentives to optimize are not very high. How they act at this margin could in some cases determine the success or failure of the regulatory policy, and the implications of such suboptimal behavior should be examined carefully. In some applications the compliance decisions are made by groups rather than individuals, and future research should study whether groups' rationality is also bounded similarly (e.g., Cason and Mui, 1997; Blinder and Morgan, 2005).

If bounded rationality in this context displays a robust influence on behavior, then enforcement models themselves should also be more accurate if they incorporate bounded rationality explicitly. For example, the Harrington model implies optimal endogenous enforcement parameters to maximize efficiency (for each particular compliance cost) in which the firm only slightly prefers to comply rather than violate in the high intensity inspection group. Since at this margin the firm is nearly indifferent between the two strategies, the alternative behavioral prediction from the quantal choice model instead predicts that the firm would comply only about half the time. This obviously has important implications for the choice of the optimal enforcement rule in practice.

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Table 1: Payoff Parameters for Enforcement Game

	Group 1		Group 2	
	Comply	Violate	Comply	Violate
Inspection Probability	$p_1 = 0.2$		$p_2 = 0.5$	
No Inspection	c = 100, 200, 375 (baseline c = 7)	0	c = 100, 200, 375 (baseline c = 7)	0
Inspection	c=100, 200, 375	$F_1 = 50$	c = 100, 200, 375	$F_2 = 300$
		moved to G_2 with Prob =1	Prob(moved back to G_1) = u =0.1, 0.9	

Table 2: Expected Payoff of Alternative Policies

Policy	Expected Payoff if in Group 1	Expected Payoff in Group 2
Always comply: f_{00}	$\frac{R-c}{1-\beta}$	$\frac{R-c}{1-\beta}$
Comply only in Group 1: f_{10}	$\frac{R}{1-\beta}$ - $\frac{cp_1\beta + p_1F_1(1-\beta+p_2u\beta)}{(1-\beta)(1-\beta+p_1\beta+p_2u\beta)}$	$\frac{R}{1-\beta}$ - $\frac{c(1-(1-p_1)\beta)+\beta p_2 u p_1 F_1}{(1-\beta)(1-\beta+p_1\beta+p_2u\beta)}$
Never comply: f_{11}	$\frac{R}{1-\beta}$ - $\frac{p_1F_1(1-\beta)+\beta p_1 p_2 F_2}{(1-\beta)(1-(1-p_1)\beta)}$	$\frac{R-p_2F_2}{1-\beta}$

Table 3a: Predicted and Observed Violation Rates for Inspection Group 1

Probability an Inspected, Compliant Firm Exits Group 2		Compliance Cost=7	Compliance Cost=100	Compliance Cost=200	Compliance Cost=375
u=0.1	Observed Violation Rate		371/511 = 73% (158/206=77%)	210/243 = 86% (59/68=87%)	198/221 = 90% (47/50=94%)
	Predicted Violation Rate		1	1	1
u=0.9	Observed Violation Rate	136/795 = 17% (69/395=17%)	506/607 = 83% (151/177=85%)	538/603 = 89% (210/218=96%)	502/539 = 93% (277/276=97%)
	Predicted Violation Rate	0	1	1	1

Note: Data for late sequences 5-7 only are shown in parentheses.

Table 3b: Predicted and Observed Violation Rates for Inspection Group 2

Probability an Inspected, Compliant Firm Exits Group 2		Compliance Cost=7	Compliance Cost=100	Compliance Cost=200	Compliance Cost=375
u=0.1	Observed Violation Rate		116/526 = 22% (54/217=25%)	359/732 = 49% (115/244=47%)	529/655 = 81% (229/262=87%)
	Predicted Violation Rate		0	1	1
u=0.9	Observed Violation Rate	28/188 = 15% (21/130=16%)	65/359 = 18% (20/135=15%)	138/369 = 37% (45/154=29%)	255/399 = 64% (128/204=63%)
	Predicted Violation Rate	0	0	0	1

Note: Data for late sequences 5-7 only are shown in parentheses.

Table 4: Compliance Strategy Classification Rates, Allowing for 0% Error Classification Threshold

Probability an Inspected, Compliant Firm Exits Group 2	Compliance Policy	Compliance Cost=7	Compliance Cost=100	Compliance Cost=200	Compliance Cost=375
	f_{00} frequency (rate)		0 (0%)	0 (0%)	0 (0%)
	f_{01} frequency (rate)		0 (0%)	0 (0%)	0 (0%)
	$f_{0?}$ frequency (rate)		4 (4%)	0 (0%)	0 (0%)
	$f_{1?}$ frequency (rate)		6 (5%)	7 (6%)	11 (10%)
	f_{10} frequency (rate)		21 (19%)	9 (8%)	2 (2%)
	f_{11} frequency (rate)		2 (2%)	3 (3%)	14 (13%)
u=0.1	$f_{?0}$ frequency (rate)		5 (5%)	8 (7%)	0 (0%)
	$f_{?1}$ frequency (rate)		2 (2%)	6 (5%)	30 (28%)
	other freq. (rate)		71 (64%)	77 (70%)	52 (48%)
	Total subjects		111	110	109
	f_{00} consistent (rate)		9 (23%)	8 (24%)	0 (0%)
u=0.1 Summary	f_{10} consistent (rate)		**32 (80%)**	24 (73%)	13 (23%)
	f_{01} consistent (rate)		6 (15%)	6 (18%)	30 (53%)
	f_{11} consistent (rate)		10 (25%)	**16 (48%)**	**55 (96%)**
	Classifiable subjects		40	33	57
	Optimal Policy		f_{10}	f_{11}	f_{11}
	f_{00} frequency (rate)	30 (27%)	2 (2%)	0 (0%)	0 (0%)
	f_{01} frequency (rate)	0 (0%)	0 (0%)	0 (0%)	0 (%)
	$f_{0?}$ frequency (rate)	31 (28%)	1 (1%)	0 (0%)	0 (%)
	$f_{1?}$ frequency (rate)	1 (1%)	3 (3%)	14 (13%)	13 (12%)
	f_{10} frequency (rate)	5 (5%)	45 (41%)	35 (32%)	18 (16%)
	f_{11} frequency (rate)	2 (2%)	0 (0%)	2 (2%)	19 (17%)
u=0.9	$f_{?0}$ frequency (rate)	1 (1%)	1 (1%)	0 (0%)	0 (0%)
	$f_{?1}$ frequency (rate)	0 (0%)	0 (0%)	1 (0.9%)	5 (5%)
	other freq. (rate)	41 (37%)	57 (52%)	58 (53%)	56 (50%)
	Total subjects	111	109	110	111
	f_{00} consistent (rate)	**62 (89%)**	4 (8%)	0 (0%)	0 (0%)
u=0.9 Summary	f_{10} consistent (rate)	7 (10%)	**49 (94%)**	**49 (94%)**	31 (56%)
	f_{01} consistent (rate)	31 (44%)	1 (2%)	1 (2%)	5 (9%)
	f_{11} consistent (rate)	3 (4%)	3 (6%)	17 (33%)	**37 (67%)**
	Classifiable subjects	70	52	52	55
	Optimal Policy	f_{00}	f_{10}	f_{10}	f_{11}

Note: The percentage rates shown in the *frequency* section of the table are percentages of the total number of subjects making choices in that treatment condition. The percentage rates shown in the *consistent* section of the table are percentages of the classifiable subjects in that treatment condition. These latter percentages sum to greater than 100 percent because some subjects' observed choices are consistent with multiple compliance policies. The numbers in **bold** are the number of classifiable subjects consistent with the optimal policy.

Table 5: Best-Fitting Compliance Strategy for Each Subject in Each Treatment

Probability an Inspected, Compliant Firm Exits Group 2	Compliance Policy	Compliance Cost=7	Compliance Cost=100	Compliance Cost=200	Compliance Cost=375
	f_{00} frequency (rate)		30 (27%)	31 (28%)	8 (7%)
	f_{10} frequency (rate)		**85 (77%)**	66 (60%)	32 (29%)
u=0.1	f_{01} frequency (rate)		20 (18%)	36 (33%)	55 (50%)
	f_{11} frequency (rate)		35 (32%)	**59 (54%)**	**96 (88%)**
	Total subjects		111	110	109
	Optimal Policy		f_{10}	f_{11}	f_{11}
	f_{00} frequency (rate)	**89 (80%)**	14 (13%)	3 (3%)	2 (2%)
	f_{10} frequency (rate)	21 (19%)	**93 (85%)**	**88 (80%)**	67 (60%)
u=0.9	f_{01} frequency (rate)	43 (39%)	9 (8%)	9 (8%)	10 (9%)
	f_{11} frequency (rate)	8 (7%)	21 (19%)	49 (45%)	**75 (68%)**
	Total subjects	111	109	110	111
	Optimal Policy	f_{00}	f_{10}	f_{10}	f_{11}

Note: The percentage rates shown in the *frequency* section of the table are percentages of the total number of subjects whose choices minimize the number of deviations from the indicated strategy in that treatment condition. The optimal policy is highlighted in **bold**. The percentages sum to greater than 100 percent because some subjects' observed choices are best fit by two different compliance policies, particularly when they do not make compliance choices in one of the inspection groups.

Table 6: Quantal Choice Model Maximum Likelihood Estimates

Dataset	μ estimate (standard error)	Log-likelihood	Number of Observations
All Periods	976 (35)	-2927.6	5764
Early Sequences 1-4	1144 (57)	-1915.4	3553
Late Sequences 5-7	747 (39)	-992.6	2211

Figure 1: Predicted and Observed Overall Violation Rates, by Treatment, for Two Sets of Later Periods

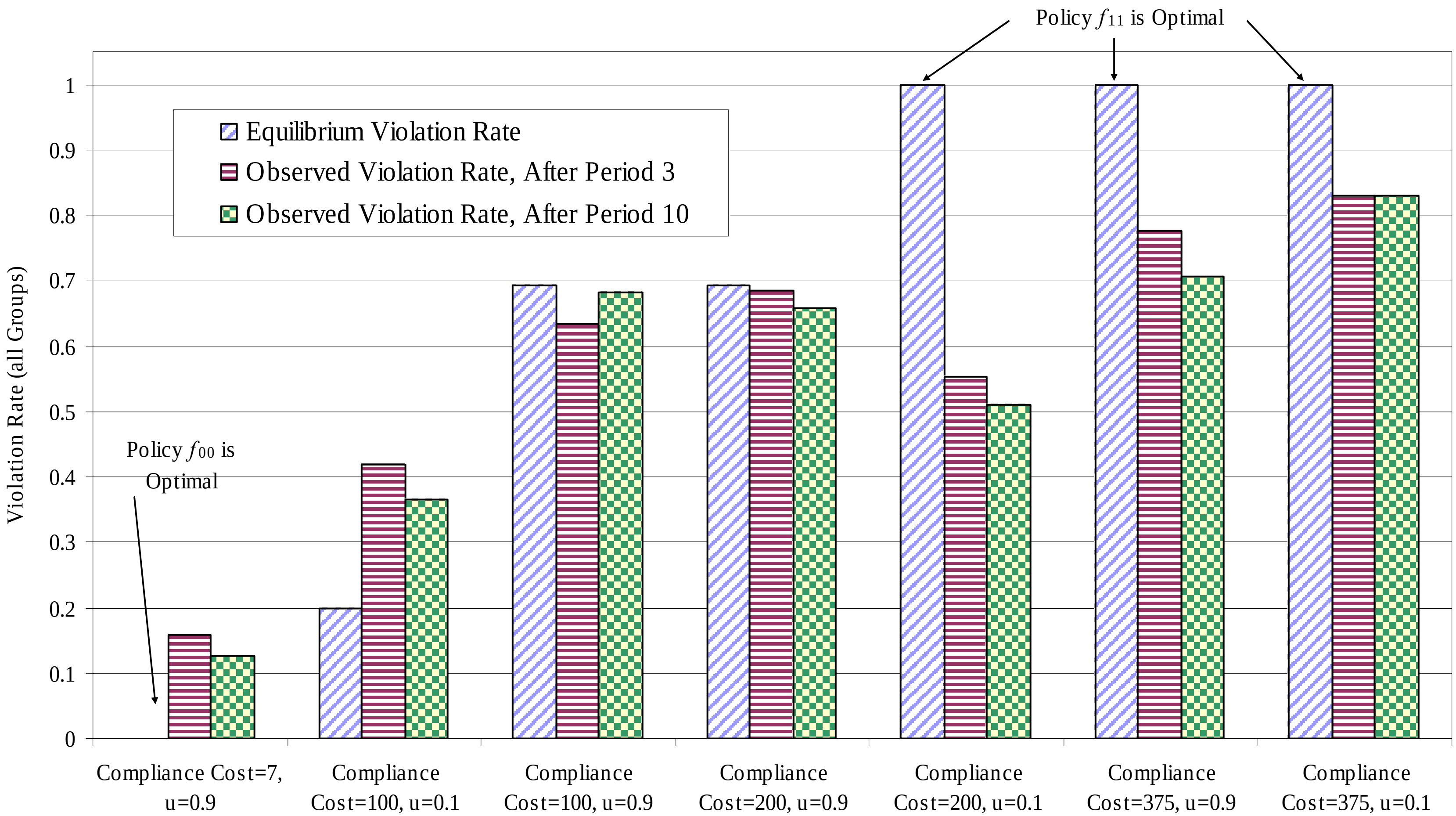


Figure 2: Predicted and Actual Violation Rates when in Inspection Group 2

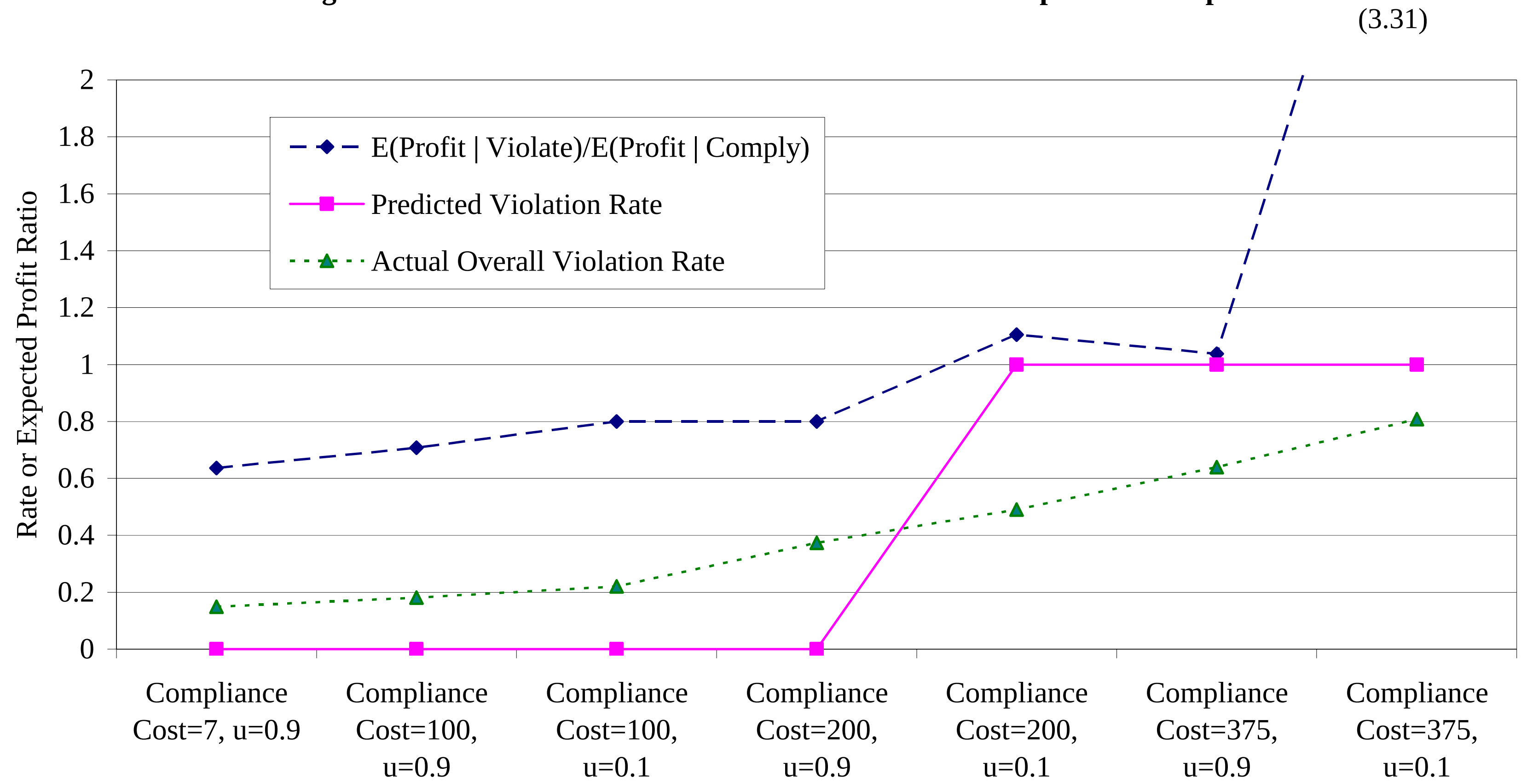
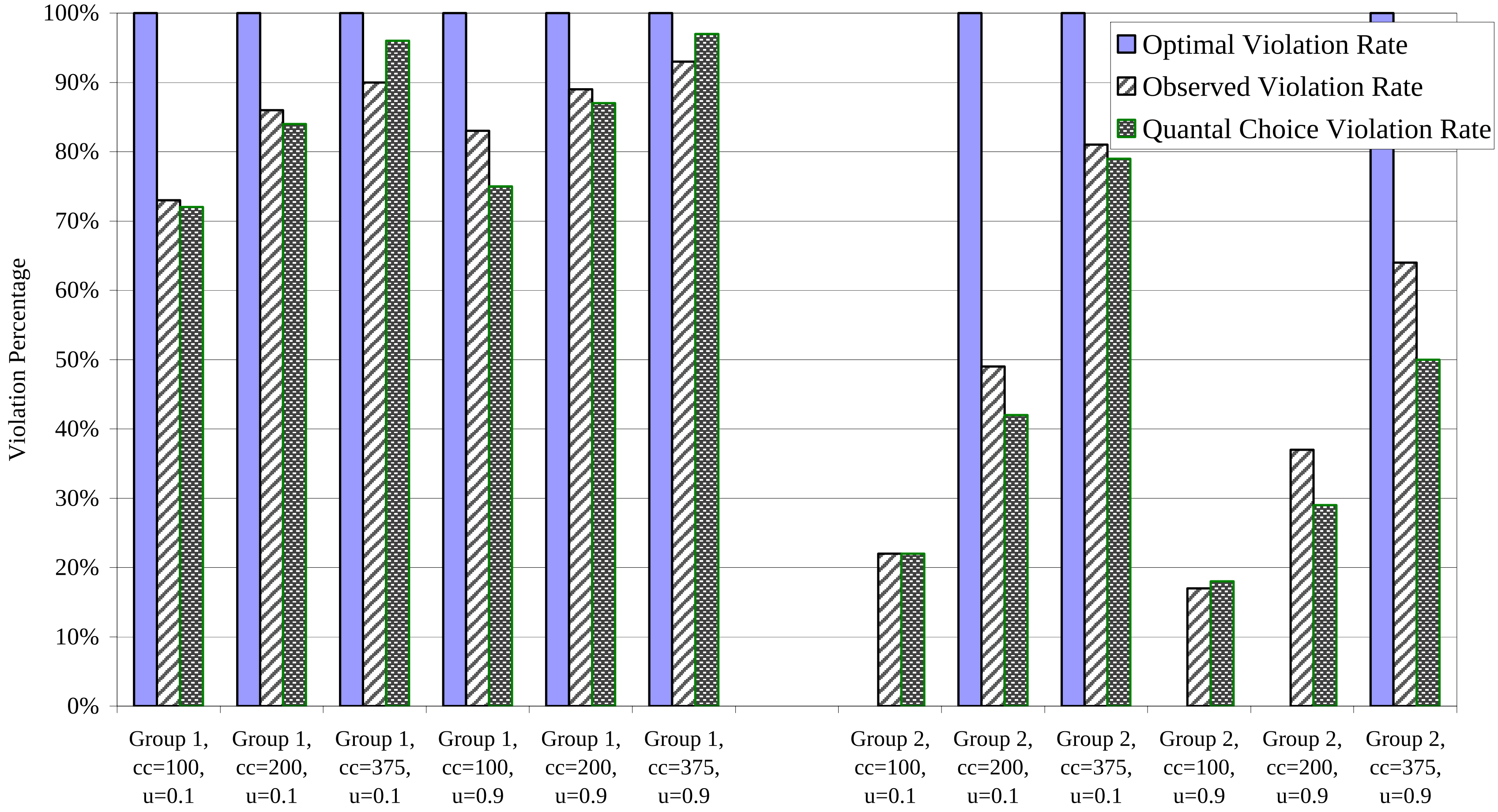


Figure 3: Observed and Predicted Violation Rates (Quantal Choice and Perfectly Optimal Benchmarks)
All for μ=976



Appendix

Table A1: Wilcoxon Signed Rank Tests Comparing Violation Rates in Inspection Group 1 to Inspection Group 2.

Probability an Inspected, Compliant Firm Exits Group 2	Compliance Cost=7	Compliance Cost=100	Compliance Cost=200	Compliance Cost=375
u=0.1		**1072.5****	489.5**	99.5**
u=0.9	184.5**	**1757****	**1517.5****	960.5**

Note: The numbers reported in each cell are the values of the Wilcoxon signed rank test statistic. Only the **bold** numbers reflect differences that the model predicts to be significant.
**: Indicates significance at the 1% level.

Table A2: Wilcoxon Signed Rank Tests Comparing Violation Rates for Different Compliance Costs.

Probability an Inspected, Compliant Firm Exits Group 2		Inspection Group 1	Inspection Group 2
u=0.1	Cost = 200 versus Cost = 100	181**	**800****
	Cost = 375 versus Cost = 200	39	1121**
u=0.9	Cost = 100 versus Cost = 7	**2084****	23
	Cost = 200 versus Cost = 100	283**	264.5**
	Cost = 375 versus Cost = 200	126	**576****

Note: The numbers reported in each cell are the values of the Wilcoxon signed rank test statistic. Only the **bold** numbers reflect differences that the model predicts to be significant.
**: Indicates significance at the 1% level.

Table A3: Wilcoxon Signed Rank Tests Comparing the Violation Rates for Different Probabilities of Exiting from Group 2 (*u*)

Inspection Group	Compliance Cost=100	Compliance Cost=200	Compliance Cost=375
1	-80.5	-19.5	-27
2	207.5**	**566****	518.5**

Note: The numbers reported in each cell are the values of the Wilcoxon signed rank test statistic. Only the **bold** numbers reflect differences that the model predicts to be significant.
**: Indicates significance at the 1% level.